Fuzzy Granulation Approach to Color Digital Picture Recognition

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Abstract. This paper presents a new approach to color digital picture recognition, especially classification of pictures described by linguistic terms. Fuzzy granulation is proposed to express a picture as a composition of fuzzy granules that carry information about color, location, and size, each of these attributes represented by fuzzy sets characterized by membership functions. With regard to the color, the CIE chromaticity triangle is applied, with the concept of fuzzy color areas. The classification result is obtained based on fuzzy IF-THEN rules and fuzzy logic inference employed in a fuzzy system.

1 Introduction

Color digital pictures are very popular nowadays. The number of such pictures we collect are still growing. In addition, the picture resolution increases. Therefore, we need new methods for searching, recognition, and retrieving a particular picture from a large collection of them.

Color is a very important attribute of digital pictures. It carries significant information that helps to distinguish, recognize, compare, and classify different pictures or objects presented on various pictures. As a matter of fact, color should be considered as a triplet, i.e. hue (pure color), saturation, and lightness; we describe the color properties in Section 2. However, the name "color" is commonly used as a synonym of "hue". Hence, in the case where it can be accepted, sometimes we also treat these two terms interchangeably.

In this paper, with regard to the color digital pictures, fuzzy granulation approach – introduced by Zadeh [19] – is proposed to describe fuzzy location of pixels as well as fuzziness of their color. Thus, we can consider a color digital picture as a collection of pixels or groups of pixels which we call macropixels, and treat them as fuzzy sets [16]. In the framework of the fuzzy granulation, the macropixels can be viewed as fuzzy granules that carry information about the color, location, as well as size of the macropixels. Hence, a color digital picture is a composition of the fuzzy granules that represent fuzzy relations (see e.g. [11]) between the attributes of color, location, and size. In addition, interactions between the granules are expressed by their fuzziness that results in the overlapping of the granules within the picture.

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The fuzzy granulation approach applied to color digital pictures may be very useful for problems of picture classification where classes are distinguished based on linguistic description. Such a problem is considered in Section 8, and its solution can be obtained based on fuzzy IF-THEN rules formulated in this section and applied to a fuzzy inference system (see e.g. [11]).

In Section 7, the fuzzy granulation approach is outlined, with regard to image processing and color digital picture recognition, referring to other sections, especially to Section 6 where the idea of macropixels is introduced. The new approach, based on the fuzzy granulation, is more precisely described, including some mathematical formulas, in Section 8.

Sections 2, 3, and 4 concern the color attribute while Section 5 as well as Section 6 are interested in the location of pixels in a digital picture. As mentioned earlier, Section 2 provides general information about color, hue, and color models (that take into account saturation and lightness). Section 3 describes a particular type of color models that is the CIE chromaticity triangle which is applied in the problem considered in this paper. In Section 4, we focus our attention on the color areas of the CIE chromaticity triangle, viewed as fuzzy regions (fuzzy sets) characterized by membership functions. In Section 5, fuzzy sets and their membership functions are proposed to represent the pixel locations. Section 6 refers to the third attribute of the granules, i.e. size.

In Section 9, some conclusions and final remarks are included, as well as further research directions outlined. This paper presents a new concept of fuzzy granulation approach to color digital picture recognition that can be extended in many directions and applied to various new problems formulated in the area of image processing and recognition.

2 Color Properties and Models

The pure color is called "hue". Usually, colors with the same hue are distinguished with descriptive adjectives such as "light blue", "pastel blue", "vivid blue", "dark blue", which refer to their lightness and/or chroma (saturation). Exceptions inlude "brown" which is a dark "orange", and "pink" that is a light red with reduced chroma. Hue is one of the main properties of a color. Saturation (also called chroma) and lightness (also called brightness, value, or tone) are two additional properties of a color. Hue is the term for the pure spectrum of colors that appear in the rainbow as well as in the visible spectrum of white light separated by a prism.

Theoretically all hues can be mixed from three basic hues, known as primaries. There are different definitions of the primary colors. i.e. painters primaries, printers primaries, and light primaries; for details, see e.g. [1].

