Medical Image Retrieval based on Multi-class SVM and Correlated Categories Vector

Ki-Hee Park* ***Associate Member***, ByoungChul Ko*, Jae-Yeal Nam* ***Regular Members***

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ABSTRACT

This paper proposes a novel algorithm for the efficient classification and retrieval of medical images. After color and edge features are extracted from medical images, these two feature vectors are then applied to a multi-class Support Vector Machine, to give membership vectors. Thereafter, the two membership vectors are combined into an ensemble feature vector. Also, to reduce the search time, Correlated Categories Vector is proposed for similarity matching. The experimental results show that the proposed system improves the retrieval performance when compared to other methods.

Ⅰ. Introduction

With the increase in digitalized medical images, various medical assistance systems have also been introduced that integrate database management, an image search engine, image classification, and image annotation. In particular, the image classification and content-based image retrieval of medical images are important issues for computer-aided diagnosis.

Since medical images can be interpreted differently according to the observer's viewpoint and sometimes consist of important foreground regions and meaningless background, diverse classification and retrieval methods are required depending on the type of medical image. Traditionally, medical images have been classified by experts and retrieved using just text. Yet, traditional classification and retrieval can produce irrecoverable mismatches according to the subjectivity and viewpoint of the experts[1]. Furthermore, this kind of retrieval is costly and time consuming. Thus, to overcome these problems, various types of classification and retrieval methods[2]-[6] have been proposed over the last few decades.

Liu and Dellaert[2] proposed an image retrieval framework centered on a classification-driven search using a weighted similarity metric based on the image semantics. In this case, image classification is used as an image index feature selection tool to find a good similarity metric for image retrieval, and 3D grey-level neuroradiological images were used to test the performance.

Mojsilovic et al.[3] proposed a new approach for the automatic categorization of medical images according to their modalities. In this method, a semantic set of visual features, relevance, and organization methods are used to capture the semantics of different image modalities.

Greenspan[4] proposed a continuous and probabilistic image representation scheme using Gaussian Mixture Modeling (GMM) along with information-theoretic image matching via the the KL (Kullback-Leibler) distance. The GMM-KL framework is then used for matching and categorizing x-ray

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* 계명대학교 컴퓨터공학과 ({khp5500, niceko, jynam}@kmu.ac.kr)
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images by body regions.

Bhattacharya et al.[5] presented a learning-based framework for medical image retrieval by linearly combining supervised (probabilistic multi-class support vector machine) and unsupervised (fuzzy c-mean clustering) learning techniques. From the membership scores obtained from the learning algorithm, a fusion-based similarity matching function is employed to retrieve the most similar images compared to the query image.

Mueen et al.[6] proposed a multilevel automatic medical image annotation and retrieval method via keywords based on a concept hierarchy or class hierarchy. For automatic feature extraction, a multilevel feature extraction approach is used, which provides global and local level features according to the pixel intensity. To address the concept modeling, a concept hierarchy is constructed by exploiting annotations, while a support vector machine is used to classify images into different classes at every concept hierarchy level. A query is then performed using only keywords (class name).

Accordingly, this paper proposes a novel algorithm for the classification and retrieval of medical images. To classify medical images, a Color Structure Descriptor based on a Harris corner detector (H-CSD) is proposed for color features, while an Edge Histogram Descriptor (EHD) is used for texture features. Next, these extracted feature vectors are applied to a multiclass-SVM, respectively, yielding membership vectors for each image, and the H-CSD and EHD membership vectors are then combined into one ensemble vector. Thereafter, to improve the retrieval accuracy and reduce the search time, a similarity matching method is proposed based on a Correlated Categories Vector (CCV). That is, using the ensemble vector, the CCV records each dimension as '1' or '0' according to the membership score of the corresponding ensemble vector. Finally, similarity matching is only performed for dimensions with a value of '1' in the corresponding CCV.

