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Heterogeneous Medical Image Retrieval using Multi-Trend Structure Descriptor and Fuzzy SVM Classifier

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Abstract*: This research work contributes a system for heterogeneous medical image retrieval using Multi-trend structure descriptor (MTSD) and fuzzy support vector machine (FSVM) classifier. The MTSD encodes the local level structure in the form of trends for color, shape and texture information of medical images. Experimental results demonstrate that the fusion of MTSD and FSVM significantly increases the retrieval precision for heterogeneous medical image dataset. The simplest Manhattan distance is incorporated for measuring the similarity. The feasibility of the proposed system is extensively experimented on benchmark dataset and the experimental study clearly demonstrated that proposed fusion of MTSD with Fuzzy SVM gives significantly superior average retrieval precision.

Keywords* : Multi-Trend Structure descriptor, Manhattan similarity measure, Local structure, Fuzzy Support Vector Machine.

I. INTRODUCTION

In the domain of medicine, enormous volume, more complex, numeral diversity and ever increasing image datasets are generated by the hospitals using various medical imaging devices such as CT, MRI, X-Ray, PET, SPECT, PEM and US. The medical image provides an understanding and visual facts of various diseases which assist the physicians in clinical findings, understanding the minute variations in various stages of diseases, treatment planning, etc. Thus, many techniques have been suggested and advanced in the past in order to address the problems with manual analysis of medical images.

For instance, the knowledge encoded in the form of lexicons, thesauri and ontologies were used in [1]. In [2], gray level co-occurrence matrix based 11 texture features are computed from the region of interest (ROI) which is a normal or abnormal regions of an image and the significance of each computed texture feature is computed using the multivariate T test and is normalized for image retrieval. The center symmetric local binary pattern is introduced in [3] and it uses the gray level co-occurrence matrix for computing the co-occurrence of pixel pairs inn local pattern map in different directions and distances and the authors reveled that co-occurrence of pixel pairs is more significant than the frequency details of local pattern map for OASIS MRI, texture and face datasets. Kumar and Singh suggested a retrieval system for hepatobiliary images in [4] and it combinely ues SIFT (scale invariant feature transform), Hu-moments and gray level co-occurrence matrix to exactly retrieve the images of various diseases of liver and biliary system. Wei et al., [5] suggested a novel method to measure the similarity of lung nodules in CT images in which semantic relevance between query and target ROI is measured first then visual similarity is measured between query and retrieved ROI, and the approach is named as two-step CBIR system. To confirm the effective performance of novel similarity approach, the authors used three categories of texture features in [5]. In [6], biomedical image retrieval using directional binary wavelet patterns are presented for MRI and CT images and is extracted from the binary wavelet transformed sub-bands of 8-bit gray scale image.

Murala and wu [7] introduced a method called local mesh patterns for CT and MRI image retrieval which computes the relationship between the surrounding neighbors for a given pixel rather than the relationship between the referenced pixel and its surrounding neighbors as that of local binary pattern. A local ternary co-occurrence pattern is presented in [8] which compute the co-occurrence of similar ternary edges computed from the gray values of center pixel and its surrounding neighbors for biomedical image retrieval. Dubey et al., described local wavelet pattern for CT image retrieval that computes the relationship between the neighboring local wavelet decomposed values and transformed center pixel values [9]. Deep convolutional neural networks and Fast Fourier Transform is combinely suggested for radiology and endoscopy image retrieval in [10]. Contribution of deep learning methods for the domain of medical image analysis and the difficulties in deep learning methods is discussed in [11]. Nowakova et al., introduced a fuzzy system for mammogram image retrieval using vector quantization with fuzzy signatures and fuzzy S-trees [12]. In [13], a retrieval system for liver CT images is presented in which a new term similarity measure is suggested for reducing the semantic gap by considering the both automatically predicted ontological terms and image based content. Hsu et al., presented web based spine X-ray image retrieval in [14] and is extended to analysis the cervical images also.

