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Fuzzy Color Space for Apparel Coordination

Pakizar Shamoi [A], Atsushi Inoue [B], Hiroharu Kawanaka [C]

[A] Department of Information System Management, Kazakh-British Technical University, Tole bi 59, Almaty, Kazakhstan, Almaty, Kazakhstan, p.shamoi@kbtu.kz
[B] Department of Computer Science, Eastern Washington University, 668 N. Riverpoint Blvd Suite A, Spokane, Washington 99202, USA, ainoue@ewu.edu
[C] Graduate School of Engineering, Mie University, 1577 Kurimamachiya, Tsu, Mie, 514-8507 Japan, kawanaka@elec.mie-u.ac.jp

Abstract

Human perception of colors constitutes an important part in color theory. The applications of color science are truly omnipresent, and what impression colors make on human plays a vital role in them. In this paper, we offer the novel approach for color information representation and processing using fuzzy sets and logic theory, which is extremely useful in modeling human impressions. Specifically, we use fuzzy mathematics to partition the gamut of feasible colors in HSI color space based on standard linguistic tags. The proposed method can be useful in various image processing applications involving query processing. We demonstrate its effectivity in the implementation of a framework for the apparel online shopping coordination based on a color scheme. It deserves attention, since there is always some uncertainty inherent in the description of apparels.

Type of Paper and Keywords

Short communication: *HSI, color space, fuzzy sets, perceptual color space, apparel coordination*

1 Introduction

Nowadays, the meaning of color is becoming more and more important almost in every industry. It has been widely used in many computer vision applications, especially for Content-Based Image Retrieval (CBIR) in multimedia databases [2][4].

More and more related research efforts are oriented towards application of fuzzy set theory to various tasks in image processing [1]. This can be explained by the fact that digital images are mappings of natural scenes, and they thus 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 human's 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.

Human visual system is very complex – we can differentiate between millions of colors and describe the image by few colors at the same time. The number of unique colors can reach up to 16 million. Most of these colors are perceptually close and cannot be differentiated by human eye that can differentiate only between 30 colors in cognitive space. Humans perform the grouping of colors automatically, but from the computational perspective, it is a challenging task.

To tackle this problem, we need to define human-consistent color features to represent the image contents. This paper introduces the new methodology for color processing based on fuzzification of HSI (hue-saturation-intensity) color model. We also discuss how it can be applied in apparel online shopping to perform image retrieval based on user-friendly queries.

2 MOTIVATIONS

It is a well-known fact that most search engines nowadays are based on indexing. For example, if we try 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 is obvious.

Now let's provide another suitable example that can prove the validity of the proposed approach. Nowadays, "Taobao" website for online shopping is becoming extremely popular in Kazakhstan. After a talk with Taobao consultant, we identified two problems that most users experience. The first problem is that very often users wish to find similar items at lower prices. The other one is that they want to be able to find a certain item given a picture from Internet, without knowing the brand, for instance. There is a plenty of sites, which provide the service of finding goods on Taobao based on the image that the user uploads. However, the functionality of these sites is limited. Specifically, they can only find goods with the absolutely same photo. That is why even if you download the photo from Taobao, the service won't find the corresponding item in case we change the image a bit – add shading, brightness, cut some edges, flip it, etc. This happens because such services can find goods based on exactly the same images, not similar images.

3 OVERVIEW OF COLOR REPRESENTATION METHODS

Color space is a method of color representation. There are a number of color spaces popular today, but none of them can dominate the others for all kinds of images. Based on some color spaces we can develop Fuzzy color spaces, in order to systematically organize the set of all possible human color perceptions. Let's consider some of the most popular color spaces.

The well-known RGB system represents additive color combinations (e.g. overlapping lights, display on LCD). It is convenient for color image display, but not for analysis, due to high correlation [8]. So, if intensity changes, all *r*, *g* and *b* values change accordingly. As a result, chromatic information can be lost.

Another popular system is CMYK, which is based on subtractive color combinations (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 additive and subtractive color models (i.e. RGB and CMYK spaces) does not represent color differences in the way human visual system perceives them [8][9]. Due to this non-uniformity and high correlation among their components [10], it is very difficult to define the similarity between colors based on their distance in RGB or CMYK space [2][3].

The HSI model is also a popular color model at present, and it has good performance. In HSI model, colors are expressed using 3 attributes: 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.

In most cases, the RGB model is often used to depict the color information of an image [3]. 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.