The contributions of this paper as follows. (1) A modified Color Structure Descriptor based on a Harris corner detector (H-CSD) is proposed for the extraction of color feature from only salient foreground. (2) The output scores of the 2n SVM classifiers are appended to one ensemble vector to preserve the eigen properties of each feature vector. (3) A Correlated Categories Vector (CCV) is proposed for reduce searching time and improve the retrieval performance.

The remainder of this paper is organized as follows. Section 2 describes the algorithms for feature extraction using visual descriptors, and the proposed classification and retrieval for medical images is introduced in Section 3. Section 4 evaluates the accuracy and applicability of the proposed classification method based on experiments, and some final conclusions and areas for future work are presented in Section 5.

Ⅱ. Extraction of Feature Values using Visual Descriptors

For the efficient classification of a lot of medical images into pre-defined categories, feature vectors are first extracted from images stored in a database. In this paper, a Color Structure Descriptor (CSD) is used for color and an Edge Histogram Descriptor (EHD) for texture, as defined in the MEPG-7 standard. In addition, a Harris corner detector is used to modify the CSD, named H-CSD, so that it is only extracted from salient foreground regions.

2.1 Color Structure Descriptor using Harris Corner Detector

Color is one of the most widely used visual features in image retrieval, since it is relatively robust to the viewing angle, translation, and rotation of the image. Therefore, this paper uses a Color Structure Descriptor (CSD) to extract a color vector, as it focuses on identifying localized color distributions using a small window. Furthermore, a CSD supports a better retrieval performance and is also easier to implement than other color descriptors. A CSD represents an image using both a color histogram of the image and the local spatial structure of the color[7]. The elements of a CSD, its size and the number of sub-samplings,

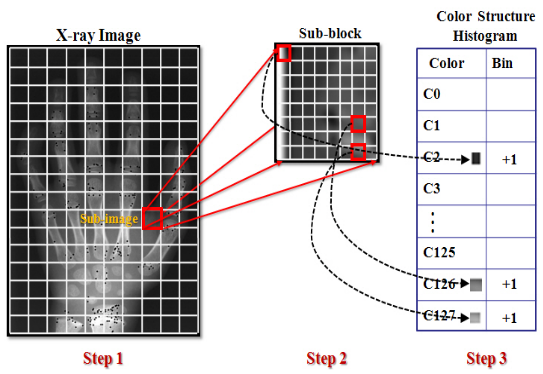

Fig. 1. Feature extraction process of H-CSD using Harris corner detector

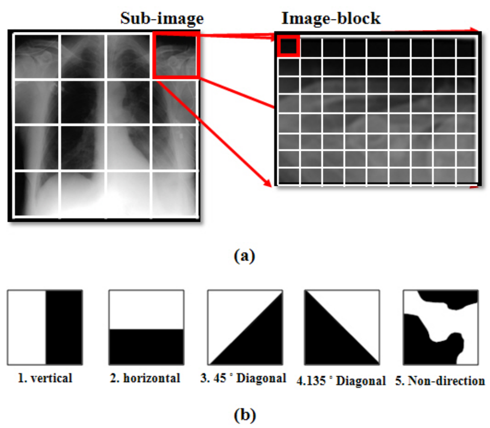

Fig. 2. (a) Definition of sub-image and image-blocks (b) five edge types for edge extraction

are determined flexibly according to the size of the image.

First, the image is quantized based on 128 gray levels, as X-ray images only have a dark background and bright foreground. The image is then divided into N x N sub-blocks, where the size of a sub-block is 8 x 8 pixels, as defined by the MPEG-7 standard. In this paper, a sub-block performs the same function as a structuring element. As shown in Figure 1, since X-ray images contain useless background regions, these regions need to be removed before generating a CS Histogram. Therefore, the Harris corners[8] are first detected from the quantized image, and only sub-blocks containing one or more Harris points are selected. The Harris corner detector is a popular point detector due to its strong invariance and stability against a variation of viewpoint, the illumination direction, scale, and noise. From the selected sub-blocks, a 128-bin CS Histogram is then extracted from an image represented in the 128-quantized gray color space. Thus, the CSD is a 1-D array of m bit-quantized values.

