EFFECTIVE SEARCH OF COLOR-SPATIAL IMAGE USING SEMANTIC INDEXING

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ABSTRACT

Most of the data stored in libraries are in digital form will contain either pictures or video, which is tough to search or browse. Methods which are automatic for searching picture collections made large use of color histograms, because they are very strong to wide changes in viewpoint, and can be calculated trivially. However, color histograms unable to present spatial data, and therefore tend to give lesser results. By using combination of color information with spatial layout we have developed several methods, while retrieving the advantages of histograms. A method computes a given color as a function of the distance between two pixels, which we call a color *correlogram. We propose a color-based image descriptor that can be used for image indexing based on high-level semantic concepts. The descriptor is based on Kobayashi's Color Image Scale, which is a system that includes 130 basic colors combined in 1180 three-color combinations. The words are represented in a two dimensional semantic space into groups based on perceived similarity. The modified approach for statistical analysis of pictures involves transformations of ordinary RGB histograms. Then a semantic image descriptor is derived, containing semantic data about both color combinations and single colors in the image.*

KEYWORDS:

correlogram, color-based image descriptor, kobayashi's color image scale, semantic image descriptor, Content Based Image Retrieval.

1. INTRODUCTION:

The aim of the digital libraries is to solve the problems of providing intelligent search techniques for multimedia collections. There are many efficient tools for searching normal text rather than pictures which are more difficult. If the pictures are designed by hand which will be searched through a textual approach, this approach is too labor-intensive to scale up with large digital libraries. An efficient methods are used for searching large picture collections. This requires a simple method for effective image for comparing images based on their overall appearance. This is insensitive to all small changes in viewing positions. Histogram is a core characterization of a picture, where images with very different appearances can have similar histograms.

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Figure 1: Two images with similar color histograms

Histograms may include a spatial data, where several techniques have developed to improve spatial data with color. [Hsu, Stricker, and Smith]. The paper describes about retaining the advantages of histograms for combining color data with spatial layout.This approach computes the spatial correlation of combination of colors as a function of the distance between pixels, this is a *color correlogram*[7] (the term ``correlogram'' is adapted from spatial data analysis). The other approach is based on computing joint histograms of several local properties. Just as color histograms joint histograms can be compared as vectors. Whatever might be the color histogram any two pixels of the same color are efficiently indentical. The joint histograms, share several pixel properties beyond color, this approach is called *histogram refinement* [7]. This approach is easy to compute more information of the image.

Most of the systems use image labeling or Content Based Image Retrieval which uses objects as their image descriptor. Complicated tasks are replaced by pictures containing certain text (cars, afruit, a scenery, a flower etc). In these days , the interest in image labeling and retrieval approaches based on high-level semantic concepts, such as emotions and aesthetics, which has been increased rapidly. In a recent survey by Datta et al[8] the subject is listed as one of the upcoming topics in Content Based Image Retrieval. The work we use Shigenobu Kobayashi's system[13] for color semantics of single colors and three-color combinations, called the *Color Image Scale*. The *Color Image Scale* is a well known tool used within Graphic Arts, for the selection of colors and color combinations. If the same system can be applied in indexing of multi-colored pictures then their arises a question. The new method is useful in large scale image indexing. We can illustrate it for 8000 images on a small database. The findings are implemented in a public which are available for demo search engine [1], is very important where readers can interact with the search engine. While continuing, we should not except the new technique to deliver semantic indexing for possible image. Color semantics concept is influenced by many factors, such as cognitive, perceptual, cultural, etc. Not only color semantics, by various kinds of image content high level picture semantics are obtained. Possible relationships between color semantics and other types of high-level semantics are beyond the scope of this paper. The method presented is a first step towards a broader use of high-level color semantics in image labeling and Content Based Image Retrieval.

