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Feature Selection on Segmented Image using Automatic Subjective Optimality Model

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ABSTRACT

Medical imaging acts as a significant function on medical informatics and it is listened on recognition and categorization of diseases. Variable nature of image features, such as size, shape, intensity, color, texture etc., cause complexity in the image segmentation and analysis of the image nature. To overcome the segmentation issues, our previous work presented unsupervised learning model to extract features from the medical images based on scale invariant feature transformation. This would enrich the features extracted from the medical image for segmentation. But the previous work does not discuss about the segmentation for selected spatial and hierarchical features and provides less efficiency in performance. To enhance the process, in this work, a schematic procedure is used 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. Subjective optimality refers to the context of image analysis to be made i.e., tumor, non-tumor, and edema dependent feature sets. The experimental performance is evaluated with benchmark data sets extracted from research repositories of both real and synthetic data sets. The performance parameter used for the analysis of the proposed feature selection on segmented image using automatic subjective optimality model are Feature transformation factor, Selection size, Image Subjective-Optimal ratio.

Keywords: Medical image analysis, Feature selection, automatic subjective-optimality model, schematic procedure

1. 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.

Remedial Imaging knowledge, such as CT, MRI, Positron production tomography (PET), US have been extensively useful to a variety of medicinal procedures. Compared to conventional remedial diagnosis, they present non-invasive however authoritative means to examine the domestic structures and actions of human bodies. With the assist of such methods, doctors are able to achieve multidimensional information such as 2-D slices, 3-D volumetric images and videos of ROI, which assists the presentation of both qualitative and quantitative examination.

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 should capitulate segments that 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.

Processing of multiframe images, i.e., detaining of the similar sight by diverse sensors and synthesis of the congregated data for attaining a enhanced accepting of a specified circumstances, is extensively achieved in satellite isolated intellection and astronomy, in microscopy imaging, and too, in armed and observation applications. In such cases, an improved illustration of the factual sight is usually required from a series of probably dishonored attainments. Analogous cases can be processed in remedial imaging. For instance, in magnetic resonance imaging (MRI), the accessibility of numerous rapid scans of the similar organ enforces the demanding charge of their amalgamation into a higher-quality edition of the correct original image. In numerous other image detaining applications, the imaging sensors engender poor-quality and probably poor-resolution sight representations.

In this work, 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. Subjective optimality refers to the context of image analysis to be made i.e., tumor, non-tumor, and edema dependent feature sets. This paper is well thought-out as follows; Section 2 deals with the review of literature. Section 3 described about the feature selection on segmented image using automatic subjective optimality model. Section 4 and 5 offered to Experimental result and discussion .Finally the conclusion of this paper in Section 6.

2. LITERATURE REVIEW

Recently in the literature, many new methods have been implemented for segmentation and classification of medical images. In 1994, Adams has proposed the various image segmentation methods and the Seeded Region Growing (SRG) algorithm [1]. It is a fast, robust and parameter-free method for segmenting intensity images given initial seed locations for each region. In SRG, the individual pixels that satisfy some neighborhood constraint are merged if their attributes, such as intensity or texture are similar enough. The seed location, an optimal threshold value and a similarity measure need to be determined either manually or automatically. There has been some research in the field of texture analysis in medical image segmentation. Karkanis [2] has applied a multilayer feed-forward neural network based on second order gray level statistics to classify cancer regions in colonoscopy images in the year 1999.

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 [3], 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. 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 [4] might be achieved to decide the disease period or monitor its measured sequence over time.

A new enhanced mountain clustering technique [5] is planned, 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 a appraisal of information and practical by computational convolution [6]. Swift development in medical image processing [7] has commenced routine and semi-automatic techniques to facilitate more specific and consistent diagnosis and treatments. Segmentation is regularly executed during parametric methods [8] and its exactness can be enhanced using *a* priori information of probabilistic maps [9].

Feature space [10] based techniques have been generally utilized to execute low-level image examination [11]. In [12], 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 [13] in images similar to fingerprint [14]. The author in [15] proposed a method includes k-means and enhanced watershed segmentation algorithm [16] for medicinal image segmentation. Nevertheless, its disadvantages comprise over-segmentation and compassion to forged edges. Intensity based image segmentation [17] is completed to manage with the disadvantages declared above and the examination of k-means clustering [18] with Gaussian distribution is discussed in [19]. In this work, a schematic procedure for image segmentation based on different sets of features and the automatic subjective optimality model is presented for feature selection.