However, the visible spectrum consists of much more colors than a computer monitor can display. The well known RGB (red, green, blue) refers to the application in computer screens where colored light is mixed. If all three light primaries are mixed the theoretical result is white light. The RGB is an additive color model, combining red, green, and blue light. In computers the RGB color model is used in numerical color specifications.

It has been observed that the RGB colors have some limitaitons. The RGB is hardware-oriented and non-intuitive which means that people can easily learn how to use the RGB but they rather think of hue, saturation and lightness, and how to translate them to the RGB.

Two most common representations of points in the RGB color model, based on hue, saturation and lightness, are HSL and HSV. The former stands for "hue", "saturation", and "lightness", while the latter for: "hue", "saturation", and "value". The HSV is also called HSB (where B stands for "brightness"). A third model, common in computer vision applications, is HSI, for "hue", "saturation", and "intensity". The HSV, HSB, HSL color models are slight variations on the HSI theme.

Saturation defines a range from pure color to gray at a constant lightness level. A pure color is fully saturated. Lightness indicates the level of illumination, and defines a range from dark (no light) to fully illuminated.

In a color space, colors can be identified numerically by their coordinates. There are precise rules for converting between the HSL and HSV spaces, defined as mappings of the RGB. The convertion between them should remain the same color; however it is not always true with regard to different color spaces (e.g. RGB to CMYK that is a subtractive color model, used in color printing). Since RGB and CMYK are both device-dependent spaces, there is no simple or general conversion formula that converts between them. The CMYK color model is based on the printers primaries, i.e. cyan, magenta, and yellow. In addition, the key (black) component is used. Color printing typically employ ink of the four colors (including black). Mixing the three printers primaries theortically results in black, but imperfect ink formulations do not give true black, which is why the additional key component is needed. It is worth noticing that secondary mixtures of the CMY primaries (cyan, magenta, yellow) results in red, green, blue.

It is worth emphasizing that the RGB model is usually employed for production of colors while the HSI for description of colors. Conversion between RGB and HSI is also possible; see e.g. [4], [5].

Some color spaces separate the three dimensions of color into one luminance dimension and a pair of chromaticity dimension. For example, the chromaticity coordinates x and y are used in the xyY space, in the CIE color model, described in the next section.

Luminance is the physical measure of brightness; the standard unit of luminance is candela per square meter. Luminance is the amount of visible light leaving a point on a surface in a given direction. We can simply say that luminance is the amount of light reflected from a hue (on a physical surface or an imaginary plane). Brightness is the perception elicited by the luminance of a visual target. A given target luminance can elicit different perceptions of brighness in different contexts.

Formerly the term "brightness" was used as a synonym for "luminance". Lightness was the term used in the CIE world (see Sections 3), and thought of as synonym for reflectivity as well as intensity.

The CIE procedure converts the spectral power distribution of light from an object into a brightness parameter Y and two chromaticity coordinates x, y. The brightness parameter Y is a measure of luminance which is light intensity factored by the sinsitivity of the normal human eye.

Chromaticity is an objective specification of the quality of a color regardless of its luminance. The CIE diagram removes all intensity information, and uses its two dimensions to describe hue and saturation.

More information on this subject we can find in many publications refering to color theory, computer vision, etc.; many interesting details are available on the Internet, including Wikipedia.

3 The CIE Chromaticity Triangle and Fuzzy Color Areas

The CIE color model was developed to be completely independent of any device or other means of emission or reproduction and is based as closely as possible on how humans perceive color. This model was introduced in 1931 by the CIE that stands for Comission Internationale de l'Eclairage (International Commission on Illumination).

The CIE chromaticity diagram represents the mapping of human color perception in terms of two CIE parameters x and y, called the chromaticity coordinates, which map a color with respect to hue and saturation.

Color names have been assigned to different regions of the CIE color space (chromaticity triangle) by various researchers; see e.g. [3], [4]. These are approximate colors that represent rough categories, and not to be taken as precise statements of color. Therefore, we can treat them as fuzzy sets, and boundaries between the regions may be viewed as not crisp but belonging to the distinct areas with a certain membership value.

The original CIE 1931 color space was updated in 1960 and 1976 so that the chromacity spacing would be more perceptually uniform, and also more convenient for industrial applications (e.g. food, paint, etc.). The main advantage of the 1976 CIE chromaticity diagram is that the distance between points on the diagram is approximately proportional to the perceived color difference.

