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Research Article

A Fuzzy Color-Based Approach for Understanding Animated Movies Content in the Indexing Task

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This paper proposes a method for detecting and analyzing the color techniques used in the animated movies. Each animated movie uses a specific color palette which makes its color distribution one major feature in analyzing the movie content. The color palette is specially tuned by the author in order to convey certain feelings or to express artistic concepts. Deriving semantic or symbolic information from the color concepts or the visual impression induced by the movie should be an ideal way of accessing its content in a content-based retrieval system. The proposed approach is carried out in two steps. The first processing step is the low-level analysis. The movie color content gets represented with several global statistical parameters computed from the movie global weighted color histogram. The second step is the symbolic representation of the movie content. The numerical parameters obtained from the first step are converted into meaningful linguistic concepts through a fuzzy system. They concern mainly the predominant hues of the movie, some of Itten's color contrasts and harmony schemes, color relationships and color richness. We use the proposed linguistic concepts to link to given animated movies according to their color techniques. In order to make the retrieval task easier, we also propose to represent color properties in a graphical manner which is similar to the color gamut representation. Several tests have been conducted on an animated movie database.

1. INTRODUCTION

One of the most important human senses, maybe the most important one, is human vision. We sense, explore,and understand the surrounding world by using our visual perception. For every object we interact with, we create a mental image of its specific colors: the sky is blue, the forest is green, the sand is yellow, and so forth. In this way, we can easily recognize similar objects. Moreover, individual colors or groups of colors create particular feelings, for example, blue gives the sensation of cold, orange gives a warm sensation, black and white create a contrast, excessive red creates a discomfort, and so on. Inspired by real life, researchers attempted to replicate our senses by developing systems capable of providing automatic understanding of the visual information. Color, in particular, has been extensively used, now, for more than three decades to describe the image visual perception [4].

One conventional approach is to capture the image color distribution using *color histograms*. They are computed either on the entire image or for some regions of interest. Histograms are very reliable statistical measures which describe the global color distribution. They are invariant to some geometrical transformations of the image (e.g., rotations, resolution change, etc.) [11]. However, histograms are sensitive to global illumination changes. To overcome this problem, histograms can be computed from specially tuned color spaces which separate the illumination information from the chromatic information (i.e., the HSV or YCbCr color spaces) [1].

In addition to the information provided by histograms, *color names* are used to describe the human color perception. Associating names with colors allows everyone to create a mental image of the color. The color names are typically retrieved from a dictionary which is the result of a color naming system. The existing naming systems use different techniques for delivering a certain universality, as the color names should comply with different cultures and human perceptions [2]. For example, they model the color membership to a specific color name with fuzzy membership functions, they associate color names with wavelength intervals according to the physical color representation, or they use predefined lookup tables. These methods are not completely automatic and require the human intervention [3].

Another way to characterize the color perception is through *the sensation* induced by the color. In this case, colors are analyzed in relation with other colors. For example, Itten in 1961 defined a first set of formal rules to quantify the perception effects achieved by combining different colors. They are known as the *seven color contrast schemes*: the contrast of saturation, the contrast of light and dark, the contrast of extension, the contrast of complements, simultaneous contrasts, the contrast of hue, and the contrast of warm and cold [21]. Similarly, Birren later defined some color schemes which induce particular visual effects, which he called color harmony schemes, that is, the monochromatic principle, the adjacent principle, or the complementarity principle [22]. Analyzing color relationships can also be done with the help of *color wheels*. They are basically color spaces where several elementary colors are arranged in a perceptually progressive manner [14].

This paper tackles the issue of the automatic understanding of the color content of video material in the video indexing task of the animated movies. The proposed approach uses a fuzzy-based system to derive meaningful symbolic/semantic linguistic concepts from the movie's color content.

Very little research has been done in this field, especially in the animated movie domain [6]. Many of the existing color characterization methods have focused naturally on the static image indexation task as they describe local image properties. Most of them describe the image color content with low-level parameters [4]. However, few methods try to tackle the "semantic gap" issue and thus to capture the semantic meaning of the color content. For example, in [14] the color artistry concepts are extracted for the indexing task of artwork static images. The relationships between colors are analyzed in a perceptual color space, namely LCH (luminosity, chroma, and hue), and several color techniques are used: contrasting color schemes, Itten's seven color contrasts, and color harmony schemes. A similar approach is the query by image content (QBIC) system proposed in [15]. It supports two types of syntactic color search: the dominant color search and the color layout search where the user specifies an arrangement of a color structure. However, these approaches are applied to static images. The understanding of the color content of a movie requires a *temporal color analysis*.

In the video indexing field, color content analysis, together with other low-level features, such as texture, shape, and motion, has extensively been used for the low-level characterization of the image local properties. Few approaches tackle the description of the color perception of video material by adding a temporal dimension to the local image-based analysis. Such a system which takes the temporal color information into account is proposed in [16]. The art images and commercials are analyzed at emotional and expressional levels. Various features are used, not only the color information but also motion, video transition distribution, and so on, all in order to identify a set of primary induced emotions, namely, *action, relaxation, joy, and uneasiness*. The colors are analyzed at a region-based level by taking the spatial relationships of the object in the image into account. The proposed system is adapted to the semantic analysis of commercials. Another connected approach is the one proposed in [17], where fuzzy decision trees are used for data mining of news video footage. In this case, color histograms are used to successfully retrieve two types of semantic information: the textual annotations and the presence of the journalist.

Our approach is different. We are addressing here the problem of delivering a global color content characterization of the animated movies. The proposed approach captures the movie global color distribution with the global weighted color histogram proposed in [8]. The color content perception is then analyzed at a symbolic level using color names and the sensations induced by the colors. This global color description is possible thanks to the peculiarity of the animated movies of containing specific color palettes [19], unlike conventional movies which usually have the same color distribution. The proposed approach is carried out in two steps. The first one is the low-level analysis where the movie color content gets represented with several global statistical parameters retrieved from the movie global weighted color histogram. The second step is the symbolic content representation. The numerical parameters obtained with the first step are converted into meaningful linguistic concepts using a fuzzy rule system. They are mainly concerned with the predominant hues of the movie, some of Itten's color contrasts and harmony schemes, color relationships and color wealth. Using a clustering approach, we are discussing the possibility of employing the proposed content descriptions to sort animated movies according to color content.

The "International Animated Film Festival" [5], one of the major events in the worldwide animated movies entertainment, which has taken place in Annecy (France) every year since 1960, stands as the applicative support of our approach. Every year, hundreds of movies coming from all over the world are competing. Some of these movies are currently being digitized by the city of moving pictures (CITIA), which is the organization managing the festival, to compose a numerical animation movie database, soon to be available online for general use (see Animaquid at http://www.annecy.org). Managing thousands of videos is a tedious task. An automatic tool that allows artists or ordinary people to analyze or to access the movie content is thus required. The existing tools, as is the case of CITIA, are limited to use only the textual information provided by the movie authors, that is movie title, artist name, short movie abstracts, and so on. However, the available text information does not totally apply to the rich artistic content of the animation movies. The artistic content is strongly related to the visual information, which is poorly described with textual information. Deriving semantic or symbolic information from the color concepts or the visual sensations induced by the movie should be an ideal way of accessing its content in a content-based retrieval system.

The paper is thus organized. Section 2 presents the peculiarity of the animation domain. Section 3 presents the general description of the proposed analysis system. In Section 4, we discuss the movie temporal segmentation and

Figure 1: Animation techniques (from left to right): 3D synthesis, color salts, glass painting, object animation, paper drawing, and plasticine modeling.

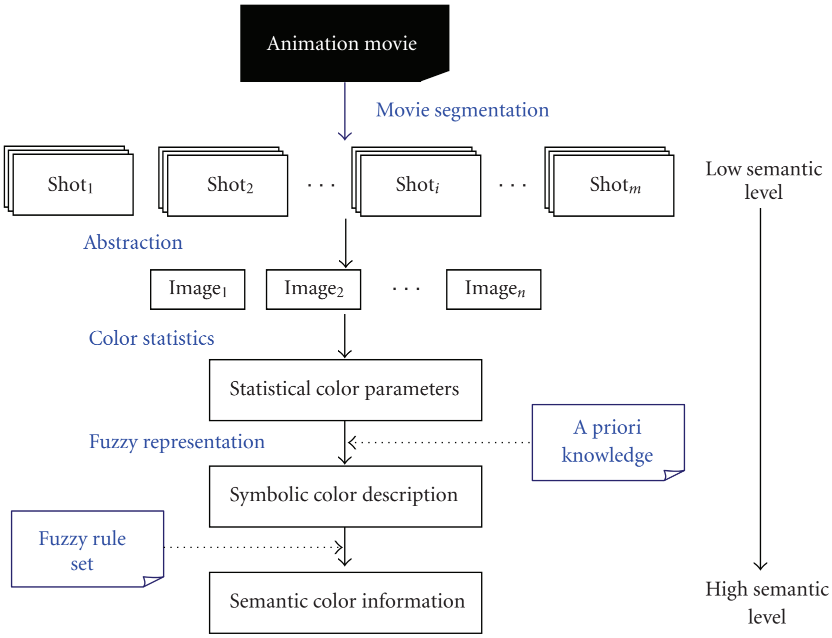


Figure 2: The diagram of the proposed symbolic color content characterization system.

abstraction. Section 5 deals with the color reduction issue. The computation of the global weighted histogram is presented in Section 6 along with the low-level color content description. The semantic color characterization is achieved in Section 7 using a fuzzy approach. In Section 8, several experimental tests are conducted on an animation movies database. Finally, the conclusions and future work are discussed in Section 9.

