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An Image Retrieval Method Based on Multi-Subblock Dominant Colors and Weight Matrix Feedback

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Abstract: In order to improve the efficiency of color-based image retrieval, this study proposed to apply multi-subblock strategy algorithm in image retrieval with sharp dominant colors. Multi-subblock strategy and subblock matching are helpful to control retrieval granularity and locate subject screens displaying the contents. On this basis, weight feedback of subblocks is added and repeated retrieval is conducted so as to capture the users' intents and improve the retrieval accuracy. Key issues of multi-subblock strategy, selection for color space, improvement for vector quantization and renewal of weight matrix was analyzed and a prototype of retrieval system was established while contrast experiments were launched. Experimental data prove that compared with Global Retrieval Method and Simple Subblock Cumulative Histogram Retrieval Method, such a method combining multi-subblock dominant colors and relevance feedback can improve retrieval precision rates.

Key words: Multi-subblock dominant colors, HSV quantification, weight matrix, relevance feedback, image retrieval

INTRODUCTION

As a type of vivid, visualized and easily-understood medium data form, image is important information retrieval object in "Big Data". Content-based Image Retrieval (CBIR) Technology offers a practical approach to image retrieval without both annotation and index from Big Data. CBIR refers to such a technology that index is established according to color features, texture features, shape features and spatial relations of image, similarity distance between query image and target image is calculated and then retrieval is conducted according to similarity matching.

Among inherent properties of image, color is one of the most significant features. Endowed with rotation invariance and scale invariance, color is widely used in image retrieval. Color features include color histogram, color moment, color set, etc. Relevant retrieval methods are correspondingly put forward, for example, Color Histogram Intersection Method (Montagna and Finlayson, 2012) firstly proposed by Swain *et al*. This method boasts the advantages of simple feature extraction and efficient similarity calculation, but it is dwarfed by the lack of information on spatial distribution of colors. Improved methods for Swain's rudiment include Retrieval Algorithm Adopting Cumulative Histogram (Shioyama *et al*., 2000), Color Pair Retrieval (Losson and Macaire, 2012), Image Retrieval Algorithm Based on Uniform Subblock (Khan *et al*., 2012) and the like. However, with the expansion of image library scale and user demand for higher retrieval accuracy, the characteristics of underlying features have been insufficient to properly depict the concepts and semantics of image. Therefore, it is quite necessary to introduce Interactive Learning Method to fill the retrieval gap. Currently, many types of relevance feedback technologies prevail, such as Parameter Adjustment, Cluster Analysis, Probabilistic Learning and Neural Network (Rasli *et al*., 2012; Nilpanich *et al*., 2010).

In this study, advantages and disadvantages of various color retrieval algorithms and strategies are compared in the experiments. In consideration of the shortcomings that global histogram and uniform subblock fail to reveal spatial distribution information and demonstrate image subject screens, a type of retrieval method based on multi-subblock dominant colors is herein proposed which is combined with weight matrix relevance feedback method to achieve more precise retrieval under the human-computer interaction.

RETRIEVAL BASED ON MULTI-SUBBLOCK DOMINANT COLORS

Algorithm of multi-subblock dominant colors retrieval: Retrieval method based on multi-subblock dominant colors follows such a basic idea: Partitioning the image

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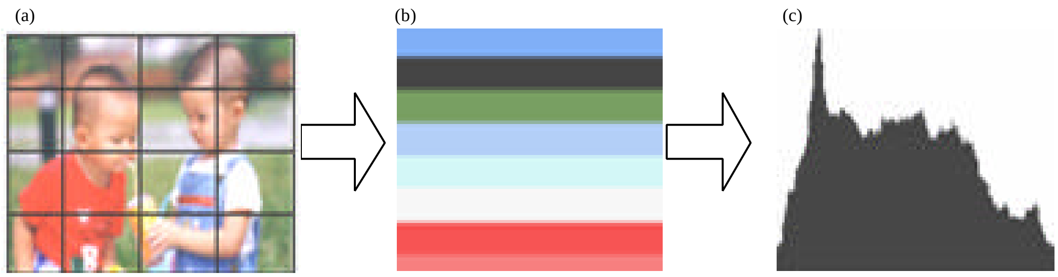

Fig. 1(a-b): Dominant colors extraction under multi-resolution subblock (a) 4×4 subblock, (b) Dominant color extraction and (c) Histrogram drawing

space according to a variety of subblock strategies and then calculating dominant color for every subblock as color characteristic of such subblock. Dominant color of subblock refers to such color with the maximum number of pixels in respective subblock. In the retrieval process, it is necessary to calculate the distance between dominant colors of corresponding subblocks one by one and then actual distance between two images is weighted accumulative total of such distances between all subblocks to some extent. The smaller distance between two images results in less visual difference. Extraction of dominant colors is as shown in Fig. 1.

