

# Effective Classification of Radiographic Medical Images Using LS-SVM and NSCT based Retrieval System

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**Abstract**— This paper presents a Content Based Medical Image Retrieval (CBMIR) system for diverse collection of radiographic images. Non-Subsampled Contourlet Transform (NSCT) and Fuzzy C-Means (FCM) technique is used to construct the image signature which is used as the image representative feature vector. Least Square-Support Vector Machine (LS-SVM) and Earth Mover's Distance (EMD) is used to classify the images. Preliminary studies on a radiographic image Database (DB) consisting 1550 images of 31 different modalities show promising result.

**Keywords**- CBMIR; NSCT; LS-SVM; EMD; FCM.

## I. INTRODUCTION

Over the last few decades, medical imaging is playing a significant and vital role in a large number of healthcare applications like diagnosis, treatment, research and education etc. To provide support to the physicians in their clinical diagnosis and treatment, various modalities of medical images have become available. In large hospitals and diagnostic centers, several terabytes of digital medical images are generated and stored every year for diagnosis, treatment, research and education etc [10, 13]. In radiology workflow, these images are archived in Picture Archiving and Communication System (PACS) [15]. Using PACS the radiologist may want to browse through similar content medical images in the archive to ensure an accurate diagnosis [2]. Effectively and efficiently searching in these large image collections poses significant technical challenges, and raises the necessity of constructing intelligent retrieval systems.

PACS still provide access to the medical images by alphanumeric description and textual meta-information. Conventional medical archives allow for textual searches particularly using the Digital Imaging and Communication in Medicine (DICOM) header [2]. Even though DICOM headers contain some important information and most of the modern imaging devices are DICOM compliant, it remains deficient for a number of reasons. Firstly, the high cost of manual annotation. Secondly, manual annotation induces errors (error rate up to 16% have been reported in the header file) [5].

Moreover, There may be a large number of Regions of Interest (ROI) in a single medical image and each of which may be important for the medical image expert for diagnostic task but could be overlooked during manual annotation. Therefore information on all possible ROIs should be available in the attached header in an ideal retrieval system. Finally automatic categorization procedures are required for fast archiving of secondary digitized images that were acquired by film-based modalities or non-DICOM digital devices [4].

An open challenge for automatic annotation of medical images is the inter-class vs. intra-class variability problem: an image that belongs to the same visual class might look very different, while images that belong to different visual classes might look very similar [8, 14]. Several CBMIR prototypes have been proposed to address this problem using local and global features [12, 6]. Majority of these systems are developed around a specific imaging modalities and retrieval methods in these systems are task and modality specific. There are few Content Based Image Retrieval (CBIR) systems that can handle diverse image collections [9]. The current state-of-the-art in CBMIR approaches has been presented in [1, 10].

Most of the existing CBMIR systems require high dimensional image representative feature vector. Moreover, these existing systems often have to search the entire image database to retrieve the similar images. These result in high computational complexity. In the proposed CBMIR system, NSCT and FCM algorithm is used to create an image representative feature vector having low dimensionality. Furthermore, the computational complexity is reduced using a LS-SVM based pre/post classifier. Preliminary studies on a radiographic image DB consisting 1550 images of 31 different modalities show promising retrieval result.

The rest of the paper is organized as follows: Theoretical preliminaries used in the proposed retrieval system are described in Section II. Section III, presents the proposed CBMIR system. Experimental results are given in Section IV, and we draw conclusion in Section V.

## II. THEORETICAL PRELIMINARIES

In this section, we briefly describe the theoretical preliminaries used in the proposed system.

### A. Non-subsampled Contourlet Transform (NSCT)

NSCT is a fully shift-invariant, multi-scale, multi-direction and overcomplete transform with a fast implementation [3]. NSCT achieves the shift-invariance property by using non-subsampled pyramid filter bank (NSP or NSPFB) and non-subsampled directional filter bank (NSDFB).

NSPFB is a shift-invariant filtering structure, accounting for the multi-scale property of the NSCT, which is achieved by using two-channel non-subsampled 2-D filter banks. It has no down-sampling or up-sampling and hence, it is shift-invariant. The perfect reconstruction is achieved provided the filters satisfy the following identity

$$H_0(z)G_0(z) + H_1(z)G_1(z) = 1 \quad (1)$$

where  $H_0(z)$  is the low pass filter,  $H_1(z)$  is the high pass filter decomposition filter,  $G_0(z)$  is the low pass reconstruction filter,  $G_1(z)$  is the high pass reconstruction filter. The equivalent filters of a  $k^{\text{th}}$  level cascading NSPFB are given by