2. ANIMATED MOVIES ARE PARTICULAR

Animated movies are different from conventional movies and from cartoons in many respects. Some of them are presented below.

The animated movies from [5] are mainly fiction movies. Typically the events do not follow a natural sequence: objects or characters emerge and vanish without respecting any physical rule; the movements are not continuous; a lot of color effects are used that is the “short color changes” [7]; artistic concepts are used: painting concepts, theatrical concepts.

A lot of animation techniques are used: 3D synthesis, object animation, paper drawing, plasticine modeling, and so on. The movie color content gets thus related to the technique used (see Figure 1).

Animated movies have specific color palettes. Colors are selected and mixed by the artists using various color artistry concepts, all in order to express particular feelings or to induce particular impressions such as contrast, depth, energy, harmony, or warmth. Understanding the movie content is sometimes a difficult task. Some animation experts say that in the case of more than 30% of the animated movies from [5], it is difficult for an amateur viewer, if not impossible, to understand the movie’s story.

Therefore, the proposed analysis techniques should be capable of dealing with all these constraints.

3. THE PROPOSED APPROACH

The proposed color characterization approach exploits the peculiarity of the animation movies of containing specific color palettes. It uses several analysis steps which are described in Figure 2.

First, the movie is divided into shots by detecting the video transitions, namely, cuts, fades, dissolves, and an animated movie specific color effect called “short color change” or SCC [7]. A movie abstract is composed by retaining a percentage of each shot frame.

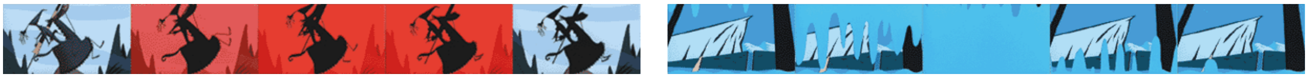


Figure 3: Several frames from two SCCs, movie "Francois le Vaillant."

After color reducing of the frames of the movie abstract, we capture the movie global color distribution with the global weighted color histogram proposed in [8]. The color content is further described with several statistical parameters which are to be computed on the global histogram, that is, light, dark, warm, cold color ratios.

Meaningful symbolic/semantic color information is extracted from the statistical color information using a fuzzy representation approach which uses a priori knowledge from the animated movies domain. The proposed characterizations concern some of Itten's color contrasts [21] and color harmony schemes [22], which are to be found in the animated movies. In the sequel of the paper, we will describe each of the processing steps.

4. TEMPORAL SEGMENTATION AND ABSTRACTION

The temporal segmentation of the movie is a basic processing step required by most of the higher-level video analysis techniques. The movie is divided into shots, which means detecting the *video transitions* [23]. We detect the sharp transitions, or *cuts*, using a specially tuned histogram-based algorithm [7] adapted to the peculiarity of the animated movies. From the existing gradual transitions we detect only the *fades* and the *dissolves* as they are the most frequent gradual transitions. The detection is performed using a pixel-level statistical approach [9].

In addition, using a modified camera flash detector [7] we detect an animation movie specific color effect named "short color change" or SCC. An SCC stands for a "short-in-time dramatic color change", such as explosion, lightning, and short color effect (see Figure 3). Generally SCCs do not produce a shot change but unfortunately are, by mistake, detected as cuts. Detecting the SCCs allows us to reduce the cut detection false positives.

The video shots are further determined by considering the video segments limited by the detected video transitions. Less relevant frames (e.g., the black frames between *fade-out* and *fade-in* transitions, the *dissolves* transition frames, etc.) are to be removed as they do not contain meaningful color information.

To *reduce the movie temporal redundancy* and thus the *computational cost*, the movie is substituted with a movie abstract which is automatically generated by retaining some key frames for each video shot. As action most likely takes place in the middle of the shot, key frames are extracted as consecutive frames near the middle of the shot. The achieved frame sequence is centered on the middle of the shot and it contains p% of its frames. In this way, more details will be captured for the longer shots as they contain more color information (the choice of the p-value is discussed later in Section 6.1). This video abstract will stand as the basis for all further processing steps.

5. COLOR REDUCTION

Working with true color video frames requires processing 16 million color palettes which makes the color analysis task very difficult (i.e., computing color histograms). To overcome this problem typically a *color reduction step* is adopted. The color reduction techniques aim at reducing the number of colors without or with minimal visual loss. Depending on the application, a compromise between the visual quality and the execution time should be considered. In our case, the success of the reduction step is crucial for the relevance of the proposed content descriptions.

Generally, color image quantization involves two steps: *palette design* and *pixel mapping*. There are two general classes of quantization methods: fixed (using a universal predefined palette) and adaptive (using a customized palette) [13]. Fixed palette quantization is very fast, but sacrifices the quantization quality which is related to the size and color richness of the palette. On the contrary, the adaptive quantization determines an optimum set of representative colors for each image [25].

In our application, the color reduction method should first provide an *accurate representation of the initial colors*, ideally without color distortion, all in order to preserve the visual perception of the original image. The best color reproduction is achieved using an adaptive color reduction that determines the optimum palette for each frame. However, this operation is time consuming and in this way each image gets represented with a specific color palette. As a result, the total number of colors used to represent the color distribution of the entire movie will be high and will contain unnoticeable and undesired small variations of the same elementary colors. Comparing the color distribution of different movies will in this case be inaccurate and difficult [18, 26]. On the other hand, the animated movies have the advantage of using reduced color palettes (see Figure 1) hence allowing us to reduce the quantization quality loss which occurs in the case of the use of a fixed quantization approach.

Describing the color techniques used by the movie requires to analyze the human perception. One simple way is the use of the color names. Associating names with colors allows everyone to create a mental image of a given color. A fixed-color palette approach simplifies this task as the predefined palette could be composed of colors for which a color naming system is available [2]. On the contrary, an adaptive palette cannot be manually designed, being automatically determined for colors for which a textual description is not available.

Color content characterization also requires to analyze the perceptual relationship between colors. One simple and efficient way is the use of the artwork color wheels [22]. Several color wheels have been proposed in the past: Runge (1810), Chevreul (1864), Hering (1880), Itten (1960), and so on. A color wheel is essentially a specifically tuned color space whose topological arrangement exhibits relationships articulated according to the theory of color contrast and harmony [14]. Its particular arrangement of primary colors allows us to define some perceptual color relations, such as adjacency (e.g., neighboring colors on the wheel) and complementarity (opposite colors on the wheel) relations (see Figure 4(a)). A predefined color palette is the best match for this task as it can be designed with respect to one of the existing artwork color wheels.

In conclusion, the use of a *fixed predefined palette quantization* should in our case be the best compromise between visual quality and computational cost. In addition, this approach will make the color comparison task required in a video indexing system easier. The quality of the color reduction will now depend on the quality of the used color palette, therefore the choice of the palette is conclusive for the success of our approach.

Several color palettes satisfying more or less the requirements of our approach have been analyzed, that is, Chevreul's color wheel, Hering's color palette, the Gretag Macbeth color checker, Itten's color wheel, and the Webmaster palette. We found that the Webmaster nondithering 216 color palette [27] (see Figure 4) is the only palette meeting to all the previously listed requirements, thus providing the following:

(i) the right compromise between color richness and number of colors (216): it contains *12 elementary colors*, namely: orange, red, pink, magenta, violet, blue, azure, cyan, teal, green, spring, and yellow, and *6 gray levels* including white and black, well suited for representing the reduced color palettes of animated movies;

(ii) high color diversity: variations of 12 elementary colors and 6 gray levels, resulting in reduced color distortion;

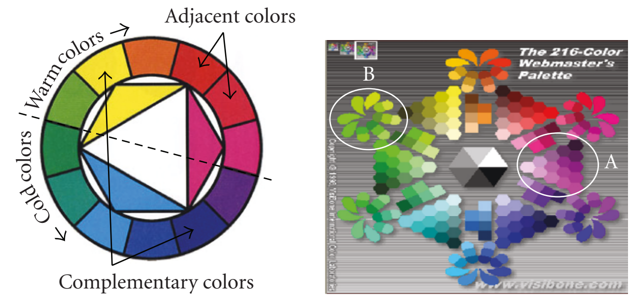
(iii) the availability of an efficient color naming system: each color is named according to the degree of hue, saturation, and brightness, facilitating the analysis of the human color perception. An example is depicted in Table 1;

(iv) the analogy with Itten's color wheel: elementary colors are arranged on a wheel with respect to Itten's perceptual color relations (see Figure 4).

Concerning the pixel mapping technique, we have decided to use Floyd-Steinberg's error diffusion filter [20] applied on the XYZ color space [25]. First, the colors are selected in the Lab color space from the Webmaster color palette using the minimum Euclidean distance criterion. We use the Lab color space because it is a perceptually uniform color space, thus the Euclidean distance between colors is highly related to the perceptual distance. Then, the color approximation error is propagated using the Floyd-Stenberg's filter mask applied on the XYZ color space.

TABLE 1: Color naming examples from the Webmaster palette.