$$CSD = \overline{h_s}(m),\ m \in 1, \ldots, M \tag{1}$$

where M is chosen from the set {256, 128, 64, 32} and s is the scale of the associated structuring element (sub-block). At each sub-block position, the CS Histogram is updated (accumulated) on the basis of the color present within the sub-block. For example, if eight gray levels and eight CS Histograms are created in an 8 x 8 sub-block, the number of relevant bins increases by 1 when the position of the CSD sub-blocks in the image correspond to the pre-divided CS Histogram. In this way, the feature values of an image are the distribution of the number of CSD sub-blocks corresponding to each recorded color histogram. In the final step, the extracted 128-bin CSD is normalized to the range 0~1 for the training of the Support Vector Machine.

2.2 Edge Histogram Descriptor

An EHD[9] represents the distribution of the regional edges in an image. Specifically, the image space is divided into 4x4 non-overlapped sub-images, and then each sub-image is further divided into non-overlapping square image blocks, as shown in Figure 2-(a). The local-edge distribution for each sub-image can be represented by a histogram. To generate the histogram, the edges in the sub-images are categorized into five types: vertical, horizontal, 45 diagonal, 135 diagonal, and non directional edges, as shown in Figure 2-(b). To divide an input image into the same sized sub-images, the size of the image block is decided using Eq. (2).

$$x = \sqrt{\frac{width \times height}{desired\,Nmblock}},\ blocksize = \left\lfloor \frac{x}{2} \right\rfloor \times 2 \tag{2}$$

where the desired Num block is the total number of image blocks in the image. Through experiments, the default value was determined as 1100. Each image-block is then classified into one of the five edge categories mentioned above or as a non-edge block. After extracting the feature values using each filter, the edge detector with the maximum edge value is then identified. If the edge value is above a given threshold, the corresponding edge orientation is then associated with the image-block. Since there are 16 sub-images, a total of 5x16=80 histogram bins are generated.

In the classification and retrieval of medical images, edges are a critical feature to improve the accuracy, especially for X-ray images. Therefore, five global edge histograms with 5 bins are also extracted. Similarly, for semi-local edge histograms, 13 different subsets are grouped and edge distributions generated for five different edge types. As a result, a total of 150 edge histogram feature values are used by combining 80 regional edge histograms, 5 global edge histograms, and 65 (5 x 13) semi-local edge histograms.

Ⅲ. Classification and Retrieval of Medical Images

After the feature extraction, the images are classified into predefined classes using multi-class Support Vector Machines (SVM) and two feature vectors, H-CSD and EHD. Using the training results, each image receives membership scores for 20 categories, and these membership scores are estimated from the H-CSD and EHD, respectively, and combined as one feature vector, called an ensemble vector. From the ensemble vector, the proposed Correlated Categories Vector (CCV) records each dimension as ‘1’ or ‘0’ according to its membership score in the corresponding ensemble vector. Finally, the ensemble feature vector is used in the proposed content-based medical image retrieval system, MISS (Medical Information Searching System).

3.1 SVM classifier training using H-CSD and EHD Feature Vectors

An SVM can provide a good generalization performance for pattern classification problems without incorporating problem domain knowledge. Furthermore, an SVM does not require heuristic feature parameters for determining image classification.

Given the training data $x_1,\dots,x_N$ that are vectors in space $x_i \in R^d$ and their labels $y_1,\dots,y_N$ where $y_i \in (+1,-1)^N$ the general form of the binary linear classification function is

$$g(x) = w \cdot x + b \tag{3}$$

which corresponds to a separating hyperplane.

$$w \cdot x + b = 0 \tag{4}$$

where x is the input vector, w is the weight vector, and b is the bias. The main goal of an SVM classifier is to find the parameter w and b for the optimal hyperplane that correctly separates the largest fraction of data points, while maximizing the distance of either class from the hyperplane.

