Doctoral dissertation

Fuzzy Model For Human Color Perception and its Application in E-commerce: Apparel Color Coordination

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Abstract

Current dissertation proposes the novel approach for color information representation and processing using fuzzy sets and logic theory. Our method is based on the fuzzification of the well-known HSI color space. Specifically, we use fuzzy mathematics to partition the gamut of feasible colors in HSI space based on standard linguistic tags. As a result we obtain a set of fuzzy colors, a human-consistent color model - FHSI (Fuzzy HSI) color model. In FHSI color channels distributions are expressed with fuzzy membership functions. Soft boundaries between color zones were defined empirically. In fact, membership functions were derived from the experimental results we got from a survey. In FHSI, colors are modeled considering the imprecision, subjectivity, context dependency and non-uniformity of color distributions.

Fuzzy sets are very suitable for this purpose since humans have different levels of visual sensitivity and different color perception abilities. Fuzzy logic is tolerant of imprecise data, so it enables us to make borders between red and orange, harmonious and non-harmonious somewhat blurred. In addition, fuzzy approach allows us to define query conditions on the basis of linguistic terms, which is more natural way for a user to express his desire. It also allows to account for the non-uniformity of color distributions. This method enables to directly model colors such "light blue" or "deep red" and retrieve images based on fuzzy dominant colors expressed through linguistic descriptions.

We also provided objective measures for finding the image similarity in a way that matches human evaluation. Our formula takes into account the notion that different hues have various value ranges, due to linguistic conventions of the society (e.g. green color). In our color difference method, we use the saturation as a weighting factor, giving priority to the hue when the saturation is high, and giving priority to the intensity value when colors have low saturation.

Colors are in general imprecise. For example, it is not possible to draw a clear boundary delimiting blue and green colors. So, "blue" is a gradual concept and the boundary between what is blue and what is not blue is fuzzy. By adopting fuzzy set representations we solve the problem of the semantic gap between color representation in computers and high-level linguistic terms and aesthetic concepts. By performing color feature extraction of images, FHSI model is further exploit in the application of image indexing and retrieval.

The currently most popular and widely used approach for image retrieval is based

on text annotations. Thus, images are associated and indexed with certain keywords and tags, which are used to search for images. However, TBIR has limitations like subjectivity (i.e., different people may interpret an image differently) and incompleteness because they do not necessarily reflect the low-level image features very well. Moreover, TBIR systems require humans to manually describe every image in the database, which is obviously impractical for large databases.

Developed apparel online shop with underlying fuzzy color processing mechanisms allows to overcome the limitations of the traditional e-commerce search by providing automatic labelling. It supports the processing of three types of queries: linguistic, exemplar(involving a reference image) and combinational.

Our system has two important parts: assigning a fuzzy colorimetric profile (indexing stage) to the image and processing the user query (retrieval stage). System is also able to process impressions like *formal* (dark colors), *creative* (yellow, orange), *luxury*(violet, golden), *romantic*, *warm, pastel, elegant, neutral, fresh*, etc.

In addition, we use FHSI to develop a technique to predict the aesthetic preference for color combinations from an individual color preference and harmony. One of the possible applications of that is to to deal with the uncertainty linked to apparels images for the online shopping coordination.

People regard color as an aesthetic issue, especially when it comes to choosing the colors for their clothing, apartment design and other objects around. Aesthetic experiences are omnipresent in modern life. However, there is no scientifically comprehensive theory that can explain, evaluate and predict aesthetic preferences. Visual stimuli are usually multidimensional, while their perception is subjective. Color is one of such dimensions and is considered to be the main variable affecting aesthetic preferences.

Important variables involved in aesthetics are preference and harmony. FHSI space was successfully used for quantitative evaluation of the harmony and preference phenomena for the intended application of apparel coordination. Preference for color schemes is predicted by combining preferences for the basic colors and ratings of color harmony. For example, in the context of apparel coordination, it allows predicting a preference for a look based on clothing colors.

The model was experimentally validated with three different types of experiments - *Two Alternative Forced Choice, Rank Ordering* and *Rating.* According to experiments, the model results in useful predictions of ratings of harmony and preference - the predictive power was quite high in all sessions. In addition, we analysed the system performance based on standard recall and precision metrics. We also developed a software and a library implementing the model.

Our system differs from traditional image retrieval systems in a number of aspects, like automated item description based on color schemes and natural query language, account for a personal variation. It has potential in a wide range of color image applications and is suitable for a number of domains, including fashion, design, marketing, and art.

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Chapter 1

Introduction

What is needed for any product to arouse interest? The answer is - it needs to create an impression on a potential customer. Color plays a significant role in an overall impression that the object creates. Color is often considered to be one of the most important and distinguishing visual features. It is one of the features that humans remember the most and very often regard it as an aesthetic issue. Currently, color is omnipresent and affects nearly all aspects of life [14] , including human culture, psychology, and shopping habits. In some cases, color plays a determining role in making a decision to buy some commodity, especially if it is clothes. According to [86], color sells products - it accounts for 85% of the reason why consumer purchases a product. Color influences purchasing behavior - to a certain extent, it is a reflection of human's likes and dislikes.

In addition, color is a low-level feature that is computationally inexpensive [90]. Its meaning is growing almost in every industry. In particular, it has been widely used for many applications in computer vision, especially for Content-based Image retrieval (CBIR) in multimedia databases [13], [66], [58]. We can use the aesthetics of colors to attract customers and to fill them with color-related associations [14]. The problem is that matching human color perception is not an easy computing task, because humans perceive colors very subjectively.

RGB color model arising from color display hardware is not user-friendly, offering a choice of 16 million colors. In image processing applications, other color spaces such as HS* (HSI, HSV) are more preferable [43]. However, HS* family spaces do not consider non-uniformity of color distributions. Color histograms created using modern color spaces neither consider the color similarity across different bins nor the color dissimilarity in the same bin.

The current work aims to develop a methodology for retrieving images in e-commerce field based on fuzzy dominant colors expressed through linguistic descriptions[70]. In order to achieve this, we analyze the processes underlying human color perception. Next, we try to mimic them using a theory of visual attention and a fuzzy set theory as it is widely recognized as a tool for effective imprecision modelling in image processing[50],[27].

Indeed, color naming is inherently imprecise, so we use the fuzzy semantics of color names in the HSI (Hue, Saturation, Intensity) color space. This process involves two steps:

1. Assigning a fuzzy colorimetric profile to the image

2. Processing the user query

1.1 Color Theory Fundamentals

1.1.1 Physical Explanation of Color

Obviously, we do not need to know everything about physics of colors to understand color theory. So, in this subsection we just want to shed a bit light on color physics to understand the color theory more consciously.

First phenomena that novices in color theory tend to resist is that color is not an intrinsic object property, but is a function of the human visual system. Therefore, objects do not "have" color as a property, they give off light that "appears" to be a color. Yes, color exists only in the mind of the beholder [11].

Color is derived from reflected light. Fig. 2.1 illustrates the process of how we see colors. First, light goes from the source (e.g., the sun) to an object. White sun light is actually a combination of all colors. Second, we see colors that are reflected, and the rest is absorbed by the object. Next, our eyes tell our brains special about the light. So, color is determined first by frequency and then by how those frequencies are combined or mixed when they reach they eye. Humans have a special brain part that is called neocortex. It is responsible for numerous activities related to language, movement, and problem solving [14]. The decision – whether to buy or not to buy – can be referred to as a small problem solving. Neocortex earns almost all information through the eyes. Obviously, everything we see is colored. So, now we are closer to the very important process of impression creation. The workflow is as follows. A customer sees a product - a light with the respective wavelengths enters his retina. Then, special sensitive receptors fire up and send certain signals to our brain. This eventually results in the perception of color. Then the decision to buy or not to buy is done. In addition, certain associations, norms, individual experience, different perception abilities influence this process. Each individual perceives colors slightly differently, by reason of different physiology and so as sensitivity. Thus, human perception of color is subjective to a certain degree [45].

1.1.2 Human Color Perception

Humans perceive colors in a very subjective manner. Matching human sensitivity and subjectivity in color perception is a great challenge to the research community. Color

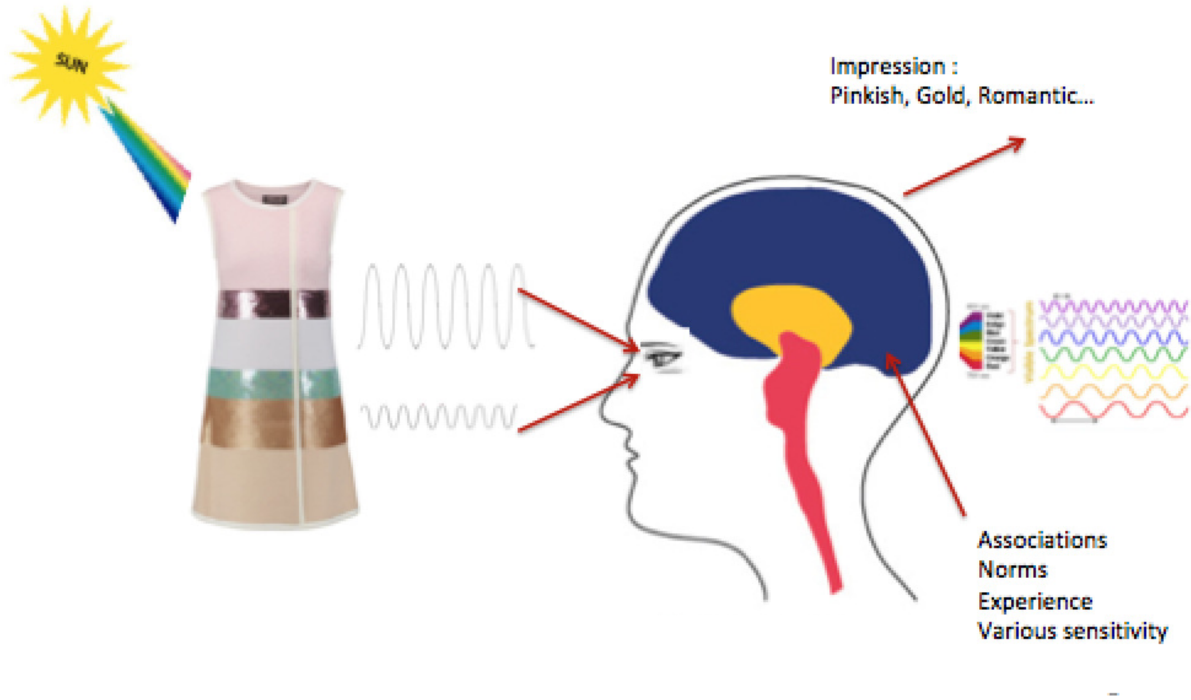


Figure 1.1: Color perception process.

is one of the features that the humans remember the most and it plays an extremely important role in an overall impression that some object creates on humans. It has attracted a great interest in various fields, especially in e-commerce and marketing.

What is human color perception? Since individuals have differences in visual sensitivity, they have different color perceptions. Recently a single dress image polarized the whole Internet into two aggressive groups of people arguing whether a picture depicts a blue dress with black lace fringe or white with gold lace fringe. This is a great example to explain human color perception. An explanation for this lies in a complex structure of a human visual system.

As we know, light enters the human eye through the lens (i.e. various wavelengths corresponding to various colors). Then, the light hits the retina in the back of our eye, exactly at a place where pigments "wake up" neural connections to the special brain part that processes those signals into an image. Our visual system tends to extract information about the real reflectance and throw out information about the illuminant. So, it automatically tries to subtract the chromatic bias of the daylight axis when a human looks at the object[21]. The fact that the daylight varies from pinkish to blue-white (dawn and noon) makes different people see colors presented at some object differently. The trick with this image is that it hits some kind of perceptual boundary. In most cases, the system works fine and differences are not so critical[21]. However, they still exist. That is the primary motivation to count subjectivity in color perceptions.

Figure 1.2: The original disputing image is in the middle. At left it is white-balanced and seems white-gold. At right, white-balanced to blue-black. In the reality, it is blue-back.

Usually, color perception involves attaching a label to a color so as to categorize it. Humans perform perceptual categorization through the processes of visual recognition and attentional selection[5]. According to Bundesen[5], a perceptual categorization has the form "x belongs to i" (denoted by $E(x,i)$, $E(x,i) \in [0,1]$), where x is an input element in the visual field to be categorized (called *perceptual unit*) and i is a *perceptual category*. The collection of all perceptual units is denoted by S and the collection of all categories is denoted by R.

In his work Bundesen discusses 3 types of perceptual categories, namely a color category, a shape category and a location category[5]. Our image retrieval model is founded mainly on color analysis. Therefore, we can follow the notation proposed in[5] with the assumption that perceptual categories are represented solely by colors.

Let's review the main concepts from a theory of visual attention[5]. *Saliency* of x to i stands for the strength of sensory evidence that element x belongs to a perceptual category i, denoted by $\eta(x,i)$. Every category i is assigned a *pertinence* value π_i, representing its current importance for a certain task T. Knowing pertinence and salience values we can derive an attentional weight of x :

$$\omega_x = \sum_{i \in R} \eta(x,i)\pi_i \tag{1.1}$$

Note that in Eq. (1.1) $\pi_i > 0$, so only categories having positive pertinence values contribute to ω_x. In addition, it is important to point out that pertinence of a category is highly context-dependent and can vary across various tasks. For example, in color theory, hue usually draws more attention rather than saturation and intensity. However, certain pertinence values may vary for various contexts and tasks (e.g., medical image processing, e-commerce).

Two accompanying mechanisms for visual attention are filtering and pigeonholing. Filtering is selecting an item $x \in S$ for a target category i. In e-commerce context, it might be the case when a user searches for e.g., *a pale green dress*, "filtering" an online store catalog. On the other hand, given a certain item $x \in S$, pigeonholing is the process of selecting an appropriate category $i \in R$ for x. For example, when a system collects user relevance judgments on some clothing items, conducting an online survey, a user might be offered to categorize the items as being, e.g., *white and blue, deep red*, etc.

1.1.3 Color Spaces

Color space is a method of color representation. Color spaces provide a way to represent, process, and manipulate colors. There are a number of color spaces popular today, but none of them can dominate the others for all kinds of images. So, the choice of a suitable color model remains a challenge for researchers working in the field of color image processing [66], [26], [69]. In general, this is largely dependent on the target system requirements.

In this subsection, we consider some popular color models with the aim of providing the background against which selection of the proposed system that is used as a base for the human-consistent fuzzy color representation takes place. Based on some color space we can develop Fuzzy color space, in order to systematically organize the set of all possible human color perceptions. Lets consider some of the most popular color spaces.

The choice of a suitable color model is largely dependent on the application. We adopt the HSI color space, because of its similarity with the way a human observes colors and the fact that the intensity is separated from chrominance, so the chromatic information of the original image will be preserved. In addition, HSI is not only more intuitive than raw RGB values, but also efficient - the conversions to/from RGB are fast to compute.

Additive and Subtractive Color Spaces

Perhaps the most well-known color model is RGB (red, green, and blue), which functions by representing additive color combinations(e.g. overlapping lights, display on LCD) [81]. Although it is useful for displaying color images (on LCD monitors, projectors, etc.), the boundaries between the color categories in the RGB model are too complex to be determined [4]. It is not convenient for analysis, due to high correlation [82]. So, if intensity changes, all r, g and b values change accordingly. As a result, chromatic information can be lost.

In another popular system, CMYK, colors are considered as subtractive mixtures of varying quantities of cyan (C), magenta (M), yellow (Y), and black ink (K) colorants. Actual color printing additionally uses black ink (K), to limit the use of expensive colored inks and speed drying times. It is mostly used for color printing(e.g. mixing dyes, inks, pigments). Pigments display colors by the way of absorbing some wavelengths of lights and reflecting the remaining ones.

It is important to note that the distance between colors in both the additive and subtractive color models (i.e., the RGB and CMYK spaces) does not represent color differences in the way the human visual system perceives them [2] , [20]. Owing to this non-uniformity and the high correlation among their components [81], it is very difficult to define the similarity between colors in the RGB or CMYK space [58], [38].

HS* Family of Color Spaces

Color spaces that have been defined with the aim of solving the problem of perceived luminance are HSL, HSV (or HSB), and HSI, all of which are color spaces of the HS* family [58]. In comparison to the RGB and CMYK spaces, the HS* spaces are based upon how colors are conceptualized in human vision in terms of such attributes as hue, lightness, and chroma. They transform the RGB cube into a representation of cylindrical coordinates. HSL and HSV are widely used in color pickers and image editing software [20]. The third model, HSI, attempts to balance the advantages and disadvantages of the other two systems. HSI has found application in computer vision and image analysis. Besides being more intuitive, HS* models are also efficient - conversions to/from RGB can be rapidly computed. This is highly important, because input images are usually provided in RGB format.

In HSI model, colors are expressed using 3 attributes, namely, hue (e.g. red, orange, green), intensity (light vs dark) and saturation (intense vs dull). So, it is closer to the way colors are conceptualized in human visual system, since the latter is based on three understandings of the color: the category, the purity and the brightness, which fits HSI exactly.

We adopted the HSI color space for our approach, mainly because it is perceptually intuitive [4] and tends to outperform other color models in image retrieval applications having good performance. In addition, this model is compatible with the vision psychology of human eyes [69], and its three components are relatively independent [2]. The HSI model has another important advantage in that it separates the intensity from the chrominance; hence, the hue is invariant to shading/highlights. This greatly simplifies the process of identifying colors that are perceptually close and combining them into homogeneous regions.

In most cases, the RGB model is often used to depict the color information of an image [38]. However, recent researches in the field of image processing mostly make use of HSI space. The reason is that in HSI the specific color can be recognized regardless of variations in saturation and intensity, since hue is invariant to certain types of highlights, shading, and shadows. So, it will be much easier to identify the colors that are perceptually close and combine them to form homogeneous regions representing the objects in the image. As a result, the image could become more meaningful and easier for analysis.

Other Color Models

Other models, including CIELAB or CIECAM02, are considered to offer improved uniform color display, but their adoption has been slow. Their drawback is that they are much more computationally expensive and conversion to/from the RGB model seems infeasible for real-time systems. Uniform color spaces from CIE* family also have limitations like producing intensive computations and difficulties in getting a tone modifier.

Another competitive color model is the Munsell color space, which uses a method based on a color atlas. However, it is based on subjective observations rather than perceptual experiments or direct measurements. Recent research unveiled the fact that the Munsell space is not as perceptually uniform as it was originally claimed to be [58]. Moreover, it cannot be directly integrated with additive color schemes such as RGB.

As we see, there are various color spaces, each with its own advantages and limitations. RGB is one of most widely used color space. However, high correlation between its channels hinders its work in many applications.

1.2 Visual Information Retrieval

Color has been widely used in many computer vision applications, especially for Content-based Image retrieval (CBIR) in multimedia databases [35][41].

1.2.1 CBIR and TBIR

At present, online shopping systems mostly use approach for image retrieval which is based on text descriptions, tags, and keywords. This technique is referred to as a text-based image retrieval (TBIR). This method is disadvantageous for a number of reasons. One of them is the subjectivity and possible incompleteness of text annotations, in particular, color information of clothing items[72]. The other reason is that text-based retrieval requires performing the manual image tagging, which is expensive, time-consuming and impractical for large multimedia databases.

Content-based image retrieval (CBIR) is a popular technique nowadays. Google, Microsoft, Baidu and other companies have recently launched CBIR-based services. However, CBIR is still not disseminated among the shopping portals, like Amazon, eBay, Taobao, Lamoda, etc., they do not offer color indexing, so color names and other text-based descriptions are treated as common keywords/tags. Reliable operation of such systems requires understanding the correspondence between the linguistic terms and colors. For instance, it is difficult for current systems to find out that deep red is more similar to crimson rather than to Turkish red.

Modern search engines are able to find clothing items by brand, basic characteristics, color, like “deep blue” or, for instance, by its aesthetic category, like “elegant” or “formal”. Most current online shopping systems perform this kind of search simply by keywords/tags matching. So, if a web page contains, for example, the word “bright”, it will be returned as a result of the search query “bright shirts” [70].

Current recommendation systems are based entirely on customer data (profile info, interaction history, including the purchasing behavior). Many other combinations of matching clothing apparels may exist (e.g., based on a color harmony). However, they are not disseminated at present.

1.2.2 Overview of Current Image Retrieval Techniques in E-commerce

With the continued rapid growth and development of e-commerce, an online shopping has become a very easy process, with a number of intelligent technologies simplifying the work user needs to perform to find a perfect match. For example, smart search engines, that are able to not only find clothing commodities by its brand or basic characteristics, but also by its color, like “dark green” or, for instance, by its aesthetic category, like “elegant” or “romantic”. However, the machine itself does not understand aesthetics or colors in the same way as humans do - it only retrieves the shopping items according to corresponding tags specified by humans[76]. So, if a web page contains, for example, the word “bright”, it will be returned as a result of the search query “bright shirts”. The obvious drawback of this approach is that some bright shirts, that are not indexed, will never be included in the search results.

Another great technology that has made a modern online shopping easier is recommendation systems. For example, when a user tries to find some commerce related item using Google search engine, the system uses user’s preferences, profile information and interaction history to provide recommendations for the object and can re-rank search results accordingly. In addition, some online stores, like Amazon, deploy item-to-item correlation recommender systems based on purchase data[65]. What it means is that if a user added, for example, a dress into his shopping cart, and many other people, who bought this dress, purchased some bag, the system will make an offer to a user to co-purchase this bag along with the dress. However, such systems are based entirely on user input data (interaction history). Many other combinations of matching apparel pieces may exist (e.g., based on a color harmony), but the machine will never know it without human intervention.

At present, a traditional e-commerce search is based on keywords matching. Indeed, most online shops tend to use conventional text-based image retrieval (TBIR), in which items are retrieved from the database based on the given tags, keywords or text annotations. In contrast, CBIR is image-based and makes use of visual content, like color, texture, shape, to fetch images from databases.

Although it is a popular technique nowadays (e.g. Google search by image) its still not disseminated in e-commerce. Even the most popular shopping portals, like Amazon, eBay, Taobao, etc. do not provide color indexing, so color names and other text-based descriptions are treated as common keywords/tags.

Users of such IR systems express their query using the text containing the keywords. Therefore, reliable operation of such systems makes it necessary to understand the correspondence, or mapping, between the content and text. To be more specific, between the linguistic terms and colors. There are 2 problems here. Firstly, sometimes users are not able to express their intentions precisely using the text. Secondly, the retrieval system lacks the understanding of the query. There are some attempts to solve these problems, like the adoption of an ontology for unifying the semantically close terms. However, they are not sufficient to find the semantic connections between concepts. For instance, it is difficult for current systems to find out that deep red is more similar to crimson rather than to Turkish red.

Another issue to be pointed out regarding the conventional online shops is that, in most cases, the output results are too strict. In other words, they exactly fit the query and some of the results that do not match the query absolutely, but still to a high degree to be interesting for a user, may be lost. However, human curiosity and a need for being exposed to different things during the exploration processes cannot be overestimated[60].

Currently, there is a necessity for e-commerce systems, supporting:

i Simple and human-consistent interaction methods

ii Good time performance (e.g. by avoiding an online image processing and using low-level features for indexing)

iii Search functionality based on the reference image. This is particularly important in case of lack of relevant information for a linguistic query specification

iv Smart recommendation mechanisms

Image retrieval for e-commerce has a huge commercial potential[60]. Using it in the coordination of online apparel shopping is a very interesting topic. We believe that image retrieval systems need to use deeper color semantics defined on the certain color space. The subjectivity of humans and managing the correspondence between low-level color visual features and high-level semantic content are major issues that we plan to tackle in this research.

1.3 Motivation

Nowadays, the increasing availability of huge amounts of multimedia information and the corresponding rapid growth of image databases and its users in various domains requires effective and efficient image retrieval systems for managing the visual data[22]. Various fields may benefit from smart content-based image retrieval (CBIR), like e-commerce, GIS, art galleries collections, medical image processing, etc. A number of CBIR systems have already been proposed, such as QBIC, MARS, Virage, VisualSEEk, PhotoBook, among others. However, no similar works have been done in e-commerce area.

It is a well-known fact that most search engines nowadays are based on indexing. For example, if we try to google elegant dresses, we get the result set for what we were searching. If we open the provided links, it can be easily seen that the corresponding web pages contain the word elegant in the header. But it is obvious that there are some really elegant dresses which are not indexed. Unfortunately, users will never see them in search results. So, the disadvantage of giving the keywords and using TBIR approach only is obvious.

Although image retrieval for e-commerce field has a huge commercial potential, e-commerce oriented CBIR is still very raw. Modern online shopping systems have certain limitations. In particular, they use conventional tag-based retrieval and lack making use of visual content. So, most e-commerce websites use textual descriptions and annotations to provide the color information of clothing items. Thus, images are associated and indexed with certain keywords and tags, which are used to search for images. Although this represents quite a useful technique, the descriptions must be made by humans and so they are subjective (i.e., different people may interpret an image differently) and incomplete because they are do not necessarily reflect the low-level image features very well. Moreover, labeling items manually is very expensive, time-consuming and seems to be infeasible for many applications. It requires a huge amount of human labor in order to manually annotate large-scale image databases, which is obviously impractical for large databases.

Despite color omnipresence and a growing interest in color in various domains, there is a lack of research devoted to computer color models and color aesthetics specifically is not a well-developed area [15]. Plenty of research data on color preferences is puzzling, confusing, and controversial [42]. People regard color as an aesthetic issue, especially when it comes to choosing the colors of their clothing, apartment design and other objects around. No doubt, color influences purchasing behavior - to a certain extent, it is a reflection of human's likes and dislikes.

Choosing the adequate color representation for some computer vision task is challenging nowadays. The reason is that modern color models are far from being human-consistent. Every color a human sees is unique, but the fact is that humans brains can perfectly group an uncountable number of colors into a few small categories. Humans don't perceive small variations of hue, especially when color is green or blue [70]. For example, a majority of people would call turquoise, tiffany, teal, royal, navy, sapphire, azure, oxford, carolina, cornflower as simply blue. Humans dont have to learn dozens of words to describe them [14]. For humans, it requires no effort to perceive, identify and group colors [45]. Computationally, it is an extremely difficult task.

To address these concerns, we need to define human-consistent and efficient color features that can represent image contents. Today, there is no single best representation of color; instead, multiple models that characterize the color features from different perspectives are used. Yet most of these models lack perceptual similarity strategies and are not human-consistent [66], [90].

As we see, all these mechanisms working in our visual system have an underlying profound complexity. However, people usually take those unique abilities for granted. In our research we try to impose a bit of order on color's chaos, to allow computer systems become closer to humans. We do this by drawing a map, a causal relationship between various colors and impressions (see Fig. 1.3). Fuzzy logic represents a magic wand in this challenging task. Even Newton defended the idea that there is no ideal way to separate and name the rainbow colors. Colors are changing insensibly from one to the other. We cannot judge on where one color ends and the other begins, it will be subjective and unreasonable anyway [14]. Here it comes to fuzzy-based techniques, allowing us to handle imprecision and process linguistic terms during an online clothing search. Proposed fuzzy sets for the color model take into account the non-uniformity of color distributions. S and I attributes are also represented through linguistic qualifiers. Such model can be effectively used to automatically label images and to retrieve images of shopping items based on fuzzy dominant colors. In addition, we use FHSI to develop a technique to predict the aesthetic preference for color combinations from an individual color preference and harmony.