1.1. THE COLOR CORRELOGRAM:

"Correlograms[7] are graphs (or tables) showing how autocorrelation changes with distance." Traditionally the distance meant the time distance between pairs of observations. Spatial analysts adapted the idea to spatial distance, and we adapt this idea to spatial distance of color pixels in an image.

The spatial correlation of pairs of colors changes with distance is called a color correlogram. Informally, a correlogram for an image is a table indexed by color pairs, where the *d*-th entry for row *(i,j)* specifies the probability of finding a pixel of color *j* at a distance *d* from a pixel of color *i* in this image. Here *d* is chosen from a set of distance values *D*. An *autocorrelogram* captures spatial correlation between identical colors only. This information is a subset of the correlogram and consists of rows of the form *(i, j)* only. An example autocorrelogram is shown in figure 2.

Since local correlations between colors are more significant than global correlations in an image, a small value of *d* is sufficient to capture the spatial correlation. We have an efficient algorithm to compute the correlogram when *d* is small. This computation is linear in the image size

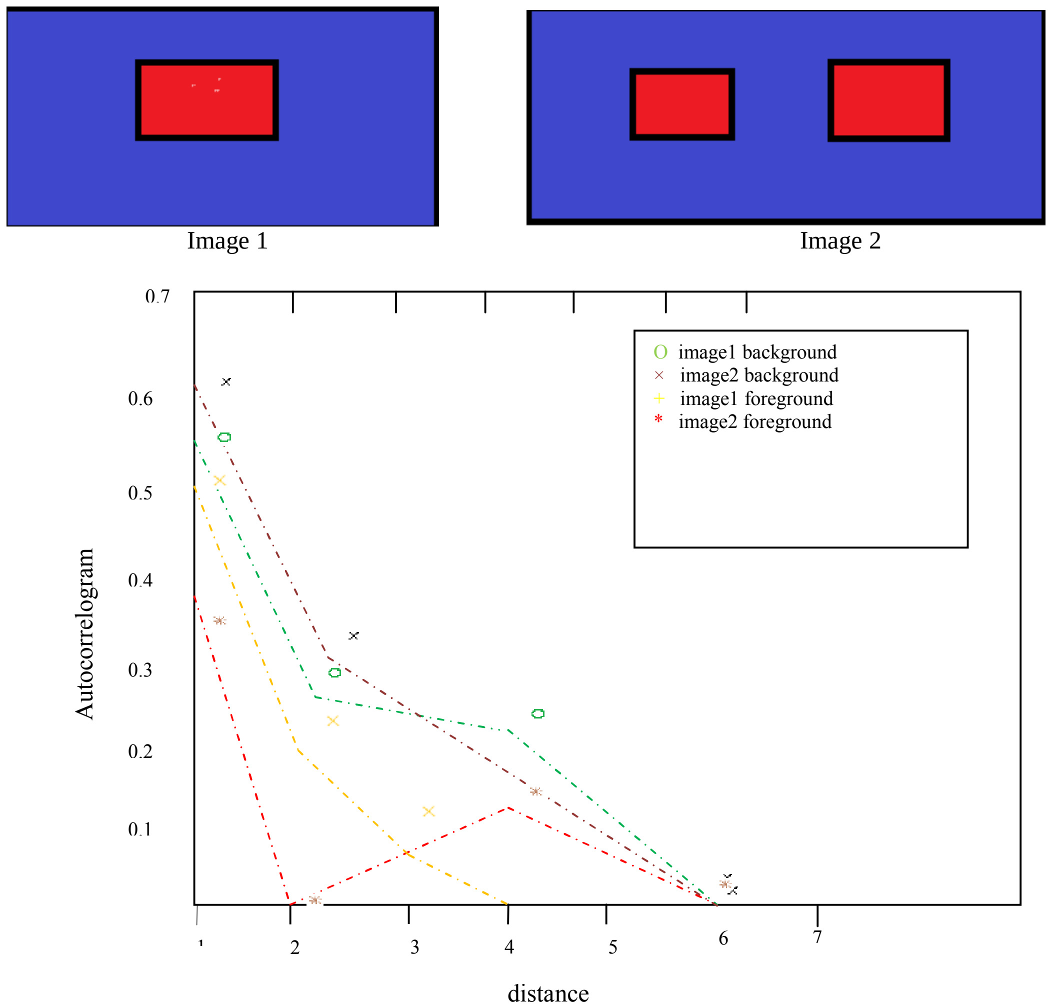


Figure2: Two images with their auto correlograms.