The SVM classification function is defined by [10]:

$$f(x) = sign\left(\sum_{i=1}^{l} v_i \cdot k(x, x_i) + b\right) \tag{5}$$

where $k(\cdot,\cdot)$ is the kernel function, v_i is the weight of the outputs for each kernel, b is the bias term, and the sign of $f(x)$ determines the class membership of x, such as +1 class and -1 class. The decision function $f(x)$ from the hyperplane determined by the support vectors can be used to measure how much an image belonging to one category (+1) is different from the other categories (-1). Intuitively, the farther away a point is from the hyperplane, i.e. a larger positive $f(x)$, the more reliable the classification result.

For a linear SVM, the kernel function is just a simple dot product in the input space. However, in a non-linear SVM, the kernel function effectively projects the samples to a feature space of higher

Table 1. Training classes and images per class for SVM

Category	Body Part	#of training data
1	Breast	100
2	Pelvis	100
3	Front head	100
4	Side head	100
5	Throat	100
6	Knee	100
7	Toe	48
8	Front ankle	100
9	Side ankle	100
10	Hand	100
11	Finger	100
12	Wrist	100
13	Kneepan	100
14	Shoulder	100
15	Vertebrae	100
16	Front breast	100
17	Side breast	100
18	Fleshy	47
19	Elbow	21
20	Foot	38

dimension F and constructs a hyperplane in F[10]. The SVM training algorithm then estimates a hyperplane that separates the data in F into two classes using the largest margin.

This paper uses a multi-class SVM with an RBF (Radial-Basis Function) Kernel instead of a binary SVM, as x-ray images need to be classified into 20 classes according to the regions of the body. The RBF kernel is known to work well for SVM-based image classification when the relation between the class labels and the attributes is nonlinear[5]. For a multi-class SVM, there are several commonly used methods, such as one-against-all, one-against-one, and a directed acyclic graph[11]. Here, the one-against-all method is used, as it has already been widely used to handle multi-category problems. The one-against-all method constructs n SVM classifiers, where n is the number of classes and the *i-th* SVM is trained using all the examples in the *i-th* class with positive labels (+1) and all the others with negative labels (-1).

To perform the training, 1,754 images were randomly selected from 20 image categories, as shown in Table 1. The X-ray images were all from IRMA (Image Retrieval in Medical Applications), as used for ImageCLEFmed2007[12]. In this paper, since two feature vectors were used respectively for the training, 2n SVM classifiers were generated.

3.2 Ensemble feature vector generation

After the SVM training, all the database images with H-CSD and EHD feature vectors are fed to the corresponding SVM classifiers, and category membership scores obtained as the output. For example, image x is fed into the *i-th* SVM classifiers, and the one with the highest output score(d_j) is selected as the final class.

$$d_j(x) = \max_{i=1,\dots,n} d_i(x) \tag{6}$$

where d_j is the output score about the *i-th* class for input image x. The output scores o f the 2n SVM classifiers are then appended to one ensemble vector.

In Fig. 3, the extracted feature vectors, F_C and F_E (F_C: H-CSD feature vector, F_E: EHD feature vector) for the database images are fed to the 2n SVM(2x20) classifiers, respectively. Then SVM classifiers then output 20 membership scores, $\overrightarrow{S_C}$ and $\overrightarrow{S_E}$, for each feature vector. Finally, the ensemble vector, $\overrightarrow{E} = [S_{c1}, S_{c2}, \dots, S_{c20}, S_{e1}, S_{e2}, \dots, S_{e20}]$ is obtained by appending all category membership scores. In our experiments, an ensemble of feature vectors shows the better performance than an linear combination of feature vectors because it preserve the eigen properties of each feature vector.

3.3 Similarity Matching using Correlated Categories Vector

Typically, image categories can be classified as independent or correlated. For example, category 1 (Breast) is generally independent of category 11 (Finger). Meanwhile, category 10 (Hand) and category 11 (Finger) are correlated[13]. Therefore, since each correlated category should be considered for similarity matching, this paper proposes a Correlated Category Vector (CCV) with the same dimensions as an ensemble vector, to record the correlation of a particular category.