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A multi-tiered image retrieval system for microscopic images is presented by Akakin et al., in [15]. Lan et al., [16] introduced a histogram of compressed scattering coefficients for image retrieval in which the scattering coefficients are computed from the scattering transform then from the computed compressed scattering coefficients, histogram of bag-of-words is constructed. Thus, their approach [16] utilizes the advantages of scattering coefficients and bag-of-words for medical image retrieval. To reduce the semantic gap, a new similarity method called context-sensitive similarity measure is proposed in [17] for lung CT image retrieval which uses the shortest path algorithm over the weighted graph to measure the both semantic and visual similarities.

Image retrieval system for heterogeneous medical images is proposed in [18] by combining the color autocorrelogram, micro-textures and enhanced edge orientation autocorrelogram features, computed using a framework based on Full range Autoregressive model and it is reported that it is superior in efficiency because of comprising color, texture, shape and its spatial information at both local and global level. Akgül et al., [19] described that the varied, rich and subtle information in the radiology images increases difficulty in retrieval and also reported that the advantages of semantics are not yet fully employed. Kumar et al., [20] studied the challenges of medical image retrieval in the view of retrieval of two and three or more dimensional images, using the non-image data for medical image retrieval, retrieving the images of various modality and diverse datasets. Accordingly, we suggested a system for retrieving medical images using the multi-trend structure descriptor (MTSD) and fuzzy k-nearest neighbor's classifier [21].

Though many advances in different perspectives achieved in CBMIR, permeation of aforementioned systems has been limited [22-24] in accuracy due to the complication in differentiation of medical images. Thus far, there is a need for finding a more effective and efficient medical image search tool. Therefore, in this paper, we attempt to present a retrieval system for heterogeneous medical images which is an enhanced version of a system presented by us in [21]. The proposed system comprises of MTSD, Fuzzy Support Vector Machine (FSVM) and Manhattan distance measure. The experimental results revels that proposed combination significantly outperforms existing approach [21] in terms of accuracy and time.

The rest of the paper is organized as follows: In section 2, the methods used in proposed retrieval system are described. Section 3 describes experimental results and discussion. The conclusion is presented in section 4.

II. PROPOSED MEDICAL IMAGE RETRIEVAL SYSTEM

In this section, the feature calculation using MTSD, classification of estimated feature vector utilizing fuzzy SVM classifier and the similarity and performance measures incorporated in the proposed work are discussed.

A. Feature extraction

The MTSD [25] is used to compute the local structure in the form of equal, large and small trends for color, texture and shape information. In general, most of the medical imaging devices produce gray scale images. Thus, in the proposed system, only texture and shape information are computed using MTSD for gray scale images whereas color information is also computed for color medical images.

For color medical images, an image in RGB color model is converted into HSV [25] then color quantization is performed as described in [25] and it results in 12, 3 and 3 quantization levels, and texture and shape information detected using Sobel operator in V component is quantized into 20 and 9 respectively [25]. Whereas for gray scale images only texture and shape information are quantized.

In order to compute the structures at local level in the form of equal, small and large trends along 0°, 45°,90° and 135° orientations, image is divided into number of 3 x 3 non overlapping blocks. Subsequently, the 3 x 3 mask is moved from bottom to top and left to right direction throught the entire image to discover the number of equal, small and larg trends. According to Zhao et al., pixel values from small to large, pixel values from large to small and pixel values are same along 0°, 45°, 90°and 135° orientations for each non overlapping blocks corresponds to large, small and equal trends respectively [25]. In the same manner, large, small and equal trends are identified for each texture and edge quantized values respectively. The color, edge and texture information estimated by MTSD are concatenated for histopathological images and color information is excluded for gray-scale medical images where the role of color is not significant in distinguishing the images. Thus, the feature vector is expressed as $(N_E^{Q_c}, N_S^{Q_c}, N_L^{Q_c})$, $(N_E^{Q_t}, N_S^{Q_t}, N_L^{Q_t})$, $(N_E^{Q_e}, N_S^{Q_e}, N_L^{Q_e})$ in which N, Q_c / Q_t/ Q_e , E, S and L represents the number of trends, quantized color/texture/edge value, equal, small and large trends respectively. Therefore, MTSD is feature vector of quantized color/texture/edge values versus trends. The feature matrix computed by the MTSD for color is depicted in Fig.1 where number of equal, small and large trends for quantized colour value 0 to 108 is depicted. Small and large trends along 0° and 45° and equal trends along 90° and135° is illustrated in Fig.2.