Computationally more expensive models, including CIELAB or CIECAM02 are considered to be better in uniform color display, but their adoption has been slow. Another competitive color model is a Munsell color space, which is based on subjective observations rather than direct measurements or perceptual experiments. Recent researches unveiled the fact that the Munsell space is not as perceptually uniform as it was originally claimed to be.

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 computed fast [8].

4 METHODOLOGY

The main idea of the proposed methodology is to provide the mapping of different colors and human impressions of them (see Figure 1). 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, Mass Assignment Theory, surveys, and histograms among others.

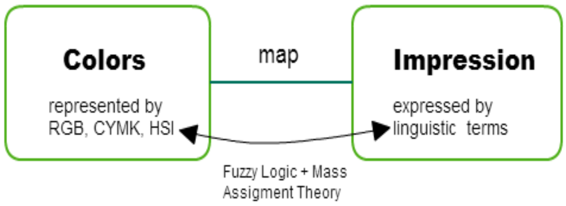

Figure 1: The essence of the proposed methodology

4.1 Taxonomy

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 impressions, they are expressed by linguistic terms (e.g. formal, black and white, pale blue, etc.). Table 1 below depicts the taxonomy, i.e. classification of color impressions.

Table 1: 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

In fact, the same colors 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.

In case of composite color impressions, which are based on atomic ones with the help of various connectives, we need to employ basic formulas from fuzzy theory. Specifically, for the intersection (*and*) and union (*or*) we take the minimum and maximum of two memberships respectively, to get the resultant membership value [10]:

$$\mu A(x) \cap \mu B(x) = \min[\mu A(x), \mu B(x)]$$
$$\mu A(x) \cup \mu B(x) = \max[\mu A(x), \mu B(x)] \quad (1)$$

In addition, we use the following formula for the α-*cut* (Alpha cut), which is a crisp set that includes all the members of the given fuzzy subset *f* whose values are not less than α for 0< α ≤ 1 [9]:

$$f_\alpha = \{x : \mu_f(x) \geq \alpha\} \quad (2)$$

Alpha cuts and set operations are connected in the following way:

$$(A \cup B)_\alpha = A_\alpha \cup B_\alpha\,,\ (A \cap B)_\alpha = A_\alpha \cap B_\alpha \quad (3)$$

These formulas enable us to find the result of a query with a certain threshold (which is actually an Alpha cut) – α, containing *or* or *and* operations. We first find the α-*cuts* and then take the crisp or / and operation.

If we analyze Table 1, 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.

4.2 Color Space Fuzzification

We believe that color should be analyzed from the perspective of human color categories, in order to relate to the way people perceive colors and also to reduce the data from 16 million colors. Based on perceptions, the colors can be modeled as fuzzy sets in HSI color space. As already mentioned, colors will be described by linguistic terms. Let's consider how the fuzzy encoding can be done on each of the parameters of HSI color space.

Hue variable is specified by 8 linguistic labels, specifying various hues. Such division was done based on the subjective perception – we just conducted a number of experiments and adjusted the fuzzy sets. In the future this can be done by experts in specific domain. Anyway, this division was done just for the purpose of demonstrating the fuzzy encoding process. In the future we can construct the membership functions with the help of the survey based on human color categorization, for more information refer to [6]. So, the term set consists of 7 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, the 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 below presents the information about fuzzy variables in our color space.

Table 2: Description of fuzzy variables

Fuzzy Variable	Fuzzy Sets	Universal Set
Hue	{"Red", "Orange", "Yellow", "Green", "Cyan", "Blue", "Violet", "Magenta"}	{0, 1, 2, ..., 359, 360}
Saturation	{"Low", "Medium", "High"}	{0, 1, …, 99, 100}.
Intensity	{"Dark", "Deep", "Medium", "Pale", "Light"}	{0, 1, …, 254, 255}

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. The fuzzy sets for 3 HSI parameters are provided below.

4.3 Dominant Color Identification

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 [7], etc.