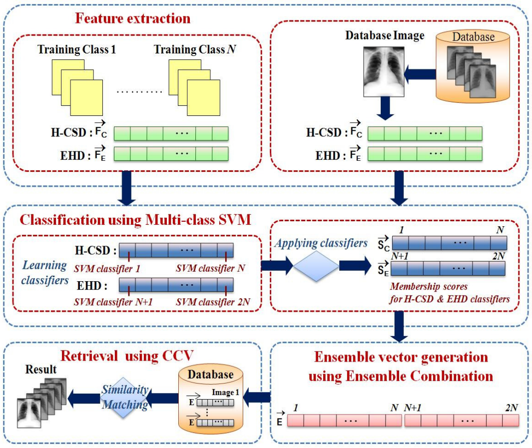

Fig. 3. Flow diagram of training process and ensemble vector generation for database images

To generate a CCV, the ensemble vector is first extracted from the query image, and then '1' or '0' is recorded to *i-th* dimension of the CCV if it satisfies the following equation:

$$CCV[i] = \begin{cases} 1, \text{if } \vec{E}[i] \geq \theta \\ 0, \, otherwise \end{cases} \tag{7}$$

where θ is the threshold for deciding correlated categories and $\vec{E}[i]$ is the membership score of the *i-th* dimension of the ensemble vector. In this

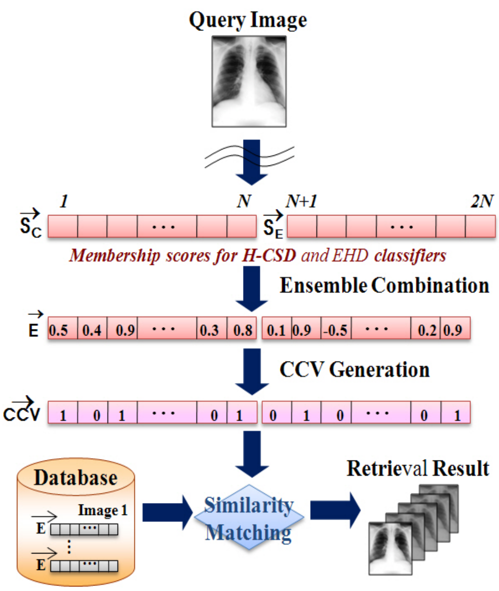

Fig. 4. Flow diagram of similarity matching process

paper, θ is set at 0.5.

After a CCV is generated, similarity matching is only performed on the i-th ensemble value when the CCV code of the corresponding *i-th* dimension is '1'. Using the ensemble vector and CCV, the final distance is then estimated using (8), and the closest images are displayed in ascending order of the final distance

$$S(Q,T) = \frac{1}{M}\left(\begin{array}{l} w_1 \cdot \sum_{i=1}^{N} \left| \overrightarrow{E_Q}[i] - \overrightarrow{E_T}[i] \right| \\ + w_2 \cdot \sum_{i=N+1}^{2N} \left| \overrightarrow{E_Q}[i] - \overrightarrow{E_T}[i] \right| \end{array} \right) \tag{8}$$

$$\text{for } CCV[i] = 1$$

where $\overrightarrow{E_Q}[i]$ is the membership score of the *i-th* query ensemble vector, $\overrightarrow{E_T}[i]$ is the membership score of the *i-th* target (database) ensemble vector, M is the number of '1s' included in the CCV, and w_1 and w_2 are the weight of the membership scores for the H-CSD and EHD, respectively. To determine the value of weights w_1 and w_2, the precision average was calculated using different values based on choosing five images randomly from all database categories. As shown in Fig. 5, when w_1 and w_2 were set at 0.3 and 0.7, respectively, the precision performance was relatively higher. From the results, it was also found that the EHD was the more important feature for classifying medical images. Therefore, in this paper, w_1 and w_2 were set at 0.3 and 0.7, respectively.

