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Research Article

Automative Multi Classifier Framework for Medical Image Analysis

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Abstract: Medical image processing is the technique used to create images of the human body for medical purposes. Nowadays, medical image processing plays a major role and a challenging solution for the critical stage in the medical line. Several researches have done in this area to enhance the techniques for medical image processing. However, due to some demerits met by some advanced technologies, there are still many aspects that need further development. Existing study evaluate the efficacy of the medical image analysis with the level-set shape along with fractal texture and intensity features to discriminate PF (Posterior Fossa) tumor from other tissues in the brain image. To develop the medical image analysis and disease diagnosis, to devise an automotive subjective optimality model for segmentation of images based on different sets of selected skin texture from the unsupervised learning model of extracted features. After segmentation, classification of images is done. The classification is processed by adapting the multiple classifier frameworks in the previous work based on the mutual information coefficient of the selected features underwent for image segmentation procedures. In this study, to enhance the classification strategy, we plan to implement enhanced multi classifier framework for the analysis of medical images and disease diagnosis. The performance parameter used for the analysis of the proposed enhanced multi classifier framework for medical image analysis is Multiple Class intensity, image quality, time consumption.

Keywords: Feature extraction, feature selection, medical image analysis, mutual information, scale invariant feature extraction

INTRODUCTION

Medical imaging is the method and practice utilized to generate images of the person body (or parts) for medical purposes or medicinal science. Medicinal imaging utilizes state of-the-art knowledge to present 2 or 3-dimensional images of the existing body. Imaging revises can analyze disease or dysfunction from outer the body, provided that information exclusive of tentative surgical procedure or other persistent and probably hazardous diagnostic techniques. In current years, the meadow of medicinal imaging has undergone severe changes which in circle have assisted the surgeons in efficiently analyzing the diseases. But, still there is group of capacity to obtain novel techniques for efficiently recognizing the disease. In the field of remedial imaging, segmentation acts as a main role in pleasing the pre-surgery and post-surgery conclusion for earlier revival of the diseases.

In computer vision, collection of data obtained by casing the similar prospect or object at diverse times, or from diverse viewpoint, will be in diverse synchronization systems. Image registration is the procedure of changing the diverse collections of data into one synchronization system. To be defined it engages deciding alterations that transmit spatial information expressed in one image to that in one more or in corporeal space.

Image registration is achieved on a progression of no less than two images, where the position of the image to which all the others will be recorded. The medical images plays a significant role in all image examination tasks in which mixture of different data sources is essential as in Image fusion. Technical progresses in medical imaging have allowed radiologists to generate images of the person and its domestic construction with exceptional declaration and practicality. Two vital kinds of medical images are completed: body images like SPECT or PET scans present information for an anatomic map of the body. Diverse medical imaging methods might present scans with opposite and irregularly information. The amalgamation of images can frequently guide to supplementary scientific information not obvious in the sequence set of images. The objective of image combination is to impress a structural anatomic support on functional images.

Processing of multi-frame imagery, i.e., detaining of the similar panorama by diverse sensors and combination of the group data for attaining a better

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considerate of a specified situation, is extensively attained in astronomy and satellite remote sensing, in microscopy imaging, and also, in military and observation applications. In such cases, an improved illustration of the correct view is usually required from a series of probably degraded acquirement. Similar cases can be bumped into medical imaging. For instance, in Magnetic Resonance Imaging (MRI), the accessibility of numerous rapid scans of the similar organ enforces the demanding task of their arrangement into a higher feature version of the proper original image. In several other image detaining applications, the imaging sensors produce poor-quality and probably poor-resolution scene illustrations. Usually, numerous low-resolution edges of the scene are confined during sub pixel motion of the camera. In account of this, these images go through from sensor and visual blur ring (motion-induced or out-of-focus) and blast (quantization errors, sensor dimension, representation errors, etc.). Consequently, image renovation techniques are essential to be processed on the dishonored data.

