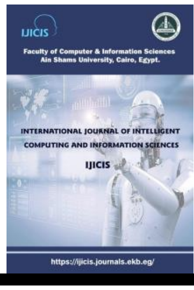
IJICIS, Vol.22, No.1, 60-75
DOI: 10.21608/ijicis.2022.105794.1140

IMAGE RETRIEVAL USING BLENDING OF EXTENDED FEATURE COMPONENTS

International Journal of Intelligent Computing and Information Sciences

https://ijicis.journals.ekb.eg/



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Received 2021- 11-13; Revised 2021-12-24; Accepted 2022-01-07

Abstract: *Receiving the most relevant images from image databases is a challenging and critical issue in many applications. Texture is a substantial feature of an image which depicts the spatial behavior of gray-levels in any given neighborhood. Color features uses a variety of color systems and are meaningful to differentiate image segments. Presently, many of the favorable methods for image content description use local descriptors as their starting point with several conducts. The content in an image may appear in some feature descriptor's components more accurately than other components. This paper presents an innovative idea for local image retrieval using a new methodology for feature extraction welding named Blend of Extended Features' Components (BoEFC). The paper shows that an image's content may be described individually by the feature descriptor's components or collectively through the Extended Feature Components (EFC). Retrieval options are attempted using a selection method of Feature Components then the relevant results are collected and ordered according to newly adapted feature similarity measures. The experiments were performed using a general-purpose image database which itself represent a challenge and the INRIA Holiday image database. The experiments was performed by varying the EFCs to compute recall, precision and draw the Precision-Recall (PR) curves which showed increased recall and precision with some components. In addition, calculating mAP and mAR showed increased performance due to the BoEFC blending process.*

Keywords. *Local feature extraction, Edge detection, Image processing, Content-based Image Retrieval, and analysis*

1. Introduction

Image feature extraction is an active research area in computer vision. Content-Based Image Retrieval systems searches for similar images in content (such as similar in colors, shapes, and textures) not the

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exact same query image. Hence, the most similar image should be the query image if it is stored in the image database (/dataset). Many of the skilled methods for image content description are local features [1] and [2]. Global features describe the visual content of the entire image, irrespective of the content of isolated pixels. Local features which is usually more complex describe the visual content of image points, patches, lines, regions, or blobs. The two vital attributes of local image features are the detector and descriptor. The detector discovers interest points or regions, and the descriptor models features to describe the detected interest regions. Local image features contribute to applications such as video surveillance, object detection and tracking, panorama stitching and image retrieval. Furthermore, there are local features that proven its efficiency such as SIFT [3], SURF [4], LBP [1, 5] which are robust to rotation and scale invariance. Invariant Moments and HOG are examples of global descriptors. Venkatrayappa D et. al. [6] presents a new image patch descriptor for object detection and image matching. The descriptor is based on the standard HoG pipeline to pack more curvature information. The descriptor is generated by embedding the response of an oriented anisotropic derivative half Gaussian kernel in the HoG framework. The authors claimed that the descriptor performs better than SIFT. The Local Color histogram (LCH) is one of the methods for separating different portions of an image. In [7] there is a survey for image retrieval using LCH to develop image retrieval techniques. Much research have used features in different color spaces, for example C. D. Ruberto et al [8] has used Local binary patterns with Lab, HSV, and others to identify which is suitable for medical image databases. Some of the features were Grey-Level Co-Occurrence Matrix, Grey-Level Difference Matrix and Grey-Level Run-Length Matrix. The experimental results showed that the performance of features extracted from the HSV, and Lab color spaces are very close and performs better. Texture features are popular in the literature such as EEHD [9], LBP, and SIFT, an exclusive survey for texture features is found in [10]. In this paper, a novel experimental methodology named BoEFC is presented for local image retrieval by using color and texture features. The BoEFC retrieval is based on the individual and accumulated feature component of the EEHD and LCH to produce a better personalized retrieval for the user query. Section 2 presents an outline for EEHD and LCH image descriptors, section 3 presents the BoEFC procedure modules and section 4 offers the experimental results and discussion.

2. The Applied Feature Extraction Techniques

Edges play a key role for image perception, and it can retrieve semantic similar images and especially good for images with nonuniform edge distribution. The Extended Edge Histogram Descriptor (EEHD) [9] is a common approach for texture analysis that holds the information of the different types of image edges and is used to extract image features in various visual recognition tasks with a low computational cost. EEHD captures the local distribution of edges in the four directions as well as non-directional edges. The edge extraction is based on defining small image blocks as a basic unit for edge extraction rather than on pixels. The EEHD-based image retrieval performance can be significantly improved if gathered with color descriptors such as a color histogram descriptor.

2.1. Local Color Histogram Descriptor

In general, LCH [11] includes information concerning the color distribution of regions. The CIE Lab color space describes mathematically all perceivable colors in the three components and better separates luminance and chrominance. The 'L' color space component for lightness ranges from 0 (black) to 100 (white). The 'a' color space component measures the color redness (positive value) or greenness (negative value). The 'b' color space component measures the color yellowness (positive value) or blueness (negative value). The space is nearly linear where the Euclidean distance between two colors is comparable to their perceived difference by humans.