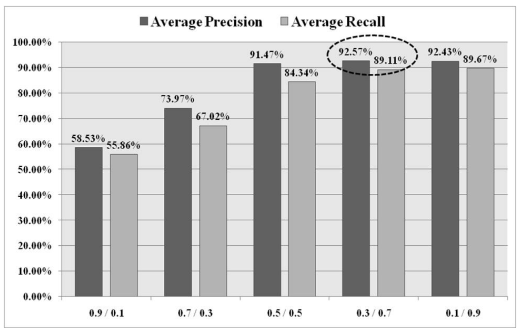

Fig. 5. Performance comparison between two different weights (Left percent: average precision, Right percent: average recall)

Table 2. Titles of twenty categories and number of images used in test

Category	Body Part	#of test data
1	Breast	60
2	Pelvis	60
3	Front head	50
4	Side head	50
5	Throat	50
6	Knee	50
7	Toe	45
8	Front ankle	50
9	Side ankle	50
10	Hand	60
11	Finger	50
12	Wrist	50
13	Kneepan	60
14	Shoulder	50
15	Vertebrae	60
16	Front breast	60
17	Side breast	50
18	Fleshy	40
19	Elbow	20
20	Foot	35

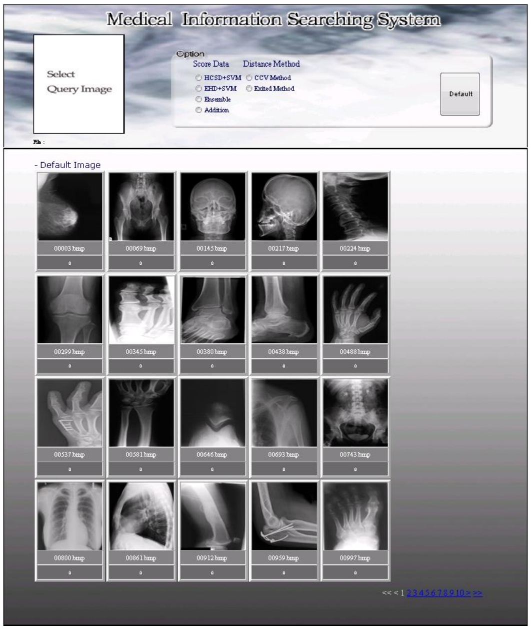

Fig. 6. System interface of MISS

Ⅳ. Experimental Results

The proposed system was developed using Visual C++ 6.0 language for off-line training and the test system developed based on ASP.NET 2.0 using C# language. For the test, 1,000 images were used (20 categories) from IRMA (Image Retrieval in Medical Applications)[12]. Table 2 shows the 20 categories used for the test and number of test images used.

To complete a query, the user pushes the 'default' button and selects one retrieval method among six methods. Next, the user clicks any image that they want to retrieve, and the top 20 nearest neighbors are returned. Fig. 6 shows the retrieval interface of MISS.

To validate the effectiveness of the proposed approach (Ensemble + CCV), its retrieval precision was compared with that of two other approaches. First, 'Ensemble' used Eq. (8) with the same weights as 'Ensemble + CCV' without using a CCV. Second, 'Addition' added the membership vector of H-CSD ($\overrightarrow{S_C}$) with the membership vector of EHD ($\overrightarrow{S_E}$) and estimated the distance using the city-block distance between the query and the database images.