Color	R, G, B	Color name
	255, 255, 51	"Light hard yellow"
	204, 0, 102	"Dark hard pink"
	204, 204, 204	"Pale gray"



(a) (b)

FIGURE 4: The predefined color palette: (a) Itten's color wheel, (b) Webmaster color palette [27] (zone A contains variations of an elementary color, i.e., violet, and the zone B contains elementary color mixtures).

6. LOW-LEVEL STATISTICAL COLOR PARAMETERS

The first step towards the color content description is the computation of several statistical color parameters. To determine which color properties we should capture with the low-level parameters, first we have manually analyzed a large amount of animated movies from [5]. As each movie uses a specific color palette, the global color histogram and the elementary color histogram are naturally the best candidates to describe the color content. Color intensity, saturation, and warmth are also important color features of the animated movies. They allow us to make the distinction between different movie types or genres. For instance, the movies using the plasticine modeling as animation technique use typically dark cold color palettes (see Section 8). Other important parameters which are related to color richness are the color variation and diversity. For example, funny movies generally come with a high color diversity or a pastel color palette. Finally, color relationships are useful to make the distinction between movies using different color techniques like analogous color schemes, complementary color schemes, and so on (see also Section 8).

6.1. Color histograms

First, the movie global color distribution is captured with the *global weighted color histogram*, $h_{\mathrm{GW}}()$, proposed in [19]. It is defined as the weighted sum of the movie shot color histograms, thus

$$h_{\mathrm{GW}}(c) = \sum_{i=0}^{M}\left[\frac{1}{N_i}\sum_{j=0}^{N_i} h^j_{\mathrm{shot}_i}(c)\right]\cdot w_i, \tag{1}$$

where M is the total number of video shots, N_i is the total number of the retained frames for the shot i (representing p% of its frames), $h^j_{\text{shot}_i}()$ is the color histogram of the frame j from the shot i, $c \in \{0, \dots, 215\}$ is the color index from the Webmaster palette, and w_i is the weight of the shot i. A shot weight is defined as

$$w_i = \frac{N_{\text{shot}_i}}{N_{\text{total}}} \tag{2}$$

with N_{shot_i} the total number of frames of the shot i and N_{total} is the total number of frames of all the movie shots. The longer the shot, the more important the contribution of its histogram to the movie's global histogram.

The $h_{\text{GW}}()$-values are related to the color apparition percentage in the movie and they are normalized with respect to 1 (frequency of occurrence of 100%). Moreover, the values of p%, representing the percentage of the retained frames for a given shot, affect the accuracy of the obtained global color histogram and thus the color characterization. Taking $p \in [15\%, 20\%]$ has proven to be a good compromise between the achieved processing time and the quality of the obtained color representation [8]. The quality of the color representation drastically decreased only when, owing to the reduced percentage of the retained images, some shots did not even get represented in the global histogram. This is the case of $p = 1\%$ where very short shots (less than 4 seconds) are not represented by any image.

Another important color feature of the animated movies is the elementary color distribution. Using $h_{\text{GW}}()$ the *elementary color histogram*, $h_E()$, is defined as

$$h_E(c_e) = \sum_{c=0}^{215} h_{\text{GW}}(c)|_{\text{Name}(c_e) \subset \text{Name}(c)}, \tag{3}$$

where c_e is an elementary color index from the elementary colors set, Γ_{elem}, of the Webmaster palette, with $\Gamma_{\text{elem}} = \{$*"orange," "red," "pink," "magenta," "violet," "blue," "azure," "cyan," "teal," "green," "spring," "yellow," "gray," "white," "black"*$\}$, c is a color index from the Webmaster palette, and $\text{Name}(c)$ is the operator which returns the color c name from the palette dictionary.

Each available color of the used color palette is projected in $h_E()$ on to its elementary hue, therefore disregarding the saturation and intensity information. This mechanism makes $h_E()$ invariant to the variations of the same hue. For example, a dark red and a bright red are getting represented in $h_E()$ with the same elementary color, which is red. Computing $h_E()$ from the movie global weighted histogram, $h_{\text{GW}}()$, ensures that its values correspond to the apparition percentage of the elementary colors in the movie.

6.2. Global weighted histogram color statistics

Using the global weighted color histogram, $h_{\text{GW}}()$, several statistical low-level color parameters are further proposed. They concern the color richness, color intensity, color saturation, and color warmth.

The first parameter, called *the color variation ratio*, P_{var}, reflects the amount of the *significant* movie colors and it is defined thus as

$$P_{\text{var}} = \frac{\text{Card}\{c \mid h_{\text{GW}}(c) > 0.01\}}{216}, \tag{4}$$

where $c \in \{0, \dots, 215\}$ is a color index from the Webmaster palette, Card() is the cardinal function which returns the size of a data set. The threshold value 0.01 was empirically determined after analyzing several animation movies. Therefore, a color of index c is considered to be significant for the movie global color distribution if it has a frequency of occurrence of more than 1%.

The next parameter is related to the color intensity: *the light color ratio*, P_{light}, reflects the amount of bright colors in the movie. The brightness is reflected in the color names with the words: *"light", "pale," or "white"* (white corresponds to the highest brightness level). Thus, P_{light} is defined thus as

$$P_{\text{light}} = \sum_{c=0}^{215} h_{\text{GW}}(c)|_{W_{\text{light}} \subset \text{Name}(c)}, \tag{5}$$

where c is a color index with the property that its name, returned by Name(), contains the word W_{light}, with $W_{\text{light}} \in \{$*"light," "pale," or "white"*$\}$.

Using the same reasoning, we define the following low-level color parameters. Opposite P_{light} is *the dark color ratio* parameter, P_{dark}, which reflects the amount of dark colors in the movie. The darkness is reflected in the color names with words like *"dark," "obscure," or "black"* (black reflects the lowest brightness level).

The hard color ratio parameter, P_{hard}, reflects the amount of high/mean saturated colors (or hard colors) in the movie. The high saturation is reflected in color names with words like *"hard" or "faded"*. In this case the 12 elementary colors, designated with Γ_{elem}, are also to be considered as hard colors, being defined as 100% saturated colors. *The weak color ratio* parameter, P_{weak}, opposite P_{hard}, reflects the amount of low saturated colors (or weak colors) in the movie. The low saturation is reflected in color names with words like *"dull" or "weak"*.

The warm color ratio parameter, P_{warm}, reflects the amount of warm colors in the movie. In art, some hues are commonly perceived to exhibit some levels of warmth. "Yellow," "orange," "red," "yellow-orange," "red-orange," "red-violet," "magenta," "pink," and "spring" are the warm color names. On Itten's color wheel the warm colors are distributed on one half of the wheel, starting with spring, continuing with yellow, and ending with magenta (see Figure 4). Opposite P_{warm} is *the cold color ratio* parameter, P_{cold}, which reflects the amount of cold colors in the movie. "Green," "blue," "violet," "yellow-green," "blue-green," "blue-violet," "teal," "cyan," and "azure" are the cold color names. On Itten's color wheel, unlike warm colors, the cold colors are distributed on the other half of the wheel, starting with violet, continuing with blue, and ending with green (see Figure 4).

6.3. Elementary histogram color statistics

The next color parameters are computed from the elementary color histogram. The first parameter, called *color diversity ratio*, P_{div}, is related to the richness of color hues. It is defined as the amount of the movie's *significant* elementary colors, thus

$$P_{\text{div}} = \frac{\text{Card}\{c_e \mid h_E(c_e) > 0.04\}}{13}, \tag{6}$$

where c_e is an elementary color index from Γ_{elem} (see (3)), with $c_e \in \{0, \ldots, 12\}$ (12 elementary colors and gray, where white and black are to be considered as gray levels in this case). The threshold value 0.04 was empirically determined. Similar to the computation of P_{var} (see (4)), an elementary color is considered to be significant for the movie global elementary color distribution if it has a frequency of occurence of more than 4%.

The next two color parameters are related to the concept of color perceptual relation, namely the adjacency and complementarity relations. The complementarity relation refers to the complementary relationship of hues. Using Itten's color wheel, a straight line drawn across the center of the wheel is used to derive complementary color pairs. On the other hand, the *adjacent colors* (analogous) are defined as neighborhood pairs of colors (see Figure 4).

The adjacent color ratio parameter, P_{adj}, reflects the amount of adjacent colors contained with the movie's elementary color distribution, thus

$$P_{\text{adj}} = \frac{\text{Card}\{c_e \mid \text{Adj}(c_e, c_e') = \text{True}\}}{2 \cdot N_{c_e}}, \tag{7}$$

where $c_e \neq c_e'$ are the indexes of two *significant* elementary colors from the movie, $\text{Adj}(c_e, c_e')$ is the adjacency operator returning the *true* value if the two colors are analogous on Itten's color wheel, and N_{c_e} is the movie's total number of significant elementary colors. Using the same reasoning, we define *the complementary color ratio*, P_{compl}, as the amount of complementary colors contained with the movie's elementary color distribution.

7. FUZZY SEMANTIC COLOR DESCRIPTION

The previously proposed statistical color parameters are used further to extract higher-level semantic color information regarding the movie color perception. The approach we use is a linguistic representation of data using *fuzzy sets* [19].