In this paper, we apply the original CIE chromaticity triangle, with the labeled regions presented in [3], [4]. Thus, we employ 23 fuzzy regions of the CIE color space, assosiated with the following colors (hues): red, pink, reddish orange, orange pink, orange, yellowish orange, yellow, greenish yellow, yellow green, yellowish green, green, bluish green, bluegreen, greenish blue, blue, purplish blue, bluish purple, purple, reddish purple, purplish pink, red purple, purplish red, white.

The CIE chromaticity diagram shows the range of perceivable hues for the normal human eye. We can say that the chromaticity diagram plots the entire gamut of human-perceivable colors by their x, y coordinates. The inverted-U shaped locus boundary (that is the upper part of the horseshoe shaped boundary) represents spectral colors (wavelengths in nm). The lower-bound of the locus is known as the "line of purples" and represents non-spectral colors obtained by mixing light of red and blue wavelengths. Colors on the periphery of the locus are saturated, and become progressively desaturated in the direction towards white somewhere in the middle of the plot.

Any color within a triangle defined by three primaries (red, green, blue) can be created (or recreated) by additive mixing of varying proportion of those primary colors. The area of the triangle is much less than the entire chromaticity diagram. The triangle (located in the CIE diagram), which is the gamut of additive coverage with RGB primaries, represents the colors that can be displayed by a particular monitor (not including any brightness information). Another gamut (a smaller area), included in the RGB triangle, indicates the range available to commercial four-color printing process; see [15]. It is important knowing that different display technologies (e.g. CRT, LCD, plasma, inkjet printers, laser printers) may have inherently different color gamuts. Printers can display much less colors than monitors. It is worth noticing that in some areas the RGB gamut is "outside" that of the CMYK space (applied in color printing).

As a matter of fact, there are different types of RGB spaces depending on the technical reasons, professional requirements, and display devices. The most common are Adobe, Apple, ProPhoto, and sRGB (created cooperatively by HP and Microsoft in 1996), as well as CIE RGB i.e. the above mentioned gamut located in the CIE diagram. For details, see e.g. [6], [8].

4 Membership of Pixels to the Color Areas of the CIE Triangle

Color digital pictures are composed of pixels (picture elements, i.e. smallest units of 2-dimensional images). The pixels have a color associated with each of them. Using the RGB color model in computers, the color of a pixel is expressed as an RGB triplet (r, g, b) where each of the components (RGB coordinates) can vary from zero to a defined maximum value (e.g. 1 or 255). An RGB triplet (r, g, b) represents the 3-dimensional coordinate of the point of the given color within the cube created by 3 axes (red, blue, and green) with values within [0,1] range. In this model, every point in the cube denotes the color from black (0,0,0) to white (1,1,1). The triplets (r, g, b) are viewed as ordinary Cartesian coordinates in a euclidean space.

The (r, g, b) coordinates can be transformed into the CIE chromaticity triangle, i.e. to the color areas located on the 2-dimensional space (of the CIE diagram) with (x, y) coordinates. Detailed information concerning the transformation from RGB to XYZ space and vice versa as well as color gamut representation in the CIE diagram of different RGB color spaces is presented e.g. in [6]. It is also possible to convert RGB coordinates between sRGB and other types of RGB spaces; see [7]. Mathematical formulas describing the transformation from XYZ space to xyz and then to xy can be found in many publications, e.g. [4]. The transformation is also explained and the mathematical equations are included in [14].

For considerations in this paper, it is sufficient to use the following equations

$$x = f_1(r, g, b), \quad y = f_2(r, g, b) \tag{1}$$

which in this general form describe the transformation from the RGB color space (3-dimensional) to the 2-dimensional xy space of the CIE chromaticity diagram. Of course, for the calculations we employ the precisely defined functions (1), presented in the publications cited above.

Knowing the functions (1), we can transform each triplet (r, g, b) associated with particular pixels of a digital color picture to the CIE chromaticity triangle (the gamut). In this way, we can assign a proper color area of the CIE diagram to every pixel of the picture.