The test was performed using 20 categories and 5 query images from each category. In all the experiments, the performance was measured using the average retrieval precision and recall. As shown in Fig. 7, the average precision performance of the proposed approach outperformed that of the other two methods as the percentages of 81.6%, 85.47%, and 92.57%. The average recall performance also has a higher performance of 89.11% compared

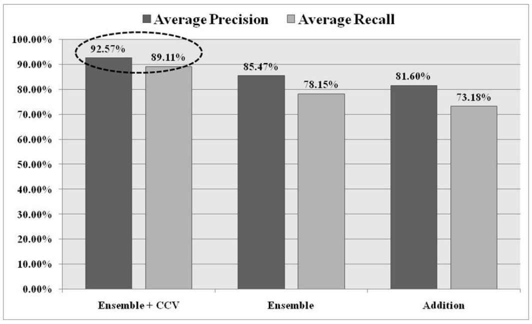

Fig. 7. Performance comparison of 100 queries by average precision and average recall among 'Ensemble + CCV', 'Ensemble', and 'Addition' methods. The average precision and average recall of each method was about (92.6%, 89.11%), (85.5%, 78.15%), and (81.6%, 73.18%), respectively. (Left percent: average precision, Right percent: average recall)

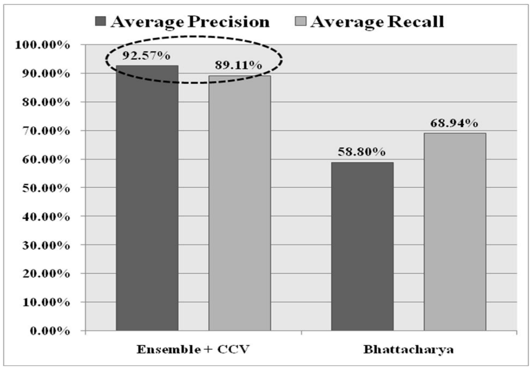

Fig. 8. Performance comparison by precision between 'Ensemble + CCV' and Bhattacharya *et al.*[5]'s method. The retrieval precision and recall of the proposed method was about 33.8% and 30.2% improved

to other two methods of 73.18% and 78.15%, respectively. In particular, the retrieval performance of the proposed 'Ensemble + CCV' method showed a 7.1% improvement over the 'Ensemble' method in precision and 11% in recall. From the results in Fig. 7, the CCV was demonstrated to improve the retrieval performance by only calculating the distance for correlated categories.

The retrieval performance of the proposed approach was also compared with that of Bhattacharya's algorithm [5]. Bhattacharya et al. combined a