Note that the change in spatial layout would be ignoring by color histograms, but causes a significant difference in the auto correlograms.

The highlights of the correlogram method are: (i) it includes the spatial correlation of colors, and (ii) it can be used to describe the global distribution of local spatial correlation of colors Unlike purely local properties, such as pixel position, gradient direction, or purely global properties, such as color distribution, correlograms take into account the local color spatial correlation as well as the global distribution of this spatial correlation. While any scheme that is based on purely local properties is likely to be sensitive to large appearance changes, (auto) correlograms are more stable to these changes; while any scheme that is based on purely global properties is susceptible to false positive matches; (auto) correlograms prove to be quite effective for content-based image retrieval from a large image database.

1.2. HISTOGRAM REFINEMENT:

In *histogram refinement* [7] the pixels of a given bucket are subdivided into classes based on basic features. There are many possible features, including texture, orientation, distance from the nearest edge, relative brightness, etc. If we consider color as a random variable, then a color histogram approximates the variable's distribution. Histogram refinement approximates the joint distribution of a variety of local properties. Histogram refinement prevents pixels in the same bucket from matching each other if they do not fall into the same class. Pixels in the same class can be compared using any standard method for comparing histogram buckets (such as the L1 distance). This allows fine distinctions that cannot be possible color histograms.

1.3. KOBAYASHI'SCOLORIMAGE SCALE:

The *Color Image Scale* [13] is a book, or collection, developed by Shigenobu Kobayashi and his team at the Nippon Color& Design Research Institute (Japan).In their psychophysical investigations they have matched 130 basic colors and 1170 three-color combinations to 180 keywords, or *image words*, belonging to high-level semantic concepts related to the ways in which people perceive colors. The 130 basic colors are defined in the *Hue and Tone System*, basically a 2-dimensional color space where the axes corresponds to hue and tone. Examples of *image words* are "elegant","romantic" and "provocative". For each of the 130 basic colors, also known as *theme colors*, nine color combinations with other basic colors have been created. Each combination is labeled with one of 180 *image words*, together with 0-5 stars indicating the frequency with which the *theme color* is used in the current color combination (a kind of popularity measurement).