The interest in using fuzzy sets instead of crisp sets is multiple. The most important advantage of the fuzzy sets is that they allow to represent the numerical low-level information (in our case the statistical low-level parameters) in a *human-like manner using linguistic concepts* [33]. Another advantage is that the fuzzy sets are based on the concept of uncertainty and *better respect the reality* which is uncertain. The fuzzy mechanism is *similar to the way the human brain is functioning*. Humans perceive the real world in an approximative way. For example, instead of describing the height of a person in centimeters, we say that he is tall, medium, small, and so on. Thus, the fuzzy representation captures the semantics of data. The fuzzy sets are also universal approximators. The discussion universe which could be very vast or even infinite is converted using the fuzzy representation into a limited number of concepts [34]. Thus, using fuzzy information, instead of statistical data (i.e., low-level parameters) for content-based semantic indexing improves the information retrieval performance as presented in [41].

To achieve the proposed semantic color content characterization, several linguistic concepts are associated to the numeric low-level parameters by defining the fuzzy membership functions. This first level is a *symbolic level*. Then, using a fuzzy rule base meaningful information is derived from the movie color techniques, which constitute the *semantic level* of description. The mechanism is described in the following sections.

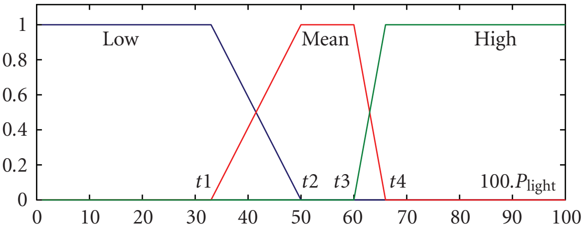
7.1. Symbolic description

The symbolic color description is achieved by associating a *linguistic concept* to each of the proposed low-level color parameters. Each concept is then described with several *fuzzy symbols*. The fuzzy meaning of each symbol is given by its membership function. These functions are defined in a conventional way using piecewise linear functions [35] which are well adapted to the linear variations of our parameters. The initial definition of the membership functions is based on the expert knowledge in the field and the observation of experimental data (the manual analysis of several representative animated movies). This mechanism makes sure that the human perception will be captured with the proposed symbols.

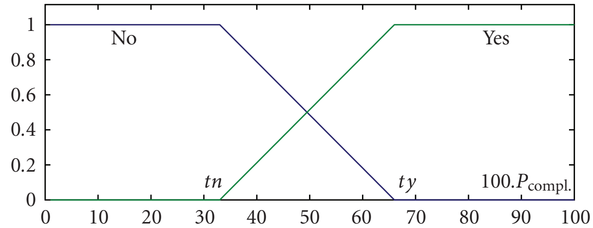
Therefore, the *light color content* linguistic concept is associated with the P_{light} parameter which is related to the amount of bright colors in the movie. The concept is described using three symbols: "*low-light color content,*" "*mean-light color content,*" and "*high-light color content*". After analyzing several representative animated movies, we found that a movie may have a color distribution "*poor-in-light colors*" (degree of truth of 1) if $100 \cdot P_{\text{light}} < 33\%$, a color distribution with "*a medium amount of light colors*" (degree of truth of 1) if $100 \cdot P_{\text{light}} > 50\%$ and $100 \cdot P_{\text{light}} < 60\%$, and finally, a color distribution "*containing high amounts of bright colors*" (degree of truth of 1) if $100 \cdot P_{\text{light}} > 66\%$. Based on these considerations, the membership functions of the *light color content* concept, namely, $\mu_{\text{LC}_{\text{low}}}$, $\mu_{\text{LC}_{\text{mean}}}$, and $\mu_{\text{LC}_{\text{high}}}$, have been designed using the thresholds $t1 = 33$, $t2 = 50$, $t3 = 60$, and $t4 = 66$, as depicted in Figure 5(a).

The following linguistic concepts (see Table 2) describe color properties in terms of color hue, saturation, intensity, richness, and relationship. Their membership functions are defined using the same reasoning as for the *light color-content* concept [42]. A particular case are the linguistic concepts describing color relationship, namely the *adjacent colors* and *complementary colors* concepts.

In this case, the two concepts are represented with only two symbols, that is "*yes*" and "*no*", meaning that the movie color distribution either uses or not uses adjacent/complementary colors. The expertise of the domain proved that in this case using only two symbols is sufficient



(a) $\mu_{LC_{low}}$ (blue), $\mu_{LC_{mean}}$ (red), $\mu_{LC_{high}}$ (green)



(b) $\mu_{C_{no}}$ (blue), $\mu_{C_{yes}}$ (green)

Figure 5: Examples of fuzzy partitions for (a) the *light color-content* concept, (b) the *complementary color* concept.

Table 2: Linguistic fuzzy concepts.

Parameter	Linguistic concept	Connotation
P_{dark}	Dark color content	Describes the amount of dark colors
P_{hard}	Hard color content	Describes the amount of saturated colors
P_{weak}	Weak color content	Describes the amount of weak saturated colors
P_{warm}	Warm color content	Describes the amount of warm colors
P_{cold}	Cold color content	Describes the amount of cold colors
P_{var}	Color variation	Describes color wealth
P_{div}	Color diversity	Describes color richness in terms of elementary colors
P_{adj}	Adjacent colors	Describes color relationship of adjacence
P_{compl}	Complementary colors	Describes color relationship of complementarity

for describing the color content. The fuzzy membership functions, μ_{A_d} and μ_{C_d}, where $d \in \{\text{“yes”}, \text{“no”}\}$, are designed using two thresholds, namely, $tn = 33$ and $ty = 66$ as presented in Figure 5(b). Therefore, the movie colors are adjacent/complementary (degree of truth of 1) if more than 66% are adjacent/complementary and are not (degree of truth of 1) if less than 33% are adjacent/complementary.

7.2. Semantic description

New higher-level linguistic concepts are built using a *fuzzy rule base* [40]. The fuzzy descriptions of the new symbols are obtained by a *uniform mechanism* according to the combination/projection principle using conjunction operators for the generalized modus ponens (i.e., the min() operator [28]). The proposed new semantic descriptions concern some of Itten's color contrasts [21] and harmony schemes [22], which are to be found in the animation movies. The rule base was designed using expert knowledge and as experimental data the manual analysis of several representative animated movies (see Section 8.1).

The first rule base regards the color intensity and it is depicted in Figure 6. Each new symbol is determined using the generalized modus ponens. For instance, the new membership function of the new semantic color description *“there is a light-dark contrast”* is given by

$$\mu_{\text{cont.}L-D}(P_{\text{light}}, P_{\text{dark}}) = \min[\mu_{\text{LC}_{\text{mean}}}(P_{\text{light}}), \mu_{\text{DC}_{\text{mean}}}(P_{\text{dark}})], \tag{8}$$

where $\mu_{LC_{mean}}$ and $\mu_{DC_{mean}}$ are the membership functions of the symbols *“mean light color content”* and *“mean dark color content”* and the conjunction AND operator is in this case the min() function. Several other operators have been tested, namely probabilistic, Lukasiewicz, and Weber, which eventually concluded to similar results. In those cases where a relevant color characterization is not possible, we output the “no description available” (NDA) symbol.

We use the same reasoning to define rule bases for generating new linguistic concepts describing color saturation: *“weak colors are predominant,” “saturated colors are predominant,” “there is a saturation contrast”* and color warmth: *“warm colors are predominant”*, *“cold colors are predominant”*, *“there is a warm-cold contrast”*. The rule base describing color relationships is slightly different as each linguistic concept has only two symbols. The new linguistic symbols are *“adjacent colors are predominant”*, *“complementary colors are predominant”*, *“there is an adjacent-complementary contrast”*. The mechanism is depicted in Figure 6.

The interest in the proposed color content descriptions is twofold. First, we provide the animation experts or other people with detailed symbolic descriptions of the movie color content. This is valuable for the analysis and evaluation of the competing movies in the context of the International Animated Film Festival [5]. On the other hand, the proposed descriptions could be used for the automatic content-based indexing of animated movie databases as it is the case of CITIA [5]. Using the proposed content descriptions movies could be retrieved in a human-like manner according to their color content.

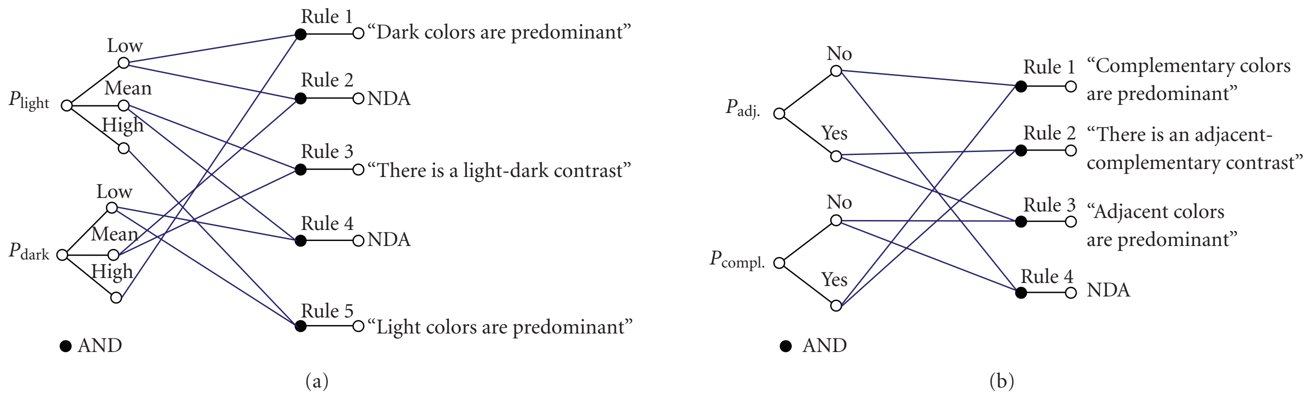


Figure 6: Fuzzy rule bases (NDA stands for "no description available"): (a) color intensity description, (b) color relationship description.