B. SVM and FSVM

Huge varieties of images produced by various modalities for various parts of the body increases the complication in the classification of medical images. In the literature, numerous techniques have been suggested for classification problem. Researchers working in this domain focused their interest and attention towards artificial neural network owing to its flexibility in modeling and acquiring reasonable accuracy in classification problems. Recently, statistical learning theory based SVM has been utilized widely in various domains due to its high generalization ability and robustness to high-dimensional data[26] and is described in this section as in [27, 28].

Given a training dataset T = $\{(x_i, y_i)\}_{i=1}^n$, where each input feature vector $x_i \in \Re^d$, d is dimension of training dataset and y_i corresponds to x_i's class label and it has only two values, -1 or +1.

If the training data set is linearly separable, the hyperplane is defined as $w^T x_i + b = 0$, which satisfies that $y_i(w^T x_i + b) \geq 0$, where w is the weight vector orthogonal to the hyperplane, b is an offset term and x_i is the data. Thus, the problem for the linearly separable case could be formulated as (1) [26, 27].

$$\min_{w,b} \frac{1}{2} w^T w \qquad (1)$$

Subject to $\quad y_i(w^T x_i + b) \geq 0$

In case the data are non-linearly separable in the input space, the previous analysis can be generalized by introducing a slack variable ξ_i to x_i, which transfers the optimal hyperplane problem into (2) [26, 27]

$$\min \frac{1}{2} w^T w + C \sum_{i=1}^{n} \xi_i \qquad (2)$$

Subject to $y_i(w^T x_i + b) \geq 1 - \xi_i$

and $\xi_i \geq 0, i = 1, \ldots n$

where the parameter C can be regarded as a regulation parameter that imposes a balance between the minimization of the error function and the maximization of the margin of the optimal hyperplane. Slack variable is used to measure the error in the SVM classifier. The optimization problem (2) can be solved by introducing a Lagrange multiplier α_i to $x_i$and then based on the Karush–Kuhn–Tucker theorem, and the dual form of (3)could be formulated as in[26, 27]

$$\max_{\alpha} w(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} y_i y_j \alpha_i \alpha_j k(x_i, x_j)$$

Subject to $\sum_{i=1}^{n} y_i \alpha_i = 0, 0 \leq \alpha_i \leq C, i = 1, \ldots, n \qquad (3)$

Finally, decision function *h(x)* of SVM classifier can be expressed as

$$f(x) = sign(h(x)) = sign(\sum_{i=1}^{n} \alpha_i y_i k(x, x_i) + b)$$

Though the SVM is superior in classification than the conventional classifiers, it is reported [26, 27] that accuracy attains by the SVM is not significantly better owing to the outliers or noises present in training data and is due to equally treating all the training data points which causes overfitting in SVM. The aforesaid problem in SVM can be addressed by fuzzy support vector machine (FSVM) in which each data point is assigned with a membership value based on its relative importance in the class and based on the membership value, all the data points are correctly assigned different degrees of importance to their own classes [28]which can avoid the phenomenon of overfitting due to outliers and noises [28]. If any data point identified as an outlier, it is assigned with a low membership, so its contribution to total error term decreases. According to [26-28], the fuzzy training set is defined as $\{(x_i, y_i, \mu_i)\}_{i=1}^{n}$, where μ_i is the membership value assigned to each data point x_i