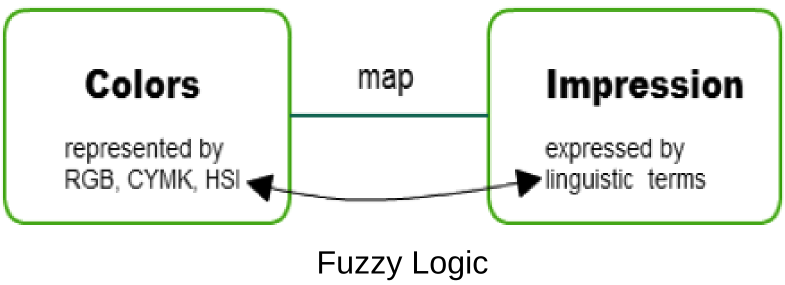


Figure 1.3: Map between colors and impressions

More and more related research efforts are oriented towards application of fuzzy set theory to various tasks in image processing [28]. Why fuzzy logic is so useful in this particular domain ? This can be explained by the fact that digital images are mappings of natural scenes and, thus, they carry a substantial amount of uncertainty, due to the imprecise nature of pixel values. Moreover, the human perception of colors is in itself not precise. In most cases, it contrasts with color theory science because these theories have always assumed perfect conditions and crisp values. However, placing rigid boundaries contradicts humans thinking style, in which ambiguity plays a key role. The importance of fuzzy set theory appears at this point, since it allows the gradual assessment of the membership of an element in a set.

1.4 Contribution of the PhD Thesis

The proposed fuzzy color space and the image retrieval system we developed based on our model offer a number of advantages. The main contribution lies in providing the correspondence between colors and linguistic expressions and bridging the semantic gap between low-level visual features and high-level concepts. In fact, the membership functions used in the proposed color space are derived from the experimental results - fuzzy partitions were implemented based on human color categorization. Secondly, the proposed FHSI can be used as a quantization scheme and color indexing technique for image retrieval, because of its low computational complexity that has been achieved. Hence, our method can help to avoid time-consuming manual image tagging. As in our system, assigning color schemes to apparels is based on FHSI. In addition, the model is consistent with the human vision, which is based on three understandings of color: the category, the purity, and the brightness.

Another contribution of this research is the development of methods for finding the perceptual difference between colors and the degree of similarity between images based on the proposed fuzzy color space. First, we employed well-known L_2 metrics (the sum of the squared differences) for these purposes. The improvements we discuss in this work enabled us to reduce the number of false positives in a prototype system compared with prior results.

Many other contributions related to e-commerce oriented apparel coordination were done, like processing user query, recommendations, looks matching based on impressions and harmonies, among others.

As for aesthetics, our contribution primary lies in providing insights on which color combinations are found aesthetically pleasing or what apartment design or outfit are aesthetically appreciated, especially from a color perspective. Although we mainly focus on e-commerce application, the mechanism we introduce can be transferred to access aesthetics levels in other domains

Finally, our approach is easily adapted to other task-specific applications, because the system we developed can be easily extended and integrated (due to MVC architecture), or it can function as an individual module.

1.5 Significance of the PhD Thesis

In a previous section we discussed the theoretical and practical contributions of this study. But how are they useful for researchers working in image processing field and for the general public, society as a whole?

Turning to benefits for society, actually this study can change the way users buy clothes online. Apparel coordination service will facilitate and encourage more consumer participation in purchasing clothes online, as online sales concierge model we developed fully replaces the real store consultant and offers even more services. Specifically, aesthetic look composition, natural query processing including fetching the items based on impressions, predicting the aesthetic preference, providing recommendations for the best fitting extra apparels for a full look. For example, using our system, a user can compile a romantic look for a wedding in a limited budget, or retrieve a crimson or pistachio t-shirt. This can considerably save time for people, since nowadays it is becoming more and more difficult to find the desired clothing online, among huge amount of items. In addition, people can save money they could spend on a personal stylist.

Furthermore, the findings of this study will redound to the benefit of e-businesses owners considering that CBIR for e-commerce field has a huge commercial potential, but e-commerce oriented CBIR is still very raw. Specifically, our method can help them to get rid of certain limitations, connected with conventional tag-based retrieval, including subjectivity and incompleteness of tags and keywords, huge amount of human labor for manual annotation of products databases, which is time-consuming and very expensive for businesses. Besides automatic color indexing, this study would help e-commerce websites owners to increase customer satisfaction and trust by providing more human-friendly and conveninet services and ultimately increasing online sales.

Next, this study would be beneficial to researchers working in image processing field. Choosing the adequate color representation for some computer vision task is challenging nowadays. The greater demand for color processing in various computer vision applications justifies the need for more human-consistent color model. Thus, researchers that apply the recommended FHSI color model will be able to get better results (an improvement in false positives), considering the fact that FHSI accounts for the non-uniformity of color distributions and controls the effect of hue while controlling for lightness and saturation and uses other principles from color theory. Moreover, FHSI is built upon fuzzy-based techniques allowing to handle imprecision inherent in colors. FHSI library we developed is free and really easy to use, plug and play.

In addition, our findings can change the way people do their jobs in particular fields, e.g., FHSI will provide a useful input to assist web developers, fashion and interior designers, marketing and branding experts in various color design applications, e.g., for measuring the aesthetic attractiveness of color scheme.

1.6 Composition of the thesis

Section 1 is this introduction. The rest of the dissertation is structured as follows. Proposed fuzzy color model and the corresponding approach for image retrieval based on this model are presented in Section 2 [69], [72]. Next, in Section 3, we describe a color harmony and a color preference notions and how we can use FHSI to process the aesthetic color judgments [72], [74]. Section 4 outlines an architecture for the online shopping system based on the method we propose and introduces an intelligent e-commerce-related system for apparel coordination as a proof of concept [73]. The in-depth details of the provided system functionality are also included. Performance evaluation along with experimental results obtained from system testing are discussed in Section 5 [74]. Finally, the last section provides concluding remarks and describes how this method can be enhanced and extended in the future.

Chapter 2

Fuzzy Color Modelling - FHSI color space

As we have explained in previous sections, image indexing and retrieval by color schemes are very important in finding certain items, e.g. online clothing search. However, simple keyword matching and semantic mediations suffer from the semantic gap[46]. The semantic gap between low-level features and high-level semantic concepts is the key hindrance in content-based image retrieval. So, we need much deeper semantics of colors to bridge this gap (see Fig. 2.1).

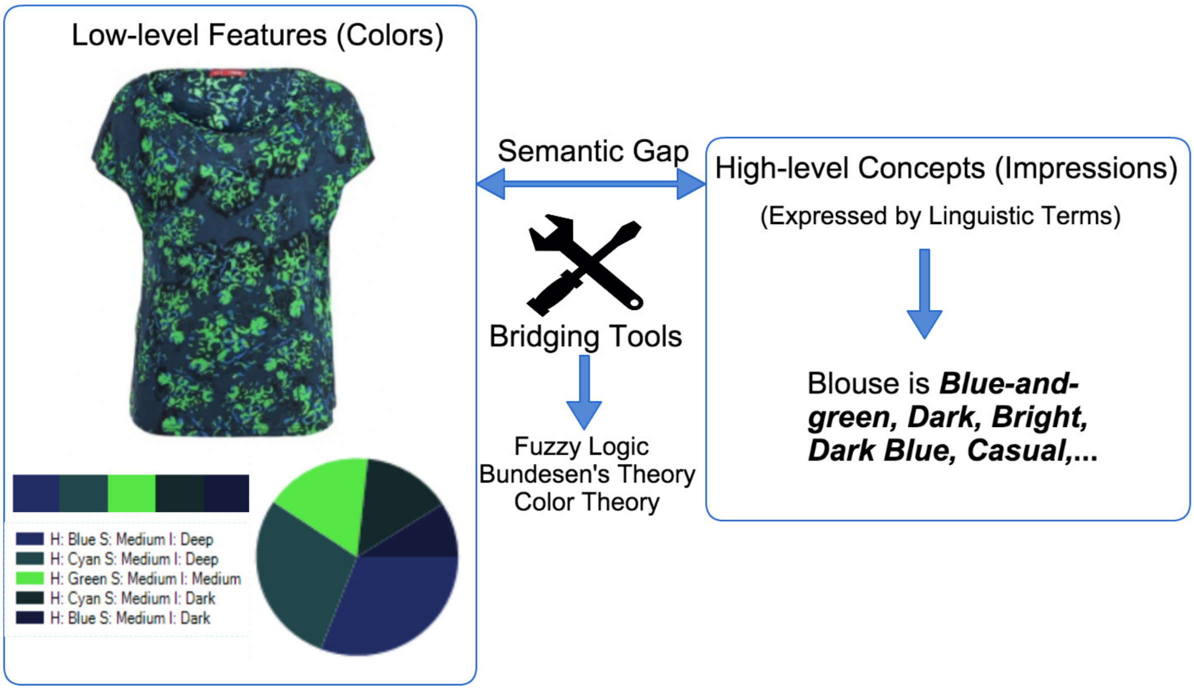


Figure 2.1: Bridging the semantic gap between low-level features and high-level semantic concepts

The main idea of the proposed methodology is to provide the mapping of different colors and human impressions of them. This will allow us to organize the set of possible human color perceptions. For achieving this, we plan to use various tools, including color theory and color harmony principles, fuzzy sets and logic, surveys, and histograms among others.

2.1 Fuzzy Sets and Logic: Basic Principles

This section is intended to provide a brief introduction to fuzzy sets and logic theory and set operators. More rigorous presentation and definitions can be found in [96], [98], [99].

2.1.1 Fuzzy Set Theory: Idea

Nowadays, most of the data processed in modern information systems has precise nature. Even In our everyday language, a great deal of imprecision, vagueness and fuzziness exists, including human characteristic (e.g. healthy), classification of patients (e.g., depressed), quantity and size (e.g., large), quality (e.g., light), age (e.g., old).

There are many concepts that cannot be sharply defined (thus intrinsically fuzzy) or can be differently specified by different persons. So, many problems are to be solved under uncertain environments with blurred and imprecise information.

Uncertainty can originate from many factors, including imprecision, complexity, randomness, ignorance, or different experience. Since people use ambiguous information and imprecision in order to solve problems, the computational methods we use must be able to represent and manipulate fuzzy uncertainties.

The fuzzy set theory, originally introduced by L.A. Zadeh, aims at creation of methods and tools for processing of the indefinite and vague information. Specifically, the concept of fuzziness can be referred to the state of ambiguity arising from the lack of certainty.

In fact, almost all expressions we use in the daily language contain fuzziness – *young-old, cold-hot, rich-poor, bad-good, short-long* etc. Ambiguity plays a major role in human thinking style, particularly, in communication, reasoning, inference, and in identifying and generalizing figures [96]. This is where the importance of the fuzzy theory appears. It provides us with the way to transform the user interfaces into a human-oriented style.

Nowadays, engineers and researchers are more and more interested in the creation of methods that will enable computers to reason with uncertainty. Classical set theory is purely based on the fundamental concept of a *set*, in which, as we know, elements can be either member or not members of a set. So, there is a precise and clear boundary for indication if an entity belongs to a set or no. Therefore, in classical set theory some element is not assumed to be in a set (means 1) or not in a set (means 0) at the same time. So, a great number of real-world problems cannot be solved by classical set theory [88].

In contrast, the fuzzy set theory accepts partial membership values ranging from 0 to 1. Fuzzy sets provide a way of representation which is very similar to the human reasoning.

Fuzzy logic is a multi-valued logic derived from fuzzy set theory. It's ultimate goal is to achieve the linguistic capacity of computer. As Zadeh said [99], "Fuzzy logic is determined as a set of mathematical principles for knowledge representation based on degrees of membership rather than on crisp membership of classical binary logic". It is very efficient in complex problems that can't be handled using standard math, like processing human elements – natural language, perception, emotion, etc. The term "fuzzy" can be defined as "not clear, blurred, or vague." For example, in fuzzy logic in the case of the fuzzy term "tall," the value 170 cm can be partially true and partially false. Fuzzy logic deals with degree of membership with a value in the interval [0, 1].

The question is how we can represent and manipulate inferences with this kind of information. Some examples are: a person's size is *tall*, and their age is classified as *young*. Terms such as *tall* and *young* are fuzzy because they cannot be crisply defined, although as humans we use this information to make decisions. When we want to classify a person as tall or young it is impossible to decide if the person is in a set or not. By giving a *degree* of membership to the subset, no information is lost when the classification is made.

2.1.2 Membership Functions and Fuzzy Sets

In 1965 Prof. Lotfi A. Zadeh introduced *fuzzy sets*. The main intriguing characteristic of fuzzy sets is that it allows degrees of membership, which are indicated with a number between 0 and 1. The point of departure for fuzzy sets is simply the generalization of the valuation set from the pair of numbers {0,1} to all the numbers in a range [0,1]. This is called a *membership function* and is denoted as μ_A(x) and in this way can denote fuzzy sets [96], [98].

Membership functions (MF) are mathematical tools used to indicate flexible membership to a set, modeling the meaning of symbols. With the help of MFs we can represent a subjective notion of a vague class, such as room size, performance, building height, etc. So, the pivotal role of MF is to translate an attribute value to a degree of membership in a fuzzy set, referred to as a possibility value.

Fig. 2.2 demonstrates membership functions that map age values into the fuzzy sets young, middle-aged and old. From the figure we can see that all ages less than or equal to 18 are definitely members of the set *young* and have possibility values equal to 1.0. Next, for ages between 18 and 35, the degree of membership to *young* gradually decreases from 1.0 to 0.0 indicating that ages closer to 18 are "younger" than ages closer to 35. For ages above 35, the set *young* gives possibility values equal to 0 indicating that ages over 35 are not members of the fuzzy set *young*.

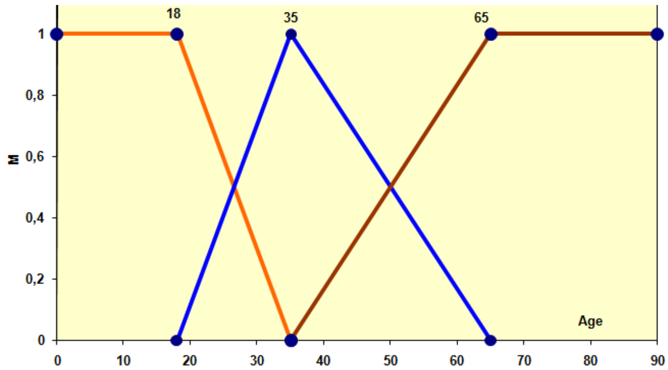


Figure 2.2: Membership functions for young, middle-aged, old

2.1.3 Linguistic Variables

One of the main hindrances of modern computing is that the concept cannot be well understood until it is expressed quantitatively. Here it comes to linguistic variables. The main motivation to prefer linguistic variables rather than numbers is that linguistic description representation is usually less specific than numerical one.

According to Zadeh [98], "By a linguistic variable we mean a variable whose values are not numbers but words or sentences in a natural or artificial language". For example, that logic, the label *dark* is considered as a linguistic value of the variable *color*, it plays the same role as some certain numerical values. However, it is less precise and conveys less information.

The set of all linguistic values of a linguistic variable is called *term set*. Although a linguistic value is less precise than a number it is closer to human cognitive processes, and that can be exploited successfully in solving problems involving uncertain or ill-defined phenomena. So, in situations where information is not precise (which are very common in our real life), linguistic variables can be a powerful tool that takes the human knowledge as model.

A computationally efficient way to represent a fuzzy number is to use the approach based on parameters of its membership function. Linear trapezoidal or triangular membership functions are good enough to catch the ambiguity of the linguistic assessments.

Besides their primary meaning, linguistic value may involve connectives such as *and, or, not* and the hedges such as *very, quite extremely, more or less, completely, fairly*, etc. about which we will talk extensively later.

2.1.4 Fuzzy Operations

Fuzzy logic provides operators that act on fuzzy sets that are counterparts to the Boolean logic operators such as equality, complement, union and intersection. For example, *intersection* and *union* are defined through the *min* and *max* operators, which are analogous to *product* and *sum* in algebra.

The α-cut (Alpha cut) is a crisp set that includes all the members of the given fuzzy subset f whose values are not less than α for $\alpha \quad \leq 1$:

$$f_\alpha = \{x : \mu_f(x) \geq \alpha\}$$

So, the main idea is to fix a certain membership degree α and thus to obtain a crisp boolean set, which is defined as the set of values having membership degrees higher or equal than α. We use α -cuts to perform virtually all operations when we need to move from fuzzy to crisp, for example, when combining the fuzzy sets. An α -cut of a FS is always an ordinary set. That is why we need to connect α-cuts and set operations (A and B are fuzzy sets):

$$(A \cup B)_\alpha = A_\alpha \cup B_\alpha, \quad (A \cap B)_\alpha = A_\alpha \cap B_\alpha$$

So, using the formulas provided above, we can first find the α-cuts and then take crisp or/and operation, in case it is more convenient.

2.1.5 Fuzzy Mechanisms for Human Color Perception

Very often people use the web to search for some items of interest. It would be convenient for a human to describe the product requirements linguistically, using a text (linguistic) query. However, it is a challenging task for a system to understand a linguistic query. So, the primary motivation for the introduction of fuzzy-based techniques is to be able to handle imprecision and process linguistic terms. This enables us to process data and present results in a human-consistent manner.

In addition, a system that uses fuzzy mechanisms will be able to handle scenarios where users want to relax their requirements. This means users can browse different items that do not match the search criteria to the highest possible degree, but still may be interesting for a user[60].

Many other related approaches in the field of cognitive science employ fuzzy modelling, since it is more natural (e.g. linguistic values instead of numbers) and flexible. An interesting approach to the development of the new attentional model which is based on Bundesen's work[5] (described in a previous subsection) with the addition of fuzzy sets[59] was suggested recently. So, they extended Bundensen's theory to cases when ω_x or π_i (or both) are not precise, but fuzzy. Moreover, saliency $\eta(x, i)$ can also be inexact, because of the imprecise nature of certain categories i, e.g., *light pink*. So, for fixed $x \in S$ and some certain task T[59] :

$$\mu_x(i) = \eta(x, i)\pi_i \tag{2.1}$$

the membership of a fuzzy set on the set of categories. Hence, the weight of a perceptual unit x can be defined as the cardinality of this fuzzy set:

$$\widetilde{\omega}_x = Card\,\{(i, \mu_x(i))|i \in R\} \tag{2.2}$$

Example 1 *Let T be the task to determine if an apparel in an image corresponds to a "dark red dress" using color scheme only. Suppose that pertinences of "red" and "dark" categories are 0.7 and 0.4 respectively.*

Note that according to Eq. (2.1) and Eq. (2.2) only categories with positive pertinence contribute to $\widetilde{\omega}_x$. So, we do not consider categories which are not pertinent at all. Also, note that in this example, hue category has bigger pertinence values, since, as we already mentioned above, hue tends to be more important in color theory rather than intensity. Exact pertinence values may vary depending on the application context.

Using Eq. (2.1) here we have $\mu_x(red) = 0.7\eta(x, red)$ and $\mu_x(dark) = 0.4\eta(x, dark)$. Next, according to Eq. (2.2) we find $\widetilde{\omega}_x$ which is a cardinality (sigma count), a sum of the values of membership function we found. Note that x can be any perceptual unit, namely pixel, image region or the whole image.

Example 2 *Let T be the task to determine if an apparel in an image corresponds to a "black and white dress" using color scheme only. Suppose that pertinences of "black" and "white" categories are both equal to 1.*

Here we have $R = \{black,\ white\}$. Sometimes, several perceptual categories may have maximum importance to the given task, as exactly in this example. So, in some cases, it is useful to set maximum pertinence (i.e. $\pi_i = 1$), which is only possible when π is considered to be a possibility distribution. This goes in contrast to probability-based approach[5], where maximum pertinence a category might have is 0.5.

Again, using Eq. (2.1) here we have $\mu_x(black) = \eta(x, black)\pi_{black} = \eta(x, black)$ and $\mu_x(white) = \eta(x, white)\pi_{white} = \eta(x, white)$. Next we have, $\widetilde{\omega}_x$ is a sum of those saliency values.

2.1.6 Applications of Fuzzy Theory

Fuzzy Sets and Logic have already been applied to many real-world problems and served as the basis for a number of industrial products. So, a great number of industries have taken advantage of the fuzzy theory. The market of products and services based on fuzzy sets and logic theory is enormous, ranging from fuzzy toasters to fuzzy golf diagnostic systems. It is important to note that their applications are keep expanding [100].

The reasons for that is that fuzzy logic systems are simple to design, and can be easily understood and implemented by non-experts in control theory. So, a person with an intermediate technical background can design a simple fuzzy controller. Fuzzy logic is not the best answer to all technical problems, but for a majority of them , where speed of implementation and simplicity are vital, it is a strong candidate. In particular, now we have fuzzy air conditioner, fuzzy video cameras, fuzzy schemes for evaluating the passenger traffic, fuzzy anti-lock braking systems, fuzzy subway systems. The range of applications where fuzzy mathematics have been successfully used are presented below.

- Environmental Control (e.g., humidifiers, air conditioners);
- Domestic goods (e.g., washing machines, toasters, rice cookers, refrigerators);
- Electronics (e.g., TV, photocopiers, video systems (auto-focus, anti-shake));
- Automotive Systems (e.g., ABS, vehicle climate control, cruise control).

And many, many others, like image processing, pattern recognition, language filtering, data analysis, decision making.

As we see, the list of applications is quite impressive and gives a brief idea of key application areas. However, you won't find a fuzzy controller in a safety critical application, like insulin pumping, for example.

2.2 Related Work

Authors' efforts to use fuzzy sets to account for the imprecise perception of colors for certain applications have led to a number of reports [8], [7], [47].

Many works stress the importance of fuzzy representation for color modeling. In [8], [7] the authors provide the formalization of a fuzzy colors space and introduce a new definition of fuzzy color frequency based on fuzzy natural numbers. The authors employed fuzzy sets to represent the hue, saturation, and intensity values. Interestingly, all intervals representing hues have the same length and were fuzzified using a trapezoidal membership function as in the Munsell color space. However, colors are not distributed uniformly in a color wheel and recent research showed that the Munsell color space is not as perceptually uniform as it was originally considered to be[58]. In our approach fuzzy partition was performed based on perceptual experiments; thus, it accounts for the non-uniform nature of color distributions.

In [47], [94], the authors describe an approach for the development of a color image retrieval system based on the fuzzy partition of HSI space and fuzzy similarity measures. Although their methods take into account the non-uniformity of hue distributions, the fuzzy partitions themselves were created subjectively. As mentioned above, in our approach fuzzy partitions were obtained based on survey results, which aggregated color perceptions of future users of the retrieval system. Most of the other metrics neglect the non-uniformity of hue distributions or the fact that H, S, and I are not equally important when comparing two colors.

2.3 Fussy Encoding of HSI

Performing a fuzzy color modeling requires us to use a crisp space as a base. Our choice is a color model based on HSI, as we already explained. HSI is consistent with human perception of color [93], [47], because the latter is based on three understandings of color: the category, the purity, and the brightness. This corresponds exactly with the attributes of the HSI space (see Fig. 2.3), which represents hue (the basic color index, e.g., blue), saturation (colorfulness, i.e., color depth) and intensity (the amount of white in the color, i.e., lightness).

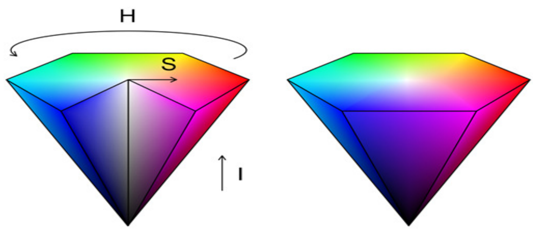


Figure 2.3: HSI color space

Colors in FHSI are modeled by means of fuzzy sets defined on an ordinary crisp HSI color space and a fuzzy partition is defined in the corresponding color feature domain (fuzzy color space). At an earlier stage, we defined fuzzy sets subjectively. One of the advancements we achieved later is that the fuzzy partition was defined on the basis of results we obtained from a survey on human color categorization based on a direct rating method. This enabled us to attempt to bridge the semantic gap that exists between the color representation in computer systems and its perception by humans.

2.3.1 Fuzzy Color

In computer systems, colors are usually represented as a triplet of numbers corresponding to coordinates in a certain color space. In turn, fuzzy color is a fuzzy subset of points of some crisp color space[80], which is the HSI space in our case. Let D_H, D_S, D_I be domains of the H, S, I attributes respectively.

Definition 1. *FHSI (fuzzy HSI) color C is a linguistic label whose semantic is represented in HSI color space by a normalized fuzzy subset of $D_H \times D_S \times D_I$.*

From Definition 1 it is obvious that for each fuzzy color C there exist at least one representative crisp color whose membership to C is 1. Now let's extend the concept of fuzzy color to a concept of a fuzzy color space.

2.3.2 Fuzzy Color Space

The fuzzy color space that we are proposing represents the collection of fuzzy sets, providing the conceptual quantization of crisp HSI color space with soft boundaries. HSI space is convenient for our purposes, but one problem with this color space is that it is not a uniform color space. So, humans don't perceive small variations of hue, especially when color is green or blue. Fuzzy sets are powerful in modeling this non-uniformity. Indeed, we can easily solve this problem by using trapezoidal membership functions for such kind of hues having a wide interval.

Using the basic definition of a fuzzy color space[80], in our case:

Definition 2. *FHSI (fuzzy HSI) color space is a set of fuzzy colors that define a partition of $D_H \times D_S \times D_I$.*

In other words, a fuzzy color space is a collection of fuzzy sets that provides a conceptual quantization (with soft boundaries) of crisp color space [8]. For the sake of simplicity, for all the fuzzy variables we employed either triangular or trapezoidal membership functions, depending on the value range of a certain color property associated with the specific label. Particularly, for a wide range we used trapezoidal membership functions, and triangular ones for all the other fuzzy sets that are not wide.

Table 2.1 shows the information about each fuzzy variable in our color space, like term set and domain. Hue variable is specified by 8 linguistic labels, specifying various hues. This choice is very intuitive since it approximately corresponds to the rainbow colors. Such division was done based on the survey on human color categorization ref6. So, the term set consists of 8 fuzzy sets - "Red", "Orange", "Yellow", "Green", "Cyan", "Blue", "Violet", "Magenta". Hue values are cyclic and vary from 0 to 360. So, we define the Hue for the domain X = [0,360], and the universal set is U = 0 ,1, 2, ,359, 360. Concerning the Saturation variable, it is represented by 3 fuzzy sets in our approach - "Low", "Medium", "High". Saturation values vary from 0 to 100, from dull to intense, so the domain X = [0, 100], and the universal set is U = 0, 1,, 99, 100. Finally, Intensity fuzzy variable is described by 5 linguistic terms, namely "Dark", "Deep", "Medium", "Pale", "Light". Intensity values lie in the range X= [0;255], with the respective U = 0, 1, , 254, 255.

Table 2.1: Description of fuzzy attributes of the proposed fuzzy color space.