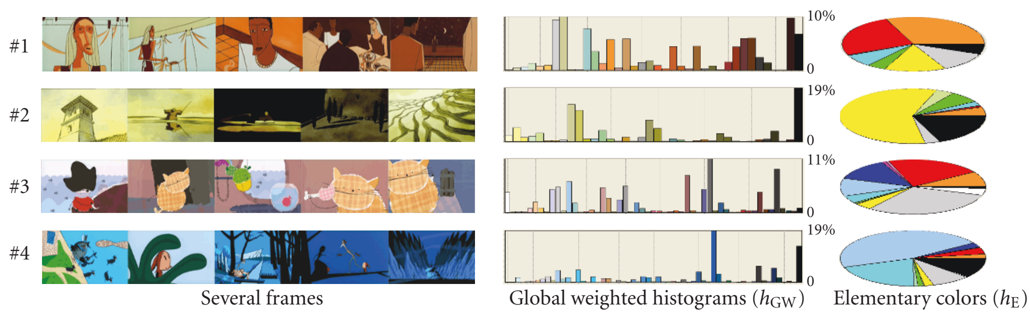


Figure 7: Color histograms ($p = 15\%$, see (1)).

8. EXPERIMENTAL RESULTS

The proposed approach has been tested on an animated movie database from CITIA [5] and Folimage Company [24]. It consists of 52 short animated movies using a large diversity of animation techniques (total time of 6 hours and 7 minutes).

First of all, we are presenting and discussing the color content linguistic descriptions achieved for several representative animated movies. Secondly, a clustering test is conducted on the animated movie database to analyze the discriminative potential of the proposed color descriptions in the automatic indexing task. Finally, we are discussing the design of a similarity measure which could make the movie content comparison issue easier.

The evaluation of our approach was confronted with the problem of the strong subjectivity of such a type of content descriptions. In this case, the evaluation is entirely related to the human perception. Different people may perceive the same movie contents in a very different way which makes the evaluation task a very subjective one. Moreover, there is no groundtruth available for this task to compute the conventional evaluation measures such as the precision and recall ratios [7]. To overcome all these issues we have substituted the groundtruth with all the available color content information retrieved from the CITIA Animaquid textual-based search engine (i.e., movie synopsis (textual abstracts), technical information, animation technique, content descriptions, etc.). Using all these pieces of information together with the manual analysis of the movie content, provided by animation experts as well as by image processing experts, we have performed the validation of the results.

8.1. Color content linguistic descriptions

In this section, we are presenting the color content descriptions achieved for four representative animation movies, namely, ♯1 "Casa" (6 minutes, 5 seconds), ♯2 "Le Moine et le Poisson" (6 minutes), ♯3 "Circuit Marine" (5 minutes, 35 seconds), and ♯4 "Francois le Vaillant" (8 minutes, 56 seconds) [24] (see Figure 7).

The obtained *global weighted color histograms*, $h_{GW}()$, and *elementary color histograms*, $h_E()$, (see Section 6.1) are depicted in Figure 7. The global weighted color histograms are depicted using column graphs. The oX axis corresponds to the color index from the Webmaster 216 color palette. Colors are presented as they appear in the Webmaster palette. The oY axis represents the color frequency (only significant colors are shown, i.e., frequency of occurrence of more than 1%). The elementary color histograms are represented using pie charts. The movie's actual colors have been formally replaced by 100% saturated elementary colors as in the elementary color histogram color saturation and intensity are not considered (see (3)).

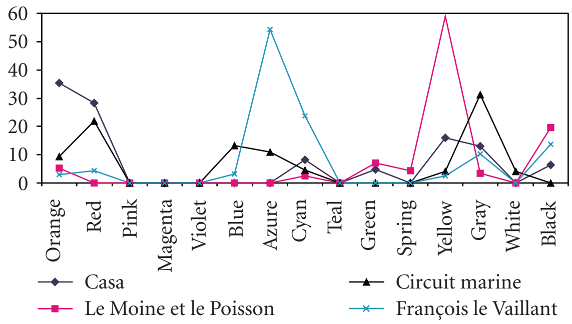


FIGURE 8: A comparison of the significant elementary colors for the tested movies.

In Figure 8 we present the achieved elementary color distributions for the four tested movies (only significant elementary colors are represented, i.e., frequency of occurrence of more than 2%).

After the manual analysis of the results we found that the proposed elementary color histogram provides an accurate color content description of the movie. For the movie "Casa," we have found 7 elementary colors from existing 6; in the movie "Le Moine et le Poisson," we found 7 elementary colors from existing 5; in the movie "Circuit Marine," we found 9 elementary colors from existing 8; in the movie "Francois le Vaillant," we found 10 elementary colors from existing 8. The difference with the actual number of elementary colors and the detected ones comes from the fact that in reality movies use color mixtures which leave the impression of primary colors.

The symbolic color descriptions of the four movies are presented with Table 3 (see Section 7.1), while the semantic color descriptions are presented with Table 4 (they are obtained using min() function as fuzzy AND conjunction, see Section 7.2). The numbers presented represent the fuzzy degrees and NDA stands for "no description available".

Compared with the reality, the proposed descriptions are to be found very relevant for the color content. The movie "Casa" uses a predominance of orange/red which is contrasted by a monochromatic color which is gray or black. Thus, the colors are warm, bothlight and dark, and we perceive a light-dark contrast. The colors are more adjacent than complementary. In what concerns the color wealth, the color variation and diversity are average as approximatively half of the available colors are being used.

The movie "Le Moine et le Poisson" uses the same color technique as the previous movie "Casa". It presents the predominance of a main hue, which is "yellow" in this case, contrasted with the presence of a monochromatic color which is "black". Thus, as in the previous case the colors are mainly warm, both light and dark, and there is a light-dark contrast. As "yellow" is used more than 60%, the colors are only adjacent. The movie uses paper painting with Gouache India ink as animation technique, which makes the colors diluted and thus *low* saturated. The color variation and diversity are also average.

The movie "Circuit Marine" uses an important number of colors (142 from the total of 216 available from the Webmaster palette), thus the color variation is high. In terms of elementary colors, the color diversity is average. The movie does not have a predominance of a certain color warmth or saturation but instead it uses cold colors, warm colors, and saturated colors in small amounts. The colors are both adjacent and complementary.

Finally, the movie "Francois le Vaillant" uses high amounts of "blue," thus the predominant colors are cold colors. Moreover, the colors are mainly dark colors. The colors are also both adjacent and complementary. In what concerns the color richness, the movie uses 187 colors from the 216 available from the Webmaster palette, thus there is a high color variation. On the other hand, as only one hue is predominant, the elementary color diversity is reduced.

Compared to the conventional boolean logic, fuzzy logic provides more accurate content description. The boolean logic uses decision rules which return only one degree of truth, namely True (1) of False (0). This typically requires the definition of only one threshold. To compare the results achieved with the proposed fuzzy approach to the ones obtained in the conventional way using boolean logic, we have constructed similar decision rules (see Section 7.2). The boolean rules have the following pattern:

$$\text{if } (100 \cdot P_{\text{prop}} > t_{\text{bool}}), \text{ then "prop colors are predominant"} \quad (9)$$

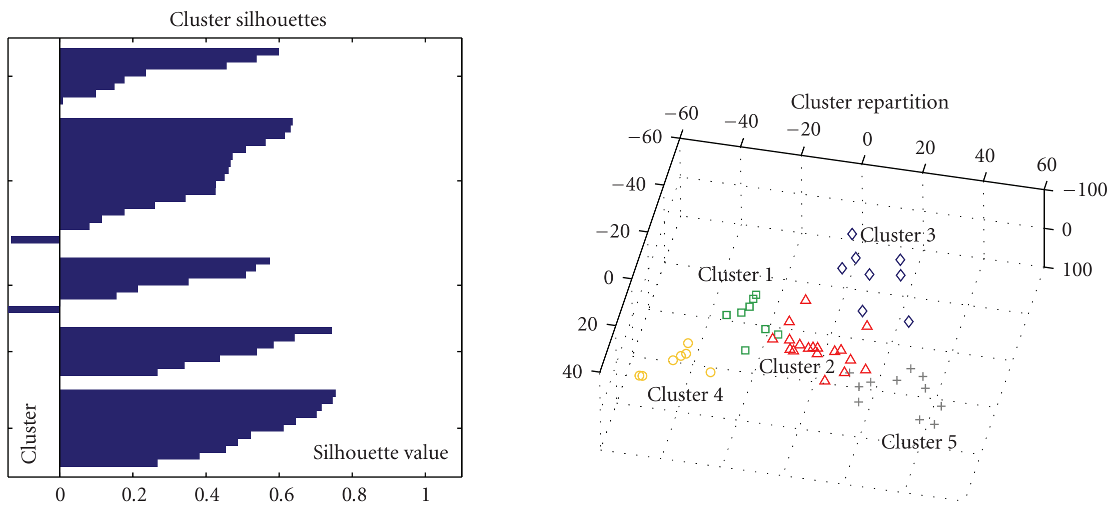
with t_{bool} the decision threshold (in our case $t_{\text{bool}} = 66\%$) and P_{prop} a low-level parameter (see Section 6).