Each pixel of the picture (color image) is characterized by two attributes: color and location. The former refers to the (r, g, b) and (x, y) in the corresponding area of the CIE gamut. The latter concerns the spatial location within the picture and will be discussed in the next section.

Let us denote:

Ω – digital color picture
M – number of pixels in the picture Ω
p_j – j-th pixel in the picture Ω, where $j = 1, ..., M$
$c_j = (r_j, g_j, b_j)$ – triplet (r, g, b) for pixel p_j, where $j = 1, ..., M$

As mentioned in Section 3, the color areas (regions) of the CIE chromaticity triangle may be treated as fuzzy regions, with fuzzy boundaries between those areas. This means that the fuzzy color areas are fuzzy sets of points (x, y) that belong to them with membership grades expressed by a value from the interval [0.1]. Thus, a point (x, y) may fully belong to a color region (membership value equals 1), partially belong (membership greater than 0 and less than 1) or not belong (membership equals 0). The membership functions of the fuzzy sets may be defined in different ways. An algorithm for creation such membership functions for the fuzzy color areas of the CIE triangle is proposed in [14].

Let Δ_{CIE} denotes the CIE chromaticity triangle, and $\{H_1, H_2, ..., H_n\}$ - crisp color areas (regions with sharp boundaries) of the Δ_{CIE}. Hence, we have the following equation

$$\Delta_{CIE} = \bigcup_{i=1}^{n} H_i \tag{2}$$

In the case of the regions presented in [3], [4] and mentioned in Section 3, the number of the color areas, n=23, and there are 23 labels (color names) listed in Section 3 assigned to each region H_i, for $i = 1, ..., 23$.

As explained in Section 3, the color areas H_i, for $i = 1, ..., n$, can be viewed as fuzzy regions. Let us denote them as $\{\widetilde{H}_1, \widetilde{H}_2, ..., \widetilde{H}_n\}$. The fuzzy sets $\{\widetilde{H}_i\}$, for $i = 1, ..., 23$, like the corresponding crisp sets $\{H_i\}$, are defined in the 2-dimensional space (of the CIE diagram) with (x, y) coordinates. This space is called the universe of discourse for the fuzzy sets. Both the crisp sets $\{H_i\}$ and fuzzy sets $\{\widetilde{H}_i\}$ are sets of points (x, y). Each of these points (elements, objects) may belong to only one of the crisp sets $\{H_i\}$ but can partially belong to more than one fuzzy set $\{\widetilde{H}_i\}$, for $i = 1, ..., n$, where n=23. When the fuzzy sets are considered, their membership functions must be known (see [16], [11]). Let us denote them as $\mu_{\widetilde{H}_i}(x, y)$. As mentioned earlier, those membership functions are determined in [14].

With regard to a digital color picture, Ω, for every pixel, p_j, $j = 1, ..., M$, its color atribute value, $c_j = (r_j, g_j, b_j)$, can easily be transformed to the point (x_j, y_j) in the Δ_{CIE}, by use of formulas (1). Hence, we can determine the membership values of c_j to the fuzzy sets $\{\widetilde{H}_i\}$, for $i = 1, ..., n$, as $\mu_{\widetilde{H}_i}(c_j) = \mu_{\widetilde{H}_i}(x_j, y_j)$.

In [12], the CIE chromaticity triangle is employed, and membership degrees of particular hues in color digital pictures are used in a classification task. However, with regard to the practical application under consideration in that case, we are not interested in the location of pixels of particular color. Thus, this is a different problem; in this paper, the pixel location is very important.

5 Fuzzy Location of Pixels in a Digital Picture

Let us again consider a digital picture, Ω, composed of pixels, p_j, for $j = 1, ..., M$, but in this case we are interested in locations of the pixels within the image. Moreover, the locations will be viewed as fuzzy areas reprezented by fuzzy sets. This concept is shown in Fig. 1 where membership functions that define the fuzzy regions are portrayed. Trapezoidal membership functions are assumed to characterize the left, central, and right parts of the picture, respectively, denoted as S_L, S_M, S_R and W_D, W_C, W_U, for both s and w axes. As a matter of fact,