2.2. Extended Edge Histogram Descriptor EEHD

In the EEHD descriptor [9], edges are grouped into five categories Horizontal(*H*), Vertical (*V*), diagonal (*D*), anti-diagonals (*A*), and Nondirectional *(N)*. First, given an image and its dimensions are multiple of two, otherwise it is padded by zeros to make it a multiple of 2. To extract the edge features from the image, digital filters/masks are applied to discover these edge directions in the spatial domain. In Figure 1, the first four are *3x3* Prewitt mask templates with constant values are ones and no weights are used for discovering the namely *H*-, *V*-, *D*- and *A*- gradients. The Prewitt mask is a discrete first-order differentiation operator computing an approximation of the gradient (/edge image) of the image intensity function by measuring the difference among the adjacent pixels grey level in the specified direction. The Prewitt detector is slightly simpler to implement computationally than Sobel. The *H*-mask is estimating the *H*-gradient in the *x*-direction (columns) and the *V*-mask estimating the *V-g*radient in the *y*-direction (rows). The *D*-mask is estimating the *D*-gradient in the 45°-direction (Diagonal). The *A*-mask is estimating the *A*-gradient in the 135°-direction (Anti-diagonal). The *2x2 N*-is a mask that estimates the *N*-gradient for the Nondirectional edges. To compute the local edge histogram EHD, each one of the five gradients is divided into 4x4 matrix of subimages, i.e., a total of 16 subimages each. Subimages are counted as a raster scan from left to right as appears in Figure 2 which reveals the order of subimages used in the computations. Thus, the histogram for each subimage represents the relative frequency of occurrence of the 5 types of edges in the corresponding sub-image. Each local histogram contains 5 bins. Each bin corresponds to one of 5 edge types. Since there are 16 sub-images in the image, a total of 5x16=80 bins is obtained in the concatenated EHD histogram.

1	0	-1
1	0	-1
1	0	-1

H

1	1	1
0	0	0
-1	-1	-1

V

0	1	1
-1	0	1
-1	-1	0

D

1	1	0
1	0	-1
0	-1	-1

A

2	-2
-2	2

N

Figure. 1: The Masks structure

To compute the 5 bins (*H*, *V*, *D*, *A*, *N*) value for each subimage in the EHD, each subimage is further partitioned into square blocks of size 2. For example, if an image is of size 640x640, then each subimage will be of size 160x160 and if the subimage is divided into 2x2 blocks then each subimage contains 6400 blocks. For each block, the mean value for its four-pixel values are calculated and this is done for all same block positions in the five gradients subimages, then the maximum mean edge value among these corresponding blocks is selected.

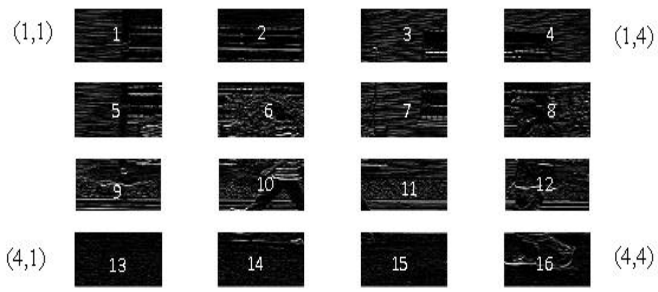


Figure. 2: Dividing a gradient into 4x4 subimages

With the maximum value of a block is above a given threshold, it is classified as edge-block with the corresponding edge orientation, otherwise it is classified as a non-edge block. For example, if a block is categorized as *V*, then the *V*-bin of its subimage is updated by increasing it by 1 and so on. Finally, a matrix M of size $16x5$ is obtained that contains the bin counts of the blocks that belong to a specific edge type for each subimage. In other words, each bin contains the counts of blocks considered as V edge for example, the cell $M(i, j)$ contains the number of blocks in subimage i that got maximum average value at gradient j, where $i=1, \ldots, 16$, $j=1, \ldots, 5$. Using M, the EHD histogram of 80 bins is constructed.

For a better performance, the EHD is expanded and named Extended Edge Histogram Descriptor (EEHD) to include global edge distribution and semi-global edge. From matrix M, these edge histograms are obtained and concatenated in one edge histogram defining the EEHD. Different grouping of subimages (extracted from the 16 subimages shown in Figure 2) are used to compute EEHD histogram that consists of 70 more bins than EHD for a total of 150 bins. A 65 bin semi-global edge histogram are calculated as follows: First, a 20 bins-Horizontal histogram is calculated from the five gradients by averaging a 4 horizontal subimages' group sets: $set1 = \{1, 2, 3, 4\}$, $set2 = \{5, 6, 7, 8\}$, $set3= \{9, 10, 11, 12\}$, and $set4= \{13, 14, 15, 16\}$. Similarly, the Vertical histogram 20 bins are calculated from the 4 vertical subimages' group sets: $set5= \{1, 5, 9,13\}$, $set6= \{2 ,6, 10, 14\}$, $set7= \{3, 7, 11, 15\}$, and $set8= \{4, 8, 12, 16\}$. Similarly, 25 bins- Neighbor edge histogram is calculated from the group sets are: $set9= \{1, 2, 5, 6\}$, $set10= \{3, 4, 7, 8\}$, $set11= \{9, 10, 13, 14\}$, $set12= \{11, 12, 15, 16\}$, and the $set13= \{6, 7, 10, 11\}$ which define the center group of subimages and its 4-neighbor subimages' groups. A 5 bins-global edge histogram represents the edge distribution for the whole image represented by accumulating edge bins for all the 16 sub-images in each gradient which results in the average bins for the 5 types of edges for the 16 subimages. Listing 2 shows the symbols used for the edge histograms.

3. The Proposed Methodology BoEFC

The BoEFC methodology introduces a new idea which is based on retrieving similar images by correlating individual or collective selection of Extended Feature Components (EFCs). The methodology consists of three phases: Feature Extraction (FE), Feature Matching (FM) and Feature Ranking (FR). In FE, the filters in Figure 1 was used with size $3x3$ except for N (size $2x2$). The filter size $3x3$ was found more suitable for gradients since the detected edges when using a larger size such as 5x5 masks produces thicker than that with a $3x3$. The BoEFC main algorithm is found in listing 6.