3. FEATURE SELECTION ON SEGMENTED IMAGE USING AUTOMATIC SUBJECTIVE OPTIMALITY MODEL

The proposed work is efficiently designed for segmenting the medical image to determine the features obtained on the given image. The proposed feature selection on segmented image using automatic subjective optimality model [FSASO] is processed under three different phases. The first phase describes the process of extracting the spatial and hierarchical features from the given medical image. The second phase describes the process of devising a schematic procedure for image segmentation based on different sets of selected features from the unsupervised learning model of extracted features. The third phase describes the process of automatic subjective-optimality model for feature selection. Subjective optimality refers to the context of image analysis to be made i.e., tumor, non-tumor, and edema dependent feature sets. The architecture diagram of the proposed FSASO is shown in figure 1.

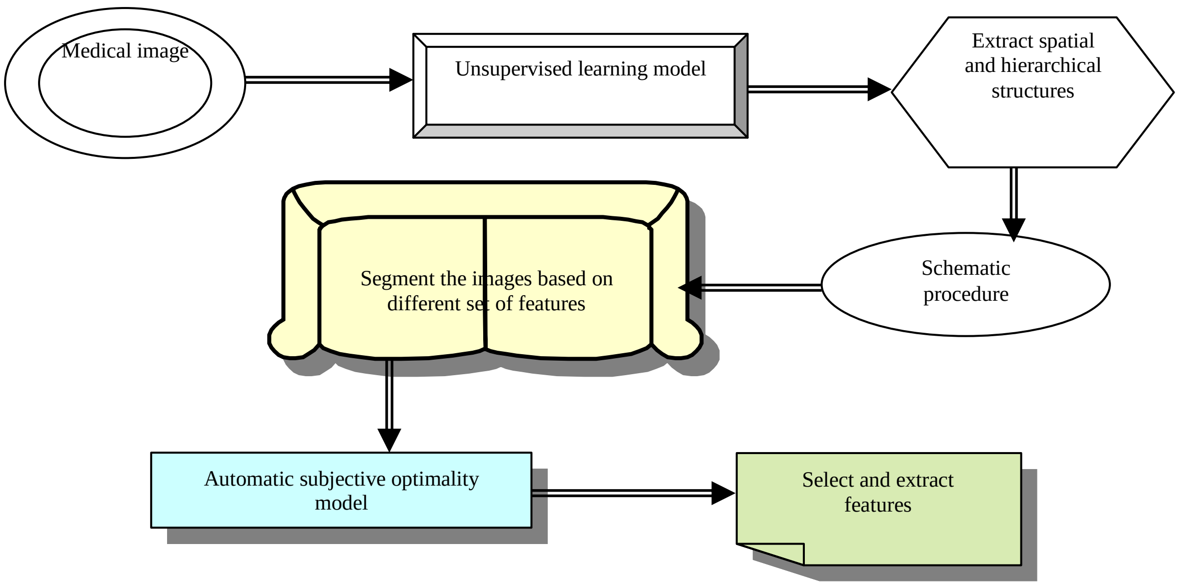

Fig 1: Architecture diagram of the proposed CHPS

The first phase describes the process of unsupervised learning model 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.

The second phase describes the process of 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. Subjective optimality refers to the context of image analysis to be made i.e., tumor, non-tumor, and edema dependent feature sets.

3.1 Extracting Spatial and Hierarchical Features

Using scale invariant feature transform mechanism, the spatial and hierarchical features are also been extracted from the given image. The four major steps are used to extract the spatial and hierarchical features. They are Scale-space extrema detection, Key point localization, Orientation assignment, Key point descriptor. Using the above steps, the SIFT not only extract the size, shape intensity features, but also spatial and hierarchical features.

3.2 Schematic Procedure for Feature based Image Segmentation

Image segmentation is the process of partitioning an image into a number of regions or classes with similar properties based on pre-defined criteria. Image segmentation, portioning the image into homogeneous regions, is a challenging task. The richness of visual information makes bottom-up, solely image driven approaches always prone to errors. To b e reliable, the current systems must b e large and incorporate numerous ad-hoc procedures to provide efficient image segmentation. Feature based image segmentation is a method that exploits exclusively the photometric information of an image on its histogram. The schematic representation of feature based image segmentation is shown in figure 2.