Typically, an image consists of many subject screens with principal contents. Without any prior knowledge of original image beforehand, the system is difficult to automatically determine the locations and sizes of these subject screens in the image. In order to improve the retrieval accuracy, the subject screens displaying image contents should be located within the same subblock by all means. Based on this, a multi-resolution subblock strategy is designed, i.e., a variety of partitioning sizes and arrangement modes can be adopted for partitioning the image. For any image, user can select many partitioning strategies. For example, (1) Partitioning Strategy a at rough level, in which subblocks are arranged under Ma×Na Array; (2) Partitioning Strategy b at moderate level, in which subblocks are arranged under Mb×Nb Array; (3) Partitioning Strategy c at refined level, in which subblocks are arranged under Mc×Nc Array. Taking into account that subject screens are likely to span over adjacent subblocks, adjacent subblocks see certain overlapping areas at horizontal and vertical directions in the partitioning process. In the specific partitioning, "Ma = Na = 8; Mb = Nb = 4; Mc = Nc = 2" are assigned and overlapping area between subblocks is set as one-fourth or one-fifth of subblock size. Consequently, for the users, every image can be retrieved at various options of "Resolution". Figure 1 shows the dominant colors extraction under 4×4 resolution subblock.

With this multi-resolution subblock strategy, it is possible to selectively adapt to subject screens with multi-granularity in different locations, thereby removing the drawbacks of single fixed subblock strategy in this regard.

Implementation of retrieval based on multi-subblock dominant colors

Improvement for HSV non-uniform quantization: Among all color spaces, HSV Color Model and CIE Color Model correspond to Painter Color Matching Model and ideally reflect humans' perception and verification abilities for colors which are suitable for color-based image similarity comparison. Like CIE Color Model, HSV Color Space and RGB Color Space change in non-linear manner. However, such non-linear inverse transformation is more easily achieved in HSV(An *et al*., 2010). For this reason, HSV Color Model is herein adopted.

Calculation quantity and storage capacity of feature extraction and feature matching will undergo non-linear expansion along with increase in the number of actual colors, so it is unrealistic to adopt true color actual in the actual retrieval process. In fact, among the actual colors of image, several dominant colors cover the vast majority of image pixels. If image is shown with these dominant colors, the image quality declines but people's correct understanding of image contents would not be impaired. Accordingly a characteristic vector quantization formula can be defined in HSV Color Space to determine a color set. Such color set should not only reflect the humans' visual perception, but also compress the original colors.
With reference to the existing research findings involved with HSV non-uniform quantization (Meskaldji *et al*., 2009; Chen *et al*., 2008; Nor *et al*., 2011), through the analysis for color models and a lot of test data, Luminance (Y) and Saturation (S) (two components of HSV Space) are also subjected to non-uniform quantization according to humans' visual perception characteristics, thereby making quantized colors more suited to humans' perception

characteristics. Hue Space is divided into 11 parts while Saturation (S) Space and Measure (V) Space are divided into four parts each which are quantified according to Eq. 1 in view of different color ranges:

$$C_M = C_{M0}(1-h)H = \begin{cases} 0, & \text{if } h \in [315,360] \| h \in [0,23) \text{ (Red)} \\ 1, & \text{if } h \in [23,50) \text{ (Orange)} \\ 2, & \text{if } h \in [50,75) \text{ (Yellow)} \\ 3, & \text{if } h \in [75,155) \text{ (Green)} \\ 4, & \text{if } h \in [155,195) \text{ (Cyan)} \\ 5, & \text{if } h \in [195,275) \text{ (Blue)} \\ 6, & \text{if } h \in [275,290) \text{ (Purple)} \\ 7, & \text{if } h \in [290,315) \text{ (Purplish Red)} \\ 8, & v == 0 \| (s == 0 \&\& v < 0.2) \text{ (Black)} \\ 9, & v == 3 \text{ (White)} \\ 10, & s == 0 \text{ (Gray)} \end{cases} \quad (1)$$

$$S,\ I = \begin{cases} 0, & \text{if } s,i \in [0.0,\ 0.08) \\ 1, & \text{if } s,i \in [0.08,\ 0.4) \\ 2, & \text{if } s,i \in [0.08,\ 0.75) \\ 3, & \text{if } s,i \in [0.75,\ 1] \end{cases}$$