3.1 BoEFC FE Phase

In $BoEFC_{LCH}FE$ (listing 1), there are 3-color space components L, a, and b for an image I so the set of feature components $FC_{LCH}= \{FC_{LCH,i}\}$, $i \in A'$, $A'= \{L, a, b\}$ then the corresponding set of Extended Feature Components EFC_{LCH} is constructed. Using the histogram bins of L, a, and b, the one ($A^{'}$), two ($A^{''}$) or three-FCs ($A^{'''}$) are constructed, each is named EFC. The set of $EFC_{LCH} = \{EFC_{LCH,i}\}$, $i \in A$, $A=A^{'} \cup A'' \cup A'''= \{L, a, b\} \cup \{La, Lb, ab\} \cup \{Lab\}$, where $FC_{LCH} \subseteq EFC_{LCH}$. The algorithm is summarized as follows: the image is first smoothed with a gaussian filter of size 7 then converted to CIE-Lab color system. Next, the image is divided into 4x4 subimage and for each subimage in each of the color space component *in* A', then a color histogram is computed. for each feature in EFC_{LCH}. For each $EFC_{LCH,i}$ where $i \in A'$, the corresponding histogram contains only two non-zero at bin number 0 and bin number 255 then the total feature values are 32 values for the 16 subimages in one image. For $EFC_{LCH,i}$ where $i \in A''$, their corresponding feature vector is the fusion of some $EFC_{LCH,i}$ where $i \in A'$. Hence for each subimage there are four values two are residing at bins number 0 and the other two at bins number 255 in their histograms, for a total of 64 values. For $EFC_{LCH,i}$ where $i \in A'''$, the feature vector contains 6 values, three at the 0 and 255 bins which gives a total of 96 values. In Listing 1, the set EFC_{LCH} is saved in FDB1 and is used in the retrieval process for the images when using EFC_{LCH} features.

Listing 1: BoEFC$_{LCH}$FE Algorithm

EFC$_{LCH}$ **=BoEFC$_{LCH}$FE (*I*)**
Input: Image I,
Output: The extended feature components ***EFC$_{LCH}$***,
Step1: Smooth *I* with Gaussian filter size 7, convert *I* into Lab color space
Step2: $\forall$color component *i* in *A'*,
  2.1- Divide *i* into a set of *4x4* subimages.
  2.2- $\forall$ subimage in *I*, calculate its color histogram, store its histogram bins'values in $FC_{LCH,i}$
  2.3- $FC_{LCH}= \{FC_{LCH,i}\}, i \in A'$.
Step3: Construct the set $\boldsymbol{EFC_{LCH}= \{EFC_{LCH,i},\ i \in A\}}$ using FC_{LCH} and then save it in FDB1.

The BoEFC$_{EEHD}$FE algorithm (listing 2 and 3) uses feature symbols to define its FCs and for constructing its EFCs. In listing 2, The set $FC_{EEHD}=\{FC\}_{EEHD,j}$, $j \in B'$, $B'=\{$ *l*, *v*, *h*, *n*, *g*, *s*, and *a*$\}$. The set of $EFC_{EEHD}=\{EFC_{EEHD,j}\}$, $j \in B$, $B=B' \cup \{lv, lh, ln, ls, lg, vh, vn, vg, hn, hg, ng, sg, lvh, lvn, lvg, lvhg\}$, where $FC_{EEHD} \subseteq EFC_{EEHD}$. Then, the set of features EFC_{EEHD} is saved in FDB2. In Fact, EFC_{EEHD} can have more than twenty-three elements, but these extra elements may give the same type and number of bins. Only the ones in listing 3 are the ones that gives different bins.

Listing 2. Name conventions for EEHD feature symbols

1. *'l'*: denotes the first 80 bins that defines the local features
2. *'s'*: denotes the Semi-global 65 bins that defines the features *'s'* and consists of the following bins:
   - *'v':* denotes the 20 bins resulted from the vertical group,
   - *'h':* denotes the 20 bins resulted from the horizontal group,
   - *'n':* denotes the 25 bins resulted from the neighbor group,
3. *'g'*: denotes the 5 bins global histogram,
4. *'a'*: denotes all these 150 bins together.

Listing 3: BoEFC$_{EEHD}$FE Algorithm

EFC$_{EEHD}$ **=BoEFC$_{EEHD}$FE (*I*)**
Input: Image I,
Output: Extended feature components ***EFC$_{EEHD}$***,
Step 1: Convert the RGB image *I* into gray image I_g.
Step 2.1: Get the set $E = \{H, V, D, A, N\}$ of the edge gradients of I_g.
  2.2: Divide each gradient in *E* into 4x4 subimages constructing a set of divided gradients *E'*
Step 3: For each same subimage *u* in *E'* do the following:
  3.1: Divide *u* into blocks, obtain the mean value of the block pixel values and get the max mean edge value among corresponding blocks in gradients of *E'*.
  3.2: Determine which bin in *E* this max value belongs to.
  3.3: Construct matrix *M* and Update the wining histogram bins
  3.4: The histograms bins are then concatenated for a local, global and semiglobal description of I_u (listing 2).
Step 4: For each $j \in B'$, Construct a feature vector $FC_{EEHD,j}$, for $j \in B'$
Step 5: From $FC_{EEHD,j}$, $j \in B'$ obtain the set, $\boldsymbol{EFC_{EEHD}= \{EFC_{EEHD,j},\ j \in B\}}$ then save it in FDB2

In $\mathrm{BoEFC}_{\mathrm{EEHD\_LCH}}\mathrm{FE}$ (listing 4), there is a set *{(m, n): m∈A and n∈B}* including *161* fused *EFCs* that are considered the main target for the BoEFC methodology. They are used to test the importance and strength of this variant collection of *EFCs* regarding image matching. By using the two sets of features EFC_{LCH} and EFC_{EEHD}, a third database FDB3 is built which is merely the fusion of the features from EFC_{LCH} and EFC_{EEHD}.