$$H_n^{\text{eq}}(z) = \begin{cases} H_1(z^{2^{n-1}}) \prod_{j=0}^{n-2} H_0(z^{2^j}), & 1 \leq n < 2^k \\ \prod_{j=0}^{n-1} H_0(z^{2^j}), & n = 2^k \end{cases} \quad (2)$$

where  $z^j$  stands for  $[z_1^j, z_2^j]$

The NSDFB is constructed by eliminating the down-samplers and up-samplers of the Directional Filter Bank (DFB) by switching off the down-samplers/up-samplers in each two channel filter bank in the DFB tree structure and up-sampling the filters accordingly [3]. This results in a tree composed of two-channel non-subsampled filter banks (NSFBs). All filter banks in the NSDFB tree structure are obtained from a single NSFB with fan filters. To obtain the next level decomposition, all filters are up sampled by a quincunx matrix given by

$$QM = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \quad (3)$$

The NSCT is obtained by carefully combining the 2-D NSPFB and the NSDFB. The resulting filtering structure approximates the ideal partition of the frequency plane.

### B. Earth Mover's Distance (EMD)

Earth Mover's Distance (EMD) represents the distance between sets or distributions of elements, and facilitates partial matches [11]. Let  $p_i$  be the centroid of each cluster of a signature  $P = \{(p_1, w_{p1}), \dots, (p_m, w_{pm})\}$  with  $m$  clusters and  $w_{p_i}$  be the weight of each cluster. Similarly,  $q_j$  be the centroid of each cluster of another signature

$Q = \{(q_1, w_{q1}), \dots, (q_n, w_{qn})\}$  with  $n$  clusters and  $w_{q_j}$  weights  $D = [d_{ij}]$  be the ground distance matrix, where  $d_{ij} = d(p_i, q_j)$ . Computing EMD thus become finding a flow between  $p_i$  and  $q_j$  which minimizes the overall cost. A flow between  $P$  and  $Q$  is any matrix  $F = (f_{ij}) \in \mathcal{R}^{m \times n}$ . Thus, EMD is defined as the work normalized by the total flow:

$$EMD(P, Q) = \frac{\sum_{i=1}^m \sum_{j=1}^n d(p_i, q_j) f_{ij}}{\sum_{i=1}^m \sum_{j=1}^n f_{ij}} \quad \text{subject to the}$$

constraints:

- $f_{ij} \geq 0, \quad 1 \leq i \leq m, \quad 1 \leq j \leq n$
- $\sum_{j=1}^n f_{ij} \leq w_{p_i}, \quad 1 \leq i \leq m$
- $\sum_{i=1}^m f_{ij} \leq w_{q_j}, \quad 1 \leq j \leq n$
- $\sum_{i=1}^m \sum_{j=1}^n f_{ij} = \min(\sum_{i=1}^m w_{p_i}, \sum_{j=1}^n w_{q_j})$

### C. Least Square Support Vector Machine (LS-SVM)

The most critical drawback of Support Vector Machine (SVM) is its high computational complexity for high dimensional data sets. To reduce the computational demand, the least square version of SVM (LS-SVM) is adopted as classifier in this paper. LS-SVM avoids solving quadratic programming problem and simplifies the training procedure [7]. Considering a linearly separable binary classification problem:

$$(x_i, y_i)_{i=1}^n \quad \text{and} \quad y_i = \{+1, -1\} \quad (4)$$

where,  $x_i$  is an  $n$ -dimensional vector and  $y_i$  is the label of this vector. LS-SVM can be formulated as the optimization problem:

$$\min_{w, b, e} \mathcal{J}(w, b, e) = \frac{1}{2} w'w + \frac{1}{2} C \sum_{i=1}^n e_i^2 \quad (5)$$

subject to the equality constraints

$$y_i [w'(x_i) + b] = 1 - e_i \quad (6)$$

where  $C > 0$  is a regularization factor,  $b$  is a bias term,  $w$  is the weight vector,  $e_i$  is the difference between the desired output and the actual output and  $(x_i)$  is a mapping function.