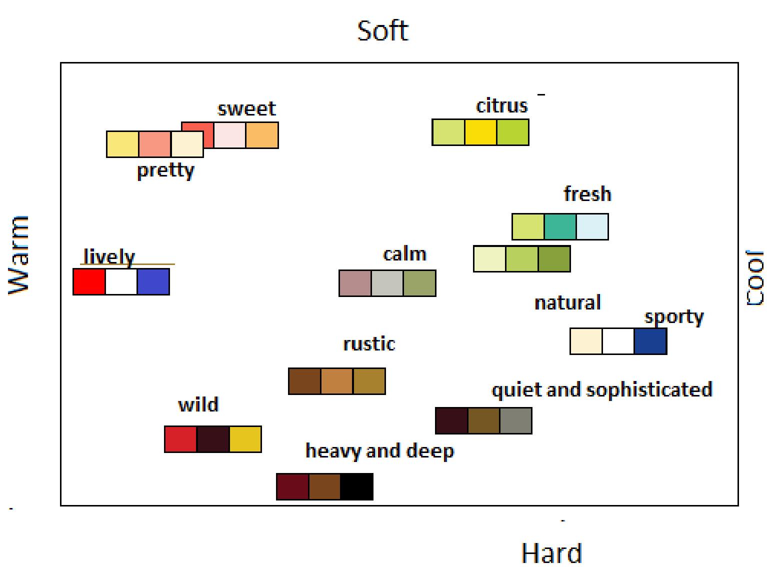


Figure 1: A few examples of three color combinations with image words

The relationship between a color combination and a single image word can be described as the lowest level of abstraction. On the highest level of abstraction, all color combinations, or corresponding image words, are located in a two-dimensional Key Word Image Scale, where the axes correspond to the scales hard-soft and cool-warm. Fig. 1 illustrates the concept explaining a some examples of color combinations, together with their image words, plotted in the Key Word Image Scale. In this two dimensional pace, Kobayashi also defines several regions or categories, called patterns. There are 15 patterns in total, each surrounding a group of image words.

1.4. HUE AND TONE REPRESENTATION:

The standard color space for ordinary digital images is the RGB color space. We must therefore first translate RGB values to the *Hue and Tone System* used by Kobayashi. RGB histograms are very common in Content Based Image Retrieval, and therefore we start with ordinary RGB histograms of images, denoted by h_R, then transform them to *Hue and Tone* signatures denoted by h_K. A typical RGB histogram consists of 512 entries with eight quantization levels (bins) per color channel. These 512 bins will be converted to a 130 components *Hue and Tone* signature corresponding to the 130 basic colors in the *Hue and Tone System*. We use a bin transformation described by a matrix T, of size 512×130 (*rows × columns*), constructed as follows. The basic colors, and the mean RGB vector foreach bin in the RGB histogram, are converted to CIELAB coordinates (for a detailed description of CIE color spaces see [10]).For component number n in the the *Hue and Tone* signature, that will be generated from column n in T, we search for the closest neighboring bins from the RGB histogram. The distance metric used is the Euclidean distance in the CIELAB color space, known as DE. Bin numbers are retrieved for all bins less or equal to 10 DE away, and their distances relative to the maximum distance 10 DE are used as weight factor in row r in T. For bin number r in the RGB histogram, with distance DEr to the closest *Hue and Tone* component, the weight is calculated as

$$t_{rn} = \left\{ \begin{matrix} 1 - \frac{\Delta E_r}{10} + 0.1 \text{ if } \Delta E_r \leq 10 \\ 0 \quad \text{else} \end{matrix} \right\}$$

for $n = 1{:}{:}{:}130$ (all columns in T). We add the constant 0:1 to avoid a weight factor close to zero (which otherwise might be a problem if all found bins have a DE distance close to 10, resulting in an almost empty *Hue and Tone* component). A problem that arises is that for some RGB bins, the closest component in the *Hue and Tone* representation is more than 10 DE away. We cannot ignore those bins since there might be images containing those colors only. Instead, if no bin can be found within 10DE, the closest bin is detected and the weight factor is set to 0:1.Since the intended usage is the use in general search engines, typically available on the Internet, where we have no control over the user environment, we make two assumptions: When transforming RGB values to CIELAB values, we assume images are saved in the sRGB color space, and we use the standard illumination D50. After multiplying the histogram vector h_R with T, we obtain the vector h_K

$$h_K = h_R . T \quad (1)$$

a 130 components *Hue and Tone* signature describing the distribution of color values in the image. In this feasibility study we do not take into account spatial relationships between colors.

2. A SEMANTIC IMAGE DESCRIPTOR:

The next steps in the process are the conversions from a *Hue and Tone* signature to *image words, Patterns,* and a position on the scales *hard-soft* and *cool-warm.*

2.1. CONVERSION FROM COLOR COMBINATIONS TO IMAGE WORD:

In Kobayashi's collection, the 130 components in *hK* are combined to form 1180 three-color (or three-components) combinations. For each color combination *n*, consisting of the three components

$$\{b_n^1, b_n^2, b_n^3\}$$

$$\sigma_{\mathrm{n}} = \min(h_k(b_n^1), h_k(b_n^2), h_k(b_n^3)) \qquad (2)$$

The signatures for all color combinations are collected in the vector h_T = (s1:::s1180). Thus h_T is a 1170 components signature describing the distribution of three-color combinations found in the image.