Fuzzy variable	Term set	Domain
Hue	T = { Red, Orange, Yellow, Green, Cyan, Blue, Violet, Magenta }	X = [0, 360]
Saturation	T = { Low, Medium, High }	X = [0, 100]
Intensity	T = { Dark, Deep, Medium, Pale, Light }	X = [0, 255]

We propose that color should be analyzed from the perspective of human color categories, to enable us relate to the way people perceive colors and also to reduce the data from 16 million colors. Recent studies have shown that human vision results in categorical perception [4], [61]. A number of CBIR systems employ the model of human color categorization, e.g., M4ART, which contains over 30,000 art images [4]. "Categorical perception" has proven its effectiveness; hence, we incorporate human color categorization into fuzzy color modeling.

We constructed the membership functions for the Hue fuzzy variable with the help of the survey based on human cognition. Different methods can be used to question the user with the aim of constructing membership functions. We selected the Direct Rating method, because it is simple, efficient, and requires fewer iterations to converge [12]. In Direct Rating the user needs to select the value from a set of possible linguistic values corresponding to a certain linguistic variable. In our experiment, humans were asked to classify various color stimuli into one of eight hue categories (term set of the Hue attribute). We utilized personal judgments collected from the survey and used them to define fuzzy sets for Hue. With each new user record, we updated the membership functions based on the frequency of particular responses. The survey was terminated on the 179th response, upon reaching convergence, which is defined as the point beyond which new user responses would have no noticeable effect on the value of the functions [12]. It is of interest to note that there was a consensus among respondents about the yellow hue, while the violet color was the most controversial one. Defining the fuzzy partition based on a perceptual categorization resulted in a considerable improvement in false positives and precision[72].

Fig. 2.4 shows the membership functions for a fuzzy hue variable, constructed on the basis of the Direct Rating method. Fig. 2.5 demonstrates the tailored functions

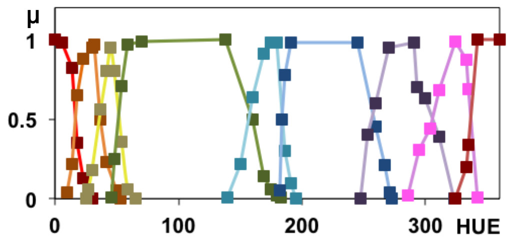


Figure 2.4: Fuzzy sets for the Hue attribute as obtained from the Direct Rating

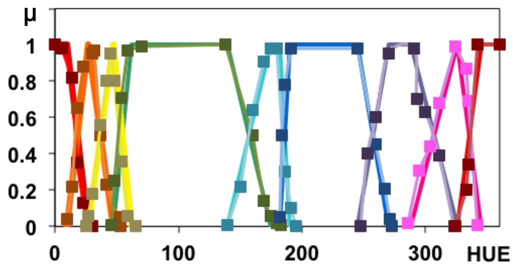


Figure 2.5: Fuzzy sets for the Hue attribute approximated to triangular and trapezoidal membership functions.

we obtained by limiting the shape of fuzzy sets to triangular or trapezoidal membership functions.

We derived the following relations based on the features of the HSI color space. They are used to identify achromatic colors (black, white, and various shades and tints of gray) and do not take into account redundant colors.

- If Saturation is low and Intensity is not light, then Hue is irrelevant (the color is a shade of gray).
- If Intensity is either light or dark, then Hue and Saturation are irrelevant

At the image processing stage, for each pixel, a trapezoid or triangular fuzzy matching function is applied to one of each of its color channels (H, S, and I) to define the membership of that pixel to one of a small number of FHSI colors. Fuzzy modeling is beneficial here, because it ensures that pixels of which the color is only slightly different (e.g., due to changes in lighting or illumination) are matched to the same bins.

This simple method allows us to directly model colors such as "dark blue" or "bright red". We developed a fuzzy color space and the main motivation for that is that indistinguishability is a fuzzy concept for humans, since, to a certain degree, colors are indistinguishable to us. That is why crisp boundaries are counterintuitive for us.

Although color naming reflects universal tendencies, it can be influenced by a wide range of factors, including culture, personality, environmental factors, and system settings

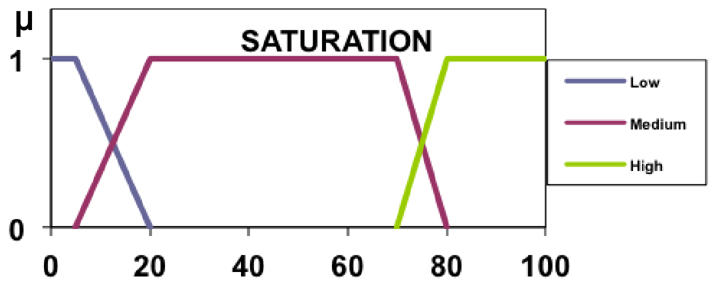


Figure 2.6: Fuzzy sets for the Saturation attribute.

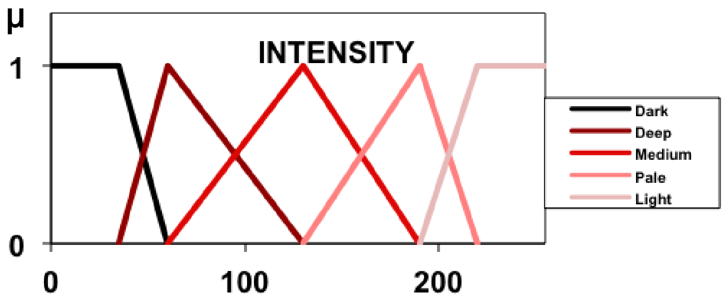


Figure 2.7: Fuzzy sets for the Intensity attribute.

[4], [26]. Therefore, it needs to be emphasized that another set of colors, which is user, task, or application specific, can be incorporated [4].

As we see, the use of linguistic labels allows us to create interpretable knowledge systems, and the choice of membership functions plays an extremely important role in their performance and success[51],[64]. As we showed above, the membership degrees we use in the system were defined by means of users knowledge. However, we need to emphasize, that sometimes, due to the possible lack of knowledge, it can be better represented by means of some extensions of ordinary fuzzy sets[6],[64],[51].

When we were conducting a survey, users indicated that there were some color samples for which they knew exactly the color, however, there were also samples for which the users were not able to determine the membership precisely - this is the ignorance. In fact, we can use fuzzy membership functions defined above to construct interval type-2 membership functions [51]. Although it brings the lack of specificity, but provides more reliability, making fuzzy sets more realistic.

So, we can modify the system by taking into account the degree of users ignorance of the membership of the pixels to some specific color, which is the result of a weak ignorance function applied to the value set as membership degree. In this case, the linguistic labels are modeled with interval-valued fuzzy sets, whose length represents the degree of ignorance[64]. Obviously, the lower the ignorance value, the more accurate the membership function will beignor1. For example, if a user is certain that the given color

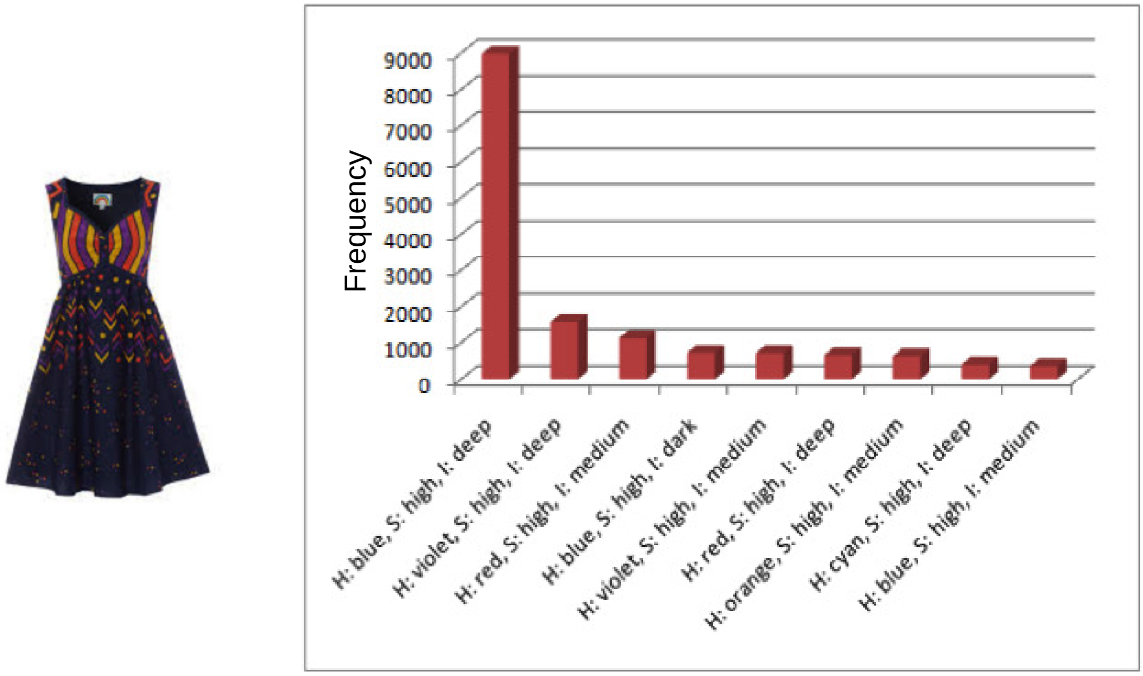


Figure 2.8: Identification of dominant colors using color histogram.

sample belongs to a certain color category, the ignorance of this particular user in the choice of the membership of a color sample must be zero.

2.4 Dominant Color Identification in FHSI

One of the most important subtasks in our methodology is identification of a dominant color(s) in the image. For that purpose, we employ a color histogram. As we know, color histograms reflect tonal distribution in digital images. They can also be used to extract other various features of an image for similarity measure, classification [75], etc.

For easy histogram purposes, we divide the colors into bins each of which contains 3 fuzzy sets specifying certain fuzzy values of hue, saturation and intensity. Since we have 8 sets for the hue, 3 for the saturation and 5 for the intensity, we obtain 120 color combinations (e.g. hue is red, saturation is medium, intensity is deep). But we can reduce it to 85 combinations taking into account the following general observation derived from the features of HSI color space: if (Saturation is low) then (Hue is irrelevant).

This relation is used to identify achromatic colors (black, white and various shades and tints of gray) and do not take account redundant colors. As we know, the Saturation measures the degree of mixing the hue with uniform white color. Therefore, low saturation means that the color is a shade of gray. For example, suppose two colors having saturation equal to 8, intensity equals to 68. It doesnt matter what the hue value is, they will both look like a dark grey color.

Furthermore, for each of the obtained combinations, we calculate the number of pixels. This serves as a primary data for building the linguistic color histogram and identification of a dominant color(s). An illustration for that is provided in Fig. 2.8.

The next subsection uses the developed FHSI space to find the perceptual difference between colors.

2.5 Perceptual Color Difference in FHSI

Current subsection proposes the mechanism to evaluate the perceptual difference (and similarity, respectively) between fuzzified color descriptions.

The literature suggests a number of ways to find the similarity degree between two colors. Among them are: doing a comparison based on RGB values (simple, but not precise and effective, since RGB space is not perceptually uniform), based on hue values only, LAB measure etc. As it is well-known, the HSI model has a cylindrical form. The most primitive and intuitive way to find the distance between a couple of HSI colors is to calculate the distance between the respective points in the HSI cylinder. However, it is well known that this distance does not always match the perceptual difference between colors. Although this number indicates how different two colors *are*, but it does a poor job in specifying how differently they are *perceived* by a human. Indeed, human eyes are far from being perfect, e.g., humans are more sensitive to green colors.

Do H, S, and I have the same importance when comparing two colors? Definitely, not. For example, a minor variation in the hue attribute leads to a large change in perception. Colors of the same nuance (i.e., with the same saturation and intensity) are only slightly different and are in close proximity in terms of their respective hues, although they are not neighbors in the human visual system.

Considering the cyclic property of the hue component, the clear way to find the distance between two H values, H_1 and H_2 is [72]:

$$d(H_1, H_2) = \begin{cases} |H_1 - H_2| & \text{if } |H_1 - H_2| \leq \pi, \\ 2\pi - |H_1 - H_2| & \text{if } |H_1 - H_2| > \pi \end{cases} \tag{2.3}$$

This formula does not work consistently in all cases. More specifically, it does not account for the fact that colors are not distributed uniformly in a color wheel. The following example demonstrates the problem. First, consider a pair consisting of orange ($H = 15, S = 55, I = 211$) and yellow ($H = 35, S = 55, I = 211$) colors. Applying Eq. (2.3) we find that the hue distance between these colors is 20. Then, consider another pair of colors that are both green ($H = 130, S = 55, I = 211$), ($H = 110, S = 55, I = 211$). Surprisingly, the hue distance in this case is also 20. Thus, both pairs of colors have the same distance between their respective hues according to Eq. (2.3). The majority of

Color1	Color2	Hue Distance
H = 15, S = 55, I = 211	H = 35, S = 55, I = 211	20
H = 130, S = 55, I = 211	H = 110 S = 55, I = 211	20

Figure 2.9: Comparing hue distances.

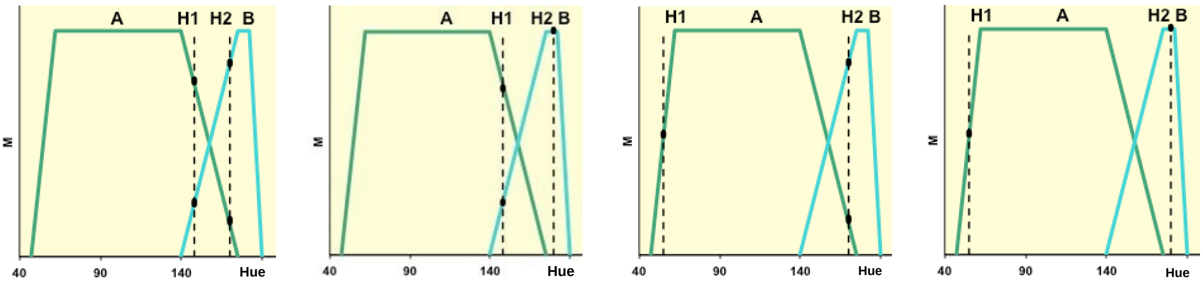
people will see orange and yellow colors on the first raw and will consider both colors on the second raw as green. However, both pairs of colors have the same distance. This leads to the conclusion that Eq. (2.3) does not take into account the fact that various hues have various ranges. For instance, green color has the largest range. We can improve Eq. (2.3) by adding a coefficient representing the difference between memberships of corresponding points. This will ensure that perceptually similar colors will have smaller a perceptual distance. Hence, for two H values, H_1 and H_2, corresponding to F_1 and F_2 fuzzy sets, we find the minimum among the absolute differences in H_1 and H_2 membership to F_1 and F_2. In other words, we find the hue that is closer to both values. Then we subtract this value from 1 to obtain the resultant coefficient (see Eq. (3.1)).

Eq. (2.3) ignores the fact that colors have a non-uniform distribution on a color wheel. Despite the fact that the first pair is different and the second pair is similar, both pairs of colors have the same distance according to Eq. (2.3).

Why does this happen? Due to linguistic conventions of the society, various hues have various ranges across different cultures. For instance, for many cultures, green color has the biggest range. In the middle of the 19th century, V. Shertsl explored color linguistic traditions among various folks[77]. Negros of a *Chi* tribe distinguish only the white, red and black colors. Tibetans don't recognize and don't use orange, purple and gray colors and do not even distinguish green from blue, mixing them in literature and everyday life. *Marei* and *Badji* tribes have no word for blue, calling it dark or black. Primitive chromatic terminology (white, red, black) is kept among *Chukchi* people to date. Another interesting example for this, people from post-soviet countries use two words for the blue hues, namely "siniy" and "goluboy". However, the rest of the modern world doesn't make this distinction and uses a solely "blue" word.

These discrepancies forced us to improve Eq. (2.3) by adding a coefficient δ, representing the degree of difference between the memberships of corresponding hue points to the common hue. The less δ , the closer colors (hues) perceptually. This will ensure that perceptually similar colors will have smaller perceptual distance. Suppose we have for two H values, H_1 and H_2, corresponding to A and B fuzzy sets (representing hues). Let's abbreviate $\Delta\mu_A = \mu_A(H_1) - \mu_A(H_2)$, $\Delta\mu_B = \mu_B(H_2) - \mu_B(H_1)$. δ represents the

$$\delta = \begin{cases} \Delta\mu_B & \text{if } \mu_A(H_2) \geq 0, \mu_B(H_1) > 0, \\ \Delta\mu_A & \text{if } \mu_A(H_2) > 0, \mu_B(H_1) = 0, \\ 1 & \text{otherwise} \end{cases} \tag{2.4}$$



(a) $\delta = \Delta\mu_B = \Delta\mu_A = 0.6$

(b) $\mu_A(H_2) = 0$ $\delta = \Delta\mu_B = 0.75$

(c) $\mu_B(H_1) = 0$ $\delta = \Delta\mu_A = 0.4$

(d) $\mu_B(H_1) = \mu_A(H_2) = 0$, $\delta = 1$

Figure 2.10: Determination of δ. For example, for case b, $\mu_A(H_1) = 0.75, \mu_A(H_2) = 0, \mu_B(H_1) = 0.25, \mu_B(H_2) = 1$. So, $\delta = \Delta\mu_B = 1 - 0.25 = 0.75$

difference in H_1 and H_2 membership to either A and B (it depends on which hue (fuzzy set) is closer to both values). See Eq. (3.1).

Four possible cases are illustrated and shortly explained in Fig. 2.10. From Fig. 2.10a it can be seen that both H_1 and H_2 have non-zero μ to each other's sets. Here $\Delta\mu_A = \Delta\mu_B$, due to fuzzy partition. So, $\delta = \Delta\mu_A = \Delta\mu_B$. Fig. 2.10b illustrates the case when H_1 has zero μ to A fuzzy set. So, B is closer to both hues we consider and $\delta = \Delta\mu_B$. In Fig. 2.10d we see that both H_1 and H_2 have zero μ to each other's sets, so the δ is maximum, $\delta = 1$.

We use this coefficient only in case $F_1 = F_2$ or F_1 and F_2 are neighboring fuzzy sets, and both H_1 and H_2 should have non-zero membership to either F_1 or F_2. So, the resultant perceptual difference d_p is:

$$d_p(H_1, H_2) = d(H_1, H_2) \times \delta \tag{2.5}$$

The role of δ in Eq. (2.10) is to ensure that perceptually similar colors will have smaller perceptual distance (due to smaller membership difference) than colors with the same hue distance, but different hue categories.

As for the distance between intensity and saturation values, it can be found just as the absolute difference between the corresponding values, since these attributes change uniformly, in contrast to hue:

$$d_p(S_1, S_2) = d(S_1, S_2) = |S_1 - S_2| \tag{2.6}$$

The same principle holds for the intensity. Combining all three attributes into one resultant formula of perceptual difference requires us to normalize them. This involves adjusting three distances (between the hues, saturations, and intensities), which have various ranges, to a notionally common scale, [0, 100]. The normalized values for the perceptual difference are denoted by upper-case D.

Actually, H, S and I attributes do not have the same importance when human judges how similar two colors are. For instance, colors of the same nuance (i.e. having the same S and I values) have small distance, although they are not similar to a human visual system. In contrast, even a small variation in H attribute leads to a big change in the perception (given medium or high S). So, the S attribute works as a weighting factor for the intensity and hue. Specifically, when we compare two colors, we need to remember that:

- If (S is high) H is more important
- If (S is low) I is more important

How can we model such phenomena from a computational standpoint? We can do it by assigning the specific pertinence values to each of the color channels (H, S and I). Suppose we have colors C_1 with attributes H_1, S_1, I_1 and C_2 with attributes H_2, S_2, I_2. Based on observations mentioned above, the pertinence of the Hue category depends on how high the $Saturation$ is, and the pertinence of the $Intensity$ depends on how low the $Saturation$ is: [1]

$$\pi_H = \frac{\mu_{high}(S_1) + \mu_{high}(S_2)}{2}, \pi_I = \frac{\mu_{low}(S_1) + \mu_{low}(S_2)}{2} \tag{2.7}$$

Therefore, based on Eq. (2.3), (3.1), (2.10), and (2.6) the perceptual difference between two chromatic colors C_1 with attributes H_1, S_1, I_1 and C_2 with attributes H_2, S_2, I_2 in the FHSI color space can be found using the formula below:

$$D_p(C_1, C_2) = D_p(H_1, H_2) \times \pi_H + D_p(S_1, S_2) \times \pi_S + D_p(I_1, I_2) \times \pi_I \tag{2.8}$$

Or simply:

$$D_p = \sum_{i \in \{H,S,I\}} D_{p_i} \times \pi_i \tag{2.9}$$

We now use Eq. (2.11) to find the perceptual difference for two pairs of colors. As you can see from Fig. 2.11 the D_p values for the two pairs are equal to 7.49 and 3.24, which seems plausible, because the second pair of colors looks much more similar to each other (they both appear green, in contrast to the pair on the left, which has a yellow and orange appearance, respectively).

[1] The pertinence of the Saturation category is always 0.5, half of maximum pertinence

Table 2.2: Comparison between color difference in FHSI and LAB color spaces

Color 1	Color 2	$D_{FHSI}(D_p)$	D_{LAB}
H = 45, S = 51, I = 154 R = 211, G = 175, B = 75	H = 24, S = 41, I = 143 R = 209, G = 136, B = 85	7.5	28.0
H = 137, S = 41, I = 159 R = 93, G = 245, B =139	H = 147, S = 39, I = 140 R = 85, G = 198, B = 136	3.2	28.0

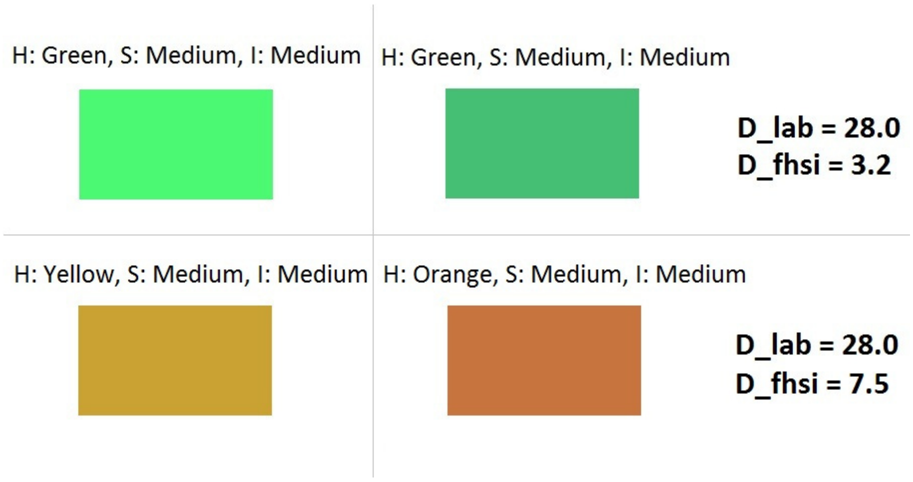


Figure 2.11: Perceptual distance for the two pairs of colors is 7.5 and 3.2, respectively.

Next, we compare the validity of our method with that of the well-known LAB color difference. In most of our experiments, both methods demonstrated consistent results. Nevertheless, there were some tests in which they produced quite different answers, for example, for the colors in Fig. 2.11 above. Table 2.2 presents these results.

Surprisingly, in the popular LAB color space, the distance is the same for both pairs, although the colors of the first two are of the same basic color category, whereas those of the second pair are in different categories (see Fig. 2.11).

It is important to note that the above formula is only suitable for chromatic colors. Achromatic colors have low saturation and represent various tints and shades of black, gray, and white; therefore, the perceptual difference between them is similar to D_p (I_1 , I_2).

The beauty of this method is that it is universal and can be used to find the perceptual distance between colors in all contexts and cultures, that use different color naming traditions. Everything they need to do is to create the fuzzy sets for the color model attributes.

2.5.1 Image Similarity in FHSI

The creation of measures for expressing image similarity is an important part of image retrieval applications. In this subsection we attempt to use of the FHSI color model and the formulas we previously defined to develop objective metrics for finding the image similarity in a way that matches human evaluation [72]. .

There are a number of approaches to measuring the image similarity, like widely used L_1 (the sum of the absolute values of the differences), L_2 (the sum of the squared differences), and $L\infty$ metrics. In most cases, these metrics perform poorly, and tend to produce many false positives for complex queries and they do not fetch all perceptually similar images, even for the simplest queries [66]. This happens because even small changes in lighting or shading may result in a considerable shift in the histogram and force metric to misjudge the images as similar[8].

Several fuzzy approaches to image similarity have also been proposed[47] ,[91],[46]. Some researchers use the common fuzzy similarity measure to perform histogram comparison[47]. The intensity and hue attributes are equally important and saturation channel is omitted in their work. The other approach employs the intuitionistic similarity measure that accounts for the membership degree, the non-membership degree and the hesitation degree[91].

The main drawback of the majority of these metrics is that they employ fuzzy histogram comparison without taking into account the similarity between bins. In contrast, according to Eq. (3.1) which we use, perceptually similar colors are separated by a shorter perceptual distance. Furthermore, most of the other metrics neglect the fact that H, S, and I are not equally important when comparing two colors. For example, small changes in the hue lead to a large change in perception. On the other hand, variation in intensity is usually slightly perceived. In our method we employ the idea proposed in [102] and use the saturation as a determining factor, giving priority to the hue when the saturation is high, and giving priority to the intensity value when the colors have low saturation (see Eq. (2.11) above).

Suppose that given a query image, we want to fetch all the images in the database whose color schemes are similar to the color composition of the query image. Below we provide the algorithm 1 along with the pseudocode that shows how to find the similarity between two images, M_1 and M_2, using Eq.(3.1) defined earlier.

1. Preprocess the image M_1 - perform conversion from RGB to HSI color model.

2. Map the colors in M_1 into a discrete color space containing fuzzy HSI colors (FHSI).

3. Compute the dominant color histogram of image M_1 , $C_H(M_1)$, which is a vector $(h_{C_1}, ..., h_{C_n})$, where each element h_{C_i} represents the frequency of color C_i in the image $/M_1$. The dominant color descriptor depicts the representative fuzzy colors and their relative distribution. Examples are shown in Fig. 2.15.

4. Pick five (the number of top colors may vary depending on the application context) colors with the maximum frequency.

5. Perform steps 1-4 for image M_2.

6. For each of the five top colors in M_1 take one of the top colors in M_2 , such that the mean average perceptual difference according to Eq. (3.1) is minimal.

Fig.2.12,2.13, and 2.14 provide examples of how the proposed algorithm works. The red number visible on the screenshots represents the perceptual difference between the images we obtained using the aforementioned method. Fig. 2.12 compares two images taken near two different lakes and at different levels of sun lighting. The system computed the difference as having a value of 13.95%. Fig. 2.13 shows photos of a flower field with a girl, taken from different points. The perceptual difference is 7.95%. Finally, the last pair of images (Fig. 2.14) represents two completely different pictures, but due to the presence of various tints and shades of the color blue, the difference is 45.94%.