$$S^{\Omega} = \{S_L, S_M, S_R\}, \quad W^{\Omega} = \{W_U, W_C, W_D\} \tag{3}$$

are fuzzy sets with following membership functions:
$\{\mu_{S_L}(s), \mu_{S_M}(s), \mu_{S_R}(s)\}$ and $\{\mu_{W_U}(w)), \mu_{W_C}(w)), \mu_{W_D}(w)\}$, respectively, for the picture Ω. Now, let us consider the Cartesian product

$$Q^{\Omega} = S^{\Omega} \times W^{\Omega} \tag{4}$$

and the fuzzy sets depicted in Table 1. The 2-dimensional fuzzy sets presented in this table are Cartesian products of 1-dimensional fuzzy sets (3). These fuzzy sets are characterized by membership functions obtained as the minimum or product of two corresponding membership functions of the fuzzy sets (3); according to the definition of the Cartesian product of two fuzzy sets (see e.g. [18], [11]). The fuzzy sets portrayed in Table 1 describe the fuzzy locations of pixels in a digital picture Ω.

In Section 4, we considered the color attribute, c_j, of pixels p_j, for $j = 1, ..., M$, of a digital picture Ω. Now we focus our attention on the location attribute of the pixels. Let us denote: $S = \{1, 2, ..., M_s\}$, $W = \{1, 2, ..., M_w\}$, where $M = M_s M_w$; see Fig. 1. Then, the location attribute of a pixel p_j in the picture Ω, denoted

Table 1. Two-dimensional fuzzy sets that represent pixel locations in a digital picture

Left Upper	Left Central	Left Down
$S_L \times W_U$	$S_L \times W_C$	$S_L \times W_D$
Middle Upper	Middle Central	Middle Down
$S_M \times W_U$	$S_M \times W_C$	$S_M \times W_D$
Right Upper	Right Central	Right Down
$S_R \times W_U$	$S_R \times W_C$	$S_R \times W_D$

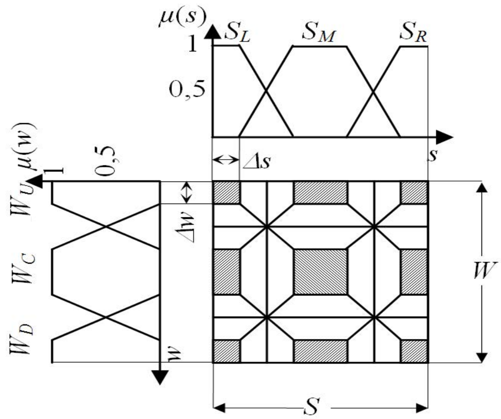

Fig. 1. Membership functions of fuzzy locations

as q_j, is expressed by coordinates (s, w) that determine the point in the space $S \times W$ corresponding to the pixel location. It is very easy to assign the proper coordinates (s, w) to every pixel p_j, where $s \in S$ and $w \in W$. It is obvious that, for all $j = 1, ..., M$, the pixel location $q_j(s, w) \in Q^{\Omega}$. In particular, this attribute of a pixel p_j belongs to the fuzzy sets illustrated in Table 1 and Fig. 1, with different membership values, depending on their membership functions.

6 An Idea of Macropixels

In Sections 4 and 5, single pixels of a digital picture have been considered with regard to two attributes: color and location, respectively. However, nowadays the number of pixels employed to represent digital pictures are usually very large. Moreover, we observe that it becomes larger and larger in digital cameras. This means that we collect more and more digital color pictures of hight spatial resolution of the images. Processing a large number of hight resolution images requires so many mathematical operations per pixel that is often a hight computational load even for today's powerful computers. Therefore, in this section, instead of individual pixels an idea of groups of pixels, called "macropixels", is proposed.

A digital color picture is viewed as a 2-dimensional array of single pixels arranged in columns and rows. In this way, the digital pictures discussed in Sections 4 and 5 have been described; see Fig. 1. To create the macropixels, we divide the whole image (digital picture) to identical rectangles that play the role of the macropixels. This means that the width and hight of the picture, S and W, respectively, are divided into intervals that build the rectangles (macropixels). Two algorithms may be proposed: incremental and decremental. The former means that the algorithm starts with individual pixels and then the rectangles that contain neighboring pixels are created. The latter algorithm starts with the whole image that is divided into smaller parts (rectangular macropixels). In the incremental algorithm, at the first iteration many small macropixels are constructed. The next iterations produce less number of macropixels of bigger size. In the decremental version of this algorithm, we start with the large macropixele equal to the whole picture, then next iterations produce smaller macropixels. We can say that on the one hand we can treat the macropixels as individual pixels while on the other hand we can view the macropixels as the whole picture.