Image segmentation is an imperative method for mainly remedial image examination tasks. Enclosing good segmentations will promote clinicians and patients as they present significant information for 3-D revelation, surgical preparation and premature disease recognition. Segmentation is the primary and most significant stair in object based image examination. This is not an easy task owing to an amount of reasons. One of them specifies to the purpose of constraint values for the segmentation algorithm. These segments are dependable with the consequential objects in that meticulous application. Nevertheless, the relation among the constraint values and the segmentation result is distant from being evident. Therefore, regulating consequently frequently acquires a time consuming annoying sequence of trials and errors.

LITERATURE REVIEW

Image segmentation indicates a procedure of partitioning an image into different regions. A huge selection of diverse segmentation approaches for images have been urbanized. Amongst them, the clustering techniques have been widely examined and used. In Lai and Chang (2009), a clustering based approach utilizing a Hierarchical Evolutionary Algorithm (HEA) is proposed for medical image segmentation. By way of a hierarchical construction in the gene, the proposed technique can repeatedly categorize the image into suitable classes and evade the complexity of penetrating for the correct number of classes.

Segmentation of tall quality brain MR images employing *a* priori knowledge concerning brain structures allows a more precise and complete explanation (Hassan and Ali, 2012). Benefits of relating *a* priori knowledge concerning the brain structures may also be engaged for image segmentation of precise brain and neural patients. Such process might be achieved to decide the disease period or monitor its measured sequence over time.

A new enhanced mountain clustering technique is planned, by Verma and Hanmandlu (2007) which is contrast with a few of the existing techniques such as FCM, K-Means, EM and Modified Mountain Clustering. The presentation of all these grouping techniques towards color image segmentation is evaluated in terms of cluster entropy as an appraisal of information and practical by computational convolution (Agawal *et al*., 2005). Swift development in medical image processing has commenced routine and semi-automatic techniques to facilitate more specific and consistent diagnosis and treatments (Berry, 2007). Segmentation is regularly executed during parametric methods (Chuang *et al*., 2010) and its exactness can be enhanced using *a* priori information of probabilistic maps.

Feature space (Toews and Arbel, 2003) based techniques have been generally utilized to execute low-level image examination. In Sen and Pal (2012), a density prescription structure that improves density map based discriminability of characteristic values in a characteristic space is planned so as to assist feature space based segmentation in images similar to fingerprint (Leung *et al*., 2009). The author in Ng *et al*. (2006) proposed a method includes k-means and enhanced watershed segmentation algorithm for medicinal image segmentation. Nevertheless, its disadvantages comprise over-segmentation and compassion to forged edges. Intensity based image segmentation (Gurbinder and Balwinder, 2011) is completed to manage with the disadvantages declared above and the examination of k-means clustering with Gaussian distribution is discussed in Prasad Reddy *et al*. (2007).

In this study, to devise a schematic procedure for image segmentation based on different sets of features and the mutual information co-efficient are presented for feature selection.

METHODOLOGY

Multi classifier framework: The proposed study is efficiently designed for performing the classification of the given medical image based on the normal body cells, infected cells and highly infected cells. The classifier is designed based on the mutual information coefficient of the selected features underwent for image segmentation procedures. The classification is done with set of rotation invariant features being selected on the lines of subjective-optimality and different classifiers are organized using different features sets trained in different data (Fig. 1).

The first process employed unsupervised learning model to extract features from the medical images using spatial and hierarchical structures based on scale invariant feature transformation.