These examples demonstrate that the proposed method is quite effective. The significant advantage of this method is that it represents progress towards obtaining machine color constancy, which is a feature of the human visual system that ensures that the perceived object color remains recognizable under changing illumination conditions [62] (see example in Fig. 2.14). Although the produced color schemes are different, the images are judged as being similar. This indicates that the system understands the extent to which the colors are affected by various shading and lighting conditions, as humans do.

The proposed method can be used in the matching engine, which implements the retrieval according to the similarity measure. In the prototype system Algorithm 1 is used in the matching engine that retrieves similar clothing items.

Fig.2.15 provides examples of how the Algorithm 1 works. Pie charts below depict the fuzzy dominant colors. Fig.4.11 compares two similar blouses. The computed difference has a value of 77.38%. Fig.4.12 compares images of similar vinous dresses. The perceptual difference is 88.62%. These examples demonstrate that the proposed method is quite effective.

Besides the works discussed above[47] ,[91],[46], there is a number of recent researches to measure fuzzy similarity and fuzzy image similarity in particular. As a possible option for the future improvement, we may consider the following approaches :

- The similarity measure between fuzzy numbers based on the Jaccard index [30].

```
Data: images M1 and M2 in RGB format
Result: similarity between M1 and M2 in %
initialization;
CH1 ← FindFuzzyDomColors (M1);
CH2 ← FindFuzzyDomColors (M2);
... /* Perform matching - for each color in CH1 take one color in
   CH2 , such that the mean average perceptual difference Dp
   between all pairs according to Eq.(3.1) is minimal.            */
return 100 − Dp;
/* Computes the dominant color histogram of the image, C_H(image),
   which is a vector (h_C1, ..., h_Cn), where each element h_Ci represents
   the frequency of color C_i in the image.                        */
Function FindFuzzyDomColors (image)
   FuzzyColors ← an empty dictionary;
   FuzzyDomColors ← an empty array;
   /* initialize the frequency of each fuzzy color to 0            */
   while not at end of image do
      read current pixel;
      process current pixel;
      /* convert a pixel from RGB to HSI, then fuzzify - convert to
         fuzzy HSI                                                 */
      fc ← computed fuzzy color;
      FuzzyColors[fc] + +;
   end
   /* Return 5 fuzzy colors having the maximum frequency.  The
      number of colors depends on the application context.         */
   FuzzyDomColors ← 5 keys from FuzzyColors with max frequency;
   return FuzzyDomColors;
```

Algorithm 1: Finding the image similarity

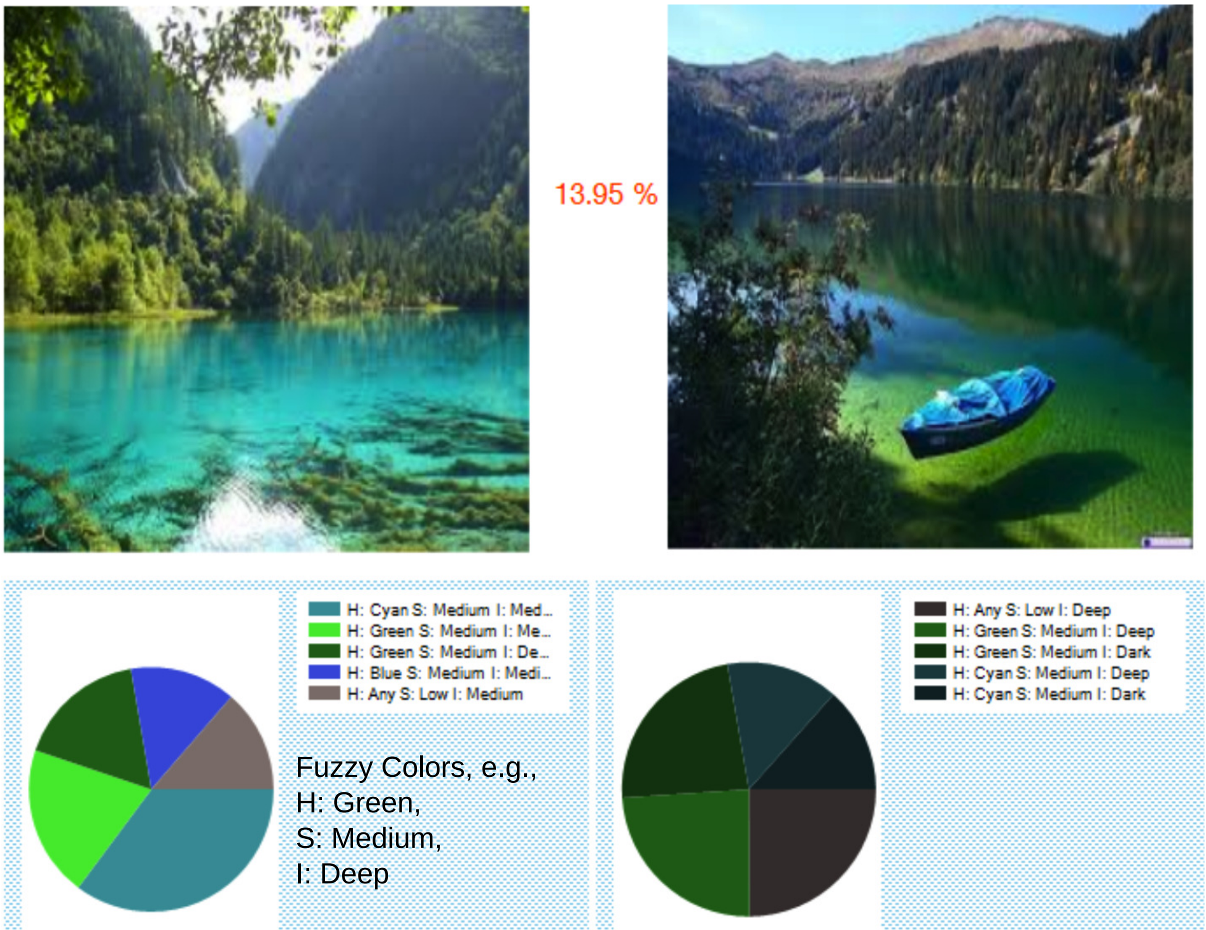


Figure 2.12: Processing the images and determining the extent to which they differ. Example 1.

- The similarity measure that uses Fuzzy-Object-Shape information as well [83].

It is important to note that the proposed method doesnt take into account the spatial relationship of color pixels. This might lead the system to judge different images with similar color distributions as similar. The simplest way to provide spatial information is to divide the image into subregions, and index them separately. However, this is not efficient to store and more time-consuming. We also plan to address it in our future research.

The proposed method for finding the perceptual difference between colors is not only used in the similarity metric we described above. It is also used to offer nice clothing combinations with harmonious colors. Although various color similarity measures were already proposed in many research works, little research was done on how to identify colors which are in a harmony. It is described in details in the next section.

Figure 2.13: Processing the images and determining the extent to which they differ. Example 2.

2.5.2 Taxonomy of Color Impressions

As we know, in computer systems colors are represented by various color spaces (RGB, CMYK, HSI). We chose HSI for a number of reasons mentioned earlier. As for color impressions, they are expressed by linguistic terms (e.g. formal, black and white, pale blue, etc.). The Table 2.3 depicts the taxonomy, i.e. classification of color impressions.

In fact, same color can create different impressions in different settings (apparel, interior coordination, medicine, etc.). So, we can claim that impressions are context-specific. Therefore, we need to emphasize that the proposed methodology aims to provide the correspondence between colors and certain impressions - atomic(red) and composite (pale red, formal and elegant) - expressed by linguistic terms in some context. In simpler words, the methodology provides Context-based Image Retrieval (CBIR) based on color scheme. The context dependency can be easily handled by fuzzy logic.

Composite color impressions, which are based on atomic ones with various connectives, can be easily handled by basic formulas from fuzzy theory [96], [98], [97]. Specifically, for the intersection (and) and union (or) we take the minimum and maximum of two memberships respectively, to get the resultant membership value [101].

If we analyze Table 2.3 , it can be easily seen that the higher the abstraction level is, the fuzzier is the correspondence between linguistic labels(impressions) and colors. This has primary importance when the methodology is customized for a certain context.

Figure 2.14: Processing the images and determining the extent to which they differ. Example 3.

2.6 FHSI library

As a result of our research efforts we have designed and implemented a Fuzzy Color Library DLL (see Fig. 2.16), which is an easy-to-use and well-documented library for representing, processing, and manipulating fuzzy colors and performing numerous operations with them. An example of how to use the library can be found in A. An example of how to use the library can be found in A. The Fuzzy Color Library API is also available for download.

2.7 Summary

The efficient operation of an image retrieval system requires the use of a considerably small number of colors to represent the image content. Although a number of color quantization methods exists, such as Color Space Partition, Color Space Clustering, and Reference Colors exist[66], they all lack perceptual rules for color mapping, which may cause considerable shifts in color. In contrast, the color zones in our approach were defined empirically, which facilitates addressing the intrinsic variability existing in the human evaluation of color similarity.

Although color, as a low-level, fast, and efficient filter, is independent of view and resolution, image retrieval that is founded purely on colors may result in too many false positives when the database is large and heterogeneous [66]. Therefore, for a more accurate result, we suggest to couple color-based features with texture/shape/edge indexing

(a) The computed similarity is 77.38%

(b) The computed similarity is 88.62%

Figure 2.15: Processing the images and finding how similar they are.

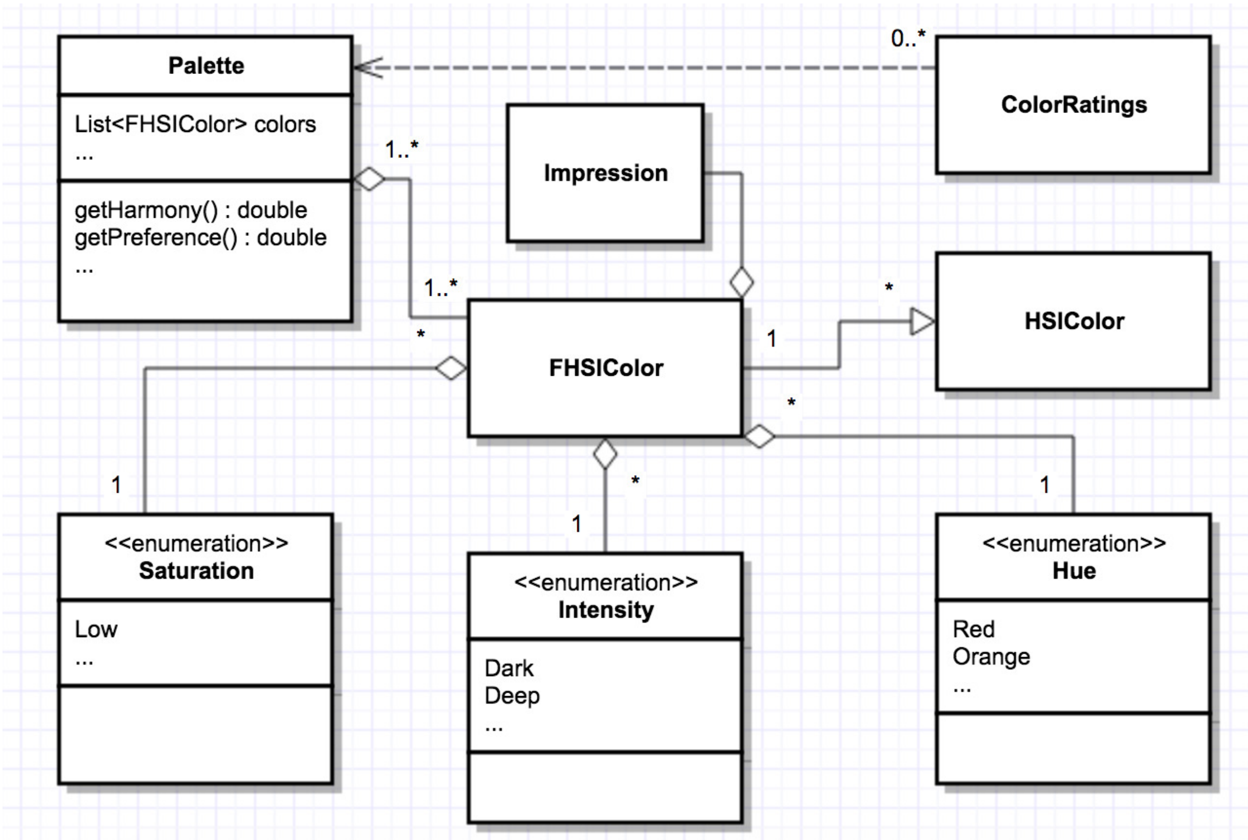


Figure 2.16: UML of the Fuzzy Color Library.

Table 2.3: Taxonomy of Color Impressions.

Level	Impressions	Comment
III	Various combinations of I and II (Pale blue, elegant and formal, deep red)	Composite, context-dependent and context-independent colors
II	Elegant, formal, casual. Pale, bright, deep	Atomic, context-dependent and context-independent colors
I	Red, blue, black	Atomic, context-independent colors

methods. Thus, our system could function as a subsystem within a huge retrieval system and its output could be further processed by more time-consuming methods.

We have developed a fuzzy sets and logic guided model of color (see Fig. 2.17), a perceptual color space (FHSI, fuzzy HSI). Fuzzy sets are perfectly suitable when boundaries between categories are difficult to determine[96]. Color channels distributions in our space were expressed with fuzzy membership functions [72]. Essentially, we modelled colors by means of fuzzy sets defined on an HSI color space and a fuzzy partition was defined in the corresponding color feature domain (fuzzy color space). There are 92 colors in FHSI. The soft boundaries between the color categories were derived experimentally through an online survey based on human color categorization. We also defined methods for finding the perceptual difference between colors Eq. (3.1) and the degree of similarity between images based on FHSI system [72], [73].

We enhance color difference formula by adding a coefficient δ, representing the degree of difference between the memberships of corresponding hue points to the common hue. The less δ , the closer colors (hues) perceptually. So, the resultant hue perceptual difference d_p is:

$$d_p(H_1, H_2) = d(H_1, H_2) \times \delta, \tag{2.10}$$

where $d(H_1, H_2)$ is an absolute difference between two hue values that considers the cyclic properties of a hue component. The role of δ in Eq. (2.10) is to ensure that

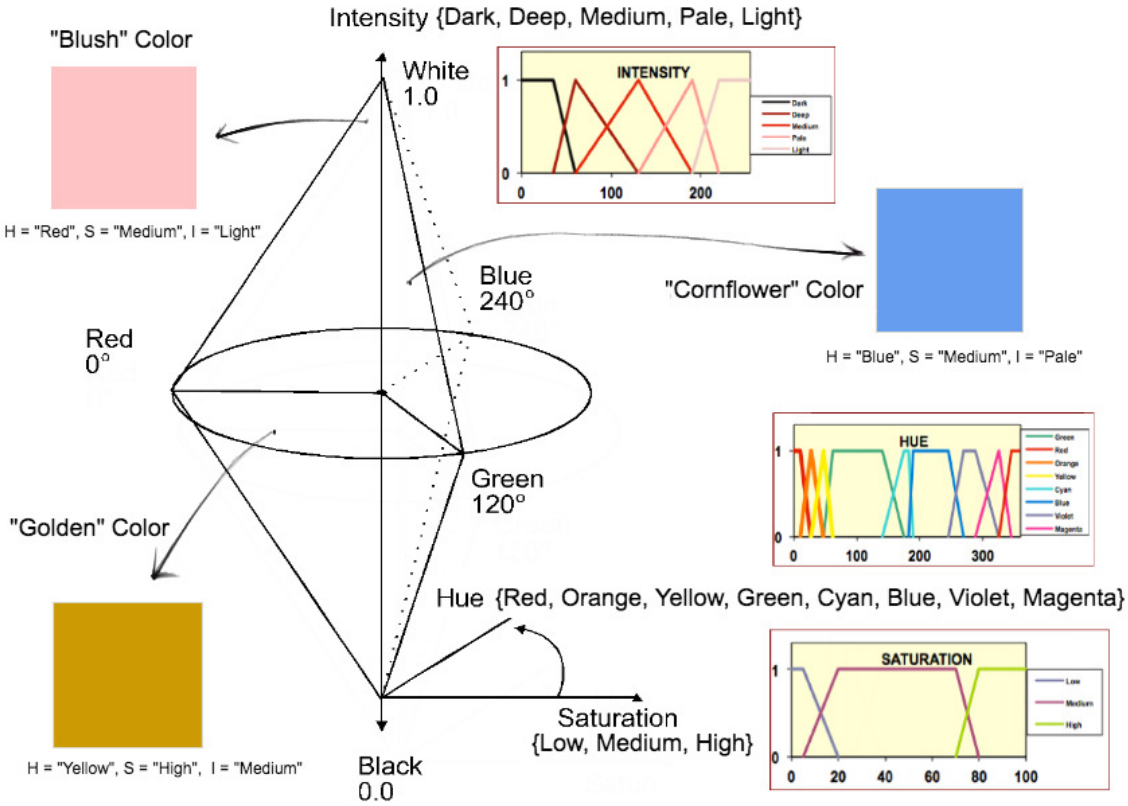


Figure 2.17: FHSI Color Model.

perceptually similar colors will have smaller perceptual distance than colors with the same hue distance, but different hue categories.

Before, almost no extant research has examined the effect of hue while controlling for lightness and saturation, though these play a critical role [15]. We inculcate into the model the fact that H, S, and I attributes do not have the same importance when human judges how similar two colors are. Our model uses the S attribute as a weighting factor for the intensity and hue. Specifically, when we compare two colors, we need to remember that:

- If (S is high) H is more important;
- If (S is low) I is more important.

In order to model such phenomena we assigned the specific pertinence values to each of the color channels (H, S and I). The pertinence of the Hue category depends on how *high* the $Saturation$ is, and the pertinence of the $Intensity$ depends on how *low* the $Saturation$ is: [2]

[2]The pertinence of the Saturation category is always 0.5, half of maximum pertinence

So, based on Eq. (2.10), Eq. (2.7) the perceptual difference can be found using the formula below:

$$D_p = \sum_{i \in \{H,S,I\}} D_{p_i} \times \pi_i, \tag{2.11}$$

where D_i. denotes normalized value for the perceptual difference.

Using this perceptual difference, we have also provided the objective metrics to measure the image similarity. FHSI model itself and all the operation in FHSI we discuss are programmed and packed into a Fuzzy Color Library (dll) we implemented.

Chapter 3

Color Harmony and Color Preference Metrics

Humans often experience colors not in an isolation, but in a combination. The aesthetic perception of a color group is strongly influenced by its overall harmony. Hence, it is essential to consider the congruency of chromatic compositions, rather than how much people like single colors[52].

In previous sections we used fuzzy sets to built up a general human-friendly model of color that can be used to deal with the uncertainty linked to apparels images for the online shopping coordination. Our main objective in this section is to model high level human aesthetic judgements and develop a novice method for evaluations of all types of perceptual responses to colors: distinct color preference, color harmony, and color combination preference. We use FHSI as a main tool to process aesthetic responses to colors.

3.1 Introduction

Aesthetics is of pivotal importance these days. Humans make judgements and choices every day based on their inner aesthetic responses to aspects of the surrounding world. We make a decision, e.g., to wear this sweater rather than that mostly because we prefer its color [55].

Making computers "understand" human aesthetic preference is a challenging task that can be highly useful for a number of industries, including design [85], marketing, and fashion (e.g., refined user-driven results for visual search engines). For example, fashion aesthetics involves many aspects, including color, various styles (e.g., sleeves types), fabric, spatial compositions, etc. However, experiments show that people usually judge an item within 90 seconds of viewing and initial assessments are mostly (62-90%) driven by colors [78].

Despite color omnipresence and a growing interest in color in various domains, there is a lack of research devoted to computer color models and color aesthetics specifically is not a well-developed area [15]. Plenty of research data on color preferences is puzzling, confusing, and contradictory [42]. Therefore, there remain a lot of unanswered questions.

By adopting fuzzy set representations [96] and the relevant calculus for them, we can solve the problem of the semantic gap between low-level color visual features and high-level aesthetic concepts. We claim that color theories must be shaped by aesthetic norms, including taste (preference for single colors) and trends (context-aware harmonious palettes). We propose a technique to predict the aesthetic preference for color combinations by introducing the new variables: color harmony and color preference. Aesthetic responses are highly influenced by a harmony of colors, since the same color can create a different impression when viewed together with different colors. We believe that concepts of *preference* and *harmony* and their relationship can serve as a tool for future investigations in aesthetics across multiple domains. We discuss color aesthetics phenomenon in Section 3.2.

In the context of e-commerce shopping, there are three main related questions:

1. How do colors influence preference and harmony judgements?
2. What colors influence buyer preferences in clothing?
3. How to predict a preference for an outfit based on colors of apparels?

We attempt to respond to the above-stated questions by predicting combination preference from an individual color preference and harmony. We use the research findings of Berkeley Color Project [53], [52], [54], and claim that:

- Higher individual preference for distinct colors implies higher preference;
- Higher harmony ratings also imply higher preference.

Our research seeks to establish relations between color stimuli and purchasing behavior. Aesthetic effects of color properties are highly relational and contextual [67]. We extract harmonious pallets from big data sets, test them by conducting a questionnaire and then use comparison algorithms based on fuzzy similarity.

The approach we propose is supported by experimental results described in Section 4.

3.2 Color Aesthetics

Aesthetics is the study of human emotions in relation to the sense of beauty [55]. Aesthetic feelings arise mainly due to an unusual degree of harmonious interrelation between objects [1].

There are two concepts related to color aesthetics, namely harmony and preference. The difference between these phenomena is crucial. Aesthetic preference for color combinations is mostly driven by color harmony and there are some common tendencies in defining them. However, there are also small differences in the degree to which people prefer harmony, with correlations in the range from 0.03 to 0.75. [52], [54]. Those differences are a result of varying individual preference for colors.

Aesthetic assessments can be very useful and handful when there are too many objects to be evaluated manually or it is expensive to use an expert. Moreover, such technology can be more reliable than human assessment, which is often subjective and prone to personal biases [42].

We can become closer to aesthetics evaluation by examining and trying to quantify the aesthetic "charm" of various psycho-physical properties of objects such as their size and color(s) (in terms of hue, saturation, and intensity). From ancient times artists make use of color harmonies in order to achieve a certain level of aesthetics. Color aesthetics involves studying of visually appealing color combinations hidden in the interior, fashion look, photographs [49], or even some piece of art. So that a user sees a composition (of any items) and gets the aesthetic pleasure. It is of interest to note that the "first impression", an initial judgement of visual stimuli happens in as little as 50 milliseconds based on a general aesthetic appeal, mostly depending on a color [19].

Each and every visual stimulus processed by the human visual system contains color data. Color is generally considered to be one of the most important and distinguishing visual features. Additionally, it is often treated as an aesthetic issue, having a significant impact on product sales, accounting for 85% of the reason why consumer purchases a product. How? By creating an impression and raising the aesthetic senses, color influences decision-making (buy or not to buy) processes in our brains.

Understanding human aesthetic preference is a challenging task that can be highly useful for a number of industries, including design [85], marketing, and fashion (e.g., refined user-driven results for visual search engines). Fashion aesthetics involves many aspects, including the color, various styles (e.g., sleeves types), materials, spatial compositions, etc. However, consumers usually judge an item within 90 seconds of viewing and initial assessments are mostly driven by colors (i.e. when a human perceives colors, a rich network of associations gets activated). So, we pay a lot of attention to color aesthetics in particular, for making personalized recommendations for images. But we need to remember that preference for harmonious color stimuli is just one factor underlying aesthetic response.

3.3 Literature Overview

Before moving on to the proposed method, let us provide a brief review of previous work in the field of color harmony and color aesthetics.

Throughout history, it has been the contradiction in research works of color theorists studying harmony. In [9] Chevreul defined the law of simultaneous contrast of colors and proposed harmonies of analogous and contrasting colors. In his theory harmony and preference were used interchangeably. Nevertheless, it is considered to be one of the most influential theories in this field. Another great color theorist, Itten, claimed that color combination is harmonious if it is composed of closely similar chromos (e.g. tones, tints and shades), or else of different colors of the same nuance[31]. In essence, his theory defines harmonious colors as colors producing neutral gray when mixed as paints. Furthermore, Munsell and Ostwald put ahead the idea that colors are harmonious if they have some relation in the given color space (e.g., if colors are similar in hue or have a triadic relation) [52].

Birkhoff [1] was the first to push forward the mathematical formalization of aesthetics. He defined M, an aesthetic measure of the object as the function f of the ratio between its order, O and complexity, C , $M = f(O/C)$. Birkhoff's formula has a very general meaning, irrespective of the mode of perception (visual, auditory) or object types. The main hindrance in the direct usage of his abstract formalization lies in specific definitions of O and C, which themselves need to be formalized. Even Birkhoff himself stated that the purpose of his research was to gain at least a basic understanding of aesthetics, even at the risk of inaccuracies.

Other theories include Goethe's approach [23], who was one of the first to associate the aesthetic qualities with colors in his color wheel (e.g. "beautiful", "noble") and formulated arguments against Newton's theory of light and colors. His works are primarily focused on exploring how color is perceived in different conditions and what is their nature. Eysenck introduced the concept of *aesthetic appreciation* (which he called as T for "good taste"), that reflected the extent to which individual rankings correlated with the average rankings of the entire group [17].

Next, Granger [24], [25] put forward the idea that preferences for color patches are entirely dependent on the interval size between components colors. There is also a conjoint measurement approach to evaluate a color harmony [57], that states that color harmony is a saturation harmony multiplied by the sum of a hue harmony and a lightness harmony. The problem with this approach is that it does not provide any rules on how to calculate a hue harmony, for example. Another popular approach, the Moon-Spencer model [44] focuses on just identity, similarity, and contrast as three main principles for color harmony. This theory also has certain limitations as it is suitable only for measuring two-dimensional harmonics [49].

Note that none of these theories were formulated on the basis of aesthetic measurements, although some have since been tested empirically [55].

As we see, the color literature is full of discrepancies. If we unite these theories into one system we will obtain that nearly every color combination can be considered as harmonious [52].

We believe that the source of this contradiction lies in the fact that there is still neither human consistent color space nor single best representation of color. There are multiple spaces that characterize the color features from different perspectives instead. This hinders the development of CBIR-based services, in which the main part is color indexing. Reliable operation of such systems requires understanding the correspondence between the linguistic terms and colors. For instance, it is difficult for current systems to find out that deep red is more similar to crimson rather than to Turkish red. Color histogram method is very popular in CBIR. However, due to limitations of color spaces similar colors are often quantized into different bins, leading to low retrieval performance. Therefore, it is a very challenging task to represent, measure and process colors and their harmony.

3.4 Typology of Color Judgements

Preference and harmony are often used interchangeably. However, these two phenomenon are similar only in case an observer likes the colors in the combination. To avoid the confusion we need to accurately define and measure them. In this section we carefully define and explain the difference between *Single Color Preference (SCP)*, *Color Scheme Harmony (CSH)*, and *Color scheme preference (CSP)*. They are all three distinct types of judgments and different ways of evaluation of perceptual responses to color schemes.

This distinction helps us to better customize the system for each user.

