Fuzzification of HSI Color Space and its Use in Apparel Coordination

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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 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 provide the fuzzification of HSI color space and further use it for obtaining the correspondence between colors and human impressions. In addition, the methodology is applied in the implementation of a framework for the apparel coordination based on a color scheme. It deserves attention, since there is always some uncertainty inherent in the description of apparels.

Introduction

Nowadays, the meaning of color is becoming more and more important almost in every industry (T. Lu and C.Chang, 2007). It is worth noting that the number of unique colors can reach up to 16 million. Needless to say, most of these colors are perceptually close and cannot be differentiated by human eye which can differentiate only between 30 colors in cognitive space.

More and more related research efforts are oriented towards application of fuzzy set theory to various tasks in image processing (L. Hildebrand and B. Reusch, 2000). 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, human perception of colors contrasts with color theory science because these theories have always assumed perfect conditions.

The paper presented herein tackles this problem by presenting the new methodology for color information processing using fuzzy set theory.

Motivations

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 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 some item given some 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.

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 space we can develop Fuzzy color space, in order to systematically organize the set of all possible human color perceptions. Let's consider some of the most popular color spaces.

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 (N. Sugano, et al., 2009). So, if intensity changes, all r, g and b values change accordingly. As a result, chromatic information can be lost. Moreover, it is not a uniform scale, so it is difficult to calculate the similarity between colors based on their distance in RGB space (K. Konstantinidis, et al., 2005; Y. Li-jie, et al., 2009).

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.

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, namely, hue (e.g. red, orange, green), intensity (light vs dark) and saturation (intense vs dull).

In most cases, the RGB model is often used to depict the color information of an image (Y. Li-jie, et al., 2009). 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.

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.

Methodology

The main idea of the proposed methodology is to provide the mapping of different colors, color combinations and human impressions of them (Fig.1). 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.

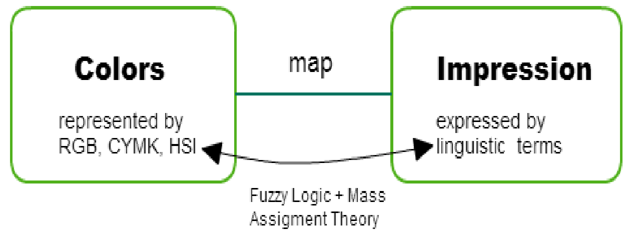


Figure 1. Scheme of the methodology

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.). The Table 1 below depicts the taxonomy, i.e. classification of color impressions.

Table 1. Taxonomy of color impressions

<table>
<tr><th>Level</th><th>Impression</th><th colspan="2">Comment</th></tr>
<tr><td>III</td><td>Various combinations of I and II (e.g. Pale blue, elegant and formal, deep red etc.)</td><td colspan="2">Composite, context-dependent and context-independent colors</td></tr>
<tr><td>II</td><td>Elegant, formal, casual</td><td>Pale, bright, deep</td><td>Atomic, context-dependent and context-independent colors</td></tr>
<tr><td>I</td><td>Red, blue, black</td><td colspan="2">Atomic, context-independent colors</td></tr>
</table>

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.

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 (Zadeh, 1996; Zadeh, 2002):

$$\mu A \cap \mu B(x) = \min[\mu A(x), \mu B(x)]$$

$$\mu A(x) \cup \mu B(x) = \max[\mu A(x), \mu B(x)]$$

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 (Zadeh, 1965):

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

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

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

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.

Color Space Fuzzication

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. 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, after a more thorough analysis fuzzy sets can be tuned. 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 1, from dull to intense, so the domain X = [0, 1], and the universal set is U = {0, 0.01,…,0.99,1}.

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}. For the sake of simplicity, for all the fuzzy variables we employed either triangular or trapezoidal membership functions (Fig. 2), depending on the value range of a certain color property associated with the specific label (A. Younes, et al., 2005).. Particularly, for a wide range we used trapezoidal membership functions, and triangular ones for all the other fuzzy sets that are not wide.