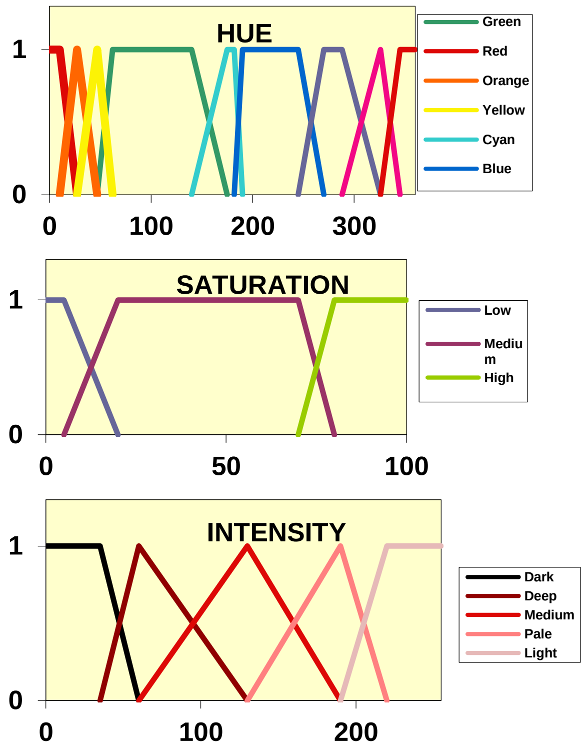

Figure 2: Fuzzy sets for hue, saturation and intensity

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 and 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, supposing two colors, whose saturation equals to 8 and intensity equals to 68, it doesn't 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 Figure 3 below.

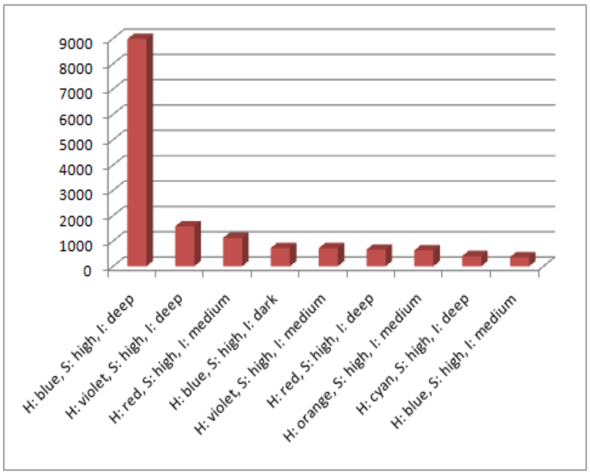

Figure 3: Identification of dominant colors using color histogram

4.4 Color Harmony

Color Harmony is one of the most interesting principles in color theory. Colors which tend to produce a good impression when seen together are said to be in a harmony. Harmony is a complex notion, which is influenced by a number of factors, including affective, cognitive and contextual ones. 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 our application example provided below we employ color harmony principles in order to identify the set of apparels that fit to a certain apparel provided by the user. 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 HSI values, but here, just in order to demonstrate it, we present some of them visually in Table 3. Note that groups might have various number of colors.

Table 3: Groups of colors in a harmony

Group ID	Colors in the group
1	
2	
3	
4	
5	
…	…

It is clear that in our color harmony table we have crisp 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 [6].

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.

5 APPLICATION

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 prototype system is written in c# language and uses database containing around 400 apparels of various types. Note that the default retrieval threshold is set to 0.5, we use it in the α-cut operations of the fuzzy sets.

5.1 Human-Friendly Queries in Apparel Coordination

The proposed method can be used in the matching engine for providing the image retrieval functionality based on the following queries:

- *Linguistic query*, in which attributes are specified by words, e.g., *find popular elegant dresses, find deep red or pale green dresses*
- *Query by example*, which allows image input to a system. This is for the case when users wish to retrieve apparels that fit to some other apparel (inputted image), by taking into account color harmony principles, among other, trivial ones. The relevance is ranked according to a color harmony measure computed from the dominant color(s) in the images. For example, *find similar dresses, find shoes that are combined with the dress on the uploaded photo.*
- *Combinational query*, which has properties of both linguistic and exemplar queries. For instance, users aim to find apparels of dark hues that are perfectly combined with some other apparel in the uploaded image, e.g. *find apparels of dark hues that are perfectly combined with jacket on the photo*.

Note that in the case of exemplar or combinational query, 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. 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 we developed in our previous works [6].

5.2 Mapping Impressions to Colors

Visual effects of specific colors and color combinations cannot be underestimated. So, besides the atomic and composite context-independent impressions (e.g. light green, white and blue) the system provides the retrieval of images corresponding to context-dependent color impressions, which represent qualitative linguistic labels, e.g. informal, elegant, etc.

Now the represented set is limited, but it can be easily extended in the future. Table 4 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.

5.2 System Operation

The work of such retrieval systems can be significantly speeded up by pre-computation of fuzzy color histograms. This ensures the system scalability, thus the growing size of the database won't impact the performance of the system. So, when the moderator uploads new shopping items, the histograms are computed on the fly and the dominant colors are saved for each apparel in the table.

