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Segmentation of Medical Images Based on LS-SVM using Low Level Features

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Abstract

The amount of medical digital images that are produced in hospitals is increasing incredibly so, the need for systems that can provide efficient segmentation and retrieval of images of particular interest is becoming very high. Image segmentation partitions an image into non overlapping regions, which ideally should be meaningful for a certain purpose. In recent years, many image segmentation algorithms have been developed, but they are often very complex and some undesired results occur frequently. In this paper, we present an effective color image segmentation approach based on pixel classification with modified least squares support vector machine (LS-SVM). In this technique, firstly the images are segmented using proposed LS-SVM approach and then its results are compared with performance matrices. This image segmentation not only can fully take advantage of the local information of color image, but also the ability of LS-SVM classifier and removes the problem of over segmentation. Experimental evidence shows that the proposed method has very effective segmentation results and computational behavior, and decreases the time, increases the quality of color image segmentation and eliminates the problem of over segmentation in comparison with the state-of-the-art segmentation methods recently proposed in the literature.

Keywords: Medical imaging, Segmentation, LS-SVM, ER, LCI, BCI.

Introduction

When humans look at a scene with their eyes, the visual system in the brain is able to segment a complex scene in an instant, into a simple scene containing a collection of objects. It is essentially the process of subdividing an image into basic parts and extracting these parts of interest, which are the objects. Therefore image segmentation is one of the fundamentals in computer vision; and it represents the first step in image analysis and pattern recognition. It is one of the most difficult tasks in image processing, because it determines the quality of the final result of analysis.

Fig.1. Image segmentation basic operation

Medical imaging is a technique which is used to create images of the human body for clinical and medical purposes such as medical procedures seeking to reveal, diagnose, or examine disease [11]. The processing of medical image data is playing an increasingly important role. With medical imaging techniques such as X-Ray, computer tomography (CT scan), magnetic resonance imaging (MRI), and ultrasound, the amount of digital images that are produced in hospitals is increasing incredibly. So the need for systems that can provide efficient retrieval of images of particular interest is becoming very high. Unfortunately, only very few medical image retrieval systems are currently used in clinical routine. Image segmentation process is very necessary to perform before image retrieval so it can be easily stored in and retrieved from the database.

Image segmentation is often required as a preliminary and indispensable stage in the computer aided medical image process, object localization, data compression etc [13]. The goal of image segmentation is to cluster pixels into salient image regions, i.e., regions corresponding to individual surfaces, objects, or natural parts of objects. Segmentation could be used for object recognition, occlusion boundary estimation within motion or stereo systems, image compression, image editing, or image database look-up. We consider bottom-up image segmentation. That is, we ignore (top down) contributions from object recognition in the segmentation process. For input we primarily consider image brightness, although similar techniques can be used with color, motion, and/or stereo disparity information. This is typically used to identify objects or other relevant information in digital images.

In this section, we first briefly review previous works which are directly related to our work. These related works include various methods used for image segmentation. Image segmentation is a process of dividing an image into different regions such that each region is nearly homogeneous, whereas the union of any two regions is not [1]. There are various methods which are used in segmentation for medical digital images:

Histogram thresholding-based methods such as Otsu's method: In histogram thresholding method [14-15] operation of converting a multilevel image into a binary image is performed, where it assigns the value of 0 (background) or 1 (objects or foreground) to each pixel of a medical digital image based on a comparison with some threshold value T (intensity or color value). If the T is constant, the approach is called global thresholding otherwise, it is called local thresholding. Global thresholding methods can fail when the background illumination is uneven so to compensate for this uneven illumination we can use multiple thresholds and the threshold selection is typically done interactively. These methods are popular due to their simplicity and efficiency. However problems in this method are that traditional histogram-based thresholding algorithms cannot process images whose histograms are nearly unimodal, especially when the target region is much smaller than the background area.

Edge detection-based methods: Edge detection [16] method is widely used to the problems of medical image segmentation. These methods locate the pixels in the image that correspond to the edges of the objects seen in the image and the result is a binary image with the detected edge pixels. Common algorithms used are Sobel, Prewitt and Laplacian operators. These algorithms are suitable for images that are simple and noise-free. But it does not work well when images have many edges and noise, and unable to easily identify a closed curve or boundary

Clustering methods, such as K-means: Clustering method [17-18] is a process in which a data set or say pixels are replaced by cluster; pixels may belong together because of the same color, texture etc. There are two natural algorithms for clustering: divisive clustering and agglomerative clustering.

Using these two methods directly is that there are lots of pixels in an image which is difficult. An alternative approach can be used is to first write an objective function and then build an algorithm. The K means and fuzzy c-means algorithms are the iterative techniques that are used to partition an image into K clusters, where each pixel in the image is assigned to the cluster that minimizes the variance between the pixel and the cluster center and is based on pixel color, intensity, texture, and location, or a weighted combination of these factors. These algorithms may not return the optimal solution. The quality of the solution depends on the initial set of clusters and the value of K. Over-segmentation and feature extraction are the problems in clustering methods.

Graph-based methods: Graph based methods [20] uses a graph in which the nodes represent the image pixels and arcs represent the neighboring pixels. The segmentation is achieved by minimizing the weight that cut a graph into sub-graphs. Generally it suffers from high computationally complexity.

Region-based methods: In region-based segmentation [21] it uses image characteristics to map individual pixels in an input image and change with the sets of pixels called regions that might correspond to an object or a meaningful part. The various techniques are: Local techniques, Global techniques and Splitting and merging techniques. If the image is sufficiently simple, simple local techniques can be effective. Over-stringent criteria create fragmentation lenient ones overlook blurred boundaries and over-merge.