The Lagrangian for problem of Eq.(5) is defined as follows:

$$\mathcal{L}(w, e_i, b, \alpha_i) = \min_{w, b, e} \mathcal{J}(w, b, e) - \sum_{i=1}^n \alpha_i \{y_i [w'(x_i) + b] - 1 + e_i\} \quad (7)$$

where  $\alpha_i$  are Lagrange multipliers. The Karush-Kuhn-Tucker (KKT) conditions for optimality:

$$\frac{\partial \mathcal{J}}{\partial w} = 0 \rightarrow w = \sum_{i=1}^n \alpha_i y_i(x_i); \frac{\partial \mathcal{J}}{\partial e_i} = 0 \rightarrow \alpha_i = C e_i;$$

$$\frac{\partial \mathcal{J}}{\partial b} = 0 \rightarrow \sum_{i=1}^n \alpha_i y_i = 0; \frac{\partial \mathcal{J}}{\partial \alpha_i} = 0 \rightarrow y_i [w'(x_i) + b] - 1 + e_i$$

is the solution of the following linear system,

$$\begin{bmatrix} 0 & -y \\ y & \Phi \Phi' + C^{-1} I \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ \bar{1} \end{bmatrix} \quad (8)$$

where,

$\Phi = [\varphi(x_1)' y_1, \dots, \varphi(x_n)' y_n]$ ,  $Y = [y_1, \dots, y_n]$ ,  $\bar{1} = [1, \dots, 1]$  and  $\alpha = [\alpha_1, \dots, \alpha_n]$ . For a given kernel function  $K(\cdot)$  and a new test sample point  $x$ , the LS-SVM classifier is given by

$$f(x) = \text{sgn} \left[ \sum_{i=1}^n \alpha_i y_i K(x, x_i) + b \right] \quad (9)$$

### III. PROPOSED CBMIR SYSTEM

In this section we described the proposed CBMIR system briefly.

#### A. Image Signature Computation

The radiographic images are mostly gray-scale images having different size. During the retrieval process, the images of the medical database (DB) are temporarily resized to size  $M \times N$ . NSCT is applied to each image  $I$  of the database.

A  $\ell$ -level NSCT decomposition of an image  $I$ , results in  $2^\ell$  sub-bands, each having the same size  $M \times N$ . Let the sub-bands of each image  $I$  be denoted by  $S_b^I$ , where  $b = 1, 2, 3, \dots, 2^\ell$ .

For each subband  $S_b^I$ , a feature map  $FM_b^I$  is computed by using Eq. (10) utilizing the concept of 'local energy' over a neighborhood  $W_{ij}$  of size  $p \times q$ , centered on a coefficient with coordinates  $(i, j)$ . The size of the window  $W_{ij}$ , is determined using the Spectral Flatness Measure (SFM).

$$FM_b^I(i, j) = \sum_{(p, q) \in W_{ij}} \left| S_b^I(p, q) \right| G(i-p, j-q) \quad (10)$$

where,  $G(i, j)$  is a Gaussian low-pass (smoothing) filter.

After computing the feature maps for an image  $I$  of the database, each feature map is clustered using FCM algorithm, into  $m$  different clusters. In the proposed CBIR system, an image  $I$  is represented in terms of a signature:

$$\text{Sig}^I = \{(C_1, w_{c_1}), (C_2, w_{c_2}), \dots, (C_m, w_{c_m})\} \quad (11)$$

where,  $C_k$  represents  $k^{\text{th}}$  cluster centroid ( $k = 1, 2, \dots, m$ ) and  $w_{c_k}$  indicates the fraction of pixels belonging to the cluster  $C_k$ .  $C_k$  constitutes the NSCT features over  $b$  feature maps and is represented by

$$C_k = [f_1^k, \dots, f_b^k] \quad (12)$$

#### B. Image Signature Computation

LS-SVM classifier is trained with 70% and tested with 30% of the labeled data using stratified random sampling method. The Radial Basis Function (RBF) kernel is used with 10 fold cross validation (CV) procedure to find the best values of tunable parameters  $C$  and  $\sigma^2$ . The value of the kernel parameter ( $\sigma^2$ ) is changed between 0.2 and 20 and value of the regularization parameter ( $C$ ) is changed between 1 and 1000 for optimization purpose using grid-search method. After finding the best values of the parameters  $C = 100$  and  $\sigma^2 = 0.6$  of the RBF kernel with a CV accuracy of 76%, they are utilized for the final training to generate the local concepts model.

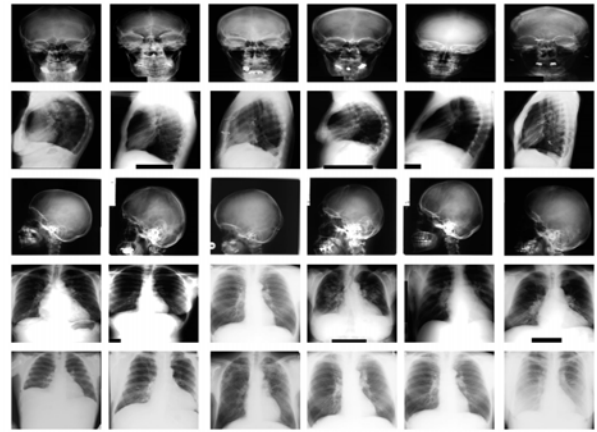


Figure 1 Query-by-example experiments: Query images (left) and Retrieved images in order of similarity (right)

#### C. Algorithm

The salient steps of the proposed system are as follows:

- The user enters the query image to the system..
- Image signature for the query image is computed as described in section III.A.
- Class identification of the query image is done by the LS-SVM classifier.
- The distances between the query image and all the images in the identified class are computed using the EMD.
- After sorting the distances in ascending order, the system retrieves the top 20 ranked images from the database and presents them to the user.