Our schematic approach to medical image segmentation is based on the insight that the distributions formed by a SIFT have a physically determined shape in medical histogram-space. We model an image as being generated by a set of dominant features (DF), where each dominant feature is described by a distribution in histogram-space. Each DF is related to a semantic object in the image.

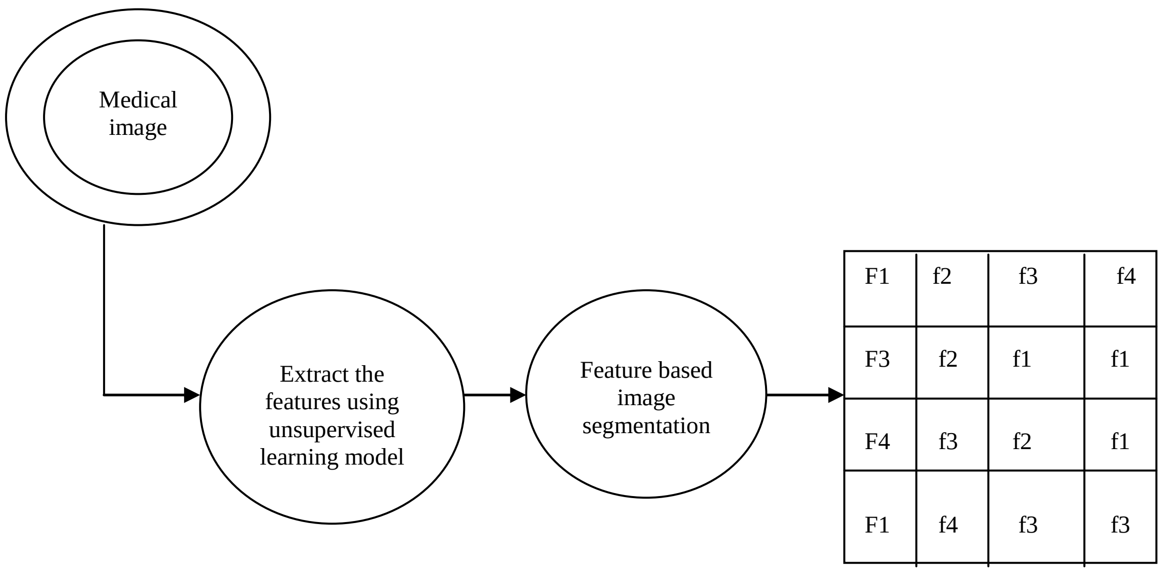

Fig 2: Schematic representation of feature based image segmentation

Let us consider a medical image I. In common, an image can be depicted as a two-dimensional function f(x, y), where (x, y) signifies the spatial coordinates and the f is the feature value at (x, y), and f(x, y) $\in$ [0, L], the set of distinct points of the feature value. An image segmentation crisis could be devised as follows. Find a feature values p of $\{R_1, R_2, . . . R_k\}$ of I with each R_j being a associated feature class of I, such that

$$\min z = \sum_{i=1}^{k} \sum_{(x,y)\in R_i} [\operatorname{Re} p(R_i) - f(x,y)]^2 \quad \ldots\ldots (1)$$

Where,

Rep (R_i) denotes the representative value of features R_i, and k is the number of features.

The above figure 2 describes the process of feature based image segmentation. In the given medical image, each part of the image is represented in a pixel format. Through the point of pixels in the image, segmentation is done. The schematic procedure first analyzes the features mentioned on each and every pixel. Then based on the features' presence in the image, segmentation is done. Consider a given medical image as I. The medical image I is divided in blocks of pixels. Each block must be assigned to one of the features by the segmentation procedure. Using unsupervised learning model, extracted not only the intensity, shape features but also the spatial and hierarchical features from the given image. Let the features is specified as f1, f2, f3, f4. Based on the features presence on the respective pixel of the image, segmentation is done. The performance of any segmentation method depends highly on the choice of pixel features.