3.4.1 Single Color Preference

Single Color Preference (SCP) reflects the contextless preference ratings. Usually, people tend to prefer some colors over others, and nearly everyone has its favourite color. Preference for single colors depend on aggregated affective response to everything associated with the color for some individual. The general pattern of preferences for single colors is complex, but there are some certainly clear and repeatable regularities. [55].

SCP measures can be obtained during or after the registration in the system. Users are just offered a small survey with simple visual content (colors) with questions (e.g., how much do you like the display?) and the responses are collected using a rating scale

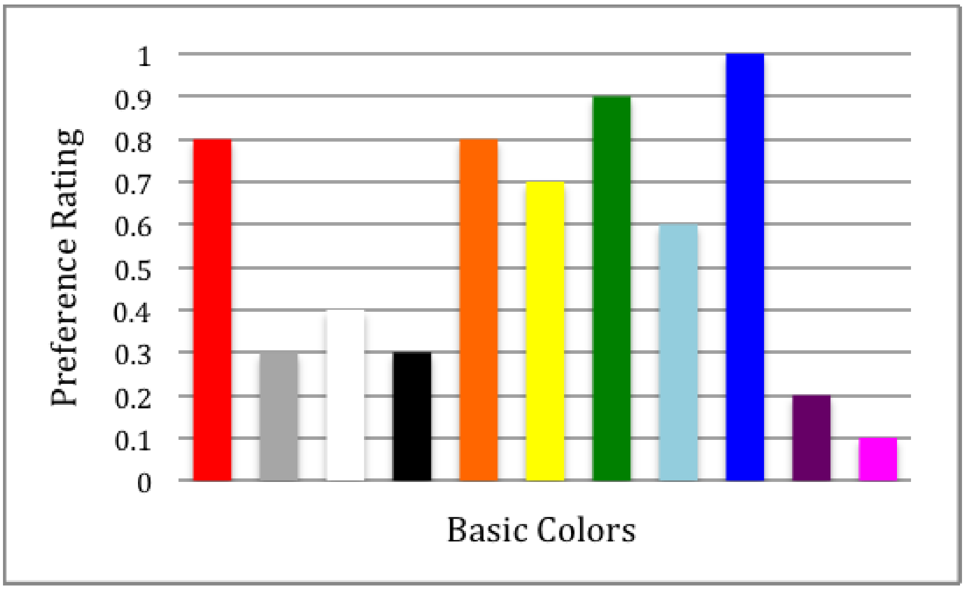


Figure 3.1: Example of Single Color Ratings

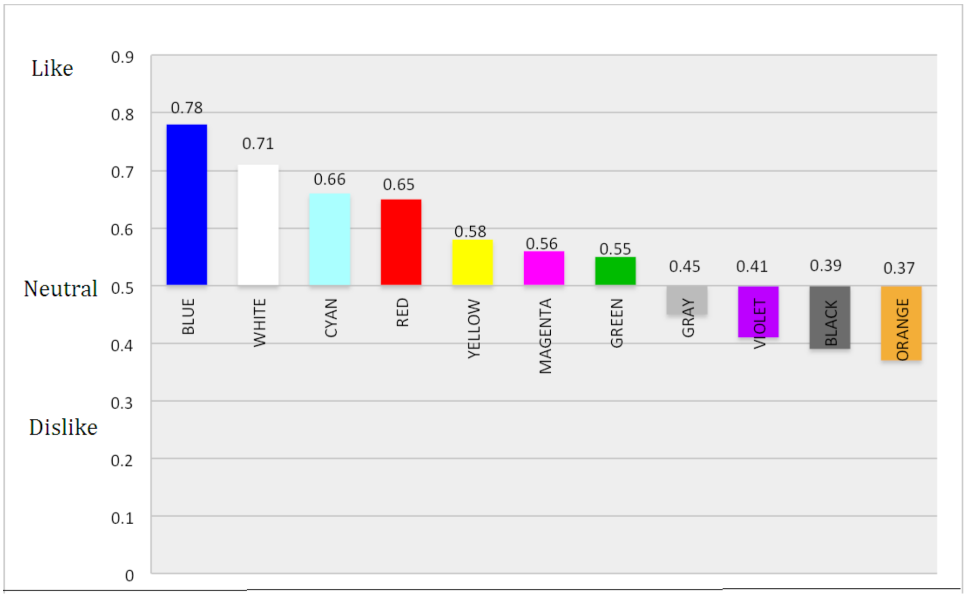


Figure 3.2: Average color preference ratings obtained from the survey

(e.g., Not at all , Good, Very much, etc.). An example of *Single Color Ratings* (individual preference) can be seen in Fig. 3.1. The idea is to account for basic colors without a considerable loss in precision. At this step, we are interested in preferences for hue independently of lightness and chroma.

Fig. 3.2 shows the overall relative color preference across the group of selected individuals. These atomic color judgements are entirely subjective because they rest on personal experiences (e.g., liking or disliking a certain color). These preferences are well correlated with results reported by Granger [25] (in which colors were ranked according to individual's preferences in the following order: blue, green, purple, red, yellow) and Palmer [55] (cool colors, like cyan or blue, are generally preferred to warm colors, like red or orange).

Environmental and cultural aspects also play a highly important role in forming of color preference. For example, according to research outcomes[63], there is a common strong preference for white color in three neighboring Asian areas, Japan, Korea, and China [63].

It needs to be emphasized that individual's single preferences are not always internally consistent, reliable, and constant over a period of time [42]. We can measure and analyse users preferences for color stimuli over certain periods of time. In the context of e-commerce online shopping, for instance, color preferences can be subject to seasonal change.

3.4.2 Color Scheme Harmony

Color harmony represents a satisfying balance or unity of colors. So, some combination is harmonious if its parts fit well together, regardless of preference.

From a design perspective, harmony is something aesthetically comfortable to the eyes [19].

In contrast, a CSH reflects how strongly the colors in the combination are going well together, regardless of whether an individual likes the given combination or not. In other words, CSH indicates the harmony of the color combination as a whole.

3.4.3 Color Scheme Preference

It is widely acknowledged that people substantially differ in their aesthetic preferences related to colors, music, art, etc. [55]. Preference reflects whether (or to what degree) individual judges or experiences some object(s) as beautiful (or ugly) [55].

A color palette (combination, scheme, group) preference is defined as how much an individual likes a given combination of colors. So, it reflects an aesthetic preference for a given palette as a whole.

SCP ratings are not enough to predict CSP. To better define palette preference we need a relational factor like harmony. The problem is how to derive it? Conventional methods are no longer valid to meet current requirements [73].

3.5 What is Color Harmony and why it is important?

Generally, a visual harmony is some combination that is pleasing to the eye[18]. When people speak about color harmony, they are evaluating the joint effect of two or more colors.

Experiments with subjective color combinations prove that individuals differ in their judgments of harmony. The color combinations called “harmonious” in common speech usually are composed of closely similar chromos (e.g. tones, tints and shades), or else of different colors of the same nuance[18]. The general idea is that colors which are combined together without a sharp contrast are in a harmony.

Harmony is one of the most interesting and intriguing principles in color theory, which is still raw. The problem with harmony is that it is a very complex notion, with many unwritten rules and factors having an impact on it, including affective, cognitive and contextual ones.

Colors which tend to produce a good impression when seen together are said to be in a harmony. So, it strongly depends on not only personal differences (i.e. gender, cultural norms, age, lifestyle in general), but also on context. Therefore, color harmony is very difficult to predict - those factors influence on how certain colors are perceived in any given situation or context. Obviously, such kind of predictions can be extremely useful in fashion, interior and graphic design.

In the sample application we describe below, we use color harmony principles in order to recommend total looks and to identify the set of apparels that fit to a certain apparel that the user inputted to a system. Obviously, this is done based on a color scheme. Basically, we need to store the set of groups of colors that are in a harmony. Specifically, we store their FHSI values. Note that groups might have various number of colors.

It is clear that in our color harmony table we have fuzzy colors. But in reality, as it was mentioned, there is nearly 16 million colors. For each possible color we need to be able to identify group(s) of colors with which this particular color is in a harmony. This is the case where we need to be able to identify the very similar color with the inputted color. Literature suggests the number of ways to accomplish this do comparison based on RGB values (simple, but not precise way due to the fact that RGB space is not uniform), based on solely hue values, LAB measure etc. We decided to develop our own method for that, it is discussed in detail in [68].

Color harmony groups were extracted based on the analysis of basic color theory and fashion images. In the future, we plan to tune the harmony knowledge base by the way of measuring the user relevance feedback.

3.6 Existing Color Harmony Rules

How to select and use color combinations so that they will be aesthetically appealing? There exist a number of conventional rules of defining harmonious colors. It is generally accepted that the human eye is satisfied or in equilibrium with a color combination, only when the complementary relation is established.

According to Itten[18], the colors are mutually harmonious if their mixture produces a neutral gray color. Any other color combinations, the mixture of which does not yield gray, are expressive or discordant. The most popular conventional techniques for combining colors based on the color wheel are represented in Fig. 3.3. For more information you can refer to[18].

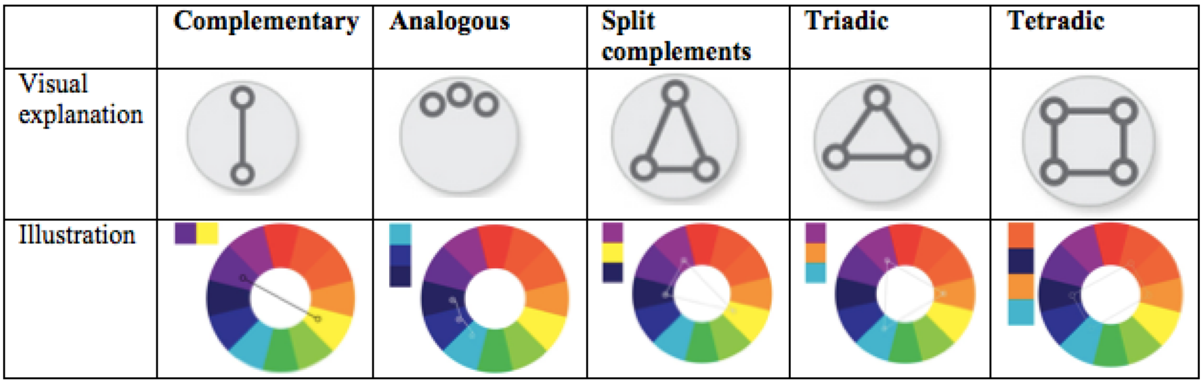


Figure 3.3: Conventional ways of combining colors.

3.7 Harmonious Palettes Derivation

Recent studies have established that, notwithstanding large individual differences, group color preferences demonstrate some systematic and reliable patterns [55].

How to "measure" color combinations harmony? We address this questions to empirical research. In [53], [52], [54] it was concluded that color harmony is a function of color similarity. What is more, people tend to prefer color combinations, which contain colors that are similar in hue, cool, and desaturated. However, we believe that harmony is a very complex phenomenon and it is nearly impossible to purely define it in terms of strict rules.

We want to extract harmonious, fuzzy color-based pallets from data set. This is done by forming groups containing looks with similar color compositions. To achieve this, we use the fuzzy model we developed, formulas for the fuzzy color difference, palettes similarity (described in [72], [73]).

As a data set, we took 10000 images with fashion looks from various sources, including the most popular fashion sites, like polyvore.com, lookbook.nu, instyle.com, dailylook.com and various style communities in SNS (Instagram, VK, Facebook). The preference was given to looks having more likes.

For each image M in a data set we perform the following:

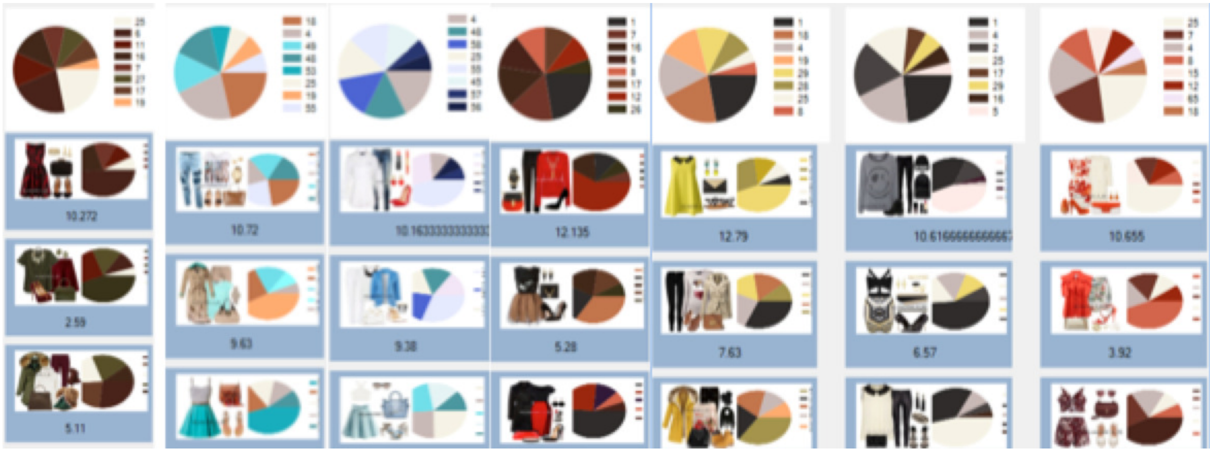


Figure 3.4: Examples of Derived Harmonious Palettes.

1. Compute the fuzzy dominant color histogram of M;
2. Compute the mean average perceptual difference Dp_{avg} between CH and members of each harmonious groups;
3. If minimal Dp_{avg} is more than the difference threshold, form a new group and add M to it. Otherwise, add M to a group with which M has minimal Dp_{avg};
4. Choose groups having at least 100 similar looks falling into a similar fuzzy color scheme.

Processing of data set took almost 7 hours (1-2 seconds for each image, depending on resolution, the current number of groups, etc.). On the 8^{th} thousand the convergence was achieved since almost all new coming images were falling into existing groups and very few new palettes were added during the processing of the last 2000 images.

In this way we obtain groups with similar fuzzy color schemes. As a result, we got 139 groups in total 59 palettes of them contained more than 100 images (Fig. 3.4 demonstrates some of them). For each group we took averaged harmonious fuzzy color palette. Some of the schemes we extracted were similar to Analogous, Contrasting, Triadic, etc. (classified by Itten [31]), but there were also schemes which are out of any rules. Examples of harmonious groups with more than 100 similar images can be seen in Fig. 3.4.

It needs to be emphasized that color preferences may change depending on semantic context [53]. Whether derived palettes provide context-aware or context-independent harmony? We can perform palettes derivation for other domains - art or interior design, for example. In following subsections we discuss this issue deeper. The very essence of this generation process is that it is becoming possible due to FHSI space.

However, the question of the origin of harmonious color combinations is still a mystery. Whether they emerge from learned associations that develop from experience, e.g. repeated combinations of colors with certain messages and concepts [15], or they have some intrinsic nature? These questions are subject to subsequent psychological research.

3.8 Harmony between Fuzzy Colors

Fig. 3.4 presents some of the color harmony groups we propose. These color combinations were obtained as a result of the deep analysis of basic principles of color theory and processing of fashion images. In our system, for each possible color we need to be able to identify group(s) of colors with which this particular color is in a harmony. To do that, we need to be able to find the very similar color to the input color and here it comes to the perceptual difference formula (Eq. (2.11)).

Now we can find $Harm(A, B)$ between two fuzzy colors A and B. If there is a palette containing both A and B, then $Harm(A, B) = 1$. Harmony of a group of fuzzy colors which is not in a knowledge base is equal to its similarity with the closest harmonious group. We use similarity measure we defined in a previous section. It needs to be emphasized that color preferences may change depending on semantic context [53]. Therefore, derived palettes provide context-aware harmony. We can perform palettes derivation for other domains - art or interior design, for example. The very essence of this generation process is that it is becoming possible due to FHSI space - palettes comparison is done using the FHSI similarity metric.

We checked the competence of the proposed and traditional harmony groups, along with the other methods by conducting an online survey, which is based on a Polling method. The survey was intended to gather people's opinions on a harmony of various color combinations. The results of this questionnaire concerning the conventional color schemes are presented in Fig. 3.5. Overall results demonstrating the proportion of people who gave positive feedback on certain color combinations are presented in Fig. 3.6. The average result for harmonies proposed in this paper is 0.45, for the ones proposed by colorstudio.com 0.16, for the traditional ones 0.11. As we see, traditional rules for combining colors don't seem to be accepted by modern society.

3.9 User Preference Prediction in Fashion Industry

Average population results provide a brief idea of preference. However, it often conceals many individual variations [42].

How to predict a preference for a look based on colors of apparels? As mentioned before, a preference for color schemes is influenced by preferences for the component

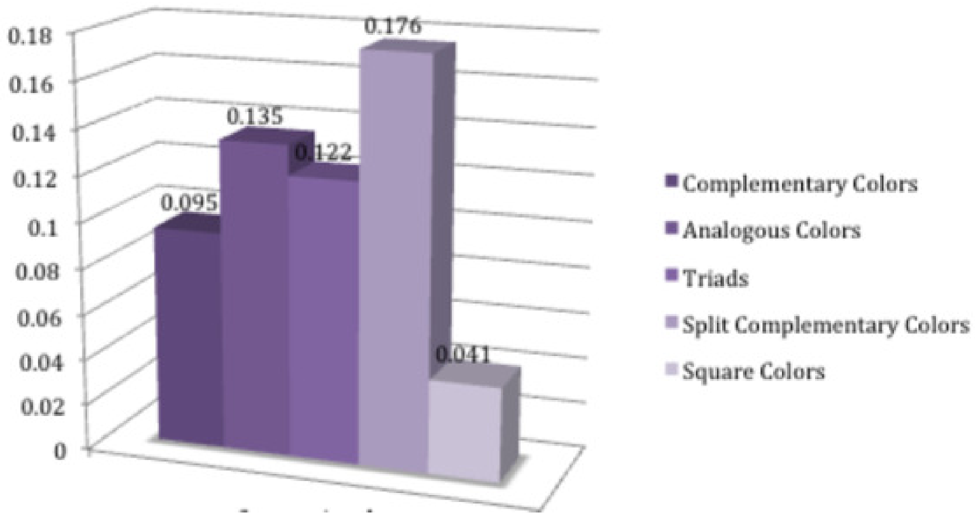


Figure 3.5: Results of a survey: users opinion on conventional ways of combining colors.

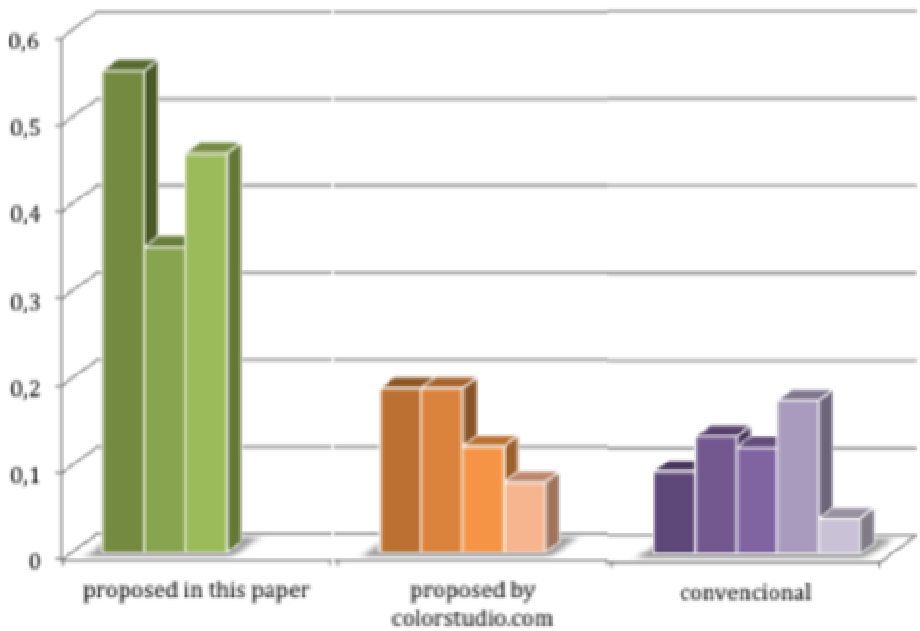


Figure 3.6: Results of a survey.

basic colors and ratings of color harmony [53]. Let's combine preferences for the single component colors and ratings of color harmony:

$$Pref(A, B) = \frac{Pref(A) \times w_A + Pref(B) \times w_B}{w_A + w_B} + Harm(A, B) \tag{3.1}$$

In Eq. (3.1) w is a weight importance of an apparel, $Pref(A), Pref(B)$ are user preferences for single colors A and B. Eq. (3.1) also works for three, four, five colors as well.

Generally, aesthetic judgements of fashion looks are influenced by dominance order. For example, dress or skirts usually make more impact on an overall impression rather than accessories. That is why we need to take into account w, apparel weight parameter:

- For dresses and costumes $w = 1$;
- For up & down clothes (e.g.,skirts, blouses.) $w = 0.75$;
- For shoes and bags $w = 0.5$;
- For accessories (e.g., glasses, watches) $w = 0.25$.

Now we can find $Harm(A, B)$ between two fuzzy colors A and B. If there is a palette containing both A and B, then $Harm(A, B) = 1$. Otherwise, we take the most similar color harmonious palette and find the similarity value (which will serve as a harmony value too in this case). Harmony of a group of fuzzy colors which is not in a knowledge base is equal to its similarity with the closest harmonious group. We use similarity measure we introduced in a previous section.

Eq. (3.1) ensures that users will not be recommended some palette although it has a high harmony, in case they don't like the colors in it.

Let us provide a couple of examples.

Example 1. Predict the preference of user X for the look in Fig. **??**. As we defined, $w_{dress} = 1$, $w_{bag} = 0.5$.

Since the apparels were preprocessed, we know the ids of fuzzy dominant colors of the dress (A, 12) and the bag (B, 1). Next, suppose the single color ratings of user X areas represented in Fig. 3.1. So, $Pref(A) = 0.8$ and $Pref(B) = 0.5$. $Harm(A, B) = 1$, since fuzzy colors 1 and 12 are both in a color harmony palette 27 , see Fig. **??**. Finally,

Figure 3.7: Look for Example 1.

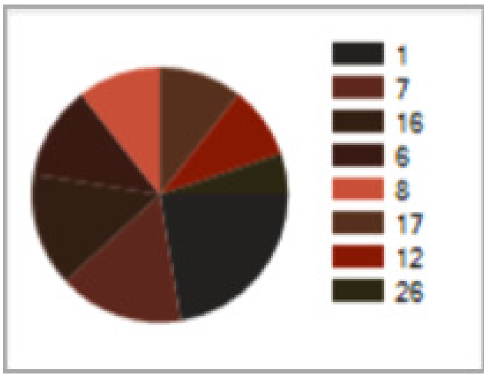


Figure 3.8: Harmonious Palette 27.

according to our preference formula Eq. (3.1), $Pref(A, B)$ for User X is 0.83 (value is normalized to a scale [0; 1]). Note that for an unregistered user (e.g. for a guest) $Pref(A, B) = Harm(A, B) = 1$.

Example 2. Predict the preference of user Y for the look in Fig. 3.10. Apparels weights for this example: $w_{up} = w_{down} = 0.75$, $w_{bag} = w_{shoes} = 0.5$, and $w_{acc} = 0.25$.

Suppose Eq. (3.9) depicts single color ratings of user Y. There is no such color harmony group containing all the fuzzy colors in the look, but there is a group 14 which is the most similar, similarity is equal to 83%, so as harmony Fig. 3.11, Fig. 3.12. According to Eq. (3.1), $Pref(A, B)$ for User Y normalized to a scale $[0; 1] \approx 0.8$.

Let us use the scientific method we introduced to investigate aesthetic experience in a fashion domain. The Table 3.1 provides several examples with calculated harmony and preference values. Second column represents fuzzy dominant colors of each outfit. For preference calculation we used single color ratings as in Fig. 3.1 discussed above. For the first outfit, although the evaluated harmony is *very strong*, the predicted preference value is *more-or-less high*. The reason is that, according to provided individual color preferences Fig. 3.1, user does not like black color that much. The preference for the second clothing outfit is *average*, influenced by disliking the gray color (according to Fig. 3.1).

3.10 Human-consistent Classification of Perceptions

Applying formulas introduced in a previous subsection, we get numerical values for harmony and preference, which are not expressive enough (e.g., preference is 0.9). Using

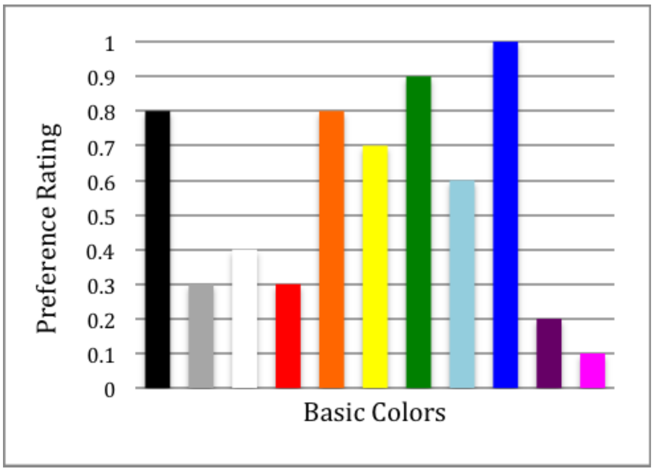


Figure 3.9: Single Color Ratings of User Y.

Figure 3.10: Look for Example 2.

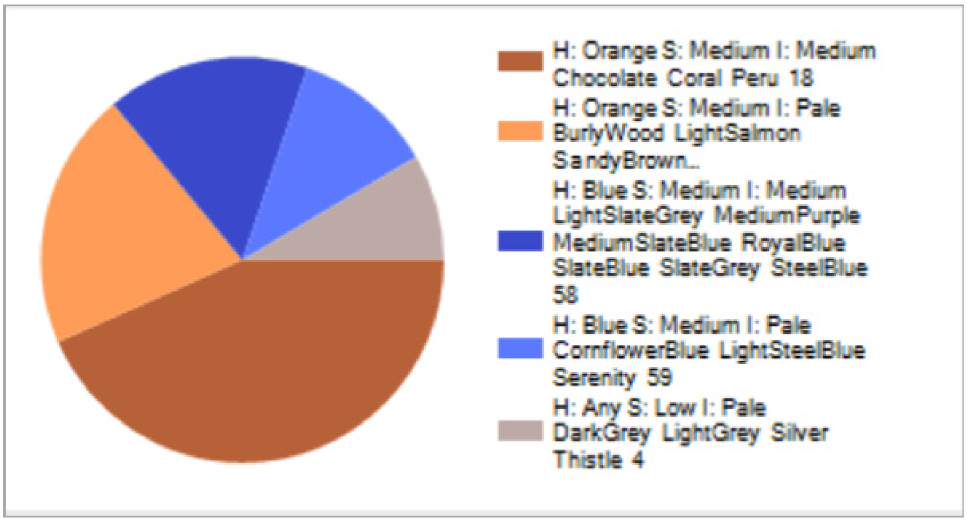


Figure 3.11: Fuzzy Dominant Color
Descriptor for Example 2.