After testing several animated movies from CITIA [5], we found that the fuzzy rules present many advantages. First of all, boolean logic *leads to false descriptions* when the P_{prop} value is close to t_{bool} while the fuzzy description provides a degree of truth, for example, for the movie "Tamer of Wild Horse", $P_{\text{dark}} = 0.657$, in boolean logic: "dark colors are predominant" (degree of truth of 0), while in fuzzy logic "weak colors are predominant" (degree of truth of 0.9) or movie "Casa", $P_{\text{weak}} = 0.612$, in boolean logic "weak colors are predominant" (0), while in fuzzy logic "weak colors are predominant" (0.3). Secondly, with boolean logic *important information is disregarded*, for example in the movie "Le Moine et le Poisson", $P_{\text{light}} = 0.489$ and $P_{\text{dark}} = 0.511$, in boolean logic: "light colors are predominant" (0) and "dark colors are predominant" (0) while in fuzzy logic there is a "mean light color content" (0.9) and "mean dark color content" (1) and moreover the joint analysis of the two provide the best description which is "there is a 'light-dark contrast' " (0.9). Finally, there are some situations where a *relevant description is missing* . In such cases, boolean logic fails by providing a degree of truth, for example in the movie "Amerlock," $P_{\text{warm}} = 0.3$ and $P_{\text{cold}} = 0.59$, in boolean logic "warm colors are predominant" (0) and "cold colors are predominant" (0), while in fuzzy logic "no description is available". The description provided with fuzzy logic is more accurate as we cannot say for sure if there is, or if there is not, a predominance of warm or cold colors.

However, the proposed approach tends to fail when owing to some animation techniques, that is crayon drawing, conventional paper drawing, in the color distribution there

Table 3: Symbolic color description.

	Light	Dark	Hard	Weak	Warm	Cold	Var	Div	Adj	Compl
♯1	Mean/0.9	Mean/1	Low/1	Mean/0.7	High/1	Low/1	Mean/0.7	Mean/1	Yes/1	Yes/0.8
♯2	Mean/0.9	Mean/1	Low/1	High/1	High/1	Low/1	Mean/1	Mean/1	Yes/1	No/0.7
♯3	Mean/1	Mean/1	Low/1	Mean/1	Low/0.9	Low/1	High/1	Mean/1	Yes/1	Yes/1
♯4	Low/1	High/1	Low/1	Low/0.9	Low/1	High/0.9	High/1	Low/0.8	Yes/1	Yes/1



(a) (b)

Figure 9: Classification in terms of predominant hues (the data repartition is displayed using the first three principal components).

Table 4: Semantic color description.

Symbol/fuzzy degree	♯1	♯2	♯3	♯4
Dark colors are predominant	0	0	0	1
Light colors are predominant	0	0	0	0
There is a light-dark contrast	0.9	0.9	1	0
Weak colors are predominant	0.3	1	NDA	NDA
Saturated colors are predominant	0	0	NDA	NDA
There is a saturation contrast	0	0	NDA	NDA
Warm colors are predominant	1	1	NDA	0
Cold colors are predominant	0	0	NDA	0.9
There is a warm-cold contrast	0	0	NDA	0
Adjacent colors are predominant	0.2	0.7	0	0
Complementary colors are predominant	0	0	0	0
There is a adjacent-complementary contrast	0.8	0.3	1	1

are high amounts of gray. The presence of "gray" in the movie is hardly noticeable for the human observer as it is responsible only for edges, pencil traces, object contours, and so on. This causes the real color content to be poorly represented with the color histograms and thus resulting in an unreliable or poor content characterization (see movie "Circuit Marine" which contains "gray" 31%).

8.2. Automatic clustering of animated movies

We are addressing here the content-retrieval issue of the animated movies in the framework of developing an automatic indexing system. The proposed content descriptions were used in several unsupervised clustering tests in the attempt of extracting knowledge from the animated movie database. The goal is to determine whether the proposed semantic/symbolic color content descriptions are discriminative enough to retrieve movies according to their color content. We present here our first attempts in this direction.

The clustering of the movies was performed using a *k-means unsupervised clustering method* due to its efficiency in terms of the reduced computational time and the good quality of the results [29]. To overcome the problem of *k*-means reaching local minimum solutions, the clustering is repeated several times (i.e., 10 iterations in our case) and the final solution is the one with the lowest total sum of distances, over all replicates. As distance measure, the Euclidean distance is used. It proved to be a good compromise between the cluster delimitation and homogeneity and the computational cost. The number N of relevant movie clusters is entirely related to the used movie database. The high diversity of the available movies makes it difficult to a priori determine the right value for N. Therefore, several experiments were performed for different values of N.

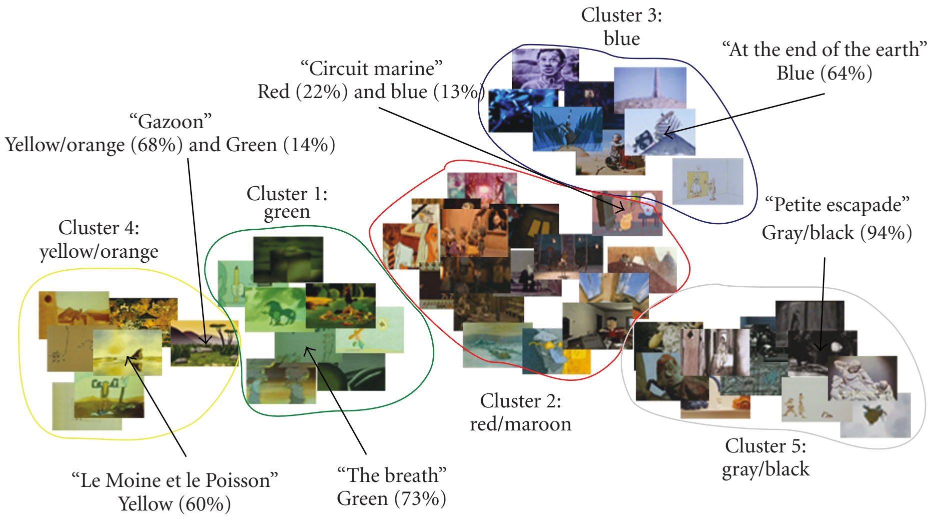


Figure 10: A 2D projection of the 3D data space of the classified data from Figure 9 (the clusters were manually delimitated with the color line for visualization purpose).

The validation of the results was performed using the manual analysis of the cluster silhouettes and object repartition. A silhouette is defined as a graphic plot which displays a measure of how close each object in one cluster is to objects in the neighboring clusters (see Figure 9). The silhouette measure ranges from +1 (maximum distance), through 0, to −1 indicating points that are probably assigned to the wrong cluster [30]. To overcome the difficulty of visualizing and thus analyzing n-order data sets, with $n > 3$, which is the case of the clustering data, we use the principal component analysis or PCA [31] to decorrelate the data. The interpretation of the results is thus performed by analyzing the plotting of only the first three principal components, as they account for as much of the variability in the data as possible. We present several experimental results here after.

8.2.1. Classification in terms of predominant colors

As we already discussed, each animated movie uses a specific color palette (see Section 8.1) which contains a reduced number of elementary hues. The richness of the elementary color palette is related to the movie artistic content and animation technique (see movies "Casa" and "Le Moine et le Poisson" in Section 8.1). For instance, a funny movie will typically use pastel colors, a sad movie will use mainly cold colors and a reduced number of hues, while a retro movie is restricted to use only gray levels. The interest in the elementary color distribution is twofold. First, retrieving movies according to their elementary color distribution in correlation with other color properties will grant the user access to the color content at a perceptual level. Second, it will allow to recognize different copies of the same movie (i.e., digitized in different conditions or using different color settings). The same movie replicates but with different illumination and/or saturation conditions will be represented with the same elementary histogram.

In this test, we attempt to retrieve the animated movies according to their color similarities. The ideal color parameter for our classification task is the elementary color histogram, $h_E()$, defined in (3), which captures the movie global elementary color distribution by only taking the hue information into account.

To determine the right number of classes, N, which should be used for the clustering, first a manual classification was performed. Several persons were asked to manually classify the movies according to their visual color similarities. After the intersection of the results, as each person classified the movies in a slightly different way, we found that in the 52-movie database there are 5-movie clusters sharing similar predominant elementary colors: cluster$_1$: green, cluster$_2$: red/maroon, cluster$_3$: blue, cluster$_4$: yellow/orange, and cluster$_5$: gray/black. The k-means was run using as input data the $h_E()$-values (see (3)) for each of the movies, thus 52 data vectors, each containing 15 values, and $N = 5$ clusters. The obtained cluster repartition is presented in Figure 9.

We have noted a good cluster homogeneity judging from the cluster silhouette: most of the values are typically above 0.4. The fact that there are movies which are to be found close to the border of two clusters (the silhouette values are smaller than 0.2) is due to the fact that some movies have several predominant colors, not only one.