3.3 Feature selection using automatic subjective optimality model .

Feature selection on the medical images is done on the basis of 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 P_{ij} within each feature points F_i , the point of equivalence among the subjective parts between the crucial medical image and its consequent model constructed through the training stage. The proposed framework commences subjective optimal feature point selection the concept of subjective conditional probability, which illustrates the geometric allocation of a subjective point P specified the identified positions of a set of *m* points i.e.,

$$P(p_i \mid p_{s(1)},...,p_{s(m)}) = P(x_i \mid x_{s(1)},...,x_{s(m)}) \quad \ldots\ldots (2)$$

Where *s* is an indexing utility and $\mathbf{x_i}$ represents the coordinates of the subjective point p. The inference of the provisional probability entails a proper deterioration model that relates the subjective points. $P_{s(1)},\ldots, P_{s(m)}$ denotes the corresponding subjective features of the given segmented medical image.
Consequently, the optimality of the subjective feature selection is assured to yield the geometrically suitable position of feature points with the best subjective outline based on the size of the features selected from the segmented image. This facilitates the exercise of significantly large feature selection in its place of the conventional normal feature selection. By using the entire image for each feature selection process, it is evident that it is easy to process with the selected features.

4. EXPERIMENTAL EVALAUTION

In this paper, the experimental simulation is conducted by using the medical image processing software package (MATLAB). 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 the previous work for medical image segmentation. Then the proposed schematic procedure is followed for feature based image segmentation. The schematic representation efficiently segments the given image based on different sets of selected features from the unsupervised learning model of extracted features. After segmentation is done the feature selection is done,which is done on the basis of 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. During experimentation, a medical image is taken as input and processed using the proposed schematic procedure and subjective optimality technique for image segmentation and feature selection of the medical image and enhanced the segmentation process compared to an existing local feature extraction method. The performance of the proposed feature selection on segmented image using automatic subjective optimality model [FSASO] is measured in terms of

- Feature transformation factor,
- Selection size,
- Image Subjective-Optimal ratio.

Feature transformation is a practice in the course of which a novel set of features is formed. The alternatives of feature transformation are feature extraction and feature construction. Both are termed as feature discovery.
Feature selection decreases the dimensionality of data by choosing only a division of considered features (predictor variables) to create a representation. Selection measure regularly involves the minimization of a precise determine of prophetic error for models robust to diverse subsets.
Subjective optimality refers to the context of image analysis to be made i.e., tumor, no tumor, and edema dependent feature sets.

5. RESULTS AND DISCUSSION

In this section, some experimental results to illustrate the effectiveness of the proposed feature selection on segmented image using automatic subjective optimality model. The FSASO scheme enriched the feature extraction and selection process of the given medical image using schematic procedure and subjective optimality model. To evaluate the performance of the proposed feature selection on segmented image using automatic subjective optimality model [FSASO], the results are compared with the existing local feature extraction method. The below table and graph describes the performance of the proposed feature selection on segmented image using automatic subjective optimality model.

Table 1. No. of features vs. feature transformation

No. of features	Feature transformation (%)		
	Proposed FSASO	SIFT	Existing LFEM
2	24	20	10
4	36	26	16
6	53	31	13
8	42	49	26
10	60	45	22

The above table 1 describes the feature transformation based on the number of features obtained. The outcome of the proposed feature selection on segmented image using automatic subjective optimality model is compared with an existing LFEM and previous work SIFT based feature extraction.

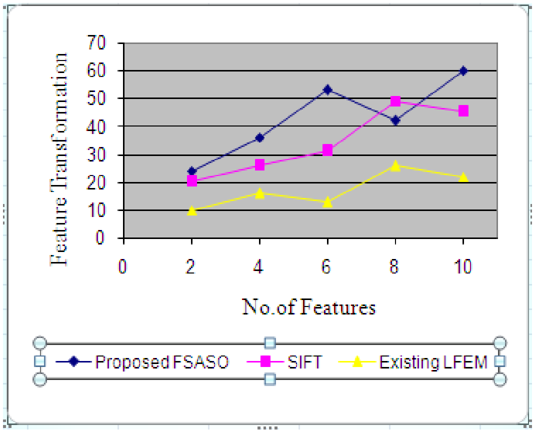

Fig 3: No. of features vs. feature transformation

Figure 3 describes the feature transformation based on the number of features obtained. Feature transformation is a practice in the course of which a novel set of features is formed. The alternatives of feature transformation are feature extraction and feature construction. In the proposed FSASO, the given image is segmented based on the different sets of features extracted using SIFT. A schematic representation is efficiently used for image segmentation based on the feature sets available. Since the image has been segmented based on the features, the feature transformation is effectively high in the proposed FSASO. Compared to an existing LFEM and previous work SIFT based feature extraction, the proposed feature selection on segmented image using automatic subjective optimality model provides an efficient feature transformation which could be varied among the feature extraction and construction.