Listing 4: $\mathrm{BoEFC}_{\mathrm{EEHD\_LCH}}\mathrm{FE}$ Algorithm
$\boldsymbol{EFC_{EEHD\_LCH}}$=$\mathbf{BoEFC_{EEHD\_LCH}}$ **FE (*I*)** **Input:** Image I, **Output:** Extended feature components $\boldsymbol{EFC_{EHD\_LCH}}$, Step1: For each $i \in A$, for each $j \in B$, 1.1. $\boldsymbol{EFC_{LCH,i}}$ =$\mathrm{BoEFC_{LCH}FE}$ (*I*) (using Listing 1) 1.2. $\boldsymbol{EFC_{EEHD,j}}$ =$\mathrm{BoEFC_{EEHD}FE}$ (*I*) (using Listing 3) 1.3 Blend the features [$\boldsymbol{EFC_{LCH,i}}$ $\boldsymbol{EFC_{EEHD,j}}$] in feature vector $EFC_{EEHD\_LCH},_{i,j}$ Step2: Save the set $\boldsymbol{EFC_{EEHD\_LCH}} = \{\boldsymbol{EFC_{EEHD\_LCH,i,j}}\ i \in A, j \in B\}$ in FDB3

3.2 BoEFC FM Phase

Similarity measures have two main factors, selecting the distance function and the method of application on feature vectors. Primarily, there are many types of distance measures in the literature, some perform well in some applications and others don't. In this paper, Chi-square distance is best used to compare histograms. The chi-squared distance between two vectors x and y is defined as: $d(x, y) = \sum_{i=1}^{n} \frac{(x_i - y_i)^2}{x_i + y_i}$. The chi-squared distance is useful when comparing histograms. The $BoEFC$ similarity measure application employs some new adapted similarity measures.

Firstly, for matching the sets EFC_{LCH} of the corresponding images, an adapted chi-square distance is used as a similarity measure and named $BoEFC_{LCH}FM$ specific to some $c \in A$ and is defined as:

$$\mathrm{BoEFC_{LCH}}FM(\alpha^c, \beta^c) = \sum_{i=1,j=1}^{16,n} \frac{(\alpha_{i,j}^c - \beta_{i,j}^c)^2}{\alpha_{i,j}^c + \beta_{i,j}^c} \quad (1)$$

Where, α^c *and* β^c both are $EFC_{LCH,c}$, $c \in A$ which are already saved in FDB1 and contains the histogram bins of the component *c* for a pair of images to be compared. The index *j* is referring to the j^{th} bin in the histogram corresponding to the i^{th} subimage, $j=1,...,n$ where *n* is the number of bins. For example, if $c=L$ then $n=2$ for each of the 16 subimages then it is total 32 values to compare for each image. This distance is used for measuring similarity of images based on EFC_{LCH} features. In general, each subimage *EFC* of a query is compared with the corresponding subimage *EFC* for each image in IDB.

Secondly, for matching the corresponding $\boldsymbol{EFC_{EHD}}$ of the images, an adapted Manhattan distance is used and named $\mathrm{BoEFC}_{EEHD}FM$ specific to some $c' \in \mathrm{B}$ and is defined as:

$$\mathrm{BoEFC}_{EEHD}FM\left(\alpha^{c'}, \beta^{c'}\right) = \sum_{j=1}^{n} \left|\alpha_{c',j} - \beta_{c',j}\right| \quad (2)$$

Where, $\alpha^{c'}$ and $\beta^{c'}$ both are $\boldsymbol{EFC_{EEHD,c'}}$, for selected $c' \in B$ saved in FDB2 and contains the histogram bins of c' for a pair of images to be compared. The index *j* is the index referring to the j^{th} bin in c' and *n* is the number of bins in the feature $EFC_{\boldsymbol{EEHD},c'}$, for example if c'=lvgh then n=150 and if c'=s then n=65.

Thirdly, for matching the corresponding EFC_{EEHD_LCH} of the images, a new similarity measure $\text{BoEFC}_{EEHD\_LCH}FM$ is defined as based on the two previous adapted measures. It is taking the mean value of $\text{BoEFC}_{EEHD}FM$ and $\text{BoEFC}_{LCH}FM$ given $EFC_{LCH,c}$, $c \in A$ and $EFC_{\boldsymbol{EEHD},c'}$, $c' \in B$, as follows:

$$\text{BoEFC}_{EEHD\_LCH}FM\left(\alpha^{c,c'},\beta^{c,c'}\right) = \text{mean}\ (\text{BoEFC}_{LCH}FM\left(\alpha^{c,c'},\ \beta^{c,c'}\right), \text{BoEFC}_{EEHD}FM\left(\alpha^{c,c'},\ \beta^{c,c'}\right)\ ) \tag{3}$$

Where, $\alpha^{c,c'}$ and $\beta^{c,c'}$ both are $\text{EFC}_{c,c'}$ for selected $c \in$A and $c' \in B$. Retrieving based on EFC_{LCH} and $EFC_{\boldsymbol{EEHD}}$ is usually used for analysis and comparisons purposes only. Regarding $\text{BoEFC}_{\text{LCH}}FM$, the image features may be compared based on any selected $EFC_{LCH,c} \in EFC_{LCH}$, $c \in A$ this offers up to seven options used to compare the subimages of different images. Concerning $\text{BoEFC}_{EEHD}FM$, the image features may be compared based on any selected $EFC_{\boldsymbol{EEHD},c'} \in EFC_{EEHD}$, $c' \in$B this offers up to twenty-three different options used to compare the subimages of different images. In $\text{BoEFC}_{\text{EEHD\_LCH}}FM$, the similarity experiment explores a huge space of *EFC*s which is utilized in retrieving more relevant images.

3.3 BoEFC FR phase

A proper approach to characterize the performance of the BoEFC is to examine the retrieved images and calculate the well-known retrieval performance measures known as the Precision (P) and Recall (R) change for different *EFC*s. P measures the accuracy of the retrieval and represents the chances of the predicted target to be a true target while R measures the robustness of the retrieval and the chance of having predicted the entire true targets. $P= r\ /\ n$ is defined as the ratio of the number of retrieved relevant images r to the total number of retrieved images n. $R = r\ /\ m$ is defined as the ratio of the number of retrieved relevant images r to the total number m of relevant images in the whole database. Relevancy can be estimated using either similar in all the image contents or part of it. For example, the image that mainly containing water, vegetation, and boats then consequently its relevant images are the images that contain one or more of these three contents. While the images that contain neither of these three contents are considered irrelevant. For example, given a rose query image, a good system ranks rose images near the top of the list and be able to retrieve a lot of rose images before retrieving any cats so P will stay high as R increases. The *NR*-precision is defined as the number of *NR*-top relevant images used as a fixed cutoff for precision calculation.