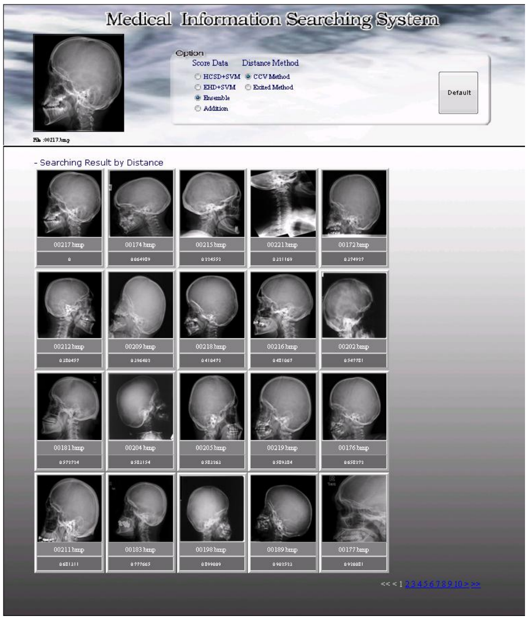

Fig. 9. Retrieval results with proposed method for 'Side Head' category #4

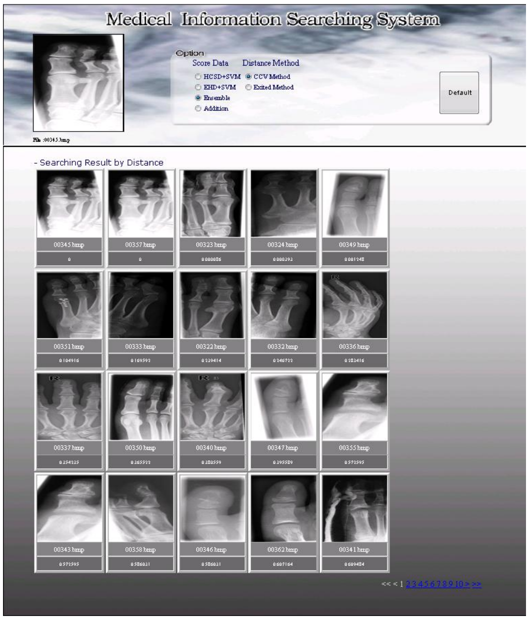

Fig. 10. Retrieval results with proposed method for 'Toe' category #7

color layer descriptor and MPEG-7 standard EHD descriptor as one feature vector and applied it to an SVM and FCM (Fuzzy C-mean Clustering). Thereafter, the output scores of the SVM and membership scores of the FCM are linearly combined for classifying and retrieving medical images. As seen from Fig. 8, Bhattacharya's method has an average precision of 58.8% and average recall of 68.94%. In contrast, the retrieval performance of the proposed method was about 33.8% improved in precision and 30.2% improved in recall.

Fig. 9 and 10 show some retrieval results when using the MISS system.

The proposed MISS system can be viewed at the following web-site, http://cvpr.kmu.ac.kr .

V. Conclusion

This paper proposed a novel algorithm for the efficient classification and retrieval of medical images, especially X-ray images. To classify medical images, color features are first extracted using a new Color Structure Descriptor (H-CSD) based on a Harris corner detector. Meanwhile, texture features are extracted globally and locally using an Edge Histogram Descriptor (EHD). The extracted feature vectors are then applied to a multi-class Support Vector Machine (SVM) to give membership scores for each image. These membership scores of the H-CSD and EHD are then combined to generate an ensemble feature vector. Furthermore, to improve the retrieval accuracy and reduce the search time, a new similarity matching method is applied based on a Correlated Categories Vector (CCV). That is, using the ensemble vector, the CCV records each corresponding dimension as '1' or '0' according to its membership score in the ensemble vector.

Finally, similarity matching is only performed on dimensions with a '1' value in the corresponding CCV dimension. When applying the proposed methods to a new retrieval system, MISS (Medical Information Searching System), the experimental results using ImageCLEFmed2007 images showed that the proposed system could indeed improve the retrieval performance when compared to other approaches and classification-based retrieval methods.

In future work, automatic annotation based on image classification is needed. Plus, new features need to be specifically developed for medical images to improve the classification performance in similar categories, such as the throat against vertebrae and fingers against toes.

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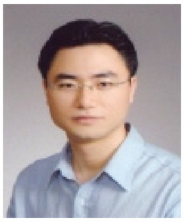
박 기 희 (Ki-Hee Park) 준회원

2008년 2월 계명대학교 컴퓨터 공학과 졸업(공학사)

2008년 3월~현재 계명대학교 대학원 컴퓨터공학과 석사과정

<관심분야> 영상처리, 컴퓨터 비전 및 패턴인식

고 병 철 (ByoungChul Ko) 정회원



1998년 경기대학교 전자계산학과 졸업(이학사)
1998년~2000년 연세대학교 대학원 컴퓨터과학 공학석사
2000년~2004년 연세대학교 대학원 컴퓨터과학 공학박사
2004년 3월~2005년 8월 삼성전자 통신연구소 책임연구원
2005년 9월~현재 계명대학교 컴퓨터공학과 조교수
<관심분야> 내용기반 영상검색, 컴퓨터 비전 및 패턴인식

남 재 열 (Jae-Yeal Nam) 정회원

1983년 경북대학교 전자공학과 졸업(공학사)
1985년 경북대학교 대학원 전자공학(공학석사)
1991년 University of Texas at Arlington 전기공학(공학박사)
1985년 5월~1987년 7월 한국전자통신연구소 연구원
1991년 9월~1995년 2월 한국전자통신연구소 선임연구원
1995년 3월~현재 계명대학교 컴퓨터공학과 교수
<관심분야> 영상압축, 영상통신, 멀티미디어 시스템