Table 2. Feature selection size vs. execution time

Feature selection size	Execution time		
	Proposed FSASO	SIFT	Existing LFEM
2	9	11	15
4	16	20	19
6	13	14	23
8	19	19	29
10	17	23	33

The above table 2 describes the execution time taken for feature selection based on the size of features obtained. The outcome of the proposed feature selection on segmented image using automatic subjective optimality model is compared with an existing LFEM and previous work SIFT based feature extraction.

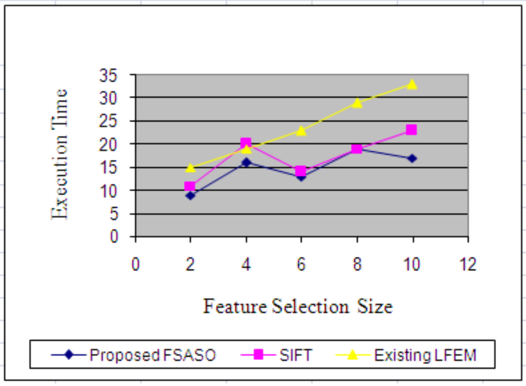

Fig 4: Feature selection size vs. execution time

Figure 4 describes the execution time taken for feature selection based on the size of features obtained. Normally, feature selection decreases the dimensionality of data by choosing only a division of considered features (predictor variables) to create a representation. Execution time is measured in terms of seconds. Based on the feature size of the given input image, execution is computed. In the proposed FSASO, the segmentation is done based on the different sets of features. So, selection of feature here consumes less time and the feature is selected relative to the subjective optimality. Compared to an existing LFEM and SIFT based feature extraction, the proposed feature selection on segmented image using automatic subjective optimality model provides an efficient feature selection process by consuming less execution time. The variance among the execution time is 40-50% less in the proposed FSASO.

Table 3. Extracted feature sets vs. subjective optimal ratio

Extracted feature sets	Subjective optimal ratio		
	Proposed FSASO	SIFT	Existing LFEM
2	20	17	10
4	36	30	19
6	49	25	15
8	60	48	23
10	54	34	29

The above table 3 describes the subjective optimal ratio based on the extracted feature sets. The outcome of the proposed feature selection on segmented image using automatic subjective optimality model is compared with an existing LFEM and previous work SIFT based feature extraction.

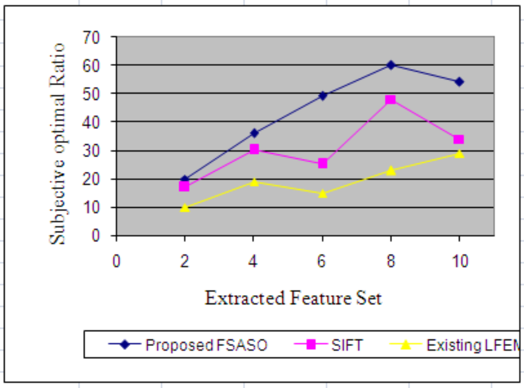

Fig 5: extracted feature sets vs. subjective optimal ratio

Figure 5 describes the subjective optimal ratio based on the extracted feature sets. The subjective optimal ration is defined as the relativity of the feature with respect to the subjects. In the proposed FSASO, first step is to segment the given image based on the different set of features obtained. After segmentation is done with the features, feature selection is done based on the automatic subjective optimal model. So, the selection of feature itself is done based on the subject relativity. Subjective optimality refers to the context of image analysis to be made i.e., tumor, nontumor, and edema dependent feature sets. Compared to an existing LFEM and SIFT based feature extraction, the proposed feature selection on segmented image using automatic subjective optimality model provides an efficient subjective optimality. The variance on subjective optimality is 50-60% high in the proposed FSASO.

Finally, it is concluded that using schematic procedure of feature based image segmentation, a given medical image is segmented based on different sets of selected features from the unsupervised learning model of extracted features. Feature selection on the medical images is also being done effectively on the basis of automatic subjective-optimality model. The performance of the proposed feature selection on segmented image using automatic subjective optimality model is also being high.

6. CONCLUSION

In this work, a schematic procedure for segmentation of images based on different sets of selected features from the unsupervised learning model of extracted features. 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. Then, feature selection is done on the medical images based on automatic subjective-optimality model. Subjective optimality refers to the context of image analysis to be made i.e., tumor, nontumor, and edema dependent feature sets. An extensive evaluation is carried out to evaluate the performance of the proposed feature selection on segmented image using automatic subjective optimality model. An evaluation concluded that the proposed FSASO is better in terms of Image Subjective-Optimal ratio and feature selection compared to an existing LFEM and previous work SIFT based feature extraction.