In Eq. 1, 11 color subspaces result from the values of H, i.e., Red, Orange, Yellow, Green, Cyan, Blue, Purple, Purplish Red, Black, White and Gray. Among which, Black, White and Gray are not possessed by Hue (H) itself. However, actually influenced by Luminance (V) and Saturation (S), images turn visually sensitive black, white or gray colors. So these three colors are added into retrieval system. In this way, HSV Space is compressed into 176 (11×4×4) subspaces and every subspace can be expressed by Label (L):

$$L = HQ_sQ_v + SQ_s + V = 16H + 4S + V \quad (2)$$

where, Qs and Qv refer to quantized series of S and V, respectively; $Q_s = Q_v = 4$; Obviously, $L \in [0, 176]$. According to Eq. 2, Subspace Li comprising color values Pi(h, s, v) of any pixel of image in HSV Color Space can be obtained. By scanning the images and calculating the number of pixels in all subspaces, HSV Color Histogram can be statistically obtained.

Extraction of dominant colors and similarity measure: For every subblock in the image, statistics should be taken for feature vector L. According to histogram of L, such color with the maximum pixels should be extracted as dominant color of subblock. In this way, color feature vector of comprehensive space is obtained, i.e., $L = (L_1, L_2, \ldots, L_n)$.

Firstly, the distance between the dominant colors of subblocks should be calculated according to Eq. 3 and then weighted sum of all subblocks should be obtained according to Eq. 4 which should be regarded as measured distance of Image p and Image q:

$$D_i(p,q) = |L_{pi} - L_{qi}| \quad (3)$$

$$D(p,q) = \sum_{i=1}^{n} W_i D_i(p,q) \quad (4)$$

RELEVANCE FEEDBACK RETRIEVAL

No matter whichever feature statistics and distance measure are adopted, the final decision on similarity of two images still depends on actual users. CBIR System should try its best to follow user-oriented philosophy rather than computer-oriented philosophy. In the retrieval with vector model, feature weight adjustment is the keynote of relevance feedback technology (Marakakis *et al*., 2011). Specifically speaking, moving query vectors and similarity weight matrix adjustment method are available.

Moving query vector with similarity: If users give relevant and irrelevant feedback information and roughly provide the relevant or irrelevant quantization degree information on corresponding image and query target, similarity can be used as weighting coefficient to move initial query vector. Specific to feature vector of subblock dominant colors herein, moving process of the query vector can be described in Eq. 5 as follows:

$$F_{new} = \sum_{i=1}^{n} (s_i F_{old}(i)) / \sum_{i=1}^{n} s_i \quad (5)$$

where, N refers to total number of relevant and irrelevant images marked by users in this feedback process; $S_i (S_i > 0)$ refers to similarity between corresponding image and target image. Greater value of S_i indicates that corresponding image is more similar to query target. New query vectors, generated under Eq. 5, may better accord with users' real intentions.

Adjusting weight matrix with variance: In many retrieval applications, users' emphasis for local parts of image may be greater than that for overall image. Users may also judge whether two images are similar according to the similarity of some local parts of image. Multi-subblock dominant color algorithm, as mentioned before, affords the possibility of capturing spatial relationship between image colors. Under different subblock strategies and even under the same subblock strategy, different subblocks make entirely unequal actual contributions to the overall meaning of image. When users make judgment for similarity, some subblocks may play greater role than other subblocks. So the system is required to prioritize the importance of different subblocks from users' feedback information and pay more attention to important subblocks in distance measure.

A series of weighting coefficients W_i, as specified in Eq. 4, are used to adjust the proportions of different subblocks in distance measure. Default initial values are given to weighting factors of all subblocks of the image which form a weight matrix. According to the users' feedback information, distance variance of subblocks is herein adopted to dynamically adjust and update matrix weights, i.e., calculating distance weighted variance between corresponding subblocks of all feedback images. Subblocks with low variance imply high mutual consistency between subblocks, so the importance of such subblocks should be strengthened. As such, under a certain subblock strategy, it is necessary to calculate weighted average variance values of the distances between all corresponding subblocks. Strategic importance of subblocks with low weighted average variance values should be strengthened.