We define a new measure called G^+-based precision as the number of retrieved is varied according to the size of the ground truth G of a query where G is determined by the image maker according to its acquision location/time because visually the relevant images can be more than G. The G^+ is determined by allowing h more relevant than G hence the precision is computed at $G^+=G+h$. For example, if there are $G=4$ ground truth images in the DB relevant to a query and h=10 then $G^+=14$ which will be the number of the top ranked images. The G^+-based precision is the relevancy fraction $NV/\ G^+$. The recall is calculated with respect to G of the query while the precision is calculated with respect to G^+.

In listing 5, the BoEFC_xFMFR algorithm is utilized in similarity and ranking, the ranking steps are shown in step 4, 5 and 6. Let $X= \{LCH, EEHD, EEHD\_LCH\}$ be the set of possible *EFC*s types and:

NR_x = Number of Retrieved images using $x \in X$,

NV_x = Number of releVant images in the retrieval results using $x \in X$,
ND = Number of relevant images in the selected Database,
Then given a query, the BoEFC performance is measured using the following adapted Precision and Recall equations:

$$\text{BoEFC\_Precision} = max_{x \in X}\ Prec_x,$$
$$\text{where } Prec_x = max_{z \in EFC_x}\ Prec_z \text{ and } Prec_z = \frac{NV_z}{NR_z}, \quad (4)$$

$$\text{BoEFC\_Recall} = max_{x \in X}\ Rec_x$$
$$\text{where } Rec_x = max_{z \in EFC_x}\ Rec_z \text{ and } Rec_z = \frac{NV_z}{ND}, where\ x \in X \quad (5)$$

The final ranking introduced to the user is based on accumulating relevant retrieval images from the retrieval results of any $x \in X$. For example, if x= *EEHD_LCH* this consists of 161 *EFCs* from which the $Prec_{EEHD\_LCH}$ is calculated then the precision is computed from the retrieval results for each *EFC* and keep the maximum precision obtained and this is the value of BoEFC_Precision. To display the final retrieval results from x, similar images repeated in different *EFCs* retrievals will only displayed once with the minimum distance obtained. In addition, the Mean Average Precision BoEFC mAP for a set of queries q is the mean Average Precision score for all queries q. Then,

$$\text{BoEFC\_mAP} = mean_{x \in X}\ mAP_x \text{ and,}$$
$$\text{BoEFC\_mAR} = mean_{x \in X}\ mAR_x.$$

Where $mAP_x = mean_{q \in Q}\, Prec_{x,q}$ and $mAR_x = mean_{q \in Q}\, Rec_{x,q}$ (6)

Precision-Recall PR curves are used as well to compare the performance of the different *EFC*s. Overall, the larger the area under the PR curve an algorithm has, the better it is as can be seen from Figure5, where it plots precision p as a function of the recall r.

Listing 5: BoEFC_xFMFR Algorithm, $x \in X$
[distances, Precision, Recall] =**$\mathbf{BoEFC_x}$ FMFR** (q, FDB_x)
Input: query image q, Feature database of x
Output: Distances between q and images in the selected FDB, Precision and recall
Step1: Extract BoEFC_x features for q
Step2: Compute BoEFC_xFM between EFC_x of q and the EFC_x of each image in FDB_x
Step3: Sort distances
Step4: Display the images in order according to the closest distance to q
Step5: Calculate $Prec_x\ and\ Rec_x$

3.4 The BoEFC key Algorithm

The methodology is demonstrated in listing 6, some features are considered by blending while some are neglected for the purpose of testing the strength of these *EFC*s. Although at the end up, all *EFC*s are adopted and examined for the final retrieval showing their strength or weakness. The retrieval results presented to the user are the relevant images jointly appeared in each of the retrieval results of the selected *EFC*s. The suggested methodology BoEFC may have a better user approval because it presents the user with the option of displaying just the relevant images by trying all *EFC*s as will explained later. Figure 3 shows the BoEFC process stream which includes two phases, the feature extraction and feature matching.

Listing 6: BoEFC Key Algorithm:

Result= BoEFC Methodology (IDB, q, choice)
Input: IDB: Image DataBase, q: query image, Choice: variable used to select which algorithm to run
Output: Result=Ranked scores, retrieval results and Performance

BoEFC FE Phase:

For each I in IDB
if $choice$=1, $EFC_{\boldsymbol{LCH}}$ =BoEFC$_{\mathrm{LCH}}$FE (I)
else if $choice$=2, $EFC_{\boldsymbol{EEHD}}$ =BoEFC$_{\mathrm{EEHD}}$FE (I)
else EFC_{EEHD_LCH} =BoEFC$_{\mathrm{EEHD_LCH}}$FE (I)

BoEFC FM Phase:

Step1: For query image q, Extract EFC_{LCH}', EFC_{EEHD}', and $EFC_{\mathrm{EEHD\_LCH}}'$
Step2: if $choice$=1,
$Scores1$=BoEFC$_{LCH}$FMFR(EFC_{LCH}', $FDB1$), Retrieve relevant images if needed
elseif $choice$=2,
$Scores2$=BoEFC$_{EEHD}$FMFR(EFC_{EEHD}', $FDB2$), Retrieve relevant images if needed
else
$Scores3$=BoEFC$_{EEHD_LCH}$FMFR(EFC_{EEHD_LCH}', $FDB3$), Retrieve relevant images to user

BoEFC FR Phase:

Calculate BoEFC_Precision, BoEFC_Recall, BoEFC _mAP, BoEFC_ mAR and draw PR-curves.