7. REFERENCES

[1] R. Adams, L Bischof,1994,"Seeded region growing". IEEE Transaction Pattern Analysis Machine Intelligency ,16, 641-647.

[2] J. E. Koss, F. D. Newman, T. K. Johnson, D. L. Kirch, 1999, "Abdominal organ segmentation using texture transform and a Hopfield neural network", IEEE Trans. Medical Imaging, Vol.18, 640-648.

[3] C.-C. Lai, C.-Y. Chang, 2009, 'A hierarchical evolutionary algorithm for automatic medical image segmentation', Expert Systems with Applications, 36, 248–259

[4] Hassan Tavakkoli & Ali Sadeqi, 2012 ,"MR Image Segmentation of Patients' Brain Using Disease Specific a Priori Knowledge", International Journal of Biometrics and Bioinformatics (IJBB), Volume (6) : Issue (1) :

[5] Nishchal K. Verma, et. Al., April 2007 "color segmentation via improved mountain clustering technique", International Journal on Image and graphics, Volume 07, Issue 02,

[6] Agarwal, S. et. Al., 2005,"A comparison of some clustering techniques via color segmentation", International Conference on Information Technology: Coding and Computing, ITCC.

[7] E. Berry. 2007," A Practical Approach to Medical Image Processing". Leeds, UK: Elizabeth Berry Ltd,.

[8] Chuang, K.-S., Tzeng, H.-L., Chen, S., Wu, J., & Chen, T.-J. 2006"Fuzzy c-means clustering with spatial information for image segmentation.Computerized Medical ImagingandGraphics",30,9–15.

[9] M. Toews and T. Arbel, ICCV 2003, "Entropy-of-likelihood Feature Selection for Image Correspondence", Proceedings of the Ninth IEEE International Conference on Computer Vision ,2-Volume Set

[10] Debashis Sen, et. Al.,2012,"Improving feature space based image segmentation via density modification", Information Sciences 191 ,169–191

[11] C.S. Leung, M. Lee, and J.H. Chan, 2009 ,"Personalized Fingerprint Segmentation", ICONIP 2009, Part I, LNCS 5863, pp. 798–809.

[12] K. M. Iftekharuddin, J. Zheng, M. A. Islam, and R. J. Ogg, "Fractalbased brain tumor detection in multimodal MRI," *Appl. Math. Comput.*, vol. 207, pp. 23–41, 2009.

[13] X. Xu andA. Zhang, 2009, "Boost feature subset selection:Anewgene selection algorithm for microarray dataset," *Int. J. Data Mining Bioinformatics*, vol. 3.

[14] M. Schaap, L. Neefjes, et. Al., 2009,"Coronary lumen segmentation using graph cuts and robust kernel regression," *Inf. Process. Med. Imag.*,vol. 5636, pp. 528–539.

[15] H.P. Ng et. Al., 2006 ,"medical image segmentation using k-means clustering and improved watershed algorithm", IEEE Southwest Symposium on Image Analysis and Interpretation.

[16] Gurbinder Kaur et. Al., Jun-Jul 2011 ,"Intensity based image segmentation using wavelet analysis and clustering techniques", Indian Journal of Computer

Science and Engineering (IJCSE) ISSN: 0976-5166 Vol. 2 No. 3 .

[17] P. V. G. D. Prasad Reddy, K. Srinivas Rao and S.Yarramalle , April 2007 ,"Unsupervised Image Segmentation Method based on Finite Generalized Gaussian Distribution with EM and K-Means Algorithm," Proceedings of International Journal of Computer Science and Network Security, vol.7,no. 4, pp. 317-321.

[18] Shaheen Ahmed, Khan M. Iftekharuddin ET. AL., march 2011, "Efficacy of Texture, Shape, and Intensity Feature Fusion for Posterior-Fossa Tumor Segmentation in MRI", IEEE Transactions on information technology in biomedicine, vol. 15, no. 2.

[19] Alexia Giannoula, et.al. February 2011, "Classification-Based Adaptive Filtering for Multiframe Blind Image Restoration", IEEE Transactions on image processing, vol. 20, no. 2.