Speaking more precisely, with regard to the decremental algorithm, every macropixel is treated as the whole picture, in each iteration, when it is divided into macropixels of a smaller size. Referring to the incremental algorithm, new macropixels of bigger size are viewed as the whole picture composed of pixels. This case concerns the proces of creating the macropixels. When the macropixels have already been constructed we can treat them as individual pixels that are characterized by two attributes: color and location. In this way, in many applications, we can focus our attention on the macropixels of specific color and location, instead of every pixel of the image.

Like with regard to the pixels, the color and location attributes of macropixels are viewed as fuzzy concepts. The color attribute of macropixels can be considered in the same way as presented for pixels in Section 4, with regard to the CIE chromaticity diagram. However, we should explain how to determine the color of macropixels based on the color attribute values, c_j, of the pixels p_j that belong to these macropixels. Every macropixel is composed of the individual pixels that are subsets of the pixels $\{p_j\}$, for $j = 1, ..., M$, that form the whole picture Ω.

Let us assume that the picture Ω consists of M_k macropixels, Ω_k, for $k = 1, ..., M_k$. Every macropixel, Ω_k, can be viewed as an individual pixel reffering to its membership to the color regions, $\{\widetilde{H}_i\}$, for $i = 1, ..., n$, in the CIE diagram.

We can propose several methods to determine the color value of the macropixel, Ω_k, for $k = 1, ..., M_k$. Among others, we can take into consideration the average value of the membership of the individual pixels that create the macropixel to the CIE color regions. In this paper, we focus our attention on an approximate color of a group of neighboring pixels (macropixel) rather than the color of individual pixels.

The location attribute of the macropixels can be considered with regard to the approach presented in Section 5 for individual pixels. The macropixels, Ω_k, for $k = 1, ..., M_k$, may be viewed as fuzzy pixels that belong to the fuzzy sets portrayed in Fig. 1 and Table 1.

In this section, we propose the macropixels of rectangular shape and the same size. However, we can introduce another attribute of the macropixels, in addition to the color and location, that is the size. Taking into account a group of pixels (macropixel) of a specific color and location (expressed by fuzzy values), the third attribute, i.e. the size may include very useful information with regard to the problem described in Section 8.

7 Fuzzy Granulation

Fuzzy granulation approach, as mentioned in Section 1, has been introduced by Zadeh [19]. Some information one can also find in e.g. [11]. New ideas concerning the fuzzy granulation approach have been developed by Pedrycz, especially with regard to neural networks (see e.g. [9]), also in application to pattern recognition [10].

According to Zadeh [17], [18], [19], linguistic variables are concomitant with the concept of granulation. As the author explained in [18], granulation, in fuzzy logic, involves a grouping of objects into fuzzy granules, with a granule being a clump of objects drawn together by similarity. In efect, granulation may be viewed as a form of fuzzy quantization, which in turn may be seen as an instance of fuzzy data compression. In the non-fuzzy case, quantization is the same as crisp granulation where granules are not fuzzy.

Image processing is one of examples where information granulation may be applied and play an important role in pattern recognition [10]. In this case, the similarity of objects that are candidats for grouping into a granule usually refers to the closeness of pixels located spatially close to each other. In the concept of information granulation, the granules can take a form of sets, fuzzy sets, rough sets, etc., but most often are concentrated on the use of fuzzy sets.

In this paper, we apply the concept of fuzzy granulation to digital color pictures. The idea of macropixels, described in Section 6, is strictly related to the fuzzy granulation approach. The fuzzy color areas of the CIE diagram, discussed in Sections 3 and 4, as well as the fuzzy locations, proposed in Section 5, can be considered in the framework of the fuzzy granulation.