To analyze the semantic meaning of the results, we use a 2D projection of the 3D data repartition presented with Figure 9, as this projection best represents the cluster delimitations. In Figure 10, instead of representing the movies as points on the 2D plot, each movie gets represented with a significant image. Similarly as the construction of a groundtruth for evaluating the proposed linguistical descriptions, evaluating the relevance of the results is a subjective task. It is difficult to give a precise measure of the quality of the classification results, such as the precision and recall measures, as even the manual classification was performed differently by different persons. Moreover, many movies use

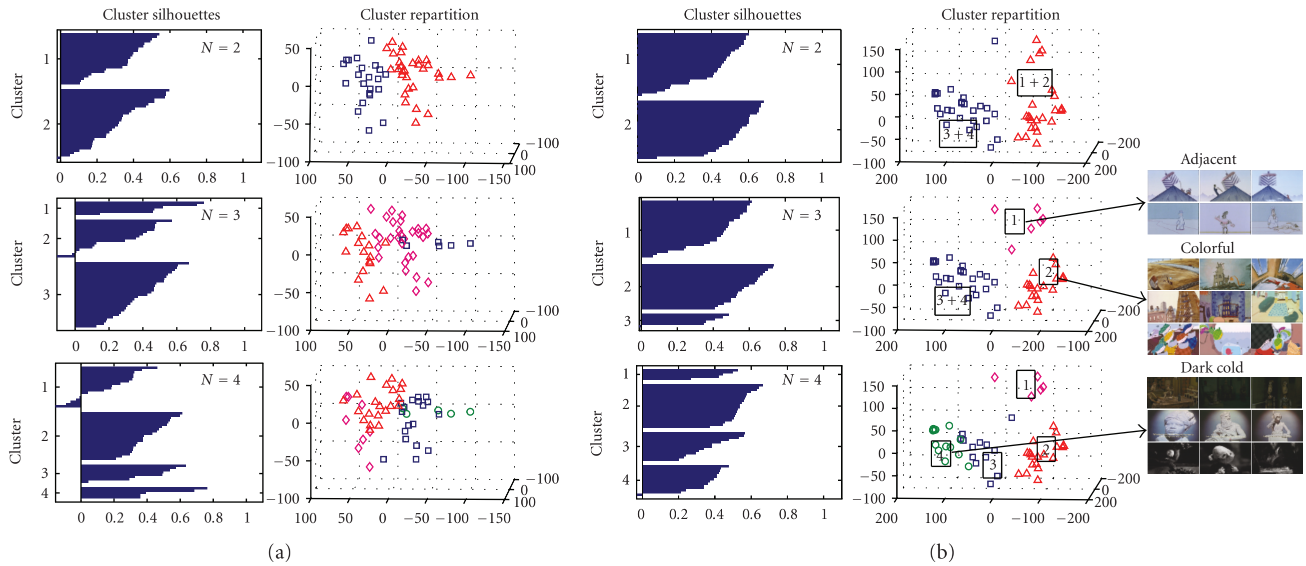


Figure 11: Low-level versus semantic clustering: (a) using low-level parameters, (b) using the fuzzy degrees of the symbolic/semantic color descriptions (N is the number of clusters, the data repartition is plotted using only the first three principal components).

several predominant hues which makes it difficult to compute the detection errors. To validate the relevance of the results, we have manually analyzed the content of each achieved cluster.

We found that the movies are grouped according to their predominant hues. Each movie sharing one predominant hue has been successfully assigned to one cluster, being close to the cluster centroid (see Figure 10). For example, the movie "Le Moine et le Poisson" which contains 60% yellow is the centroid of the yellow/orange cluster_4, the movie "At the End of the Earth" having 64% blue is the centroid of the blue cluster_3, the movie "The Breath" containing 73% green is the centroid of the green cluster_1 or the movie "Petite Escapade" containing 94% gray (gray-level movie) is the centroid of gray/black cluster_5 (see Figure 10). Meanwhile, the movies having more than one predominant hue are to be found close to the clusters containing these colors as representative colors. For example, the movie "Gazoon" containing 51% yellow and 14% green is to be found in the yellow/orange cluster_4 but close to the border with the green cluster_1. Similarly, the movie "Circuit Marine" having 22% red and 13% blue is to be found in the red/marron cluster_2 but also close to the blue cluster_3.

8.2.2. *Classification in terms of color techniques*

The second test attempts to retrieve the animated movies according to the used color techniques. For that, we first prove the advantage of using symbolic/semantic content descriptions instead of low-level statistical parameters.

Therefore, the k-means clustering was performed first of all by using only the low-level color parameters proposed with Section 6 (without the color histograms, a total of 10 parameters) and second by using as input data the fuzzy degrees of each symbolic/semantic color descriptions proposed in Section 7 (a total of 18 parameters). For the second test, the data redundancy has been reduced by using only two symbols from three in the case of the linguistic concepts represented with three symbols, as one symbol can always be deduced from the other two. Similarly, for the linguistic concepts having two symbols, only one is used.

In what concerns the number of clusters, N, it is entirely related to the animated movie database. The important heterogeneity in terms of animation techniques and movie genres of the used database makes it very difficult, even for a human operator, to determine precisely the suitable number of movie clusters to use. To overcome this issue, the k-means clustering was performed for a number of clusters, N, varying from 2 to 4. In the absence of a groundtruth, to evaluate the relevance of the movie repartitions we have manually analyzed each of the movie contents within the obtained clusters. The achieved cluster silhouettes and data repartition are depicted in Figure 11.

For the clustering using the low-level parameters (see Figure 11(a)) we found that even for different values of N the clusters are not well delimited judging from the small silhouette values which are mainly inferior to 0.4. A lot of movies are probably assigned to the wrong cluster as there is a high amount of negative silhouette values. The clusters are also superposing one another no matter the angle of view. Moreover, the manual analysis of the movies within the clusters revealed that they are not grouped accordingly to content similarities. The clusters contain movies which do not share particular common color characteristics.

On the other hand, the results of the clustering using the fuzzy degrees of the proposed symbolic/semantic descriptions proved to be very relevant. That is due to the intervention of the expert knowledge in the phase of the constitution of the linguistic concepts. In this case, new knowledge emerges from the achieved cluster repartition. First, the

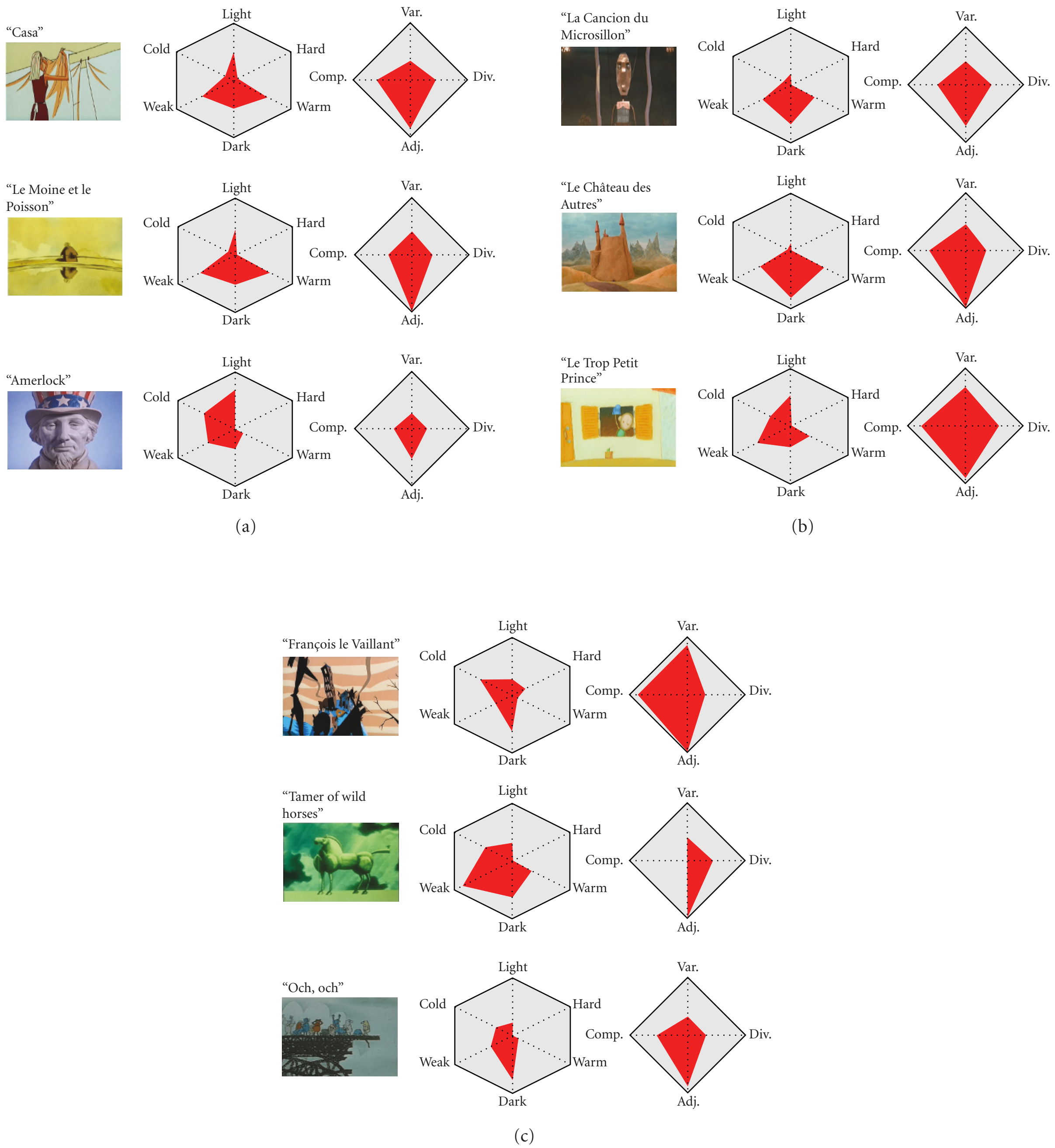


Figure 12: Examples of semantic gamuts: color properties gamut G_{prop} and color richness gamut G_{rich} for several animated movies.

clusters are better separated as most of the silhouette values are above 0.4 (see Figure 11(b)). Almost none of the silhouette values is negative meaning that most probably the movies are assigned to the adequate clusters. The manual analysis of the movies within the cluster revealed several interesting movie categories.