4. Experimental Results and Discussion

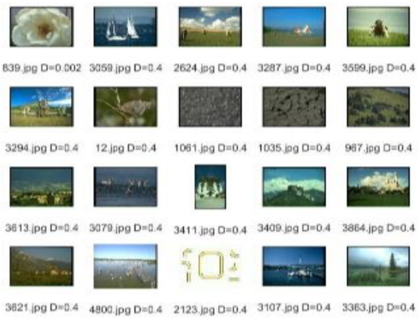
The BoEFC experiments were performed on two image databases. The 1^{st} is a general-purpose image database has number of images 10,000 images which are non-noisy, miscellaneous, and low-resolution of small size around 85x128. It was used to evaluate the Stanford Wavelet-Based Image Indexing and Searching system WBIIS [12] which was updated and categorized later to a Corel database benchmark. The 2^{nd} is the Holiday database benchmark [13] which has number of images 1490 images with non-noisy, miscellaneous, and high-resolution images of large size around 3260x2250. The following figures show some experiments on the 1^{st} database to illustrate that changing EFCs affects the retrieval results, Figure 3(a),3(b) and 3(c) shows different retrieval results using the $EFC_{LCH,L}$ and the $EFC_{EEHD,v}$, $EFC_{EEHD,h}$ and $EFC_{EEHD,vh}$. Next, changing just $EFC_{LCH,L}$ to $EFC_{LCH,a}$ and checking the retrieval then different results are obtained as shown in Figure 3(d), 3(e) and 3(f). This proves that generally varying EFCs harvests different results and hence affect the order of appearance of retrieved images. In the overall, given a query image and collecting the retrieval results from various EFCs should present better retrieval results for the user and hence more user satisfaction.

Figure 4 introduces a rose query image, where Figure 4(a) shows retrieving using the EFC_{LCH} yields 11 relevant images while EFC_{EEHD} retrieval in Figure 4(b) shows retrieval which yields 58 relevant images. In Figure 4(c) retrieval using EFC_{EEHD_LCH} results in 75 relevant images out from 101 relevant images indicating better retrieval performance for the BoEFC methodology.

a) Retrieval using $EFC_{LCH,L}$ and $EFC_{EEHD,v}$

b) Retrieval using $EFC_{LCH,L}$ and $EFC_{EEHD,h}$

c) Retrieval using $EFC_{LCH,L}$ and $EFC_{EEHD,vh}$



d) Retrieval using $EFC_{LCH,a}$ and $EFC_{EEHD,v}$

e) Retrieval using $EFC_{LCH,a}$ and $EFC_{EEHD,h}$

f) Retrieval using $EFC_{LCH,a}$ and $EFC_{EEHD,vh}$

Figure. 3: Comparing retrieval changing components for EFC_{LCH} and EFC_{EEHD}

Figure 5 shows the PR-curves of the retrieval for the image in Figure 4. In Figure 5(a), the performance of the set $EFC_{EEHD\_LCH}= \{EFC_{EEHD\_LCH,i,j}\}$, $i \in$A and $j \in B$ of all possible EFCs consisting of 161 EFCs shows the change of performance while changing the EFC. In general, this performance is heading to the top of the drawn graphs which means if resulted relevant images are collected from different EFCs it may increase the overall retrieval precision. This also means that it is most probably that the retrieval performance will be boosted by the collective retrieval and there is at least one EFC that provides a better performance and has a higher share than the other EFCs. The BoEFC$_{EEHD}$FE performance is good so far indicated in Figure 5(c). When the features EFC_{LCH} are combined with all other features EFC$_{EEHD}$ as shown in Figure 5 (d-i), it is noticed that it is also largely participates in Figure 5(a). This claims the idea that each feature component behaves differently as singular or as participator with another component. We can say that this image retrieval performance could rely on the $EFC_{LCH,L}$ since it shows that it gives better precision and recall (Figure 5(h)). But the different *EFC*s may behave differently with different images but with the advantage of introducing images returned from all *EFC*s.

a) using EFC_{LCH}: 11 relevant images

b) using EFC_{EEHD}: 58 relevant images (including c and d)

c) Continued

d) Continued

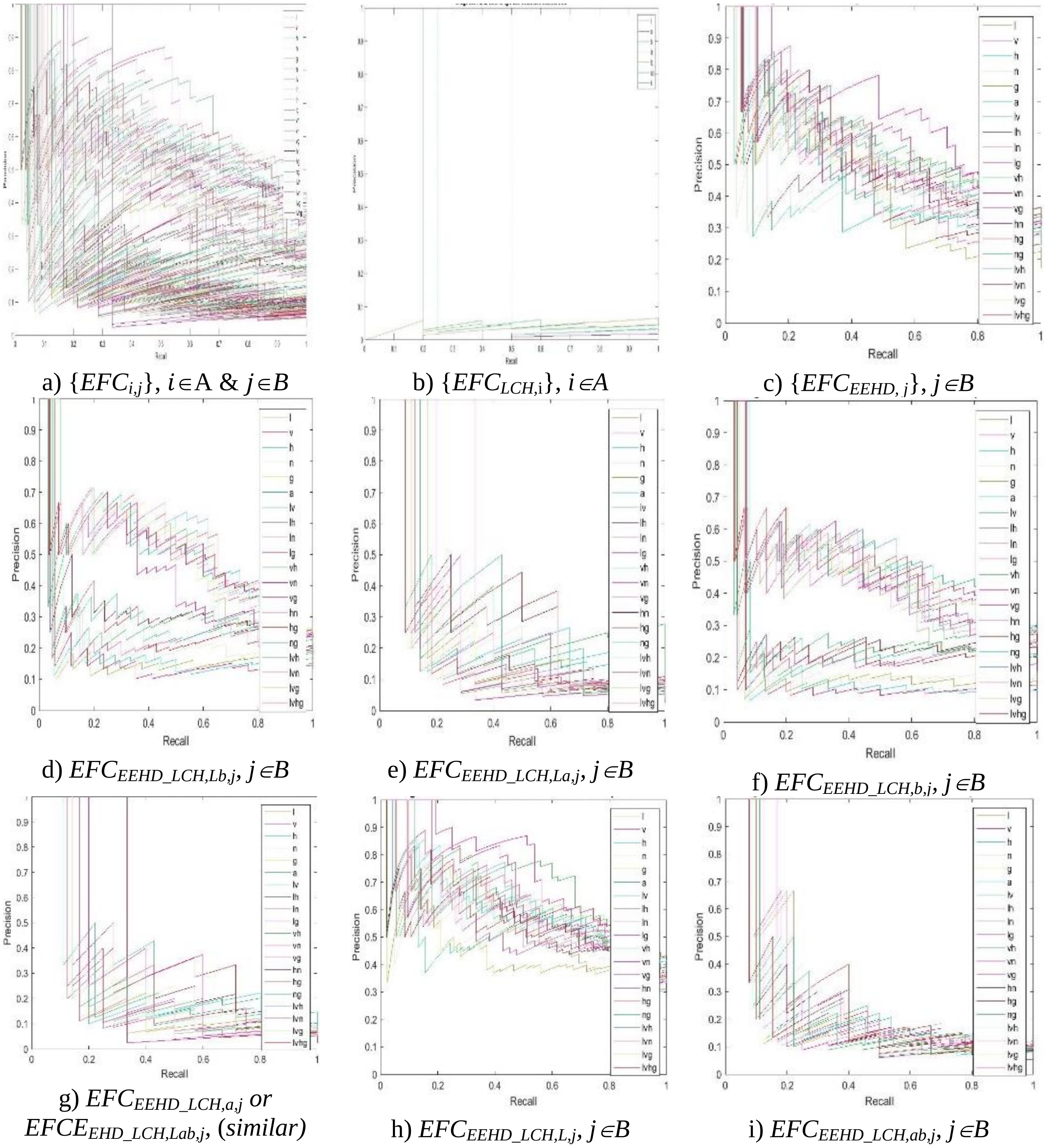
e) EFC_{EEHD_LCH}: 75 relevant images (including f, g, h)