The macropixels may be viewed as fuzzy granules that represent groups of pixels similar with regard to their location in a digital picture. When pixels of the same (or similar) color are located within a macropixel, we have a granule of the same color and location. In addition, as mentioned in Section 6, the third attribute, i.e. the size of the macropixels may be taken into account. Thus, we can see a digital color picture as a collection of macropixels associated with corresponding granules that carry information about color, location, and size. This concept is especially useful with regard to the problem considered in this paper and discribed in Section 8.

From the color point of view, the fuzzy regions of the CIE chromaticity triangle may be treated as fuzzy granules. In this case, the granules are groups of points with similar color (hue). Referring to the location, the fuzzy sets defined in the space (4) and presented in Table 1 with the illustration in Fig. 1, form fuzzy granules of the points (pixels) characterized by the same fuzzy location. Both kinds of the fuzzy granules are labeled with values of linguistic variables, i.e. linguistic names of color and location. Fuzzy IF-THEN rules with these linguistic variables are applied in the fuzzy granulation approach. Thus, information concerning colors and locations of pixels are granulated in a fuzzy way in order to inference a result of the picture recognition problem, formulated in Section 8.

8 A New Approach to Color Digital Picture Recognition

Let us consider the following problem. Having a large collection of color digital pictures, we would like to find a picture (or pictures) presenting an object characterized by three attributes – size, color, and location – with fuzzy values (e.g. a big object of a color close to red, located somewhere in the center). In order to recognize such a picture (or a group of similar pictures), we can employ the idea of macropixels (described in Section 6) along with the fuzzy approach to color (see Section 4) and location (see Section 5). The fuzzy granulation, as mentioned in Section 7, is especially useful with regard to this problem. Information granules, in this case, contain information about size, color, and location. Macropixels of different sizes and the same (or similar) color and location form the information granules.

Referring to the color, location, and size, we have the following fuzzy granules:

- For the color — $\{C_i\} = \{\widetilde{H}_i\}$, for $i = 1, ..., n$, where $n = 23$, with the membership functions $\mu_{\widetilde{H}_i}(c_j) = \mu_{\widetilde{H}_i}(x_j, y_j)$, for $j = 1, ..., M$, see Section 4
- For the location — $\{Q_l\}$, for $l = 1, ..., L$, where $Q_1 = S_L \times W_U,\ Q_2 = S_L \times W_C,\ Q_3 = S_L \times W_D,\ Q_4 = S_M \times W_U,\ Q_5 = S_M \times W_C,\ Q_6 = S_M \times W_D,\ Q_7 = S_R \times W_U,\ Q_8 = S_R \times W_C,\ Q_9 = S_R \times W_D$, where $L = 9$, in Table 1, with the membership functions of fuzzy sets (3) shown in Fig. 1; for details concerning the membership functions of 2-dimensional fuzzy sets (3) see Section 5, of course – we can consider the case of more than 9 fuzzy sets for the location
- For the size — $\{Z_m\}$, for $m = 1, ..., K$, i.e. fuzzy sets with membership functions that describe the size of macropixel Ω_k, for $k = 1, ..., M_k$ (see Section 6) as e.g. "small", "medium", "big" ($K = 3$) or "very small", "small", "medium", "big", "very big" ($K = 5$), relatively to the size of the digital color picture Ω.

Now, we assume that we have M_k macropixels of different sizes, created in the way described in Section 6. The membership functions of the macropixel size can be defined as trapezoidal-shaped functions (like in Fig. 1) or e.g. triangular or Gaussian functions. Precise definitions of the membership functions have to correspond to the above mentioned linguistic names e.g. big or small size.

The fuzzy granules, for the color, location, and size, deal with a single dimension (attribute). When a granule of the 3-dimension is considered, we take the Cartesian product of the corresponding fuzzy sets (1-dimensional granules) in each dimension (coordinate). In this way, we obtain the following fuzzy granules:

$$G^k = C^k \times Q^k \times Z^k, \quad k = 1, ..., M_k \qquad (5)$$

where $C^k \subset \{\widetilde{H}_i\}$, for $i = 1, ..., n$, $Q^k \subset \{Q_l\}$, for $l = 1, ..., L$, $Z^k \subset \{Z_m\}$, for $m = 1, ..., K$.