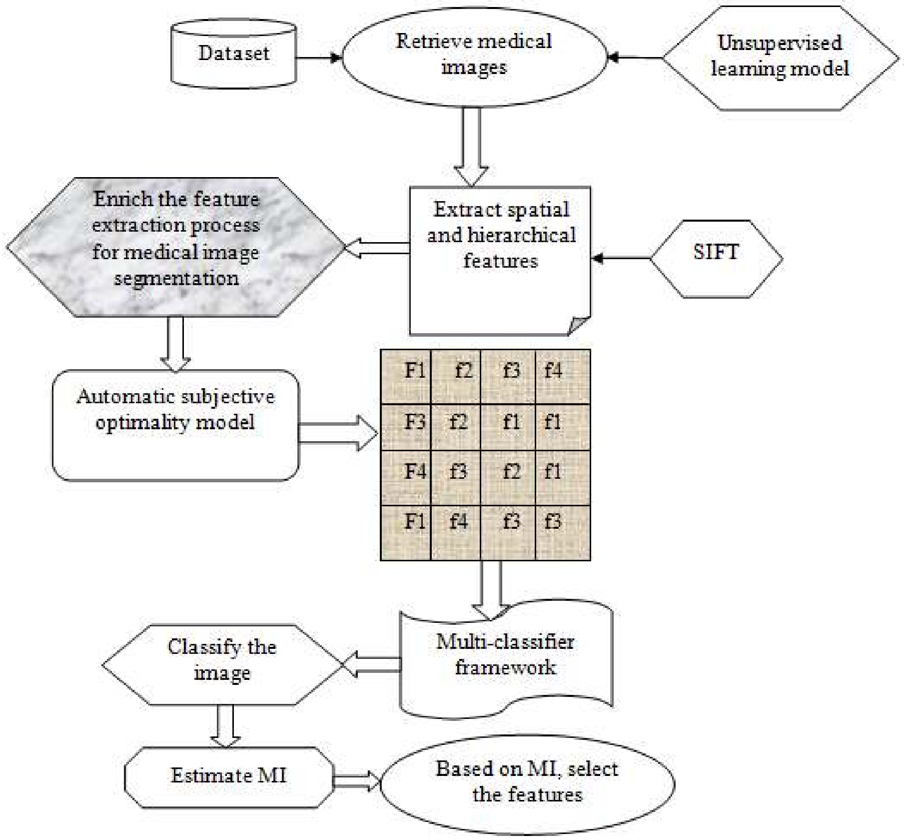

Fig. 1: Architecture diagram of the proposed method

The second process devised a schematic procedure for segmentation of images based on different sets of selected features from the unsupervised learning model of extracted features. Feature selection on the medical images is done on the basis of automatic subjective-optimality model.

The third process is planned to present a multiple classifier for the medical images based on the normal body cells, infected cells and highly infected cells. The classifier is designed based on the mutual information coefficient of the selected features underwent for image segmentation procedures.

The final process is the process of registering the images by estimating the mutual information co-efficient of each of the classified image. For each image, the MI has been measured. Based on the estimation of MI, the selection of features is done for medical image processing for disease diagnosis.

Scale invariant feature transform for feature extraction: By using Scale Invariant Feature Transform (SIFT) image has been converted into a compilation of restricted spatial and hierarchical feature vectors. Each of these features is believed to be unique and variant to any alternation, range, or alteration of the image. In the original implementation, these features can be utilized to discover individual objects in diverse images and the conversion can be unlimited to image segmentation.

Following are the major stages of computation used to extract the set of spatial and hierarchical features from medical image diagnosis.

Scale-space extrema detection: The primary phase of calculation searches over all scales and image locations. It is employed proficiently by utilizing a difference-of-Gaussian function to recognize possible interest points that are invariant to scale and orientation.

Key point localization: At every aspirant location, a comprehensive model is robust to decide location and scale. Key points are chosen based on procedures of their stability.

Orientation assignment: One or more orientations are allocated to every key point position supported on local picture grade directions. All prospect operations are executed on image data that has been changed comparative to the dispensed orientation, scale and location for every feature, thus given that invariance to these alterations.

Key point descriptor: The confined image slopes are considered at the chosen scale in the province about each key point. These are changed into a illustration that permits for significant levels of restricted shape deformation and change in clarification.

For any objective there are many features available for medical images like hierarchical and spatial structure features, appealing points on the entity that can be mined to present a "characteristic" portrayal of the object. This portrayal can then be utilized when endeavoring to situate the object in a figure enclosing several other objects.