5.3 Examples

Example 1: Context-independent linguistic query, e.g. ***"Deep red dress".*** This is a simple linguistic query. It works fast due to initial precomputation of apparels' color schemes. Using Equation 1, Equation 2 and Equation 3 we find the constraint relations are: *Hue<17* or *Hue>335, 49>Int.>95* (see Figure 4).

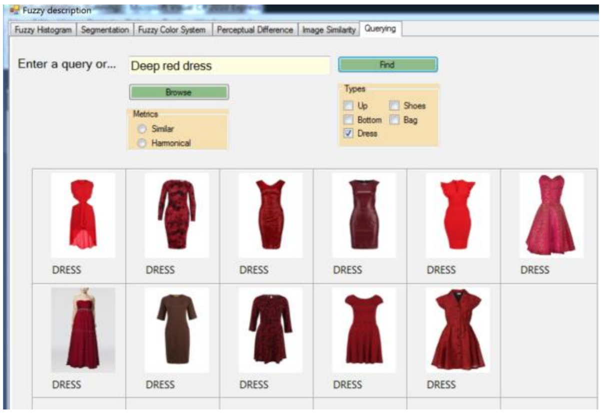

Figure 4: Application screenshot for Example 1

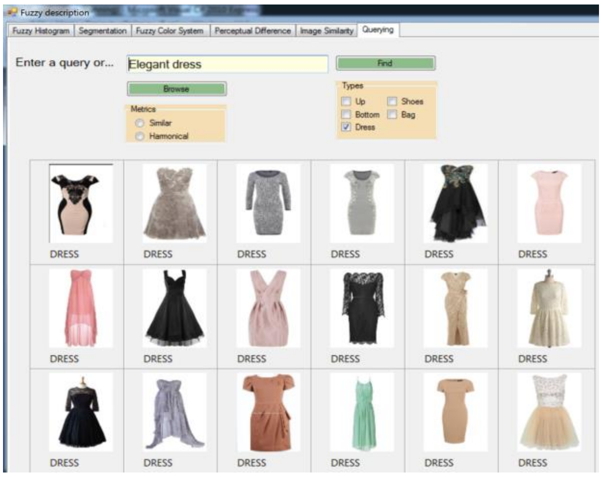

Figure 5: Application screenshot for Example 2

Table 4: Map between impressions and various colors

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

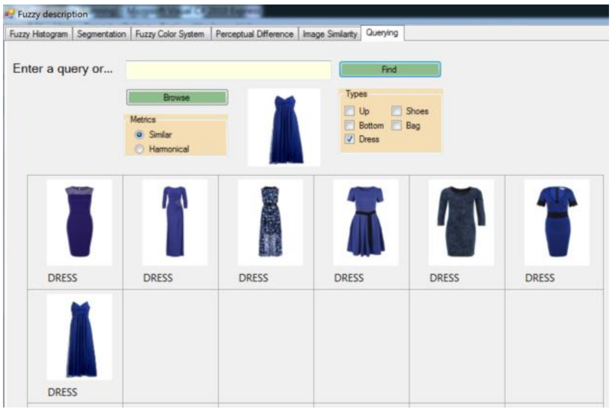

Figure 6: Application screenshot for Example 3

Example 2: Context-specific linguistic query, e.g. ***"Elegant dress".*** The mappings between impressions and colors provided in Table 4 are stored in a distinct database table *Impressions.* The system uses it along with fuzzy color scheme of apparels to retrieve the relevant results.

Example 3: Query by example based on similarity metric defined in [6]. As mentioned earlier, query by example involves image input. For example, an online shop client has a photo with apparel (taken from fashion sites or even real life) and wishes to buy an item similar to the one on the photo. Figure 6 demonstrates this example.

Example 4: Query by example based on a harmony metric. Let's suppose a user already has a skirt and wishes to find the remaining items to get the look – blouse and shoes. All she will need to do is to upload the skirt image. The system will extract the skirt's dominant colors and fetch such database apparels whose dominant colors are in a harmony with the skirt's one. Figure 7 shows this example.

Example 5: Combinational query. As we know, if users wish to find, say, ***"formal top apparels",*** it is a linguistic query. If users want to find top apparels which suit to the skirt, it is a query by example. But what if users wish to find ***"formal top apparels fitting to a skirt in the image"?*** In this case, we need to combine the procedures we perform for two different types of queries and retrieve apparels satisfying both of them (see Figure 8).