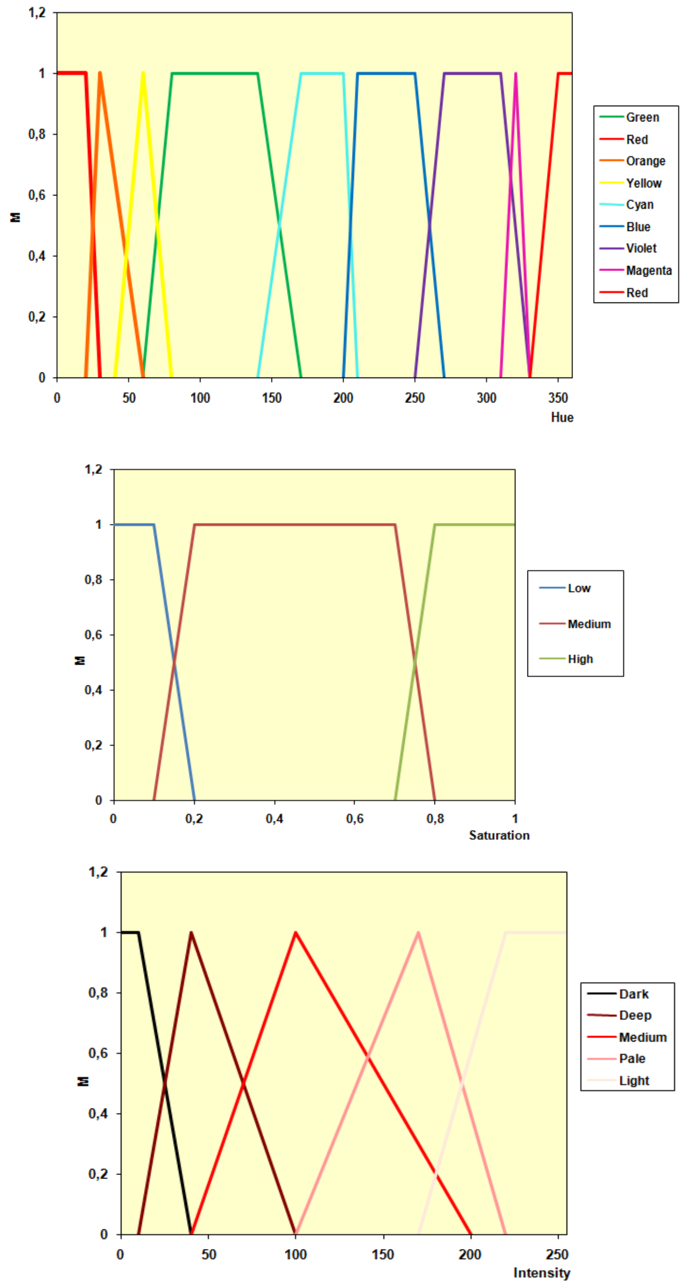


Figure 2. Fuzzy sets for Hue, Saturation and Intensity

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, etc. (N. Sharma, et al., 2011; J. Han and K. Ma, 2002).

For easy histogram purposes, we divide the colors into bins (J. Han and K. Ma, 2002), 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 86 combinations taking into account the following general observations:

- if (Saturation is low) then (Hue is irrelevant)
- if (Intensity is light) then (Hue and Saturation are irrelevant)

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.

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. 3.

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.

Context-dependent Color 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, 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. Table 2 below 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. It is assumed that the proposed system will provide the image retrieval functionality based on the following queries:

- *Linguistic query*, in which attributes are specified by words, for example, *Retrieve popular elegant dresses*.
- *Exemplar query*, which allows image input to a system. This is for the case when user wishes 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.
- *Combinational query*, which has properties of both linguistic and exemplar queries. For instance, user aims to find apparels of dark hues that are perfectly combined with some other apparel in the uploaded image.

Note that in 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 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 now, our prototype application provides the processing of just linguistic queries.

Now let's look at some use cases of the system. For the initial testing, we used database containing 65 apparels, mostly dresses. Note that the default retrieval threshold is set to 0.5, but it can be tuned in the system.