### IV. EXPERIMENT RESULTS AND COMPARISONS

Extensive experiments were carried out on a subset of IRMA 2009 radiographic image database (ImageCLEF-2009). A database of 1550 images from 31 different classes (each having 50 images) was constructed. The experiments were carried out on a Dell Precision T7400 PC with 4GB RAM and was implemented using MATLAB R2008a. Two commonly used statistical measures were computed to assess the proposed system's performance, namely precision and recall.

The outputs of some Query-by-example experiments are shown in Fig. 1 (database of 1550 images). The left image in each row is the query image. The five images on the right are ordered by similarity from left-to-right, according to the EMD distance. The results demonstrate that the retrieved images are

from the same class as the query image. Moreover, it is interesting to note that the response to a normal chest image query (fourth row) is a set of normal chest images, whereas a pathological chest image (fifth row) retrieved chest image

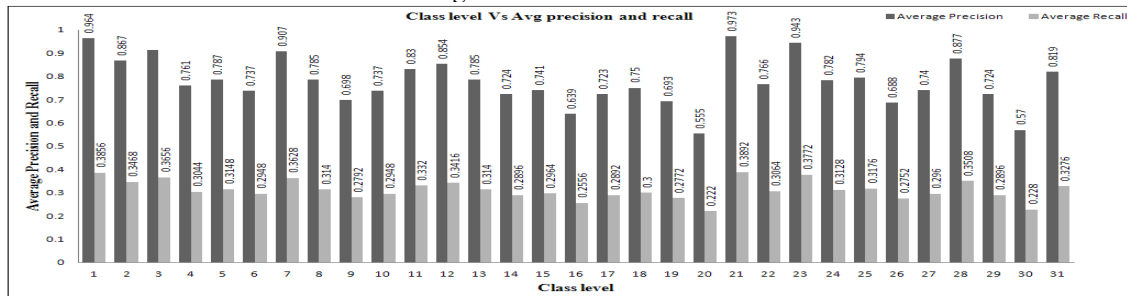


Figure 3 Classwise Average precision and Average Recall

examples of non-normal appearance (visually similar to the query input). The graph of Fig. 2 shows the performance of the proposed method in terms of Precision vs. Recall (PR) graph. The average precision and recall was computed over all the images of database. The results were taken for the retrieved image frame sizes of 5, 10, 15 and 20. The graph also shows the performance comparisons of three different similarity measures namely Euclidean Distance (ED), Manhattan Distance (MD) and EMD. It is clear from the graph of Fig. 2 that the proposed CBMIR systems based on EMD perform satisfactorily. The graph of Fig 3 shows the class wise average precision and average recall performance of 1550 images of 31 different modalities of medical images.

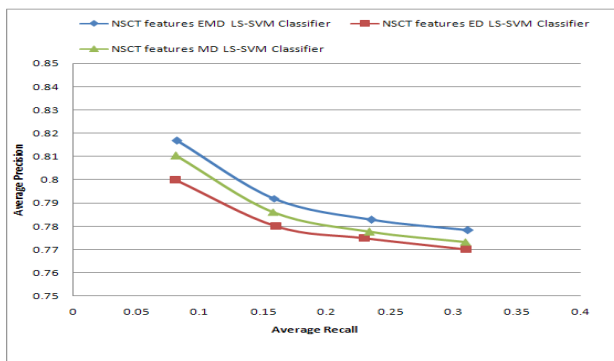


Figure 2 Average Precision Vs. Average Recall (frame size 5, 10, 15 and 20)

## V. CONCLUSION

From our experiments, we have noticed that NSCT based image coding is suitable for representing low level features of the images. Due to the less number of low level features and the use of LS-SVM classifier, the proposed CBMIR system is able to achieve the satisfactory results with low computational cost. To overcome the problem of misclassification in pre-classification process, we are trying to implement fuzzy – neuro ranking membership function. As the future scope of research, we are also trying incorporate relevance feedback mechanism into the proposed system.

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