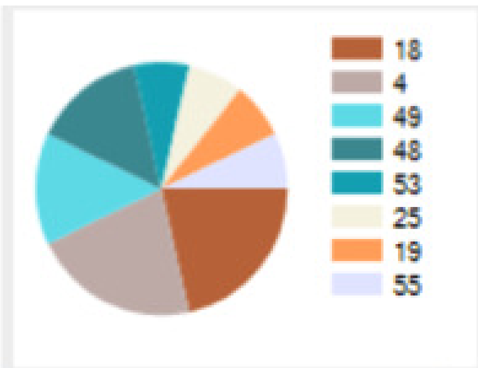


Figure 3.12: Harmonious Palette 14.

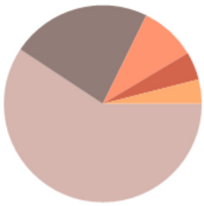
Clothing Outfit	Dominant FHSI Colors	Harmony	Preference
		*very strong* (99.63)	*more-or-less high* (82.80)
		*very strong* (95.26)	*average* (75.63)
		*very weak* (85.74)	*very low* (62.87)
		*more-or-less strong* (90.95)	*average* (79.50)

Table 3.1: Calculated harmony and preference values for some clothing outfits.

linguistic variables and modifiers, we can provide a kind of human-consistent classification of the judgments. This is really a good idea to state conclusions linguistically since such phenomena as preference and harmony are usually approximate and thus categorizing and ordering them is a challenge.

It is obvious that preference and harmony are fuzzy characterizations, then how to perform its symbolic classification management?

Instead of ordering we can provide a hierarchy with the set of all linguistic values, translating quantitative values into the matter of linguistic expressions [97].

A linguistic variable refers to a variable whose values are not numbers, but words or sentences in a natural language [98]. Therefore, we can represent harmony as an ordered list of characterizations of the linguistic variable $X = "Harmony"$ by means of primary linguistic terms $L = \{Weak, Neutral, Strong\}$. Next, preference $Y = Preference$ can be characterized by any element of a finite ordered list of primary terms $L = \{Low, Average, High\}$ (Fig. 4.3).

Let us represent some of the essential concepts we need to use [10]. Let A and B represent fuzzy sets on a universe, X. Then, the union and intersection are:

$$(A \cup B)(x) = max(A(x), B(x)) \tag{3.2}$$

$$(A \cap B)(x) = min(A(x), B(x)) \tag{3.3}$$

In our case, A and B represent linguistic expressions, so $A \cup B$ and $A \cap B$ are usually interpreted as *"A or B"* and *"A and B"*, respectively. The union of fuzzy sets refers to as t-conorm and the intersection of fuzzy sets refers to as a t-norms.

For α in a range $[0, 1]$, the α-cut of A is defined as

$$[A]_\alpha = \{x \in X | A(x) \geqslant \alpha\} \tag{3.4}$$

In the *Example 1* in a previous section the *Preference =0.83* and *Harmony = 1.* So that :

$$\Pi_{Harmony(Look2)} = VERYHIGH, \qquad \Pi_{Pref(Look2)} = MORE\text{-}OR\text{-}LESSHIGH \tag{3.5}$$

Next,

$$A \subseteq B \Leftrightarrow (\forall x \in X)(A(x) \leq B(x)). \tag{3.6}$$

The idea of approximation of a standard evidence is at the root of the concept of a linguistic hedge, or modifier [98], [99], [100]. Primary terms for harmony and preference together with a collection of modifiers enable us to generate a composite linguistic value through the use of conjunctions and disjunctions [99].

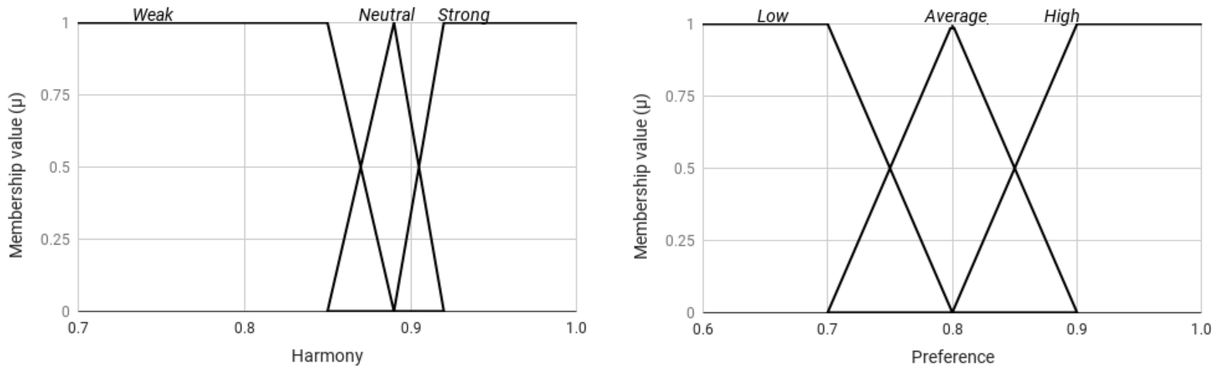


Figure 3.13: Fuzzy Membership Functions for Preference and Harmony.

An important part within the fuzzy set theory framework is devoted to the representation of linguistic terms and hedges, i.e. linguistic expressions by which other expressions are modified. Generally, a linguistic term is modelled by a fuzzy set and a linguistic modifier, therefore, by an operation that transforms a fuzzy set into another [10] . For example, applying a fuzzy modifier for *roughly* onto a fuzzy set for *high harmony* gives rise to the membership function for *roughly high harmony*.

A number of works stress the importance of modifiers (such as "very", "more-or-less") acting on the fuzzy qualifications C_i to give new characterizations $m(C_i)$, of a modifier m, associated with possibility distributions $t_m(\mu_i)$ obtained from μ_i by means of some transformation t_m [100]. In general, the purpose of hedges is to produce a bit different characterizations that are not too far from the original ones.

Linguistic hedges are very useful tools for the approximate reasoning for a number of reasons:

- They enable gradual knowledge and so gradual variation;
- They allow to avoid unnecessary computations;
- Their ability to be used in a symbolic way in the framework of fuzzy-based numerical approach.

Our modifiers set include - $\{very, more\text{-}or\text{-}less, not\}$. See Fig. 3.14 for a visual support. Fig. 3.14 depicts fuzzy sets labelled *very high preference, more-or-less high preference, not high preference, high preference.*Then, the term sets of *Preference* and *Harmony* :

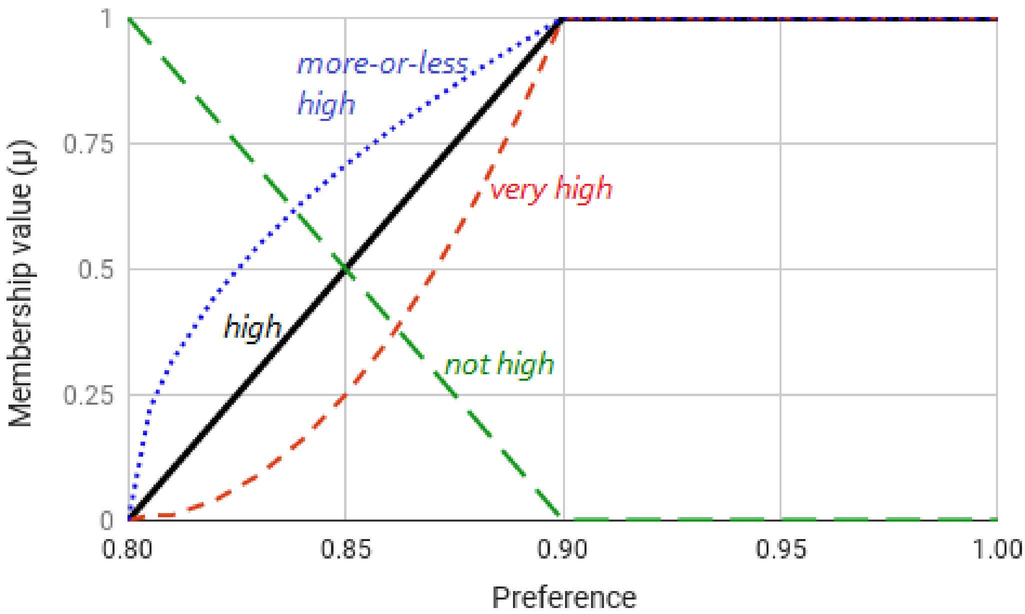


Figure 3.14: Effect of the modifiers *very, more-or-less, not* on the characterization "high preference"

T(Harmony) = weak + not weak + very weak + not strong and not weak + ... + strong + more-or-less strong + very very strong + not very strong + ...

T(Preference) = low + very very low + not very low + not low and not average + ... + average + not average + more-or-less high + very high + ...

in which + is used to denote a union, not an arithmetic sum [98]. Each such term represents a fuzzy subset of the unit interval.

We apply two families of modifiers - reinforcing and weakening modifiers. Examples of a reinforcement of a characterization C_i are very C_i , strongly C_i , really C_i.

The modifier "very" is a bright representative of reinforcing modifier:

$$t_{very}(u) = u^2 \tag{3.7}$$

The second family of modifiers is weakening modifiers. They provide new characterizations that are less strong than the original one. For instance, "more-or-less"

$$t_{more\text{-}or\text{-}less}(u) = \sqrt{u} \tag{3.8}$$

Furthermore, "not" modifier is represented as:

$$t_{not}(u) = 1 - u \tag{3.9}$$

So, we have a bundle of qualifications. In a system, in order to change the qualification of X in an adequate way, we iterate over the modifiers m and find the one (or several of them) that are the most appropriate ones.

In our fuzzy system, there is an inclusive interpretation of linguistic modifiers:

$$\textit{extremely } A \ \subseteq \ \textit{very } A \ \subseteq \ \textit{more-or-less } A \ \subseteq \ \textit{roughly } A \tag{3.10}$$

3.11 Context-Awareness

Whether color palettes harmonies are context-specific or universal? Well, colors have different associations for feelings and behaviors in various contexts [55], [15].

First, let's define what a *context* is. As such, *context* must be considered not only in terms of application domain but also in terms of culture. Moreover, there is a plenty of other extra factors like gender, race, past experience, religion, nationality, social group and natural environment [15]. People from these different groups may have systematically different aesthetic experiences to the same visual stimuli [55].

Based on our observations, we arrived at a conclusion that certain colors effects and preferences are strongly influenced by context. However, harmonious color combinations are to a large degree universal. Perhaps humans like colors to the extent that they like the emotions that fired up by those colors. As an example, there are marked differences in color preferences in different geographical contexts. For example, there appears to be a much stronger preference for white and light colors in Japan, Korea, and Taiwan than in other countries, primarily because white is a symbol of cleanliness and purity, which are highly valued in Asia [63]. Similarly, in Chinese culture, there is a high preference for red color [55].

According to our preference formula, preference for color combinations depend on the natural and universal harmony of considered colors and individual's preference for single colors in the combination. So, left part of the Eq. (3.1) is context-dependent, whereas the right one is context-independent.

Knowing how to measure preference and harmony properly, we are particularly interested in how much such aesthetic preferences might covary across different semantic contexts. For that, we need to check the palettes relevance in the different aesthetic domains in order to find out whether preferences for harmony are correlated across various domains or not. From an experiment with famous paintings (see Table 3.2) we investigated that using harmonious color schemes derived from fashion aesthetic looks in a harmony evaluation produces plausible results, providing harmony for the universal nature of a color harmony.

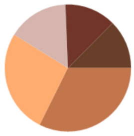
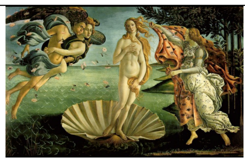
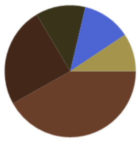
Art work	Dominant FHSI Colors	Harmony
 S. Hanenobu, "Moon Rising at Shinagawa"		*very strong* (93.03)
 Murals on tomb walls in Eqypt		*more-or-less strong* (90.84)
 Raphael, "The School of Athens"		*very strong* (97.32)
 S. Botticelli, "The Birth of Venice"		*neutral* (88.52)
 P. Picasso, "Three Musicians"		*strong* (91.2)

Table 3.2: Famous art works and calculated harmony values.

3.12 Summary

Current section presents an overview of the findings in our research focusing on quantification of the harmony and preference phenomena using fuzzy color space. Our methodology has explicit links to personal taste and domain-specific knowledge(trends). We have included personal taste as a variable that affects aesthetic experiences. According to experiments, the model results in useful predictions of ratings of aesthetic pleasantness.

Previously, the method provided us just with basic true/false response on a harmony of a particular combination. Now it is able to quantify the harmony and preference and classify them in a human-consistent manner.

Other possible improvement of the method are the following:

- Objective measurement of the outfit (or any other pattern) complexity;
- Style-related processing to provide classification of style (e.g. romantic);

Concepts of *preference* and *harmony* and their relationship can serve as a tool for future investigations in aesthetics across multiple domains. For example, automatic labelling in large image databases, furniture coordination (e.g., a user uploads a room image and requests sofas fitting perfectly the interior), accessing aesthetics attractiveness of photographs, using color aesthetics in marketing and brand promotion.

Obviously, it is totally impossible to develop a mathematical theory to measure aesthetics precisely. So, our goal is not to provide a recipe, but rules, guidelines and predictive metrics to evaluate harmony and preference, which can be helpful. But these metrics are not restrictive.

Chapter 4

Application of the FHSI Color Model

This section aims to demonstrate one of the possible implementations of the proposed approach in the context of e-commerce apparel online shopping and coordination.

4.1 Application : Online Apparel Coordination

In order to enliven our methodology we developed apparel coordination application, which is highly useful in understanding the importance and practical application of the approach. Knowing the colors that are perceived as formal for example, we can recommend formal apparels based on a dominant color in the image. It is even possible to recommend a whole look. So, the main idea of the application is to retrieve best matching images with relevant apparels corresponding to the complex query posed by user based on color scheme. The preference for a fashion look is often based on its aesthetic appeal, which is difficult to evaluate quantitatively due to its highly subjective nature [19].

As we discussed before, the currently most popular and widely used approach for image retrieval is based on text annotations and most e-commerce websites use textual descriptions to provide the color information of clothing items. Labeling items manually is very expensive, time-consuming and seems to be infeasible for many applications. The developed system aims to tackle these problems.

Our method is effectively used to perform color matching (i.e., finding images with specified colors in assigned proportions), harmonious look recommendations, and similarity searches in online apparel shopping. The basic idea is to retrieve shopping items based on fuzzy dominant colors, make compositions based on harmonious color schemes we derived, and recommend items and looks based on predictor we introduced.

The web-based prototype system for apparel coordination is written using ASP. NET platform and it uses database containing around 1000 apparels of various types.It is actually a small online shopping website. Note that the default retrieval threshold is set to 0.5, we use it in the -cut operations of the fuzzy sets.

Using the notation from the theory of visual attention[5], x is an image of an apparel, S is a database collection of all apparels, i is a category (e.g. dark, red. Note that it can be composite, e.g., black and white, deep blue, etc.), R is a collection of all categories.

Fashion aesthetics is a vast field with a number of aspects having an impact on a final decision. We don't want to reduce the role of other factors like quality, price, comfort, materials, and style. Instead, we are highlighting the immediate effect that color aesthetic appeal has on a user and on his purchasing intentions. Every potential purchase starts with a first impression, which is primarily based on colors!

Apparel coordination is just one example of method effectiveness and usefulness. The proposed approach can also be applied to automatic labelling in large image databases [79] and customized services. One example for this is furniture coordination (e.g., a user uploads a room image and requests sofas fitting perfectly the interior).

4.2 Motivation

The system we propose makes direct use of image visual content (CBIR) rather than relying on annotations provided by humans. Our method provides deeper color semantics by performing color feature extraction of images during their addition to the database or during the query processing. The color model used for these purposes is fuzzy and accounts for the subjectivity of human color impressions. It allows handling imprecision and process linguistic terms during an online clothing search. Hence, our method provides deeper semantics, accounting for the subjectivity and sensitivity of human color impressions. This is expected to be valuable for almost all CBIR systems where color is important.

Why allowing some imprecision is important? Very often the search results of online shops are too strict. In other words, they exactly fit the query and some of the results that do not match the query absolutely, but still to a high degree to be interesting for a user, may be lost [60]. Fuzzy logic takes care of these cases.

We believe customers would be happy to describe the clothing requirements linguistically, providing a text query. Currently, processing data and presenting results in a human consistent manner is of great value. Simple keyword matching and semantic mediations are not enough for these purposes. The developed system aims to tackle these problems. The results of the current research allow us to apply the model in online apparel shopping. In the subsequent sections we describe the system.

4.3 System Architecture

Our system combines two modalities - content (color scheme of the image) and text (linguistic query given by the user). User can form its request to a system either in a form of linguistic query (just textual description) or by uploading an image (query by example). For the combinational query, we need to consider the semantics of the linguistic query and query image provided by the user as well.

The shopping system we developed can run in one of two modes: administrator mode or user mode. It has three main logical parts: assigning a fuzzy colorimetric profile (indexing stage) to the image, processing the user query (proposed by us in [71]), and assisting a user in aesthetic look creation. The first one is intended for the administrator and connected with the indexing and the addition of the images to the database. This involves the precomputation of fuzzy dominant colors–apparels' color schemes. So, each clothing item is stored together with its extracted color scheme.

The second part deals with the exploitation of the database through natural query processin, which can be of 3 types. The user can form its request to a system either in a form of textual description or by providing an exemplary image and perhaps specifying other matching details (similarity or harmony measures). At the time image is uploaded into a database, fuzzy color scheme of the image is extracted and stored. For the combinational query, we need to consider the semantics of the linguistic query and query image provided by the user as well. Finally, "Create Look" module employs the harmonical and preference predictor we introduced before in order to coordinate users in aesthetic look compilation.

The work of the system was significantly speeded up by pre-computation of fuzzy color histograms. This ensures the system scalability, so the growing size of the database wont impact the performance of the system. So, when moderator uploads new shopping items, the histograms are computed on the fly and we save the dominant colors for each apparel in the table.

The high-level system architecture is presented in Fig. 4.2, 4.1.

4.4 Functionality

Our method is effectively used to perform color matching (i.e., finding images with specified colors in assigned proportions), harmonious look recommendations, and similarity searches in online apparel shopping. The basic idea is to retrieve shopping items based on fuzzy dominant colors, make compositions based on harmonious color schemes we derived, and recommend items and looks based on predictor we introduced.

The examples for all types of functionality described here are provided in the next section.

4.4.1 Processing Natural Queries

The matching engine implements the retrieval according to the either similarity or harmony metric. The system provides the image retrieval functionality based on the following queries [72], [70] :

- **Linguistic query**, in which attributes are specified by words. The examples are as follows:

  - popular *elegant* outfit
  - *deep red* or *pale green* dress

  Due to the initial offline precomputation of apparels color schemes, linguistic query processing works very fast.

- **Query by example**, which involves a reference image input to the system. This is when the user wishes to find similar apparel or apparel that matches some other

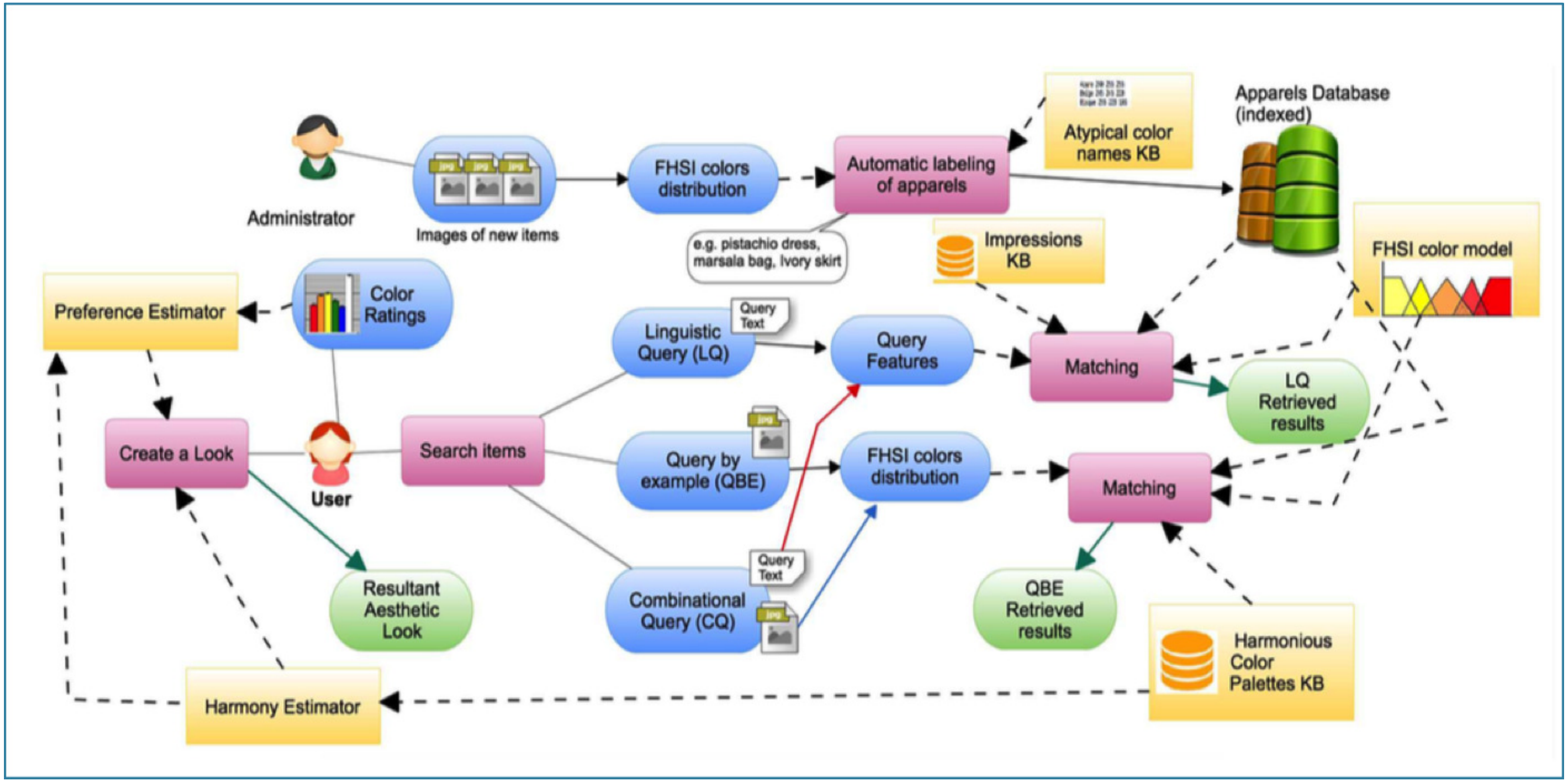


Figure 4.1: High-level system architecture used for developing a web–based prototype application. The system has three logical parts – indexing (for the administrator), retrieval and 'Create Look' module (for users)

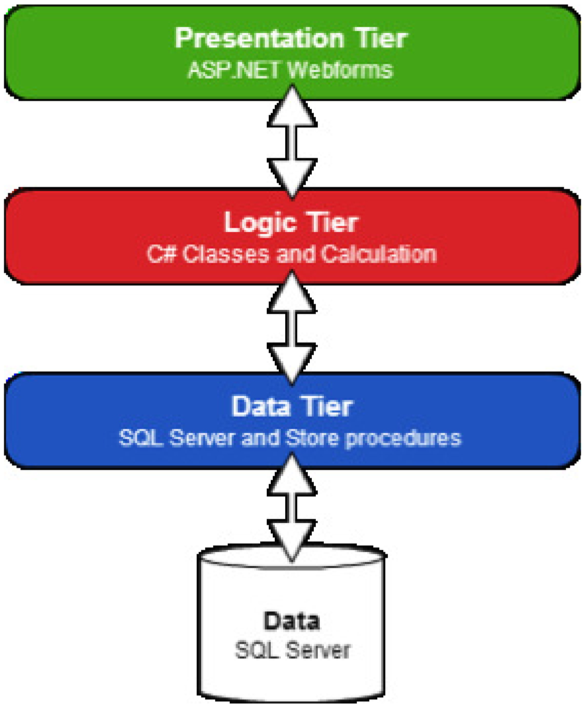


Figure 4.2: High-level System Design

apparel in the input image, by taking into account color harmony principles. The query image and compares the results to the features of the database images.

- find apparels that form a perfect *combination with the bag* on the photo
- retrieve *similar* blouzes (provided a reference image)

- **Combinational query**, which have properties of both linguistic and exemplar queries.
  - find *dark* apparels that form a perfect *combination with the jacket* on the photo
  - retrieve *romantic* blouzes forming a nice *combination with the skirt* on the photo

In the case of a query by example or combinational query, the system first extracts query image features and then matches them to the features of the database images (The given RGB image is first converted into HSI color space. Furthermore, based on the histogram, we identify the dominant color in the image and try to find similar apparels or apparels that fit to it). Subsequently, images relevant to the query are retrieved and presented to the user. We optimized the work of the retrieval system has to carry out and significantly accelerated the process by performing the pre-computation of fuzzy color histograms. This ensures system scalability, such that an increase in the size of the database would not impact the performance of the system.

A query is defined by the user and the system first extracts query image features and then matches them to the features of the database images. Subsequently, images relevant to the query are retrieved and presented to the user. We optimized the work of the retrieval system has to carry out and significantly accelerated the process by performing the pre-computation of fuzzy color histograms. This ensures system scalability, such that an increase in the size of the database would not impact the performance of the system.

According to recent studies [15], colors with atypical names were selected more than colors that were typical, proving a preference to purchase items being labeled with atypical color names. Moreover, those who selected, e.g., sweatshirts with atypical colors were also more satisfied with their choice than those who selected the ones with typical colors. Examples of atypical color names are: *golden, blush, serenity, pistachio, marsala, rose quartz, azure, Turkish red, salmon, sandy, lemonade, tan, watermelon,* etc.

Our system supports automatic processing of atypical color names, so, there is no need to tag apparels. This is done by converting the RGB representation of atypical color into the closest FHSI color [1]. Since the apparels are indexed with FHSI colors they contain, we can directly use this information to retrieve, say, "Mauve dress".

The harmony between a query image and database image is computed from the dominant color(s), using the table of color harmonies selections. For the similarity searches, we used the similarity measure described above.

4.4.2 Shopping Advisor

In a popular system Polyvore.com, users create looks by dragging items from the menu. It is clear that the color of the new object you add needs to harmonize well with colors of other existing objects, but it is very difficult for a majority of people to choose an object considering such things.

[1] RGB data and color names can be taken from official Pantone color agency (pantone.com).

Figure 4.3: Shopping Advisor application mockup.

Using FHSI model we enhanced the mechanism of plain manual look composition. First, we indexed the apparels database. Furthermore, the preference formula Eq. (3.1) allows us to sort all the commodity images according to its harmony to the given apparel or look, i.e., the more harmonious items (suiting the whole look) will be ranked more ahead. Some of the extended features include:

- Having measures for harmony and preference, we can sort the apparels on the right by harmony to the apparels on the left. The suggested apparels will be unique for each user since single color ratings allow us to refine color harmony to individual color scheme preference.
- Some of the palettes have style names like modern, classic, retro, romantic, elegant, formal, etc. User can choose several styles and see the corresponding apparels only.
- The user can input several favourite colors and the system selects colors which are in a harmony and we get many finished looks by the system and also use these harmonious colors to filter the apparels in the menu.