Feature selection using automatic subjective optimality model: After extracting the features using SIFT, selection of feature is done based on the respective pixel subjective points. Feature selection on the medical images is done in the previous work based on the automatic subjective-optimality model. Subjective optimality refers to the context of image analysis to be made i.e., tumor, non-tumor and edema dependent feature sets. The feature point selection is realized by approximating for the subjective points like tumor section, non-tumor features within each feature points, the point of equivalence among the subjective parts between the crucial medical image and its consequent model constructed through the training stage. The automatic subjective optimality framework commences subjective optimal feature point selection the concept of subjective conditional probability, which illustrates the geometric allocation of a subjective point specified at the identified positions of a set of points.

Multi-classifier framework using mutual information criterion: After selecting the features, it is necessary to classify the images according to the class and type it belongs to. For classification of segmented image, here we proposed a multi-classifier framework. The multi-classifier is designed based on the mutual information coefficient of the selected features underwent for image segmentation procedures. The classification is done with set of rotation invariant features being selected on the lines of subjective-optimality and different classifiers are organized d using different features sets trained in different data.

After identification of the mutual information (MI) in the segmented image at each pixel point, the classification is done. A multiple classifier is presented for the medical images to categorize the medical images based on the different number of classes like normal body cells, infected cells, and highly infected cells. Normally, an image has dissimilar number of classes which has several instances. To classify the image according to the class it belongs, mutual information criterion is utilized.

The multi-classifier is designed based on the mutual information coefficient of the selected features underwent for image segmentation procedures. The classification is done with set of rotation invariant features being selected on the lines of subjective-optimality and different classifiers are organized d using different features sets trained in different data. The method starts by choosing the distinct feature A_i that has the maximum MI with the output variable B and expressed in Eq. (1):

$$I(A_j;B) - \beta \sum_k I(A_k;A_j) \tag{1}$$

where, k symbolizes pre-chosen features and j symbolizes the candidate features. Parameter b gets values among 0.5 and 1.0 and its best value is identified empirically. With the selected features and mutual information, the classification is done efficiently based on different number of classes and provides an efficient data retrieval process.

Feature selection and image registration based on MI: At first, mutual information tests the ability of features to separate each and every classified image. Based on the description of mutual information content defined in the previous work, the MI for feature selection is processed as Eq. (2):

$$I(A,B) = \sum_a \sum_b p(a,b).\log\left(\frac{p(a,b)}{p(a)p(b)}\right) \tag{2}$$

Here A is the vector for the specified feature and B is the classified image. But from the Eq. (2), it is being noted that the values of A are continuous and for B is discrete. By maximizing the mutual information co-efficient, the separability of the features is also being maximized.

Joint mutual information tests the independence of features from all other features of the classified image:

$$I(A_1, A_2, \ldots, A_N; B) = \sum_{k=1,N} I(A_k; B \mid A_{k-1}, A_{k-2}, \ldots, A_1) \tag{3}$$

From all the obtained mutual information co-efficient, the sorting of MI is done based on the range of values of high to low. The selections of features are done based on the maximum and minimum values of Euclidean distance.

For the selection of set of features, based on the mutual information co-efficient, the feature with the maximum values are denoted as I (A_j, B) and the minimal values are denoted as $\sum_k I\ (A_k, A_j)$.

Experimental evaluation: The experimental simulation is conducted by using the medical image processing software package (MATLAB). An experimental performance is evaluated with benchmark data sets extracted from research repositories of both real and synthetic data sets. The medical image is given as input which includes features like size, shape, texture, spatial and hierarchical etc. The features are extracted by using SIFT described in our first work for medical image segmentation. Then the feature based image segmentation is achieved in our second work through the automatic subjective-optimality model. The schematic representation efficiently segments the given image based on different sets of selected features from the unsupervised learning model of extracted features. Subjective optimality refers to the context of image analysis to be made i.e., tumor, non-tumor and edema dependent feature sets. In this study, a multiple classifier framework is done for the segmented medical images based on the normal body cells, infected cells and highly infected cells. Easy way to comply with the conference paper formatting requirements is to use this document as a template and simply type your text into it.