f) Continued

g) Continued

h) Continued

Figure. 4: Final retrieval blending all EFCs of $BoEFC_{EEHD\_LCH}$ (1^{st} database)



a) $\{EFC_{i,j}\}$, $i \in A$ & $j \in B$

b) $\{EFC_{LCH,i}\}$, $i \in A$

c) $\{EFC_{EEHD,j}\}$, $j \in B$

d) $EFC_{EEHD\_LCH,Lb,j}$, $j \in B$

e) $EFC_{EEHD\_LCH,La,j}$, $j \in B$

f) $EFC_{EEHD\_LCH,b,j}$, $j \in B$

g) $EFC_{EEHD\_LCH,a,j}$ or $EFCE_{EHD\_LCH,Lab,j}$, (similar)

h) $EFC_{EEHD\_LCH,L,j}$, $j \in B$

i) $EFC_{EEHD\_LCH,ab,j}$, $j \in B$

Figure. 5: PR curves for the EFC_{LCH}, EFC_{EHD}, EFC_{EHD_LCH} for the image in Figure. 4 (1st database)

The INRIA Holidays database is a mixture of object and scene images and consists of vacation photographs corresponding to 500 groups based on same scene/object with different orientations, viewpoint, and illumination where the scene types include nature, man-made, water and fire effects, etc. They determine the ground truth of an image as the first image of each group is the query image and the subsequent are all the relevant images until a different theme appears. In this paper, images are compared with respect to EFC_{LCH}, EFC_{EEHD} or EFC_{EEHD_LCH}. This big variety of feature components provided better retrieval results, for example in Figure 4-(e) total of 75 consequent relevant images are collected from all feature components out of 101 consequent relevant images while most of their methodologies display the top 10 images. Applying BoEFC methodology on the an image from the Holiday database, the retrieval results were obtained for the image in Figure 6, the number of ground images relevant to this image in the database are 16 images. The quality of EFC_{EEHD_LCH} retrieved images in Figure 6(c) is better than of the EFC_{LCH} results in Figure 6(a) and of the EFC_{EEHD} results in Figure 6(b). The BoEFC results in Figure 6(c) retrieved 13 images out of the 16 ground images which came from *EEHD_LCH* results. Table 1 is showing an ascendingly increasing mAP and mAR values indicating the performance for the blending process for a set of queries Q with size 50 images. Table 2 displays number of retrieved images for some image categories in the Holidat database. It is notied that for $q \in Q$, 80% of BoEFC_Precision and _Recall obtained its maximum precision or recall is obtained from $BoEFC_{EEHD\_LCH}$ (Figures 7 and 8) which indicates that blending process is benificial to the retrieval process.

Table 1: BoEFC mAP and mAR over Q (Holiday image database)

Selected method of retrieval	**mAP (G^+-based)**	**mAR (G-based)**
$BoEFC_{EEHD}$	0.54	0.58
$BoEFC_{LCH}$	0.61	0.64
$BoEFC_{EEHD\_LCH}$	0.72	0.74
BoEFC	0.76	0.80

Table 2: BoEFC number of Retrieved images for some categories (Holiday image database)

Query Images Category	**BoEFC Number of retrieved images**
Green Landscape (see image in Figure 6)	13 out of 16
Coral Reefs	12 out of 13
Buildings	12 out of 14
Trees and street light	8 out of 14
High Buildings &water	12 out of 14

Comparison with the state-of-art

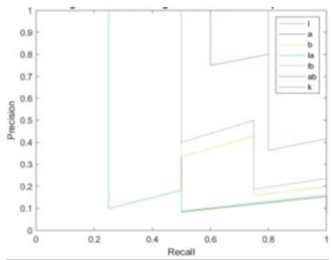
Regarding to comparison with similar methodologies in literature, there is no exact match to the proposed approach since in this paper color and texture feature components and their extension EFCs are extracted and blended and used in comparison individually and collectively. The most comparable methodologies showing the combination of color and texture feature are discussed here. The research in [9] proposed a technique to fuse color and texture features. Color Histogram is used to extract a global color information. Texture features are extracted by Discrete Wavelet Transform global descriptor and EHD. The features are created for each image and stored as a feature vector in the database. They used image database of size 1000 images which are divided into 10 themes. They utilized Manhtten distance and introduced results for fixed top 20 images with average precision 0.73 while our approach achieved average precision 0.76. The research in [14] introduces image retrieval based on the integeration between the color system YCbCr as a global feature and EEHD as local feature. It divides the luminance (Y) into eight regions, whereas each of chromic components (Cb, Cr) is divided into four regions. The three color components then are linked, thus creating a (8x4x4) histogram of 128 bins while EEHD has 150 bins. It uses Bhattacharyya distance for LCH and modified Eucledian distance for EEHD to compare local, semiglobal and global histograms correspondingly. The proposed technique is compared with the HSV histogram, Fuzzy Color and Texture Histogram and the MPEG7 descriptors.