If $\bar{F}_j$ refers to dominant color feature vector corresponding to Subblock j after moving query vector, with similarity S_i as weighting coefficient, weighted variance of every subblock can be defined according to Eq. 6:

$$\sigma_j^2 = \sum_{i=1}^{N} s_i D_j^2(F_j(i),\ \bar{F}_j) \tag{6}$$

Weighting coefficient of every subblock can be calculated according to Eq. 7:

$$\omega_{xj} = \frac{1/\sigma_j^2}{\sum_{i \in T_x} 1/\sigma_i^2} \qquad x \in \{f,\ m,\ c\} \tag{7}$$

Implementation of repeated retrieval: The abovementioned method can be applied in retrieval of multi-subblock dominant colors. From the perspective of user query, the query process is as shown in Fig. 2.

Basic idea of repeated retrieval, as shown in Fig. 2, is explained as follows: Based on retaining user's feedback image, next retrieval image is selected according to adjusted weight coefficient and then retrieval method is selected according to user needs so as to conduct the second retrieval. By this time, Image q pending for retrieval can be a certain image from the previous retrieval results selected by user so that the retrieved image is closer to the user's subjective desire.

ANALYSIS FOR EXPERIMENTAL RESULTS

Image retrieval prototype architecture is based on Windows 2000 Operating System. In consideration of the advantages of C^{++} in memory usage controllability and programming flexibility, Visual C^{++} (MFC and GDI) is selected as development tool. In some experiments, Mat Lab is adopted. Object-oriented methods are used to define DIB Processing Function Set and core CDib Class dedicated to image processing is designed. Based on CDib Class, function class required by retrieval system is set up and retrieval system prototype is achieved.

Experimental data: Test Image Library consists of colorful JPG pictures selected from Corel (standard test image library). Image themes include figures, scenery, cartoon, geography, animal and other categories. Although preliminary classification is made in original database,

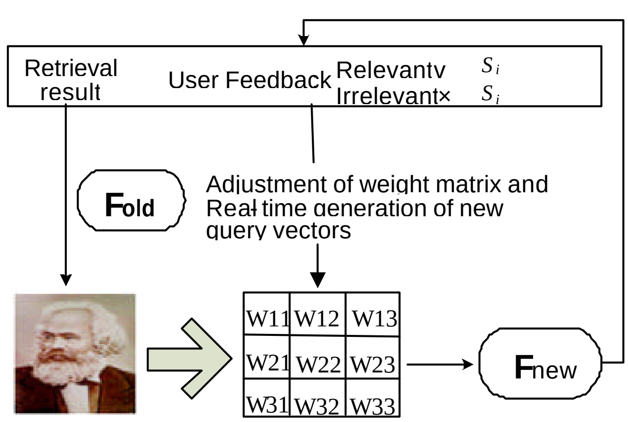

Fig. 2: Implementation flow of relevance feedback

some images of the same category differ greatly in terms of contents and visual sense. Therefore, the categories of test database are reselected and segmented. After excluding few isolated images differing from other images, 51 subcategories are available, including 20 subcategories comprising over 20 images each. Every subcategory includes 2-50 images. All images are combined to form a test database comprising a total of 714 images. In order to make the experiments more objective, judgment for similarity between two images is based on whether they are attributed to the same subcategory.

Discussion about experimental procedu-res and results

Experiment 1: Retrieval for standard image library: Five images are randomly selected from each of such ten subcategories with images totaled over 14, respectively. They become query images with a view to 50 queries. For every query, the corresponding precision rates of image 1-14 are calculated (i.e., valid query results from Image 1-14) based on query results. By summarizing the results of 50 queries, the corresponding average precision rate is obtained.

Apart from Multi-subblock Dominant Color Method (HSV-SUBM-WD, for short) as described herein, Global Histogram Method (HSV-NH-ED, for short) and Local Cumulative Histogram Method (HSV-SUB-WD, for short) are also investigated in order to make the results comparable, as shown in the curves of Fig. 3:

- The average precision rate of Multi-subblock Dominant Color Method as described herein is equal to that of Local Histogram Method which is obviously higher than that of Global Histogram Method. Multi-subblock Dominant Color Method fails to give full play to its advantages which is owed to selected query target images because query target image colors are distributed uniformly and dominant colors are ambiguous. As a result, dominant color extraction algorithm turns futile
- Obviously, Multi-subblock Dominant Color Method with focus on spatial distribution of colors loses the geometric transformation invariance which is exactly the advantage of global histogram. It is proved that Global Histogram Method is still effective on some special occasions. From the experiments, it is also found that pure color histogram may retrieve entirely dissimilar images from results. Even if the query results, obtained with the method as described herein, are not attributed to the same subcategory, they have a certain similarity apparently. Furthermore, Multi-subblock Dominant Color Method is superior to global histogram on the whole which is more suitable in the retrieval for local information of images and enjoys the predominance of average precision rate
- In Multi-subblock Dominant Color Method, subblock size plays an important role in the retrieval. Constant adjustment of subblock sizes can roll down different retrieval results. Users should dynamically adjust in the retrieval process with a view to higher retrieval efficiency

Experiment 2: Retrieval for dominant color library: Query target images are selected from another ten subcategories comprising over 14 images each, with which Experiment 2 is launched. Query target images are characterized by non-uniform distribution of colors and relatively sharp dominant colors this time. Average retrieval rate is obtained after 50 retrievals. The statistics of average precision curves are obtained, as shown in Fig. 4.

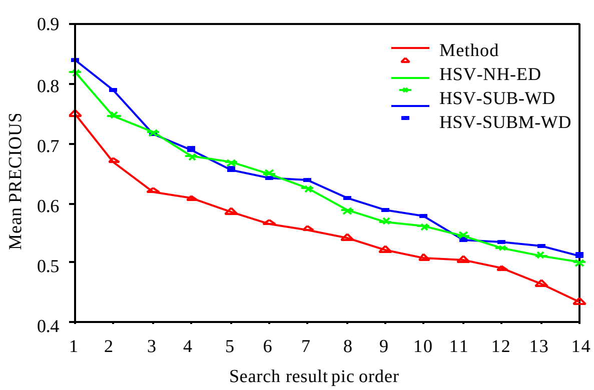

Fig. 3: Comparison for average retrieval rate of 50 queries (I)

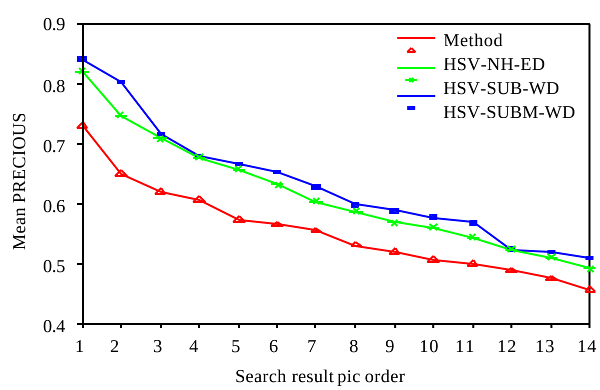

Fig. 4: Comparison for average retrieval rate of 50 Queries (II)

From Fig. 4, the following conclusions can be drawn:

- When query results of Image 1-14 are used as retrieval results, Multi-subblock Dominant Color Method enjoys cutting-edge advantages because dominant colors of every subblock are seen as color characteristics of the image and retrieval performance for images with sharp color blocks is satisfying
- In terms of retrieval speed, without image space partitioning, weighted statistical comparison or other consumptions, Global Histogram Method enjoys faster retrieval speed than Multi-subblock Dominant Color Method. According to the retrieval for 714 images in the test database, Multi-subblock Dominant Color Method takes about 2.5 times that of Global Histogram Method on average

Experiment 3: Retrieval combined with relevance feedback: In order to validate the effectiveness of relevance feedback method as described herein, Experiment 3 is designed, i.e., multiple relevance feedbacks are adopted to improve query results. In view of high correlation between the images in the last test library, favorable initial query results are readily obtained. To this end, combinations are downloaded from the website (http://www.cs.cmu.edu/~cil/v-images.html) to create another test database. In the top 20 images from query results, three images are relatively similar to query targets. After the first feedback retrieval, the number of relevant images increases to seven and relevant images are ranked higher. On this basis, the second relevance feedback operation is made and the number of relevant images increases to nine and the top eight images are all relevant. The third feedback retrieval rolls down 11 relevant images. The number of relevant images from the fourth and the fifth feedback retrievals keeps unchanged at 11. The statistics of retrieval precision rates of six feedbacks are obtained as shown in Fig. 5.