Individual elements of a look form the whole visual composition. This corresponds to Gestalt psychological theory [89], which states the entity as a whole rather than what it is formed from. Humans perceive things as a whole rather than individual components. In particular, Gestalt's patterns of similarity, proximity are used in our module for look generation. Our hypothesis is that such technique can increase sales, because in some cases, mainly because of the total look's visual appeal a user can buy an item that he would never like to purchase individually.

4.4.3 Finding Similar Apparels

Many people find it hard to exactly express what they want in words. The system allows to directly search for clothing, without providing any description, according to the reference photo of an item. The database will be scanned to find the similar apparels. A customer can simply take a photo of an item of clothing and surf through the database for something similar.

Suppose that given a query image, we want to fetch all the images in the database whose color schemes are similar to the color composition of the query image. In [70] we proposed an algorithm based on a fuzzy color space we defined, it finds the similarity between two images based on fuzzy color distributions. In the system, it is used in the matching engine that retrieves similar clothing items. This algorithm is not only used in a similarity metric, but also in providing nice clothing combinations with harmonious colors.

4.4.4 Creating Harmonious Looks

The presence of such useful functionality as a nice looks generation motivates a customer to buy not one, but multiple wearing apparels fitting to his preferences.

It can be very amusing to play with color in a random manner. However, combining apparels randomly can result in a bizarre look that lacks integrity, style, and color harmony (see the first look at Fig. 4.4). Attracting a designer who can build exciting, aesthetically appealing apparel combinations costs a lot of money and requires time. Every new collection needs new looks, creating an endless manual work. Moreover, there is no guaranty that users will love it.

To take advantage of the joint effect of two or more colors the one must understand it rationally and follow the hidden patterns. Some particular color combinations are especially agreeable to viewers while others not [45]. Conventional ways of combining colors are based on a fixed color's position on a color wheel. Traditionally, it was generally accepted that colors are in harmony if their mixture forms gray or brown colors [31]. However, we believe these methods are obsolete and there are hidden much more complex rules. In our previous work we tried to explore this topic and identify palettes in which colors work harmoniously with one another. This was done based on the deep analysis of basic principles of color theory and fashion images. We also use some of the conventional relationships proposed by Itten [18], like monochromatic, analogous, triad schemes. The reader is referred to our previous work [72] , [70] for more information.

Regarding the color combinations for a fashion look. Besides the color theory principles, our shopping system takes into account that each color of a look competes with others for the viewers attention [45]. Thus, there should not be more than 2 highly saturated colors in one look. So that some parts of the look are accentuated and demand the attention while others unsaturated ones just play supportive roles.

System suggests the whole look of complementary apparels by:

- Taking random harmonious palette from database
- Finding complementary apparels whose dominant colors belong to or very similar to the colors in the palette In order to identify group(s) of colors with which some particular color is in a harmony, the system needs to identify the very similar color with the given color and here it comes to the perceptual difference formula [72], [70].

Fig. 4.4 presents some of the looks, generated by the system. The first look was intentionally generated randomly, without account for the harmony. It seems that all items in this combinations are bizarre. Now take a look at the other fashion combination offered by the system. Apparently, even those bizarre apparels look appealing, when they form a nice color combination.

4.4.5 Fetching Items based on Impressions

Visual effects of specific color and color combinations cannot be underestimated. So, besides the atomic and composite context-independent impressions (e.g. light green,

Figure 4.4: Looks Generation. The first look was generated randomly. The remaining looks were generated in accordance with the harmonious color palettes.

white and blue) the system provides the retrieval of images corresponding to context-dependent color impressions, that represent qualitative linguistic labels, e.g. informal, elegant, etc. Now the represented set is limited, but it can be easily extended in the future. Fig. 4.5 presents some of such atomic impressions and the corresponding colors fitting to that impressions. This correspondence was obtained by deep analysis of existing online shops with tagged images, fashion blogs, and some other related resources. The list can be further extended with impressions like provocative, informal, etc. The main advantage of such systems is that they enable retrieval of images based on their content and context, not tags. As a result, there is no need in giving the tags or keywords specifying the image, with the exception of trivial ones (i.e. type of an apparel - dress, shirt, etc.). This will free administrators from spending time on describing the apparel.

Although color perception is affected by a range of factors, including gender, age, profession, ethnic roots, and cultural norms, there are certain universal reactions to color that transcend the individual peculiarities. One of our numerous goals was to identify those universal impressions that work for a majority of people. We need to emphasize

Impression	Colors (visual)	Colors (in words)
Elegant		Black, jewel, emerald, silver, bronze, and copper.
Formal, Modest		Dark and deep colors
Casual		Sweet and bright fascinating colors.
Romantic		Light to mid-tones of pink, purple, gray and blue colors. Mostly pastel colors
Vintage		Modest colors like gray variations, ill-saturated vinous color
Fresh		Bluish green, pure green, yellowish green, turquoise (of various intensities)
Passion		The dark and deep mid-tones of vinous and purple that generate a passionate feeling

Figure 4.5: Map between impressions and various colors.

that these impressions are subject to control and modification due to constantly changing fashion tendencies.

We created an application for gathering color pallets for abstract impressions, like "romantic", "formal", or "elegant". For now, this application uses Google Image Search API to retrieve relevant sample images from Internet and later can be adapted to retrieve ranked images from popular websites, like Instagram, Facebook, VK, Pinterest, etc. Fig. 4.15 is a screenshot of the developed application for pallets generation. This example shows how we obtained the palette for "elegant". After specifying the impression and the number of images to fetch for analysis, we get 2 grid views. The first view depicts the FHSI (fuzzy HSI) [72] dominant colors for each image and the second view shows the overall FHSI dominant colors and their frequencies. Depending on the frequencies, top 3-7 colors constitute the palette for the impression. In much the same way we generated the palettes for the following impressions: *romantic, formal, modest, casual, vintage, fresh, passion, positive, tiffany, etc.*

Figure 4.6: Creating the color palette for "elegant".

4.4.6 Providing Recommendations for the Best Fitting Extra Apparels for a Full Look

It is a common case for an online shop customer to search for some clothes for a particular wearing apparel he or she already has. At present, a user needs to form a special query and then decide on which ones out of the pooled results fit the apparel. Our system greatly simplifies this process by offering a user to provide the apparel image and the desired remaining clothing items (combined nicely with the given one) will be retrieved automatically.

So, when a user provides the apparel image A, the system performs feature extraction (described in our previous work [69],[72], [70]) and obtains its fuzzy dominant colors. After that, it processes each harmonious color palette to find a color which is very similar to the dominant color(s) of A (based on the perceptual color difference formula we proposed in [72], [70]). Suppose a similar color was found in a palette P. Next, the system uses colors in P to fetch clothing items with the corresponding dominant colors to provide clothing recommendations that form the perfect combination with A.

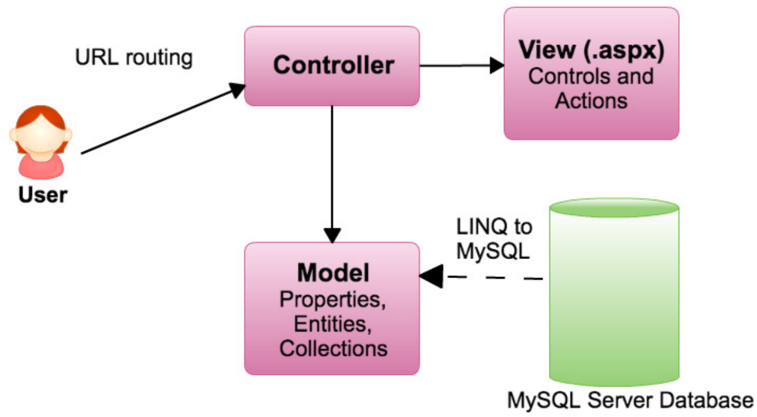


Figure 4.7: MVC Architecture

4.5 Technologies

We developed a web–based prototype application for apparel coordination using ASP.NET MVC platform. It is actually a small online shopping website. All data is stored in MySQL database.

Our web-based online shopping system has three-tier (multilayered) MVC pattern architecture [16]. The View (the presentation tier) is exposed to the end user as a usual web application, which includes ASP.NET Web forms, scripts (client-side JavaScipts), and styles (CSS). C# classes with the main functionality compose the logical Model of the system, which directly manages the data and the rules of the system. Finally, the role of a Controller is to take inputs, convert them into commands and pass on to the Model or View (see Fig. 4.7).

The high-level system architecture is presented in Fig. 4.1.

The developed system is just a small working example created as a proof of concept. It required many additions and improvements before the launching for a real usage.

4.6 Experiments and Discussions

The purpose of this section is to demonstrate the retrieval of the best matching apparels in response to the queries of various types based on a color scheme.

We use the proposed method in the matching engine used for the query processing. Currently, the system supports the processing of 3 types of queries (see "Functionality"

Figure 4.8: Administrator Panel

subsection). Note that in the case of exemplar or combinational query, the given RGB image is first converted into HSI model. Next, based on the histogram, we identify the dominant color(s) in the image and find similar apparels or apparels that fit it. The harmony between a query and database images is computed from the dominant color(s), using the table of color harmonies selections.

Before moving on to query processing, let's take a look at the administrator panel (Fig. 4.8). Administrator's functions include adding new clothing commodities and viewing/modifying the existing apparels. In addition, each database clothing item is displayed together with its fuzzy dominant colors.

Example 1. *Red apparels.* This is the simplest possible linguistic query. It works very fast due to the initial offline computation of apparels color schemes (during the indexing phase). The result is presented in Fig. **??**. The linguistic query can be more complicated, like *white and blue dress*, *dark blue*, *pale blue or deep blue*, etc. It can also contain an impression.

Example 2 *Blue apparels.*

As it can be seen from screen shots, some recommendations for looks (totally composed from database apparels) alternatively appear at a side.

Example 3. *Formal apparels* (Fig. 4.11). *Romantic apparels* (Fig. 4.12). These are linguistic queries based on impressions. As we described in a previous section, for each impression we derived a color palette. We use these palettes for finding the apparels

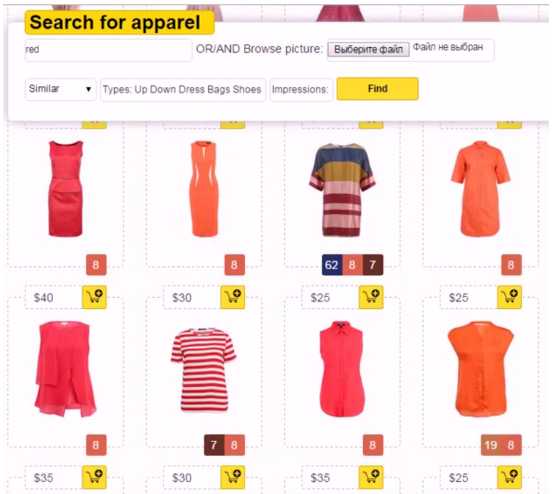


Figure 4.9: Application screenshot for Example 1 - *Red apparels.*

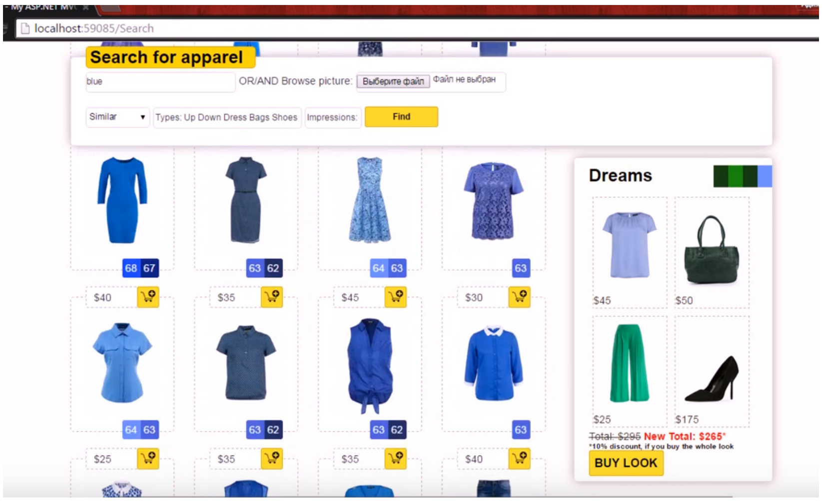


Figure 4.10: Application screenshot for Example 2 - *Blue apparels.*

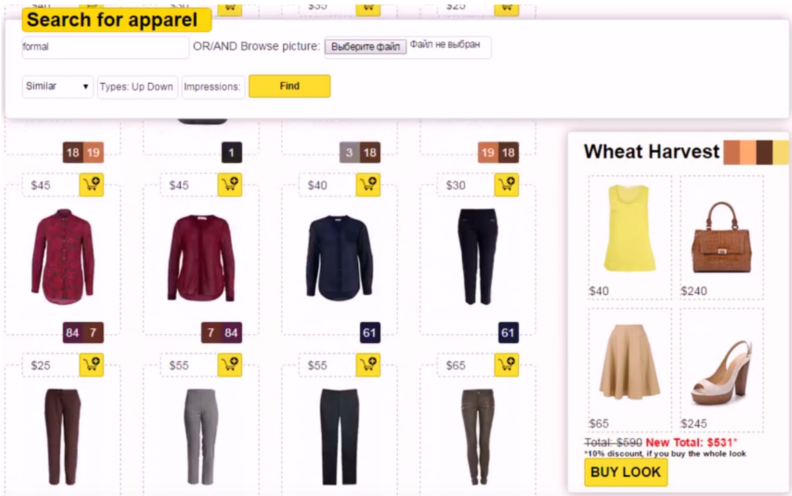


Figure 4.11: Results for Example 3. Formal Apparels

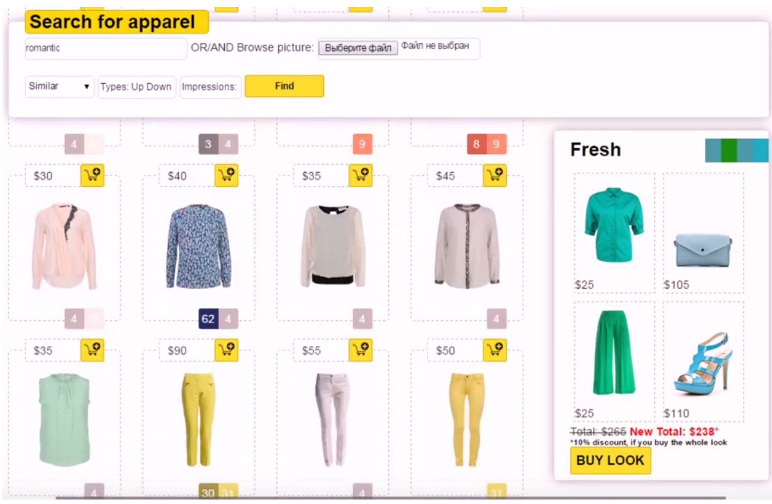


Figure 4.12: Results for Example 3. Romantic Apparels

in the database having very similar dominant colors. "Very similar" is identified by a perceptual difference formula we defined before.

Example 4. Queries by example based on a similarity/harmony metrics.

For example, a customer has a photo with apparel (taken from fashion site or even real life) and wants to find something similar. Fig. 4.13 demonstrates this example.

Fig. 4.14 presents the case when a customer wants to buy the shoes and a bag that form an appealing combination with a blouse she has. The user uploads the blouse image and the system extracts such bags and shoes whose dominant colors are in a harmony with the blouse ones.

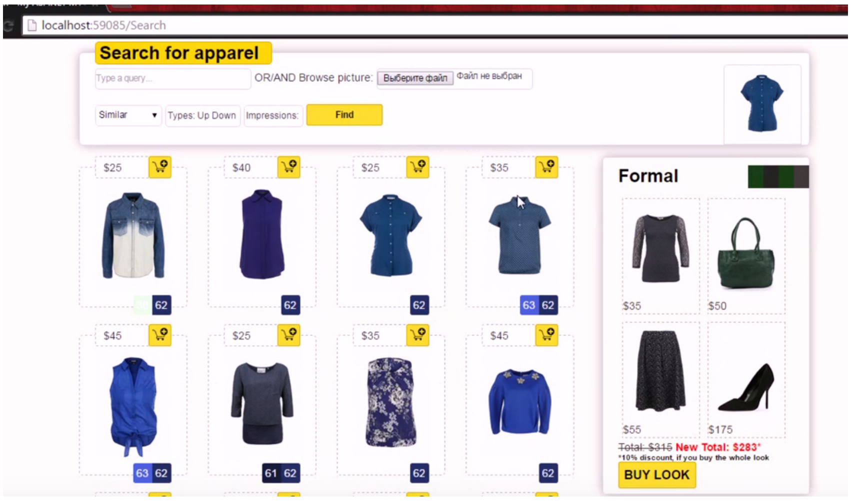


Figure 4.13: Queries by example. Using the similarity metric

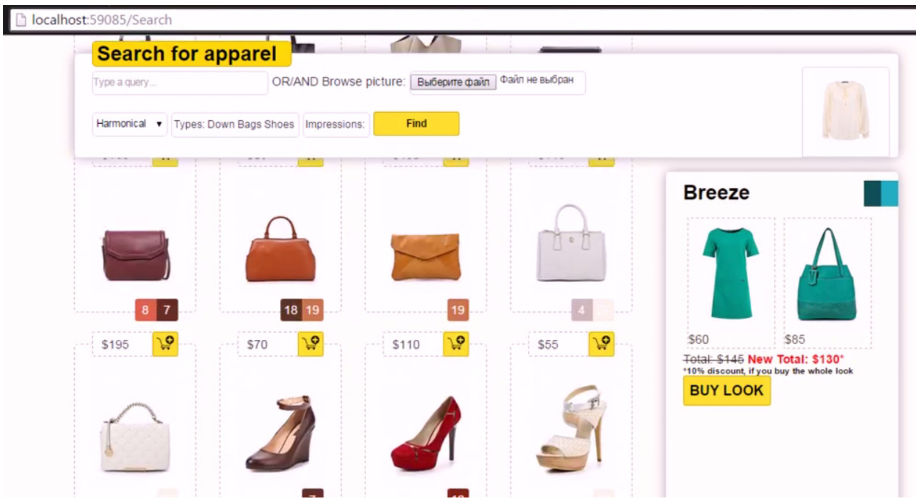


Figure 4.14: Queries by example. Using the harmony metric

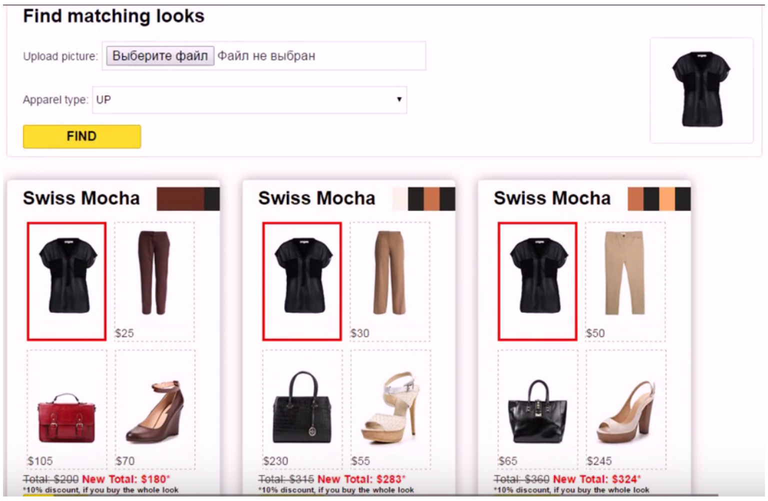


Figure 4.15: Results for Example 5. Recommendations for the best extra apparels.

Example 5. Providing recommendations for the best fitting extra apparels. The customer uploads a simple black blouse and our system offers nice combinations (see Fig. 4.15) .

Example 6 Query by example based on a harmony metric, e.g., a user already has a blouse and wants to buy the remaining apparels – pants, shoes and a bag.

The user needs to upload the blouse image and the system will extract such apparels whose dominant colors are in a harmony with the blouse ones (Fig. 4.16, 4.17).

How does the system find combinations of apparels that are pleasant to the eye? The database contains color palettes identified as harmonious. When a user provides the apparel image A, the system extracts its fuzzy dominant colors. Next, the system processes each color palette to find a color which is very similar to the dominant colors of the user's apparel (based on the difference formula we proposed). Let's say a similar color was found in a palette P. Then the system uses colors in P and retrieves clothing items with the corresponding dominant colors to provide clothing recommendations which suit to A.

Table 4.1 presents the system performance results for Example 2 and Example 3.

As we can see from the examples provided above, the system produces promising results, using such a simple filter as color. Obviously, the results can be even more impressive in case we combine our method with image texture and image segmentation methods.

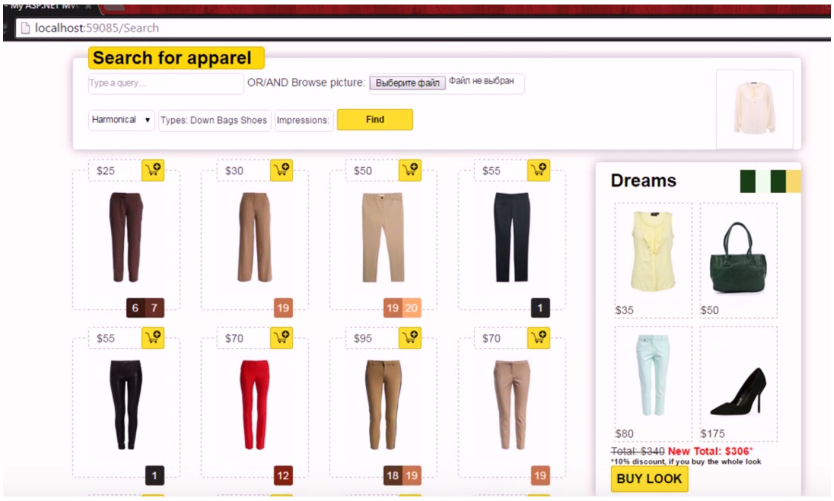


Figure 4.16: Application screenshots for Example 6. Pants suiting to a user's blouse

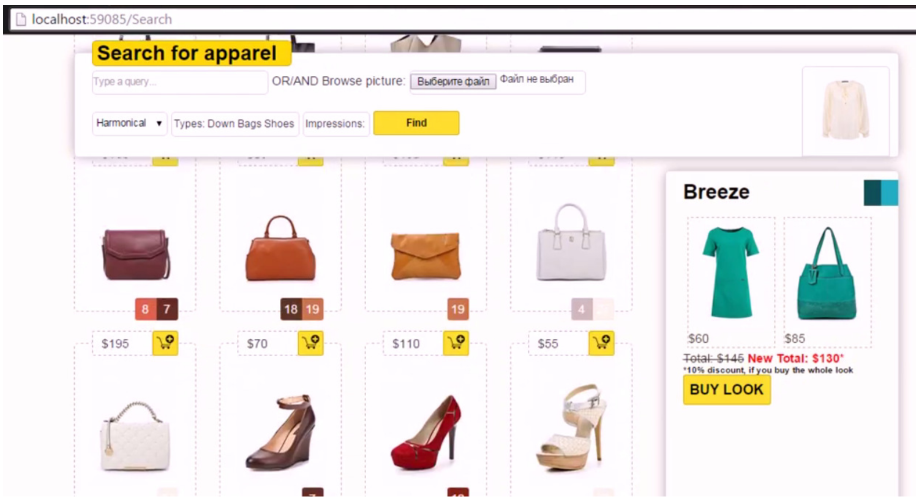


Figure 4.17: Application screenshots for Example 6. Bags and shoes suiting to a user's blouse

Table 4.1: Measuring the system performance

	Example 2	Example 3
Retrieved items	21	16
Relevantly retrieved items	19	13
False positives	2 (9.52%)	3 (18.75%)
False negatives	3	1
Precision	0.90	0.81
Recall	0.86	0.93

It is important to note that generally, image retrieval which is founded on color analysis solely may bring too many false positives when a database is large[72]. That is why, usually, color-based features are integrated with other visual features, and the corresponding module can work as a subsystem within big retrieval system or as a part of an image understanding system. Very often color features are integrated with other visual features to improve the accuracy, or serve as a cheap filter to improve performance time (its output could be further processed by more time-consuming methods). However, particularly for apparel coordination application, due to the simple nature of images having a light background with an apparel in the middle, it is not critical.

It is important to note that real-world clothes images provided by users as reference images, may have variegated, patchy background. For the purpose of simplification, this paper assumes that all images, including user and database images, have the uniform white background, just as in a majority of internet shops.

The developed online shopping system is just a prototype, a small working example created as a proof of concept. It requires a number of additions and improvements before the launching.

4.7 Summary

Comparing our method to other traditional image retrieval systems we can emphasize that it differs from them in a number of aspects, like :

- Automated item description based on color scheme of the image. In contrast to widely used image retrieval based on manually included text annotations and keywords, which are used to perform search (TBIR). Besides the need of manual image tagging, TBIR have problems connected with subjectivity and incompleteness, since the low-level image features are not always reflected very well. A sizeable majority of e-commerce sites make use of TBIR, including shopping portals like Amazon, eBay, Taobao, Polyvore, etc.

- Natural query language, which is possible due to an integration of fuzzy techniques

- Deep color semantics that accounts for the subjectivity and sensitivity of human color impressions. As it was mentioned, fuzzy partititon was performed based on survey results. Doing this helped us to reduce the number of false positives and to achieve an improvement in the precision (from 0.62 to 0.83)[72]. Now we are working on making the system even more user-driven.

Chapter 5

Performance Evaluation

5.1 Introduction

In this section, we aim to validate the model by various experiments, where human observers are judging various samples of stimuli provided, e.g., in the form of fashion clothing looks: whether they are harmonious or disharmonious, and whether they are liked or disliked. There are three different types of experiments we employ - *Two Alternative Forced Choice, Rank Ordering* and *Rating*. In addition, we aim to analyse the system performance based on standard recall and precision metrics.

A total of 22 subjects took part in a series of experiments. Before accessing the performance, all subjects passed Ichihara color test and proved to have a normal vision. The experiment consisted of a series of primary behavioural measures of aesthetic experiences (Two-alternative forced choice, Rank ordering, Rating (for harmony and preference) and evaluation of precision and recall. Overall, we had five consecutive blocks of judgements from which we got preference responses. The basic idea of all of them is to compare real preference ratings and predicted preference.

Given a specific task to judge the aesthetic quality of the displays, subjects were asked to indicate his/her evaluation as quickly as possible. We gave more importance to first impressions rather than reasoned judgements.

5.2 Measuring the precision and recall

Let us perform the system evaluation by measuring the precision and recall for five linguistic queries. In the selected context, a recall can be viewed as the probability that

Table 5.1: Results of system evaluation based on precision and recall.