Since each color combination is labeled with one of 200 *image words*, we can create a matrix that will transform color combination signatures to *image words* distributions. For each *image word n* we create an index vector w_n of length 1180, with *wn*(*l*)=1 if word *n* is associated to color combination *l*. The vectors w_n are collected in the 1170×200 matrix *W*, that can be used alone for deriving *image words* signatures. We shall include the"star"-rating by using a 1180×1180 diagonal weight matrix *M*, where the value in the diagonal entry *mll* corresponds to the "star"-rating (+1, to avoid weighting with zero) for color combination *l*. After multiplying the color combination signature, h_T , with *W*, and the weight matrix *M*

$$hC = hT\,.M.W \qquad (3)$$

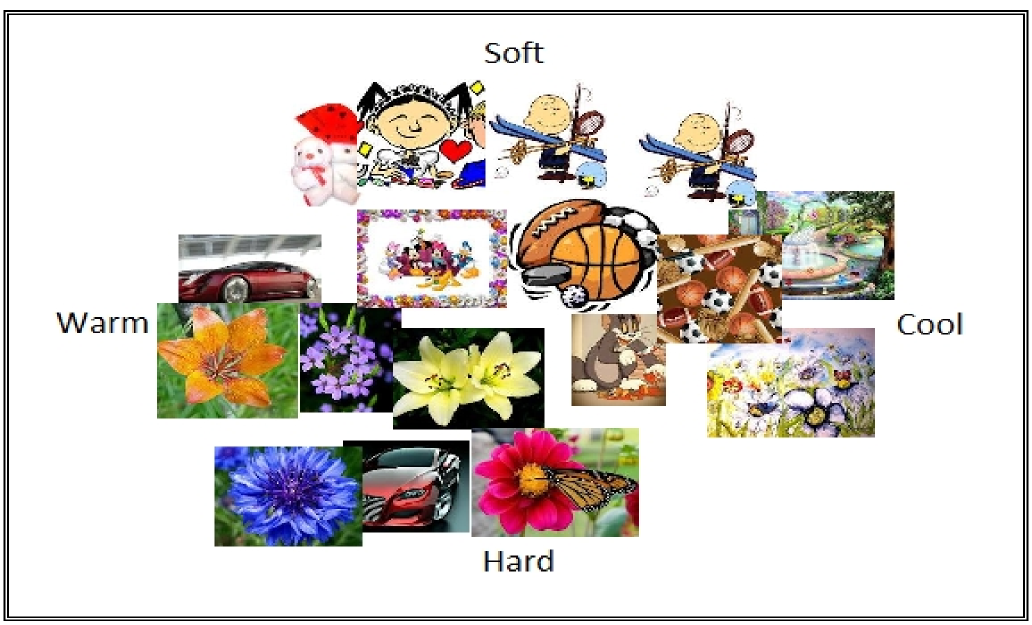


Figure 2: Images plotted according to their derived mean score in the key word Images word

2.2. CONVERTION OF SINGLE COLORS TO IMAGE WORDS:

For some pictures the method using three-color combinations will provide empty *image words* histograms. The most examples is a picture containing only two or more colors. To make descriptor more robust we definitely add the use of single colors to predict *image words*. We define the matrix L of size 130×8 by the entries.

$$t_{mk} = \begin{Bmatrix} 1 & \text{if color m is related to lifestyle k} \\ 0 & \text{else} \end{Bmatrix}$$

where m and k represent rows and columns in L. In the same way we define the matrix Q, size 8×180, by

$$q_{kn} = \begin{Bmatrix} 1 & \text{if imageword n is included in lifestyle k} \\ 0 & \text{else} \end{Bmatrix}$$

Combining the matrices with the *Hue and Tone* signature, h_K, *gives* the 180 components signature

$$h_S = h_K .L.Q \tag{4}$$

describing the distribution of *image words* belonging to single colors in the image.