The FSVM fuzzifies the penalty term in order to reduce the sensitivity of less important data points [26-28] and the penalty term will be a function of membership values, and thus the SVM is named FSVM [26-29]. In [26-28], the classification problem is formulated as

$$\min \frac{1}{2} w^T w + C \sum_{i=1}^{n} \mu_i^m \xi_i \qquad (4)$$

Subject to $y_i(w^T x_i + b) \geq 1 - \xi_i$

and $\xi_i \geq 0, i = 1, \ldots n$

where μ_i is the membership

Similar to SVM, the optimization problem (4) can be solved by introducing a Lagrange multiplier α_i to x_i and then based on the Karush–Kuhn–Tucker theorem, and the dual form of (5) could be formulated as in [26-29]

$$\max_{\alpha} w(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} y_i y_j \alpha_i \alpha_j k(x_i, x_j)$$

Subject to

$$\sum_{i=1}^{n} y_i \alpha_i = 0, 0 \leq \alpha_i \leq \mu_i^m C, i = 1, \ldots, n \qquad (5)$$

From the eq.(3) and (5), it is clear that the upper bounds of Lagrange multipliers is the only difference between SVM and FSVM [26-28]. In FSVM, data points with the same value of Lagrange multipliers may shown a different type of support vectors in FSVM due to the μ_i [26-29].

C. Similarity measurement

Different distance measures are available in the literature for analyzing the distance between two images, Manhattan distance measure is incorporated in proposed system due to its less computational complexity and effectiveness [30].

	E	S	L
0	12	2	10
1	6	2	19
.	.	.	.
.	.	.	.
.	.	.	.
108	.	.	.

Fig.1. MTSD for coloor feature

(a)

68	80	55
70	68	55
36	80	9

(b)

60	43	55
70	36	80
10	43	8

(c)

80	70	80
55	70	55
0	70	70

(d)

80	43	36
55	80	0
70	60	80

Fig.2. (a). Small trend along 0° (b). Large trend along 45° (c). Equal trend along 90° (d). Equal trend along 135°

Manhattan distance is also known as L1 distance or city block distance and it uses the sum of absolute differences of the variables [30] and is defined as a distance between two points in Euclidean space with fixed Cartesian coordinate system [30].

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The Manhattan distance between two images is defined as

$$S\left(I^{q}, I^{t}\right) = \sum_{i=1}^{k}\left(I_i^{q} - I_i^{t}\right) \quad (6)$$

where, I_i^q and I_i^t are query and target image feature vectors respectively and k-size of the combined feature vector.

D. *Performance assessment*

The precision and recall are the measures used to measure the performance of proposed system. The accuracy of retrievl out of top k retrieved images is computed using the precision and accuracy with respect to total number of relevant images in the database is computed using the recall based on the similarity value with query images. The precision and recall is defined as in [18]

$$precsion(k) = \frac{I_k}{k} \quad (7)$$

$$recall(k) = \frac{I_k}{n} \quad (8)$$

Where I_k , k and n are the number of relevant images retrieved, total number of images retrieved and total number of relevant images in the database respectively.

III. EXPERIMENTAL RESULTS

The proposed method is evaluated on heterogeneous medical image dataset [18] and the images in the datasets are transformed into feature vectors, and are stored in feature dataset. The datasets contains 83 classes of images of various modalities with ground truth. Totally 6400 images are available in the dataset. Fig.3 listed some sample images from the experimental dataset. We considered every image as query in the experiments.

Ten-fold cross validation is performed in the proposed work in which the size of each fold is approximately equal and for each run of ten- folds cross validation, nine data sub sets are used in training and the remaining one is used in testing such that all data sub sets are used in both training and testing. We used average precision and recall as a measurement to evaluate the retrieval performance of the proposed system on experimental dataset. The retrieval effectiveness of the proposed method is validated using the proposed fusion of MTSD and FSVM and is compared with the approach suggested in [21]. It can be seen from the results that the proposed fusion of techniques attains better accuracy for heterogeneous medical images due to the better classification performed by FSVM. Besides, we used Manhattan distance to measure the similarity due to its better computational efficiency and effectiveness.