	Q1 ”Pistachio apparels”	Q2 ”Brown or beige blouse”	Q3 ”Golden dress”	Q4 ”Red or black items”	Q5 ”Dark blue or marsala skirt”
Retrieved items	15	35	6	110	12
Relevantly retrieved items	13	33	6	97	8
False positives	2 (13.3%)	2 (5.7%)	0 (0%)	13 (11.8%)	4 (33.3%)
False negatives	3 (18.8%)	6 (15.4%)	1 (14.2%)	9 (8.5%)	3 (27%)
Precision	0.87	0.94	1	0.88	0.66
Recall	0.81	0.85	0.86	0.92	0.73

a relevant apparel is retrieved by the natural query. In turn, a precision indicates how many apparels satisfy user query considering all the apparels retrieved.

$$P_T = \frac{\sum_{i=1}^{T} P_i}{T}, R_T = \frac{\sum_{i=1}^{T} R_i}{T}, F_1 = \frac{2}{\frac{1}{R_T} + \frac{1}{P_T}} \tag{5.1}$$

where T is the number of selected queries, P_i = the number of relevant apparels retrieved divided by the number of apparels retrieved, F_1 *score* - provides a single measurement for a system accuracy.

Table 5.1 depicts system evaluation results for selected queries.

Using Eq. (5.1) the calculated resultant precision and recall values are $P_T \approx 0.87, R_T \approx 0.83, F_1 \approx 0.85$. Obtained experimental results show that our methodology has a good accuracy.

5.3 Two-alternative Forced choice

Method description Two-alternative Forced Choice (2AFC) is a classic psychophysical method that is considered to be optimal by many sources in the perceptual and cognitive neurosciences[87], [32], [55]. During one trial of a typical 2AFC experiment, observers indicate which of two simultaneously presented visual displays they prefer more aesthetically. This process is repeated for all possible pairs. So, 2AFC measures the subjective experience through the pattern of choices, requiring $\frac{n(n-1)}{2}$ trials to measure preferences for n stimuli.

Why psychophysicists often prefer this method over the classical "yes–no" task? Primarily because the 2AFC procedure discourages response biases as it simplifies the decision task for a subject who is given just a pair of mutually exclusive stimuli at one time. We adapted The Spearman–Karber method [87], which yields a simple yet accurate estimator for the 2AFC difference limen[1], mean, and its standard error [87].

Procedure Each observer is required to complete a series of simple decision tasks. On each repeated trial respondents need to choose which of the two simultaneously presented clothing combinations they like more (i.e., prefer more aesthetically). The stimulus pairs are of varying difference in predicted preference. Observers are forced to choose exactly one combination and this choice is to be based on aesthetic attractiveness solely. We need first to obtain single color ratings for each observer. Then, the system generates five random looks for each of them. With this conditions, there will be 10 trials for each participant. After gathering data we can compare it with predicted preferences, visualize the percentage of "Hits", and perform other analysis.

Data Interpretation Using k monotonically increasing stimulus values, $x_1 < x_2 ... < x_k$, to determine the observed response probabilities, $\hat{p}_i(i = 1, ..., k)$, associated with each stimulus value, the mean of the psychometric function is given by [87] :

$$\mu_{2\hat{A}FC} = \frac{1}{2}\sum_{i=1}^{k+1}(\hat{p}_i - \hat{p_{i-1}})(x_i + x_{i-1}) \tag{5.2}$$

The mean $\mu_{2\hat{A}FC}$ in 2AFC is also referred to as the point of subjective equality (PSE) [32]. Note that for the Spearman–Karber method we need transformed probabilities values[87].Thus, the observed set of correct response probabilities $\hat{p}_i(i = 1, ..., k)$ in a 2AFC can be transformed to the corresponding probability estimates (see Eq. (5.3).

$$\hat{p}_i = 2 \cdot \hat{g}_i - 1 \tag{5.3}$$

The observed response probabilities were $\hat{g} = (.69, .78, .89, .86, .87, 0.9, 0.89, 0.94, 0.97)$ at the stimulus values $x = (0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9)$. So, using (5.2), $\mu_{2\hat{A}FC} =$

[1]The difference limen, also known as a differential threshold, or a just-noticeable difference (JND). JND is the amount something must be changed in order for a difference to become detectable at least half the time

0.22.

We plot the results of this experiment (Fig. 5.2) as a psychometric function that reflects the empirical probability of the subject's choice as a function of stimulus (i.e., preference) difference.

We use Weibull model for approximation and fit it using nonlinear least squares. The abscissa of this figure represents the difference between two preferences corresponding to a pair of clothing combinations. The difference ranges from 0 to 1. The ordinate shows the proportion of correct responses. This proportion (hit rate) varies from the chance level of 0.5 (when two stimuli do not differ in preference for this particular user) up to 1.0 (when two stimuli are highly distinguishable in preference level).

As we see, the resulting psychometric function increases monotonically with increasing preference difference. So, this scatterplot suggests that the hit rate is directly proportional to a difference in preference. That is, with an increasing difference in predicted preference the proportion of correct responses from respondents' increases.

The perceptual discrimination threshold (JND) is commonly defined as the stimulus magnitude of the comparison at which the proportion of correct responses is 0.75. In our case JND = 0.19.

The general performance can be measured as the average proportion of correct responses (hit rate) (see Fig. 5.1). The average hit rate is 0.7.

Next, let us find the "perceptual noise" in the form of standard error (see Eq. (5.4)):

$$SE(\mu_{2\hat{A}FC}) = \sqrt{\sum_{i=1}^{k} \frac{\hat{g}_i \cdot (1-\hat{g}_i)}{n_i - 1} \cdot (x_{i+1} - x_{i-1})^2} \tag{5.4}$$

where n_i is the number of observations at stimulus level i. So, $SE(\mu_{2\hat{A}FC}) = 0.043$. In our context, the meaning of $SE(\mu_{2\hat{A}FC})$ is the standard error associated with the threshold estimate $\mu_{2\hat{A}FC}$.

5.4 Rank Ordering

Method description In a *Rank Ordering* task, an observer is required to order elements from most to least preferred. The primary advantage of this method is that it

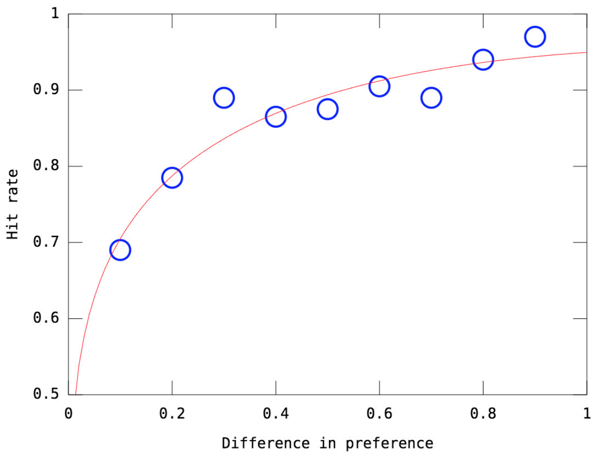


Figure 5.1: Psychometric function in a preference task. $\mu_{2\hat{A}FC} = 0.22$, $SE(\mu_{2\hat{A}FC}) = 0.043, JND = 0.19$.

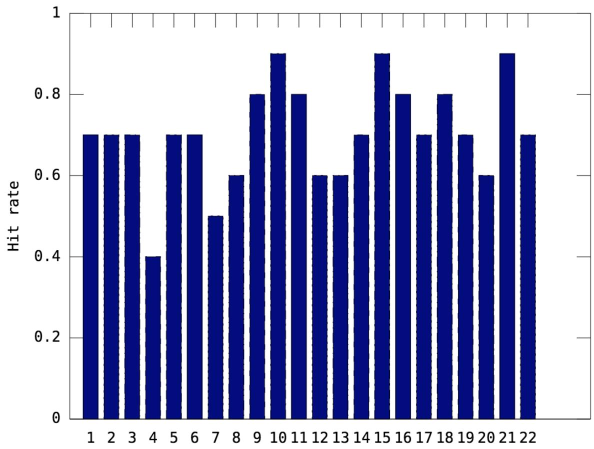


Figure 5.2: Hit rates (proportions of correct responses) for all 22 observers. The average hit rate is 0.7.

requires only a single trial. On the other hand, a respondent needs to handle a complex series of judgements to find single and coherent ordering [55] [33] [29] [34].

One of the popular correlation measures for rank ordering evaluation is Kendall's $\mathcal{T}$ [33], [34]. It shows whether the element positions at reference and hypothesis lists correlate. Kendall's $\mathcal{T}$ satisfies the basic requirements of a rank correlation measure:

- It is $+1$ if and only if the correspondence between two rankings is perfect, i.e., the lists are in the same order;
- It is -1 if and only if the correspondence is opposite - ranking lists are in reverse order.

Regarding the intermediate values, it provides an adequate measure of the compatibility [34].

In addition, we use a correlation coefficient called Ordered Area Under Curve (OAUC), the refined version of the Area Under the ROC Curve, or simply AUC. The basic idea of this measure is to weight each item in the formula by its true order, and then normalize the sum.

Procedure The clothing combinations are presented simultaneously and an observer is asked to order then according to his aesthetic preference. Our goal is to perform a comparison between two lists: the hypothetical true-order list ordered by preferences predicted by our algorithm and user-defined order list based on real preference.

Data Interpretation The formal definition of Kendall's $\mathcal{T}$ is shown in Eq. (5.5).

$$\mathcal{T} = \frac{c - d}{\frac{1}{2}n(n-1)} \tag{5.5}$$

where c is a number of concordant pairs (i.e. with correct relative ranking) and d is a number of discordant pairs. Note that we estimate whether a pair is concordant or discordant using fuzzy values, i.e., all, say, *very high* preferences are always concordant although their numerical values are different. Using experimental results, the calculated average value for the rank correlation coefficient $\mathcal{T}$ is 0.73.

$\mathcal{T}$ has a natural significance. An observer who is given a set of clothing or color combinations to rank, first of all searches for the beginning of the series, the one he prefers more. Having selected it, he compares it with each of the remainders to verify his choice. The coefficient tau gives him the mark for each comparison he made correctly and subtracts a mark for each error. So, it is a logical measure of a ranking and so very useful in psychological work [34].

For $OAUC$ calculation of an ordered list, we only need the true classification. For the ordered ranked list with n examples (half positive and half negative), let any example whose actual ranked position in a true-order list is greater than $\frac{n}{2}$ as a positive example and the remaining ones as negative. Then the ranking positions of positive examples are $r_1, r_2, ..., r_{\lceil \frac{n}{2} \rceil}$. OAUC is then defined using Eq. (5.6).

$$OAUC = \frac{\sum a_{r_i}(r_i - i)}{\lfloor \frac{n}{2} \rfloor \sum_{i=1}^{\lceil \frac{n}{2} \rceil} (\lfloor \frac{n}{2} \rfloor + i)} \tag{5.6}$$

For our data, $OAUS = 0.93$. Correlation coefficients we obtained during this behavioural task are quite high and prove the validity of our method.

5.5 Rating

Another alternative way to measure the validity of our approach is ratings of aesthetic preferences. This behavioural task is especially popular for measuring the attitudes, preferences, and opinions.

Method description We use a psychometric Likert scale [3], [36], [39] as a tool to collect user ratings. This response scale is used to obtain subjects' preferences by asking a degree of agreement with a set of statements. Each response item is assigned a numerical rating score indicating the agreement degree. Besides being a highly reliable scale, the primary advantage of using Likert Scale is that it is easy to read and complete for the participants [39]. The good thing about Likert scale is that just N trials are required to measure preferences for N stimuli.

For example, each questionnaire item has five response alternatives ranging from "Strongly disagree" (SD), "Disagree" (D), "Neutral" (N), "Agree" (A) to "Strongly agree" (SA). These alternatives allow us to inspect the difference between the real preference ratings and predicted preference.

Procedure An experiment was done with 22 subjects in 2 sessions, one is for harmony evaluation and the other for preference evaluation. The stimuli consisted of colored clothing looks in the first session and of color palettes in the second session. On each trial, observers were shown a single clothing or color combination and asked to rate how much they liked it. Evaluation questionnaire containing items with a five-point Likert scale (Fig. 5.3 shows some samples of questions).

Resultant preference values are now also fuzzified, so, instead of numbers, we offer options like "very strong preference", "weak preference", etc. The respondent was told to choose his level of agreement with a judgement based on a five-point rating scale (from "Strongly disagree" to "Strongly agree").

Data Interpretation Data analysis was based on the composite score from the series of experimental observations. Analysis measures for Likert Scale data are presented in Table 5.2. Mean, variance and standard deviation cannot validly be used with Likert scale,

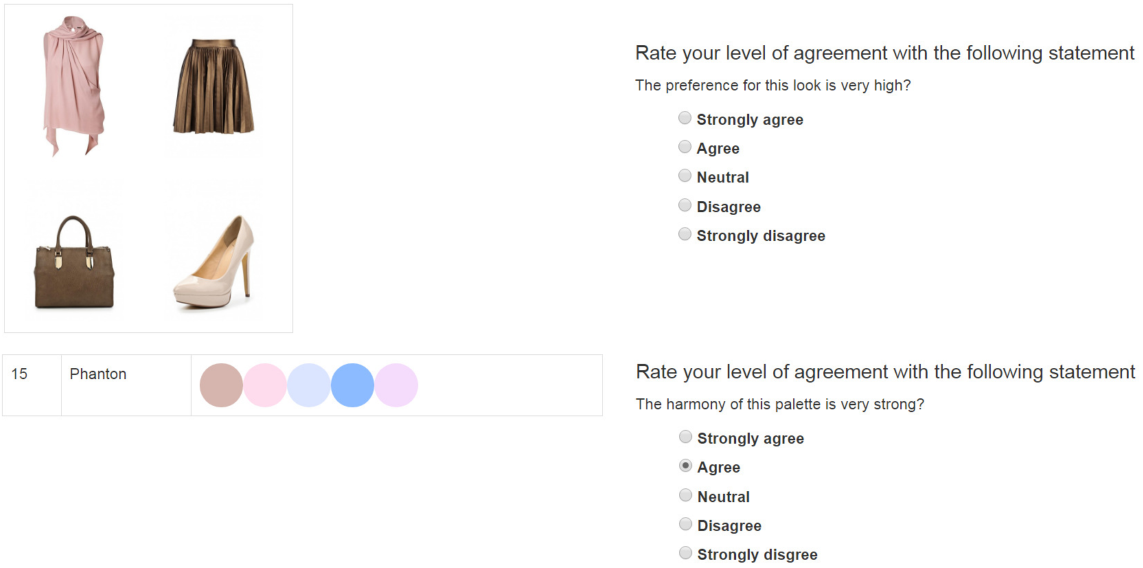


Figure 5.3: Samples of questionnaire items of the Rating Test based on Likert scale for Harmony and Preference .

because it produces ordinal data [36]. Instead, to analyze the responses, we use *mode* and *median* as the measures for central tendency, and for the variability - *Interquartile range IQR* and derived from it *Coefficient of Variation CV*.

In general, a roughly equal number of respondents in both sessions (72% and 73.3% for preference and harmony tests respectively) indicated that they agreed or strongly agreed (Median=4, Mode = 4) (see Table 5.2, Fig. 5.4). Just a very small minority of subjects (6% and 10.6% for preference and harmony tests respectively) expressed disagreement. We obtained a relatively small IQR in both questionnaire sessions which is an indication of overall consensus. However, respondents have a more consistent attitude towards harmony evaluation (IQR = 1 for harmony evaluation and IQR = 2 for preference evaluation). Possibly, one reason for this is the absence of distracting auxiliary parameters for harmony evaluation (e.g., style, materials).

5.6 Conclusion

We experimentally validated our method with three different types of experiments - *Two Alternative Forced Choice, Rank Ordering* and *Rating*. In addition, we analysed the system performance based on standard recall and precision metrics.

Table 5.2: Analysis of results of the Rating Test for Harmony and Preference

Measure	Description	Harm. test	Pref. test
Percent agree	The percent of respondents who either agree or strongly agree with the item.	73.3%	72%
Mode	The option that was chosen more often than any other.	4 (Agree)	4 (Agree)
Median	Median is the middle number in a sorted list of responses (i.e., what most subjects seem to believe).	4 (Agree)	4 (Agree)
IQR	Expresses variability, or dispersion: it shows whether the subjects opinions are clustered together or scattered across the range of all responses.	1	2
CV	Coefficient of variation, provides easier interpretation by dividing the IQR by the Median.	0.25	0.5

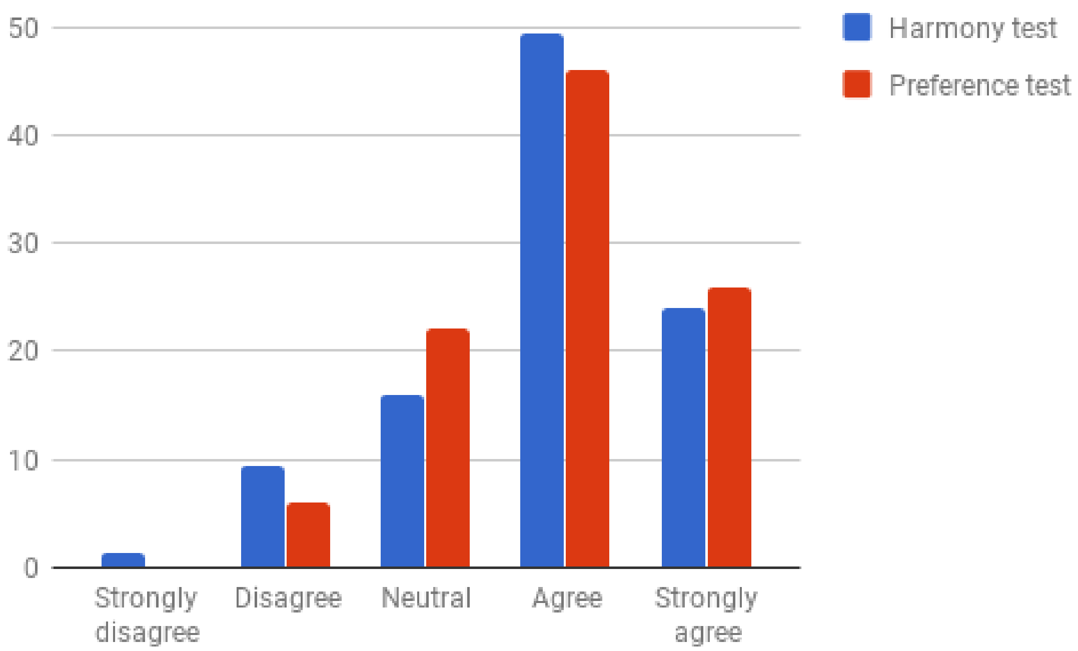


Figure 5.4: Results of the Rating Test for Harmony and Preference.

Table 5.3: Comparing the effectiveness of evaluation methods on different criteria (⊚ - very good, ○ - good, △ - neutral, × - bad).

	2AFC method	Ranking method	Rating method
Easy to select	×	○	⊚
Satisfaction	△	○	○
Usefulness	⊚	△	○
Complexity	△	○	⊚

In a separate set of experiments, we discovered that this method provides good retrieval results, a valid color scheme harmony evaluation, and has good predictive power of the color scheme preference. So, experimental results confirm the advantages of our approach. We consider the methodology to be potentially demanded in various computer vision applications.

We employed three methods for measuring the user preferences. It was difficult to choose just one, since literature did not provide any information on any competitive advantages of the methods. After conducting the experiments, we are able to compare their effectiveness for the selected context of apparel coordination based on the following criteria - how easy for users it was to select the options, satisfaction level of users, and usefulness, and complexity (simple to conduct or not).

We got the following. Rating method is the most convenient to use for our context, because it is both useful and user-friendly. Moreover, it is simple to conduct. So, during subsequent system evaluations we plan to conduct this type of experiment to get user feedback.

Chapter 6

Conclusion and Future Work

6.1 Conclusion

This thesis proposes a fuzzy sets and logic guided novel technique for a perceptually uniform human-consistent color space, FHSI, that approximates the way that humans perceive color. Our primary goal was to provide a correspondence between computer color representation and human color perception. In FHSI the boundaries between the color categories are soft and were derived experimentally and it uses color semantics specifically-tailored for a human visual system, provides automatic labeling, content-based retrieval, human-friendly query processing. We presented an apparel online shop with underlying FHSI mechanisms. It provides content-based retrieval of clothing satisfying linguistically described queries. This represents a much more natural way for a user to interact with the system. In addition, it was also successfully used for quantification of the harmony and preference phenomena for the intended application of apparel online shopping coordination system.

This proposed approach can help to avoid time-consuming manual image tagging and reduce the semantic gap between low-level features (colors) and high-level concepts. It produces results which are highly relevant to the content of the linguistic query corresponding to a human impression. It proves that fuzzy color processing can be very helpful for certain tasks that are beyond the capabilities of systems based on a standard keyword-based image database. Fuzzy approach allows us to define query conditions on the basis of linguistic terms, which is a more natural way for a user to express his intentions.

Table 6.1: Comparison between system results based on a subjective fuzzy partition and a fuzzy partition based on a survey

Type of partition	Subjective	Based in survey
Retrieved items	24	18
Relevantly retrieved items	15	15
False positives	9 (37,5%)	3 (16,6%)
False negatives	2	2
Precision	0.625	0.833
Recall	0.882	0.882

Before defining fuzzy partition based on experiments, we used subjective fuzzy partititon, and the system tended to produce too many false positives, especially for complex queries. In Section 2 we described how we created the fuzzy partition based on survey results.

Consider a simple example to illustrate the improvements in system performance. The query is *"Red dresses, skirts and pants."* Our database contains 300 examples of apparels, and the total number of relevant examples is 17. Table 6.1 shows that there is reduction in the number of false positives and a corresponding improvement in the precision.

The difficulty of measuring the harmony and preference as main aesthetics aspects lies in the procedure of expressing these qualities quantitatively. This work presents an overview of our findings in this research focusing on quantification of the harmony and preference phenomena for the intended application - apparel online shopping coordination system.

We provided a strong empirical support for the viability of our approach. In a separate set of experiments, we discovered that this method provides a valid color scheme harmony evaluation and has good predictive power of the color scheme preference. Although our primary goal was to enhance the interaction between a user and an e-commerce system, we want to emphasize that fashion designers and other experts can use the defined method as a coordination tool to improve their work quality.

Our shopping system differs from conventional image retrieval systems in a number of aspects, including the automated item description based on color schemes and natural query language. We believe that our method can promote the development of e-commerce shopping systems to a deeper level.

Making computers understand, evaluate and predict *color* aesthetics [1]leads to a lot of brand new features for e-commerce systems that we describe in the paper, including:

- making personalized recommendations for images;
- combining attractive compositions of product items (e.g. aesthetic fashion looks, room design from various furniture types);
- automatic labelling and human-friendly query processing.

Besides, the method can be used effectively to perform color matching (i.e., finding images with specified colors in assigned proportions) and similarity searches. This can be useful for a wide range of applications from CBIR, such as skin detection (e.g., blocking objectionable content), apparel and design coordination, to medical image processing (e.g., improving the performance of algorithms for enhancement, segmentation, and classification [2], allowing specialists to reduce diagnostic errors). It is also possible to use it in real-time medical decision support, interior design coordination, etc. The method can also find application in color quantization techniques, reducing the computational complexity of color analysis, compared to existing matching algorithms of image retrieval engines. Actually, it can be applied to any field in which matching color descriptions based on their fuzzy semantics is important. In addition, our method could aid research on color constancy, an intrinsic human ability to recognize colors under various conditions. The reader is referred to [26] for more information.

So, we consider the methodology to be potentially demanded in any field where color accessing is important, including various e-commerce areas. We want to close with thoughts on various prospective possibilities for subsequent related research like accessing aesthetics and improving the aesthetic attractiveness of photographs, using color

[1]Preference for harmonious colors is just one factor underlying an aesthetic response. Spatial composition and products characteristics (fabric, style, etc.) also need to be addressed.

aesthetics in marketing and brand promotion, web site aesthetic level evaluation, among others. We believe that this is an exceptionally promising research area for engineers and psychologists in which many pressing questions call for an empirical study: How do color associations develop? How powerful is the impact of these associations on human behavior? What colors affect consumer purchasing behavior (in order to make predictions for those who did not pass the survey). How to influence consumers' aesthetic perceptions of goods?

As we know, image processing rests upon analysis of color pixels and shapes. It is important to note that image retrieval which is founded purely on colors may result in too many false positives when database is large and heterogeneous [35]. Therefore, for a better result, color-based features can be integrated with other visual features, and our system can work as a subsystem within huge retrieval system. Nevertheless, color indexing is a fast filter, and its output can be further processed by more time-consuming methods. Therefore, in practice, color indexing is usually coupled with texture/shape/edge indexing methods.

In the prototype application we tried to provide the correspondence between linguistic labels and users impression of a certain color or color combinations in a specific context fashion. But impressions can greatly vary from context to context. Therefore, conducting comparative evaluation of color perceptions considering different environments (even countries!) of use is very important [56]. For example, red can symbolize something exciting, sensual, romantic, feminine, good luck, signal of danger, etc. In apparel coordination, it can mean something provocative. The problem of strong context dependency can be easily handled by fuzzy sets and logic, e.g. by way of collecting the experts opinions and building the corresponding fuzzy sets.

Clearly, there is a difference between participation in an experiment and using the system in real life. So, we plan to launch the system and get real feedback that can be used to improve the method.

6.2 Future Work

As for future improvements, there are two areas that we can work on and make better.

Firstly, we plan to introduce a feedback mechanism for adapting the item retrieval to the user sensibility. We will implement this by collecting users' relevance judgments on the correspondingly retrieved clothing items and modelling of users' relevance feedback. We have already conducted similar experiments, but in the future we aim to evaluate the system performance "on the fly", during the interaction of a system with a user.

Secondly, we plan to rank the items retrieved as a result of processing the linguistic quieries. Which tools can we use for these purposes? We can process multiple ratings of a single clothing item to get a single score indicating the goodness of an item based on Pythagorean fuzzy sets[92]. We can also use the concept of extended linguistic variables, and aggregate the linguistic ratings of each shopping item on all attributes for each user into a comprehensive assessment[37].

Finally, concepts of *preference* and *harmony* and their relationship can serve as a tool for future investigations in aesthetics across multiple domains. For example, furniture coordination, accessing aesthetics attractiveness of photographs, using color aesthetics in marketing and brand promotion.

AppendixA

Using FHSI library

```
// FHSILibraryExample.cs
using FuzzyColorLibrary;
...

  static void Main(string[] args)
        {
            FHSIColor.Initialize();
            //create some fuzzy colors
            FHSIColor blush = new FHSIColor(Hue.Red, Saturation.Medium,
                Intensity.Light);
            FHSIColor cornflower = new FHSIColor(Hue.Blue, Saturation.Medium,
                Intensity.Pale);
            FHSIColor golden = new FHSIColor(Hue.Yellow, Saturation.High,
                Intensity.Medium);
            FHSIColor black = new FHSIColor(Hue.Any, Saturation.Low,
                Intensity.Dark);

            //create fuzzy palette and compute its harmony and some user's
                preference
            Palette palette = new Palette(blush, cornflower, golden);
            double harmony = palette.getHarmonyValue();
            ColorRatings ratings = getUserColorRatings();
            double pref = Palette.getPreferenceValue(palette, ratings);
```

```
        //compute the similarity between palettes
        Palette goldAndBlack = new Palette(golden, black);
        double similarity = Palette.getSimilarityValue(palette,
            goldAndBlack);
    }
```

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