2.3. CONVERSION OF WORDS TO PATTERNS AND SCALES:

The signatures of h_C and h_S, derived from three-color combinations and single colors combinations, are combined to a single picture *image words* signature. The signature is primarily based on h_C, but if the number of color combinations found approaches zero, the weight on h_S will increase. The weighting is defined as

$$h_w = \frac{h_c}{m_c} + e^{-\sum h_c} \frac{h_s}{m_s} \tag{5}$$

Picture Image words have been positioned in the two-dimensional *Keyword Image Scale*. Words close to the origin are described by Kobayashi as ”neutral in value”. Following a dimension outwards, for instance towards *warm*, the scale passes the coordinates” fairly warm” and ”very warm”, and end in ”extremely warm”. We compute the location in the *Key Word Image Scale* as the mean value given by the word histogram, h_W. The position for each *image word n* is obtained and saved in column n, denoted e_n, in the matrix E. Multiplying h_W with E, we obtain.

$$s = h_w . E^T \tag{6}$$

s is thus an expectation vector containing the mean score for each of the scale factors: *hard-soft* and *cool-warm*.

To make the keyword scale easier to understand, Kobayashi has clustered *image words* that convey a similar image into broad categories, called *Patterns*. Each *image word* is included in at least one of totally 15 *Patterns*. To derive what *Patterns* an image belongs to we create the matrix U, of size 180×15, defined as

$$u_{mk} = \begin{cases} 1 \text{ if word n is included in pattern k} \\ 0 \text{ else} \end{cases}$$

The vector p, given by

$$p = h_W . U \tag{7}$$

is thus an expectation vector for different *Patterns*. The position with the largest value corresponds to the *Pattern* with highest probability. As we will illustrate in the next section, the descriptors obtained can be used in image indexing, and applied in both image labeling and retrieval.

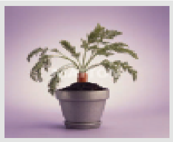
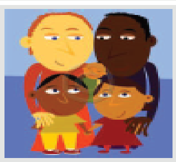
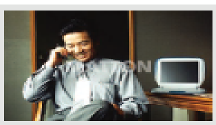
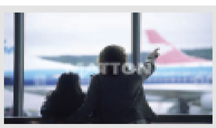
	Image Words	Pattern	Image Scale
	elegant refined subtle simple sedate	ELEGANT	Fairly cool Fairly soft
	agreeable to the touch light gentle amiable dry	ROMANTIC	Neutral in cool/warm Very soft
	bold festive forceful hot dynamic	DYNAMIC	Fairly warm Neutral in soft/hard
	distinguished precise authoritative urbane chic	MODERN	Fairly cool Neutral in soft/hard
	crystalline pure polished clean refined	CLEAR	Fairly cool Fairly soft
	polished delicate subtle solemn urbane	ELEGANT	Fairly cool Neutral in soft/hard