The results claim that the proposed technique is better than the previous approaches. The author used a database of 2338 image of almost 14 themes and their retrieval scheme is focused on fixed top ten images while in BoEFC a variant number of top image using the new G^+-based precision or recall. Hence, if number of images in the ground truth is greater than the fixed number of the top images, varying the top images number will allow better estimation for the precision and recall.

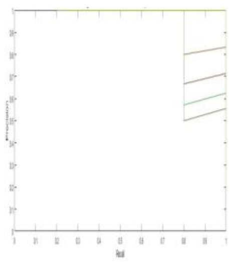
(a) EFC_{LCH} retrieval results

(b) EFC_{EEHD} retrieval results

(c) EFC_{EEHD_LCH} retrieval results



(d) using $\{EFC_{LCH,i}\}$, $i \in A$



(e) $\{EFC_{EEHD\_LCH,k,j}\}$, $j \in B$

Figure. 6: BoEFC results with Holiday datase with respect to its given Ground truth(G^+-based)

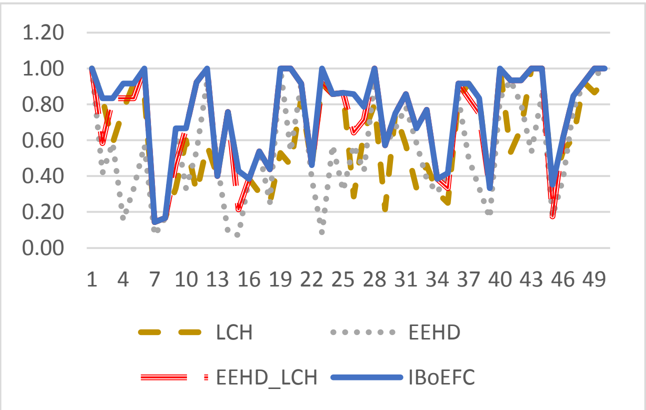


Figure. 7: BoEFC Precision of 50 queries in Holiday DB

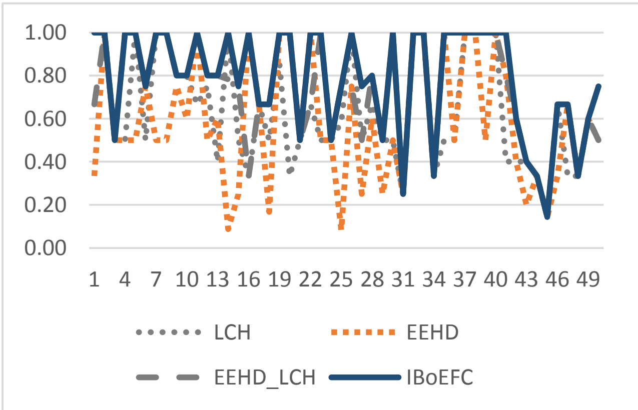


Figure. 8: BoEFC Recall of 50 queries in Holiday DB

The research in [15] which uses Holiday database proposes an approach to generate permutations for Deep convolutional neural networks for image retrieval at low computational cost, when objects to be indexed are Deep image Features. They showed that their generated permutations are more effective than those obtained using pivot selection criteria. Their calculated mAP reached 0.75 on full permutation while the proposed approach reaches 0.76 without Deep learning. The research in [16] presents a retrieval method based on combination of local texture information derived from two different texture descriptors using SIMPLICITY image database. First, the RGB color channels of the input image are separated.The texture information is extracted using two descriptors such as evaluated LBP and predefined pattern units. After extracting the features, the similarity matching is based on Euclidean distance using a weighted combination of color and texture features. In their paper, several distance metrics such as Cosine, Euclidean, Logarithmic likelihood ratio, city block, etc were tested and the Euclidean metric provided the highest retrieval accuracy. In this paper, the chi-square distance is used for matching LCH color histograms while using Manhatten distance for matching the EEHD edge histograms. Actually the Chi-square and Logarithmic likelihood metrics were tried for LCH matching and found that chi-square outperformed. In addition, Manhaten distance was tried and other metrics such as eucledian distance and found that manhaten gave good performance. Another difference is that in their approach they combine texture features from two different descriptors but in BoEFC the companents of color and texture features are combined. The research in [17] proposed a retrieval based on weighted similarity measure applied on color and texture features separatly. They varied distances to evaluate results such as Eucledian, Chebyshev, Chi-square, Manhaten, Canberra, etc. Texture features are extracted using MLBP, LNDP and GLCM and quantization color histogram is used to extract color features. Results were evaluated on Corel 1 K and Corel 10k datasets and showed that canberra distance (0.48) and its extended version gave a little better precision than Chi-square (0.42) for individual query images while in this paper mAP (0.76) and mAR(0.80) are reported giving an average precision for a group of 50 query images.

5. Conclusion

This paper presents a new methodology BoEFC for image retrieval that is based on the blending of many feature components constructing EFC to collect more relevant images for better user satisfaction. Using a varied blending of feature components gave increased result as contrasted to individual feature components. Local features are extracted by a new-found application of EEHD and LCH. Similarities are examined by customized similarity measure distances and PR-curves are plotted to show the performance of BoEFC methodology. Experimental results demonstrated more relevant images retrieval than individual feature component retrievals using an integrated blend of extended feature components. Results was compared with the state-of-the-art methodologies. This idea can be generalized to any feature descriptor by blending its components with other feature (s) components where some components may act better than others as shown by figures. The proposed methodology appears to have both better precision and recall compared to others as reported in the comparison with the state-of-art and it achieved mAP 0.76 and mAR 0.80. As a future work, learning can be used in combination with BoEFC for additional improvement.

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