According to the definition of the Cartesian product of fuzzy sets, a triangular norm (t-norm) must be applied to determine the fuzzy granule (5); for details, see e.g. [11].

The fuzzy granule (5) is a multidimensional fuzzy set that represents a fuzzy relation between color, location, and size (attributes of the macropixels). In the fuzzy granulation approach, a digital color picture is viewed as a composition of the fuzzy granules that carry information about the color, location, and size, as well as interactions between them (expressed by the fuzziness that results in overlapping of the granules).

With regard to the problem of picture recognition, described at the begining of this section, fuzzy IF-THEN rules of the following form can be formulated:

$$\textbf{IF } c \text{ is } C_i \text{ AND } q \text{ is } Q_l \text{ AND } z \text{ is } Z_m \textbf{ THEN } \text{class } D_r$$

where (c, q, z) is a point belonging to the space of fuzzy granules (5), and D_r, for $r = 1, ..., R$, denotes distinguished classes in the classification problem of the digital color pictures. For example, D_r may be a class of the pictures presenting a big object of a color close to red, located somewhere in the center.

The classification problem can be solved by use of a fuzzy system with the inference method based on fuzzy logic and the fuzzy IF-THEN rules; for details see e.g. [11]. In this way, we expect to obtain a group of pictures belonging to the specific class (e.g. with a big object of a color close to red, somewhere in the center of the picture). Then, having relatively small number of such a pictures (after the classification), it is much easier to find the one that we are searching for. Of course, it is possible to get just the only one picture from a large collection of others.

It is worth emphasizing that the approach proposed in this paper is granular oriented rather than pixel processing. Fuzziness of the granules enables to use linguistic descriptions of digital color pictures and the inference based on fuzzy IF-THEN rules. In the classification problem of picture recognition, considered in this section, it is not necessary to process every pixel of the digital picture. Instead, we can take into account only macropixels of a specific location and size, e.g. a big macropixel in the center of the picture, and classify them with regard to their color.

Referring to the color of macropixels, we can employ the method presented in [12], where an amount of specific colors (hues) in the whole digital picture is determined based on the CIE chromaticity triangle, ignoring the location of the color pixels. Now, we can apply this method to macropixels treated as the whole picture in the algorithm described in [12].

9 Conclusions and Final Remarks

The problem addressed in Section 8 may be treated as an example of a group of problems concerning recognition of color digital pictures. Various specific tasks can be formulated and solved within the framework of the fuzzy granulation approach. Among others, it seems to be very useful in image segmentation, where a digital image is partitioned into segments (groups of pixels, known as superpixels); see e.g. [2].

In this paper, we consider the problem of color digital pictures recognition that can be viewed as a special case of image processing and image recognition. As mentioned in Section 1, we are interested in a large collection of the color digital pictures that are images, of course, but typical, taken by popular digital cameras, not e.g. medical images. Therefore, we use the name "picture" rather that "image", in order to focus our attention on the application to usual photos. Moreover, the important issue is that we are now not going to recognize the exact image presented in the picture but only its specific part described by an approximate color and location.

It should be emphasized that the main idea concerning the problems considered in this paper is to describe a picture by linguistic terms that refer to color, location, and size, i.e. the attributes of macropixels. Then, our task is to recognize (and e.g. classify) pictures with specific features, expressed by the linguistic description, such as "a big object of a color close to red, located somewhere in the center of the picture". Thus, our aim is not to recognize details of the image but only selected features with approximate (fuzzy) values.

Further research on this subject may concern to include the third dimension of the CIE chromaticity triangle, that is the luminance. We expect that this can improve the recognition results with regard to the color attribute.

In addition, different shapes of the macropixels may be considered, so other shapes of their membership functions must be applied. In this way, we can obtain a better model of interactions between the granules. This should result in better representation of an image included in a digital color picture.

Then, we can extend our research to the very interesting problem of image understanding (see e.g.[13]) based on the fuzzy granulation approach introduced in this paper.

The granulation approach that we propose to color digital picture recognition differs from the granular computing in pattern recognition, presented in [10]. However, we can adopt some ideas in our future research, and use fuzzy granules to summarize a collection of pictures.

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