The results of the proposed and existing approaches are listed in Table.I and Fig.4 where the average precision and average recall for top k returned images are utilized to estimate the retrieval process. As shown in Fig.4, compared with our existing approach whose precision are 66.12% and 65.87% for color and gray scale medical images respectively with 100 images returned, the MTSD approach has better performance (67.01% and 66.23%) with FSVM and Manhattan distance. These results clearly indicate that the proposed fusion of MTSD, FSVM and Manhattan distance have superior performance for heterogeneous medical image retrieval.

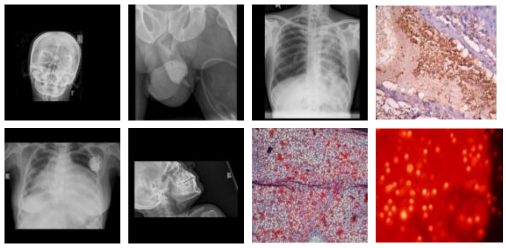

Fig.3.Sample images from the experimental dataset

Table I. The averagee precision annd recall of proposed and exissting approaches

Datasets	Performance	MTSD with FSVM and Manhaattan Distance	MTSD with Fuzzy k-NnN and Eucliddean distance [21]
Color meedical images	Precision (%)	67.01	66.12
	Recall (%)	08.89	09.26
Gray-scale meddical images (only considering thhe texture and shapee details computed by MSTD)	Precision (%)	66.23	65.87
	Recall (%)	08.01	08.93

Due to the complex structure of medical images, it is very challenge to clearly classify the medical images. Further, high time complexity limits the performance in large-scale image retrieval [31] and accuracy of retrieval system is also considerably depends on the learning ability of classifier. Thus, besides the roll of feature descriptor, the effectiveness of classifier is also very important together with the effective distance measure for effective image retrieval. In consideration with that proposed system mainly focused on effective pre-filtering and similarity matching and is achieved in the proposed work by combining FSVM and Manhattan distance with proposed feature descriptor, MTSD.

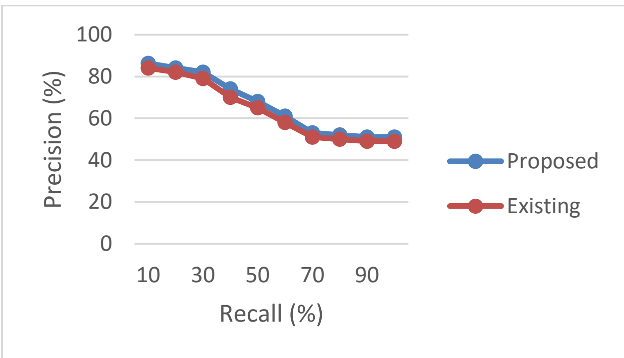

Fig.4. Precision versus recall graph for proposed and existing approaches [21]

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The computational complexities of proposed and existing [21]
approaches are represented in Table.II and it demonstrates that the combined strategy attempts to reduce the search space considerably, attains fast and higher retrieval. Core i3 processor, 4 GB RAM and 64 bit Windows 7 operating system is used in the experimental study.

Table II. The computation complexity of proposed and existing approaches

Datasets	Proposed Method-Computation time in (ms)	Existing Method [21]-Computation time in (ms)
Color medical images	68.08	60.12
Gray-scale medical images (only considering the texture and shape details computed by MSTD)	75.21	69.89

IV. CONCLUSION

Classification and distance measure are essential components in most content based image retrieval systems. In this paper, we proposed a novel approach by combining multi-trend structure descriptor (MTSD) with fuzzy SVM and Manhattan Distance measure to improve the retrieval accuracy as well to reduce the computational complexity of heterogeneous image retrieval. The effective pre-filtering process by FSVM, and the simple computation cost of Manhattan distance significantly avoids the expensive computation cost in the retrieval process. From the experimental results it is also found that the fusion of MTSD and FSVM significantly increases the retrieval precision for heterogeneous medical image dataset owing to the effective image representation and learning ability of classifier. In future, the image representation ability of MTSD may be enhanced in order to attain better retrieval results.

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