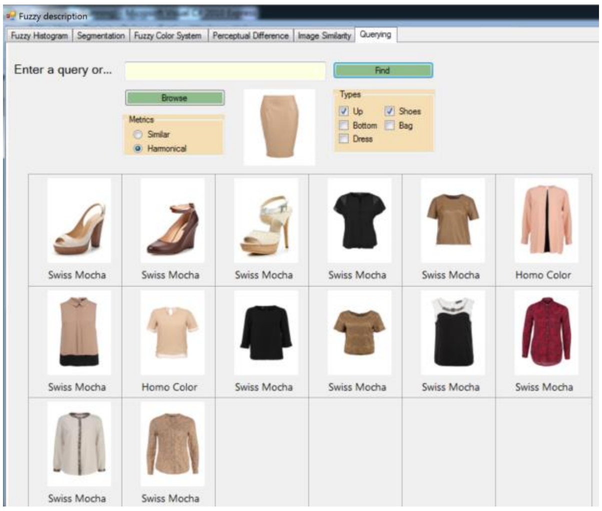

Figure 7: Application screenshot for Example 4

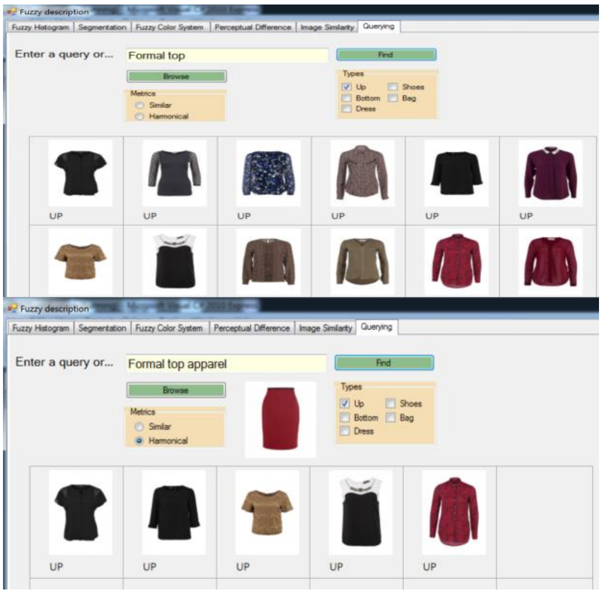

Figure 8: Application screenshot for Example 5

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.

6 Summary and Conclusions

In the present article, we propose a fuzzy set and logic guided novel technique for color processing. The proposed approach produces results which are highly relevant to the content of the linguistic query corresponding to a human impression. In the prototype application we tried to provide the correspondence between linguistic labels and user's 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 [5]. 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.

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 databases are large and heterogeneous [2]. 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 systems. 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 addition, we plan to consider another aspect for the future improvement that is related to relevance feedback. It is clear that user feedback is an essential element in the effective retrieval of information.

Finally, it needs to be highlighted that the proposed methodology is suitable for a number of domains. Namely, it is also possible to use it in real-time medical decision support, interior design coordination, etc.

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AUTHOR BIOGRAPHIES

M.Sc. Pakizar Shamoi received her Diploma (M.Sc.) in Information Systems from the Kazakh-British Technical University in 2013. Currently she is a senior-lecturer at the Department of Information System Management of the same university. Her research interests include, but are not limited to: artificial intelligence in general (fuzzy sets and logic in particular), color theory, content-based image retrieval, natural language processing, techniques for creating applications with natural language user interfaces, among others.

Dr. Atsushi Inoue is a full professor of information systems and health informatics at Eastern Washington University, Cheney/Spokane, WA, USA. His specialty is soft computing with various application domains being explored; including security, health, entertainment, finance, education, and e-commerce. He obtained his Ph.D. in Computer Science and Engineering at the University of Cincinnati, USA, in 1999. He has extensive experiences in both industries and academia such as Hitachi Ltd., Motorola, and Carnegie Mellon University. He has held visiting professorships in various countries such as USA, Japan, Kazakhstan, France, and Spain.

Dr. Hiroharu Kawanaka received a Dr. of Eng. from Mie University in 2004. After graduation, he established a company "Medical Engineering Institute, Inc." to develop Clinical Data Ware House systems. In 2009 he received his Ph.D. in Medical Science from Mie University. He visited Cincinnati Children's Hospital as a visiting researcher in 2012. He is now an assistant professor at Mie University, Graduate School of Engineering. His current research topics are medical/welfare informatics, document analysis systems, ergonomics and soft computing. He is a member of IEEE, HIMSS and some Japanese academic societies.