The classifier is designed based on the mutual information coefficient of the selected features underwent for image segmentation procedures. The classification is done with set of rotation invariant features being selected on the lines of subjective-optimality and different classifiers are organized d using different features sets trained in different data. During experimentation, a medical image is taken as input and processed with the schematic procedure for image segmentation and feature selection process. Then MI is identified for every pixel point of the segmented image. A multi-classifier framework is applied to evaluate the classification among the features obtained for the given medical image. The performance of mutual concept criterion for medical image analysis is measured in terms of:

- No. of features
- Time consumption
- Image quality

RESULTS AND DISCUSSION

In this section, provide some experimental results to illustrate the effectiveness of the proposed Enhanced Multi-classifier Framework using Mutual Concept Criterion (EMFMCC) for medical image analysis. This scheme is efficiently classified the medical images based on the normal body cells, infected cells and highly infected cells. The classification is done with set of rotation invariant features being selected on the lines of subjective-optimality using different features sets trained in different data. To evaluate the efficiency of the proposed scheme, the results are compared with the existing local feature extraction method and with our previous works.

Table 1 describes the consumption of time needed to perform the classification of rich features based on the number of features available in the segmented image. The time consumption of the proposed enhanced multi-classifier framework using mutual concept criterion is compared with the previous works Feature Selection on segmented image using Automatic Subjective Optimality model (FSASO) and Scale Invariant Feature Transform (SIFT).

Table 1: No. of features vs. time consumption

No. of features	Time consumption (sec) Proposed EMFMCC	MFMC	FSASO	SIFT
5	10	15	18	23
10	16	23	26	30
15	23	34	38	42
20	28	42	45	50
25	34	50	52	56
30	40	56	60	62
35	46	67	70	75

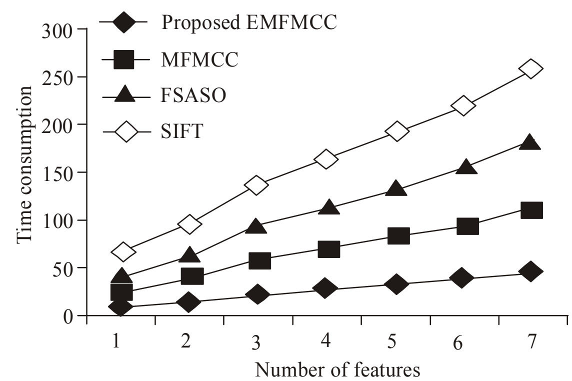

Fig. 2: No. of features vs. time consumption

Figure 2 describes the consumption of time needed to perform the classification of rich features based on the number of features available in the segmented image. Since the proposed EMFMCC followed the process of mutual information co-efficient for classification. The mutual information concept efficiently obtained the information at each pixel point in the segmented image. So, it is easy to classify the image based on the information obtained. The classification is done with set of rotation invariant features being selected on the lines of subjective-optimality and different classifiers are organized using different features sets trained in different data. The time consumption is measured in terms of seconds. Compared to the existing Feature Selection on segmented image using Automatic Subjective Optimality model (FSASO), Scale Invariant Feature Transform (SIFT), the proposed EMFMCC provides an efficient classification of medical images in a less interval of time. The variance in the consumption of time is 60-70% low in the proposed EMFMCC.

Table 2 describes the efficiency of classification of rich features based on the number of pixels in the given medical image. The efficiency of the proposed enhanced multi-classifier framework using mutual concept criterion is compared with the previous works like Feature Selection on segmented image using