Varying the number of classes, N, from 2 to 4, the clustering attempts to preserve the cluster configuration in terms of color content similarity (see Figure 11(b)), while only the nonhomogenous clusters are getting divided. For $N = 2$, the movies are divided into *colorful movies* with predominant bright colors and high/moderate color variation, cluster_{1+2}, and *dark cold adjacent color movies* with a reduced color diversity, cluster_{3+4}. Increasing the numbers of classes to $N = 3$, the previously obtained cluster_{1+2} is divided in two. The movies having a *moderate color diversity and adjacent colors*, cluster_1, are separated from the *colorful movies* having a high color variation/diversity, cluster_2. For $N = 4$, cluster_1 and cluster_2 are almost entirely preserved while cluster_{3+4} is split in two, forming cluster_3, which contains the movies having generally only a *reduced color diversity*, and cluster$_4$, which contains all the movies with *predominant dark colors and using a very reduced color palette* (2 to 4 colors). This is the case of some particular animation techniques, namely sand, paper, or plasticine modeling, as they are restricted to a very reduced color palette due to the texture of the materials.

These tests prove the certain advantage of using high-level content descriptions against the classical low-level parameters. Using the proposed color content descriptions, the movies were successfully retrieved in the following categories: adjacent color movies, using variation of a single hue, colorful movies (pastel) and dark cold color movies (see Figure 11). Obviously, the achieved results are limited to the animated movie database we used. Further tests should be performed on a much larger-scale database.

8.3. Comparing movies

We are addressing here the problem of comparing different animated movies, a task which is mandatory in a content-based indexing system [36]. In such a system, the user will typically search for movies having the same characteristics as one he knows (i.e., the same technique, the same genre, inducing the same visual feeling, etc.). To denote this property, we are saying that they are *similar* [37].

Expressing the similarity concept is a difficult task, particularly in the case of the indexing systems, where each object is represented with a large variety of features (i.e., textual features, low-level numerical parameters, color distributions, etc.). The basic solution adopted by most of the existing approaches is to express the similarity concept using some numerical distance measures [12]. But in this case each type of data requires the use of a specific distance measure which is adapted to the data set. To overcome this issue and thus to facilitate the similarity evaluation task, we propose to represent color content in an efficient graphical manner. The proposed method was inspired from the color gamut [38], used in printing devices, and we called it the *semantic gamut*. We define the *semantic gamut* as the 2D graphical representation of the semantic properties of the movie where each semantic feature gets represented on a different axis. All the axes share the same origin which is also the origin of the system. The semantic gamut is the surface determined by the feature values. The major discriminant feature of the gamut is its shape (see Figure 12).

To test the efficiency of this approach, we are constructing two different semantic color gamuts using the symbolic/semantic color content descriptions proposed in Section 7. Thus, the following holds.

(i) The *color properties gamut*, G_{prop}, displays on different axes the following information: light colors (*Light*), hard colors (*Hard*), warm colors (*Warm*), dark colors (*Dark*), weak colors (*Weak*), and cold colors (*Cold*). Within the color properties gamut, opposite color properties are to be found in the opposing ends of the gamut for visualization purpose: cold versus warm, weak versus hard, and so on. These properties are somehow complementary, that is, in a movie the amount of light and dark colors is complementary as the dark colors cannot be also light and vice versa.

(ii) The *color richness gamut*, G_{rich}, displays the following color information: color variation (Var), color diversity (Div), the amount of adjacent colors (Adj), and of complementary colors (Comp). In this case the order of the color information is not relevant.

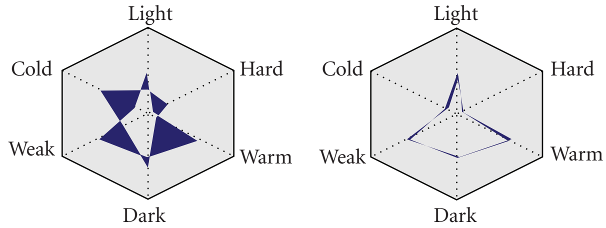


Figure 13: G_{prop} gamut substraction example.

The two gamuts have been tested on the CITIA [5] animated movie database. Some of the obtained results are depicted in Figure 12. The semantic gamut facilitates the retrieval of similar content movies. For instance, the movies "Casa" and "Le Moine et le Poisson", which share similar color techniques, namely the paper drawing as animation technique, the color distribution based on a single predominant hue (red/orange and, resp., yellow) being contrasted by the presence of gray, have similar shape gamuts (see Figure 12). Another example are the movies "La Cancion du Miscrosillon" and "Le Chateau des Autres" which are using the same elementary colors (orange, red, yellow, and gray) and similar color techniques, therefore the shapes of the color properties gamuts, G_{prop}, are quite similar.

The interest in this graphical representation is not limited measuring the content similarity. The semantic gamut could serve as visual *color content summarization* in a navigation system. Representing the movies with semantic gamuts will quickly debrief the user on the movie content characteristics and, depending on the application (i.e., database browsing), this will perform faster than a movie abstract. For instance, by looking at the gamuts in Figure 12, we can easily spot the dark-warm colors movies like "Le Chateau des Autres" or "Casa", or adjacent color movies like "Le Moine et le Poisson" or "Tamer of Wild Horses". Obviously, when a more profound content understanding is needed, video abstracts are required.

On the other hand, the semantic gamut can be used with the search engine. One can formulate the *query* by graphically designing a particular gamut shape according to his content preferences. In this way, the research task is simplified by providing a normalization of the query. Instead of using complex similarity measures applied between different types of data (features) to browse through the movie database, one can employ a simple and efficient distance measure such as the substraction of the gamuts:

$$d_{\text{surf}}(G_1, G_2) = \text{Surf}(G_1 \cup G_2 - G_1 \cap G_2), \quad (10)$$

where G_1 and G_2 are two semantic gamuts and Surf() is the operator returning the surface of a gamut. The efficiency of this type of measure is shown in Figure 13. We have illustrated the achieved d_{surf} distance (depicted with blue) for two movies havingvery different color contents, namely "Casa" and "François le Vaillant" (first graph) and for two movies having a similar color content, namely "Casa" and "Le Moine et le Poisson" (second graph). We can easily observe that the movies having a similar color content lead to a small distance, while the different ones lead to an important distance value.

9. CONCLUSION

This paper proposes a method for the symbolic/semantic description of the animated movies color content in the automatic content-based indexing task. It exploits the peculiarity of the animated movies of containing specific color palettes.

The movie color distribution is captured using a global weighted color histogram. The color content is further described with several low-level statistical parameters. The semantic description is achieved using a fuzzy set representation approach and a priori knowledge from the animation domain. It regards the color artistry concepts which are to be found in animated movies, that is, color perception, Itten's color contrast, harmony schemes, color richness.

The proposed content descriptions were used in several unsupervised clustering tests in the attempt to retrieve the animated movies according to the color techniques. The achieved results show the advantage of using semantic/symbolic descriptions instead of low-level parameters which have not been capable of delivering any semantic knowledge. The movies have been successfully retrieved according to their predominant hues and the used color techniques, that is, colorful movies (pastel, joyful movies), dark cold color movies (sad movies), or adjacent color movies. To facilitate the retrieval task, we have proposed to represent the movie color properties in a graphical manner which was called the semantic gamut. This representation proved to be very efficient in spotting movies having a similar content and in facilitating the design of a similarity measure to compare different movie contents.

The evaluation of the results proved to be a very subjective task as it mainly relies on human perception and of course on the animated database we used. However, the eloquence of the results was confirmed through the manual analysis of the results using a priori knowledge provided by the animation experts.

The interest in the proposed content description methodology is multiple. Firstly, it facilitated the *navigation task*. Instead of using movie abstracts, one may use the proposed linguistical descriptions and the semantic gamuts. Secondly, it facilitates the *research task*. The proposed descriptions could be used as human-like indexes in a content-based retrieval system. For instance, it would be an intuitive way of searching movies that share "yellow" as a predominant color or movies expressing sadness (i.e., dark cold colors). Finally, we provide the animation artists or ordinary people with detailed information regarding the movie color content and the color techniques used for *analysis purpose*.

Future improvements of the proposed methodology consist mainly in a multimodal approach where other types of information are to be considered (i.e., motion, text, and sound). We should also pursue our tests on a larger-scale animated movies database by solving the groundtruth issue.

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