Figure 3: image are labeled with five image word, pattern and image scale word

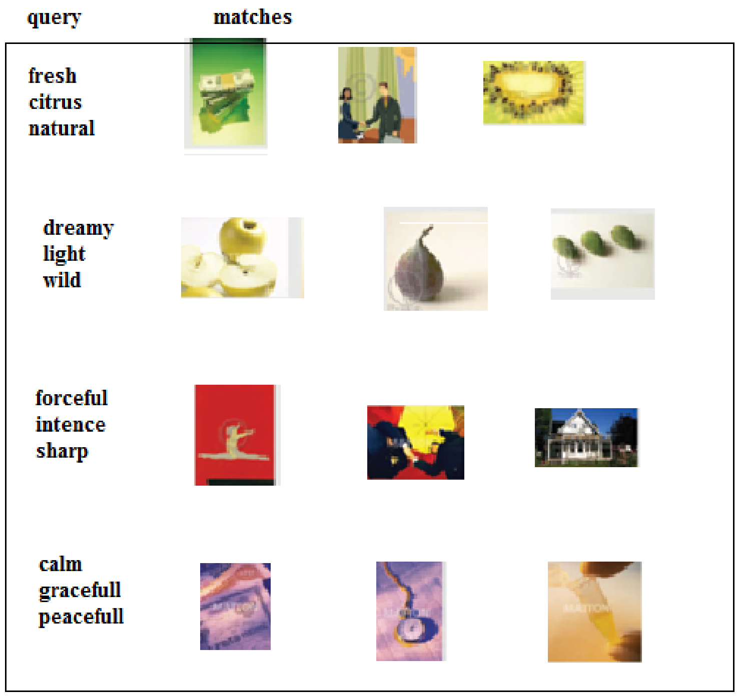


Figure 4: image retrieval based on image word histograms

3. IILUSTRATIONS:

Some results are clarified with a test database containing 600 images, both photos and graphics. The database is a arbitrary subset of a much larger database used in preceding and continuing research. Examples of tagging are shown in Fig. 3. Images are labeled in three stages of semantic abstraction: 1) The five *image words* that obtained with maximum probability 2) The most probable *Pattern* 3) A semantic grouping corresponding to the point on the *Key Word Image Scale*. Since each image is placed in the *Key Word Image Scale*, we can also define a probe by selecting a point, *sq*, in the space, and then search for images that have coordinates close to this point. Fig. 2 illustrates what images one will receive for different query points. One can also save images based on a selection of either *Patterns* or *image words*. For the later, a probe histogram, *hWq*, is created based on the selected *image words*, and the distance between *hWq* and *image words* histograms for all images in the database s derived as a measure of semantic similarity. Retrieval results based on the selection of *image words*. Fig. 4 illustrates a few retrieval results based on the selection of *image words*. The same figure holds examples where a query image is used. Here derived *image words* histograms, *hW*, are used for finding images with a similar semantic content. An alternative is to perform the search in one of the other two abstraction levels. Notice the difference to ordinary color-based retrieval, with for instance RGB-histograms. When assigning colors to semantic concepts, it is rather common that different colors are associated with the same semantic term. Several illustrative examples can be seen in Fig. 4, for instance in row 3, where completely different colors are associated with the the *image words*"calm","gracefull" and"peacefull".

3.1.EVALUATION:

The color-based high-level semantic concepts are very difficult so the performance degrades. We can evaluate using psychophysical experimentations for better results. It includes whole probable *image words*, *Patterns*, and positions on the *Keyword Image Scale*. They might be very time consuming, and outside the scope of this early study. Instead, we inspire readers to make a subjective decision by relating with the search engines which are available in public.

4. CONCLUSION:

By using color correlogram solves the problem of new image feature which are in content-based image retrieval. This feature consists of the characteristics of images in terms of the spatial correlation of colors instead of merely the colors *per se*. With respect to the distance the spatial correlation of color changes using a color correlogram. We can discriminate different images and identify similar images. By using correlograms we can compute, process and store with less cost and also satisfies other features.

By using Kobayashi's *Color Image Scale* on multi-colored images will results in new interesting techniques for image indexing based on high-level color semantics. We can design single and three color combinations by using *Color Image Scale*. The modified approach for statistical analysis of images, involves transformations of ordinary RGB-histograms, which results in a semantic image descriptor which is a tool used in both image labeling and retrieval. We can translate and use descriptor in different levels of semantic information, which spans from picture *image words* to *Patterns,* the positions on the scales are *hard, soft ,cool and warm*. Most images results in a rather compact distribution of *image words* in the *Color Image Scale*.

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