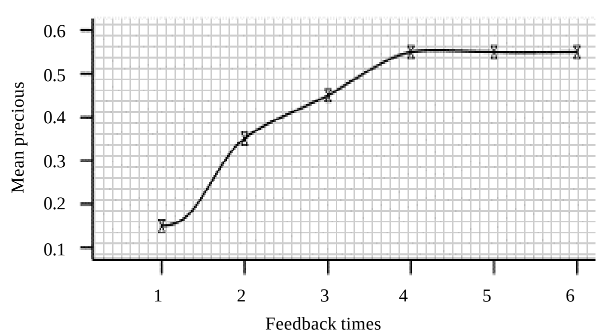

Fig. 5: Statistics of repeated retrievals

This demonstrates that relevance feedback can be used to more effectively capture the users' query intents which is a dynamic retrieval process with stepwise refinement. Relevant degree is adopted and weight coefficients of subblock weight matrix in the distance measure are adjusted, thereby integrating relevance feedback technology with Subblock Dominant Color Algorithm. In this way, the system can better achieve auto-adaptation to different subblock strategies which effectively improves the query performance based on color characteristics.

CONCLUSION

Global Histogram without regard to spatial distribution of colors is possible to treat apparently-dissimilar images as similar images. Multi-subblock Dominant Color Method as described herein can overcome this shortcoming which is particularly effective in retrieval for scientific literature image and precise retrieval for news pictures. The applications of Sci-tech Novelty Retrieval and selection and storage of news pictures in Subject Database Project entitled "Guangzhou in the Eyes of Media", launched by Guangzhou University Library, prove that multi-subblock strategy, combined with relevance feedback of weight matrix, can better capture subject screens of the images. In the retrieval environment with sharp dominant colors, such strategy effectively upgrades the overall retrieval results and boasts the remarkable retrieval applicability.

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REFERENCES

An, Y., M. Riaz and J. Park, 2010. CBIR based on adaptive segmentation of HSV color space. Proceedings of the 12th International Conference on Computer Modelling and Simulation, March 24-26, 2010, Cambridge, pp: 248-251.

Chen, T.W., Y.L. Chen and S.Y. Chien, 2008. Fast image segmentation based on K-Means clustering with histograms in HSV color space. Proceedings of the IEEE 10th Workshop on Multimedia Signal Processing, October 8-10, 2008, Cairns, Qld, pp: 322-325.

Khan, S.M.H., A. Hussain and I.F.T. Alshaikhli, 2012. Comparative study on content-based image retrieval (CBIR). Proceedings of the International Conference on Advanced Computer Science Applications and Technologies, November 26-28, 2012, Kuala Lumpur, Malaysia, pp: 61-66.

Losson, O. and L. Macaire, 2012. Colour texture classification from colour filter array images using various colour spaces. Image Process., 6: 1192-1204.

Marakakis, A., G. Siolas, N. Galatsanos, A. Likas and A. Stafylopatis, 2011. Relevance feedback approach for image retrieval combining support vector machines and adapted gaussian mixture models. Image Process., 5: 531-540.

Meskaldji, K., S. Boucherkha and S. Chikhi, 2009. Color quantization and its impact on color histogram based image retrieval accuracy. Proceedings of the 1st International Conference on Networked Digital Technologies, July 28-31, 2009, Ostrava, pp: 515-517.

Montagna, R. and G.D. Finlayson, 2012. Padua point interpolation and Lp-norm minimization in colour-based image indexing and retrieval. Image Process., 6: 139-147.

Nilpanich, S., K.A. Hua, A. Petkova and Y.H. Ho, 2010. A lazy processing approach to user relevance feedback for content-based image retrieval. Proceedings of the IEEE International Symposium on Multimedia, December 13-15, 2010, Taichung, Taiwan, pp: 342-346.

Nor, D.M., J.M. Ogier, F. Manani and M.Z.M. Jenu, 2011. Color based properties query for CBIR: HSV global color histogram. Proc. SPIE, Vol. 8285. 10.1117/12.913383

Rasli, R.M., T.Z.T. Muda, Y. Yusof and J.A. Bakar, 2012. Comparative analysis of content based image retrieval techniques using color histogram: A case study of GLCM and K-means clustering. Proceedings of the 3rd International Conference on Intelligent Systems, Modeling and Simulation, February 8-10, 2012, Kota Kinabalu, pp: 283-286.

Shioyama, T., H.Y. Wu and S. Mitani, 2000. Object detection with Gabor filters and cumulative histograms. Proceedings of the15th International Conference on Pattern Recognition, Volume 1, September 3-7, 2000, Barcelona, pp: 704-707.