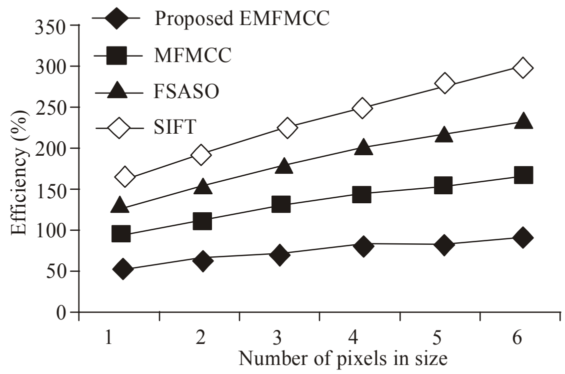

Fig. 3: No. of pixels in size vs. efficiency

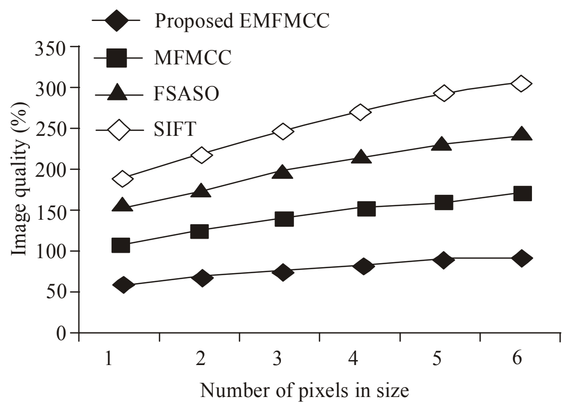

Fig. 4: No. of pixels in size vs. image quality

Automatic Subjective Optimality model (FSASO) and Scale Invariant Feature Transform (SIFT).

Figure 3 describe the efficiency of classification of rich features based on the number of pixels in the given medical image. In the proposed EMFMCC, the classification of segmented image is done reliably with the mutual information co-efficient concept of the selected features underwent for image segmentation procedures. So compared to the other works, the proposed enhanced multi-classifier framework using mutual concept criterion provides a reliable medical image analysis in terms of classification, segmentation and time consumption.

Table 3 describes the quality of the image based on the number of pixels in the given medical image. The efficiency of the proposed enhanced multi-classifier framework using mutual concept criterion is compared with the previous works like Feature Selection on segmented image using Automatic Subjective Optimality model (FSASO) and Scale Invariant Feature Transform (SIFT).

Figure 4 describes the quality of the image based on the number of pixels in the given medical image. In the proposed EMFMCC, the classification of segmented image is done reliably with the mutual information co-efficient concept of the selected features

Table 2: No. of pixels in size vs. efficiency

	Efficiency (%)			
No. of pixel in size	Proposed EMFMCC	MFMCC	FSASO	SIFT
100	54	40	35	30
200	63	48	42	38
300	72	56	50	45
400	80	62	56	51
500	84	70	62	58
600	90	74	69	62

Table 3: No. of pixels in size vs. image quality

	Image quality (%)			
No. of pixel in size	Proposed EMFMCC	MFMCC	FSASO	SIFT
100	58	50	45	32
200	67	56	50	40
300	75	63	57	47
400	82	69	63	53
500	87	72	70	59
600	92	76	72	62

underwent for image segmentation procedures. So compared to the other works, the proposed enhanced multi-classifier framework using mutual concept criterion provides a good quality of medical image based on the number of pixels in the specified image.

Finally, it is being observed that the proposed EMFMCC classified the medical images based on the normal body cells, infected cells and highly infected cells. The proposed EMFMCC is processed under the MI for feature selection process. The classifier is designed reliably based on the mutual information coefficient of the selected features underwent for image segmentation procedures. The classification is done with set of rotation invariant features being selected on the lines of subjective-optimality and different classifiers are organized using different features sets trained in different data.

CONCLUSION

Enhance multiple classifier frame work for the medical images to achieve the rich feature image classification based on different number of classes like normal body cells, infected cells and highly infected cells. The classifier is designed based on the mutual information coefficient of the selected features underwent for image segmentation procedures. The classification is done reliably with set of rotation invariant features being selected on the lines of subjective-optimality and different classifiers are organized using different features sets trained in different data. The unsupervised learning model is used to extract features from the medical images using spatial and hierarchical structures based on scale invariant feature transformation. This would enrich the features extracted from the medical image for segmentation compared to the existing method features of intensity, FD and shape model. To be clear, this study showed that the mutual information is a promising classification criterion for medical image analysis. An extensive evaluation is carried out to evaluate the performance of the proposed multi-classifier framework using mutual concept criterion. An evaluation concluded that the proposed EMFMCC is better in terms of image quality, time consumption and its efficiency compared to the existing Local Feature Extraction Method (LEFM) and with our previous works Feature Selection on segmented image using Automatic Subjective Optimality model (FSASO) and Scale Invariant Feature Transform (SIFT).

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