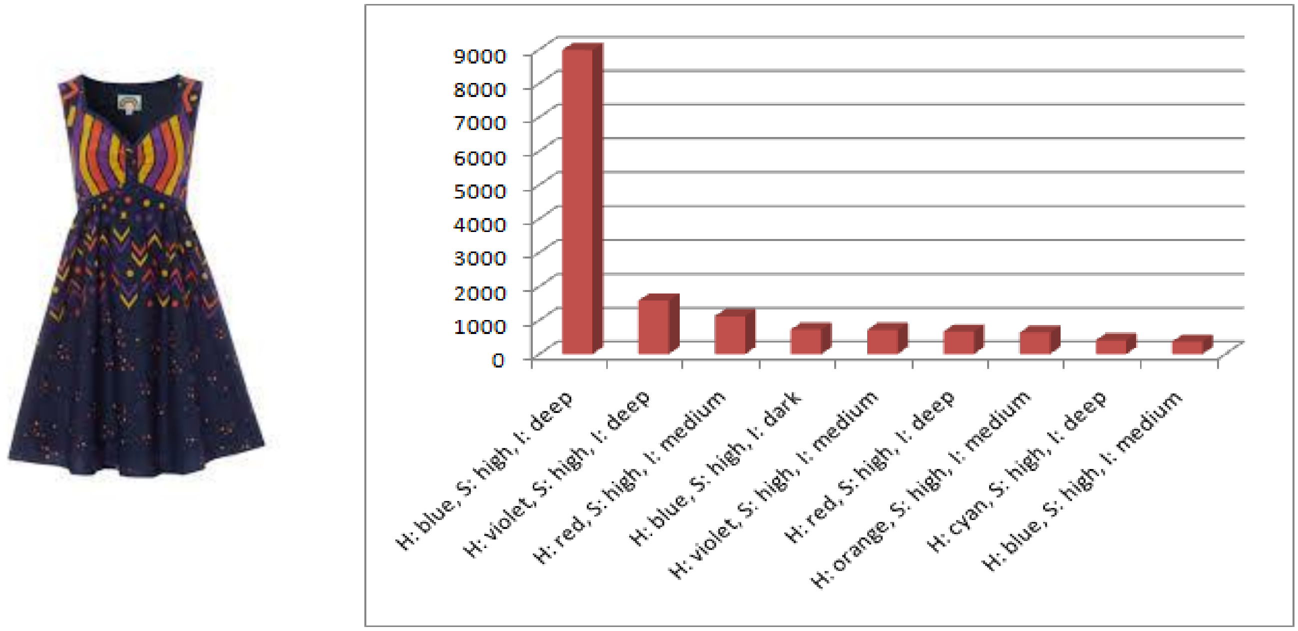
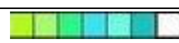


Figure 3. Identification of dominant colors using color histogram

Table 2. Map between some color impressions and colors

Impression	**Colors (visual)**	**Colors (in words)**
Elegant		Black, jewel, emerald, sapphire as well as 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

Example 1. *Deep red or pale green dress.*

Number of apparel types – 2
Number of dominant colors (apparel 1) – 1
Number of dominant colors (apparel 2) – 1
Color (apparel 1) – Color [Hue = red; Saturation = medium or high; Intensity=deep]
Color (apparel 2) – Color [Hue = green; Saturation = medium or high; Intensity=pale]

Results:

Example 2. *Elegant dress*

Based on our knowledge (see Table 2), beige, milky, mocha, black, brown, dull blue, dull green can be considered as "elegant". So, for example, for 'milky' we have:
Color1 (Milky) – Color [Hue = yellow; Saturation = medium or high; Intensity=light]
Results:

Example 3. *White and blue dress*

Number of dom. Colors - 2
Color1 – Color [Hue = any; Saturation = any; Intensity = light]
Color2 – Color [Hue = blue; Saturation = medium or high; Intensity = medium]
Results:

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.

Conclusion

In the present article, we propose a fuzzy sets 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 (O. Penatti, et al., 2012). 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. We plan to address these issues in our future works.

As we know, image processing rests upon analysis of color pixels and shapes. However, we did not focus on shape descriptors in our study, since almost all of them depend on segmentation, which is still hard and extremely application-dependent task.

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, among others.

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