These algorithms are not generally applicable to all images and particular applications require different algorithms so, different techniques can be used for segmentation like LS-SVM, LBP etc. These techniques are used for medical digital image segmentation using low level features such as color and texture features are discussed in this paper by using modified LSSVM.

LS-SVM: In this, we first present the details of Earlier LS-SVM. It is an effective color image segmentation approach based on pixel classification with least square support vector machine. In this approach following steps [1] are involved as explained in the figure1 given below.

Firstly, the pixel-level color feature, Homogeneity, is extracted in consideration of local human visual sensitivity for color pattern variation in HSV color space.

Secondly, the image pixel's texture features, Maximum local energy, Maximum gradient, and Maximum second moment matrix, are represented via Gabor filter.

Then, both the pixel level color feature and texture feature are used as input of LS-SVM model (classifier) and the LS-SVM model (classifier) is trained by selecting the training samples with Arimoto entropy thresholding.

Finally, the color image is segmented with the trained LS-SVM model (classifier). This image segmentation not only can fully take advantage of the local information of color image, but also the ability of LS-SVM classifier.

The LS-SVM considers equality type constraints instead of inequalities as in the classic SVM approach. This reformulation greatly simplifies a problem such that the LS-SVM solution can be follows directly from solving a set of linear equations rather than from a convex quadratic program. For a LS-SVM classifier, in the primal space it takes the form

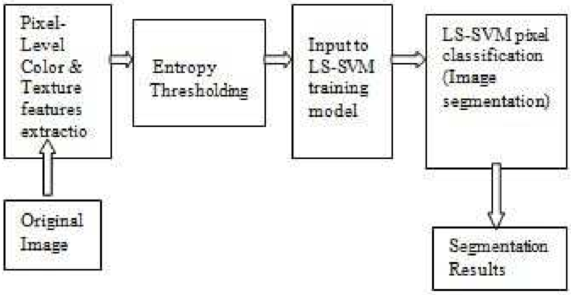
$$y (x) = \text{sign} (w^T x + b)$$

Where b is a real constant.

Because LS-SVM does not incorporate the support vector selection method, the resulting network size is usually much larger than the original SVM. To solve this problem, a pruning method can be used to achieve sparseness in LS-SVM which reduces the complexity of the network by eliminating as much hidden neurons as possible.

LS-SVM solution follows directly from solving a set of linear equations rather than from a convex quadratic program. The pixel level color feature extraction includes each pixel of an image is identified as belonging to a homogenous region corresponding to an object or part of an object. The problem of image segmentation is regarded as a classification task, and the goal of segmentation is to assign a label to individual pixel or a region. So, it is very important to extract the effective pixel-level image feature. It includes color space is selected and Compute the pixel level color feature where discontinuity and standard deviation are computed.

Then, Image pixel texture feature representation is done where color space transformation is selected and Gabor filter is applied and Local energy, local gradient and second energy moment are extracted and computed.



Block diagram of LS-SVM technique using color and texture features

The color image segmentation using automatic pixel classification with LS-SVM can be computed [1] as follows:

1) Pixel-level color and texture features extraction: Both pixel level as well as texture level features are extracted and used as input of LS-SVM model. Pixel level features can be extracted using HSV color space model while textures features are represented by Gabor filter.
2) LS-SVM training sample selection: Above model is trained by selecting the training samples with Arimoto entropy thresholding..
3) LS-SVM model training.
4) LS-SVM pixel classification: Finally the color image is segmented with the trained LS-SVM model.

Frame Work For The Proposed Algorithm

We know that the image segmentation can be taken as classification problems, which can be solved using anyone of well-known classification techniques. Modified LS-SVM is one of the classification techniques and good results of the modified LS-SVM technique in pattern recognition have been obtained, so we can choose the modified LS-SVM for solving color image segmentation problems. Also, it can be merged with other technologies.

In the current work, we present a color image segmentation using automatic pixel classification with modified LS-SVM. Firstly, the pixel-level color feature is extracted in consideration of human visual sensitivity for color pattern variations, and the image pixel's texture feature is represented via Gabor filter. Both the pixel-level color feature and texture feature are used as input of modified LS-SVM model (classifier). Then, the training samples are selected by using the two-dimensional Auto entropy thresholding, and the modified LS-SVM model (classifier) is trained with the extracted pixel-level features. Finally, the color image is segmented with the trained modified LS-SVM model (classifier).

Pixel-level color feature extraction

In this paper, each pixel of an image is identified as belonging to a homogenous region corresponding to an object or part of an object. The problem of image segmentation is regarded as a classification task, and the goal of segmentation is to assign a label to individual pixel or a region. So, it is very important to extract the effective pixel-level image feature. In this paper, the local image windows Ω x, y is firstly constructed using the Manhattan distance with radius 2. And then, we define the local human visual sensitivity for color pattern variation as the pixel-level color feature, which consists of two components: The discontinuity and the standard deviation.

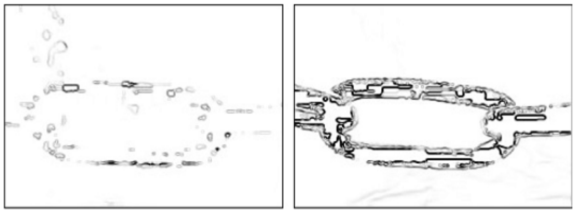


Fig 3: The pixel-level color feature matrix for H, S components of color image (a) the pixel-level color feature matrix for H component, (b) the pixel-level color feature matrix for S components.

Step 1: Compute the discontinuity

The discontinuity $c^k_{x,\ y}$ is a measure of abrupt changes in color levels of pixel component $P^k_{x,\ y}$ (k=H, S), that is, the discontinuity is described by its edge value, and could be obtained by applying edge detectors to the corresponding region. There are many different edge operators: Sobel, Canny, Derish, Laplace, and so forth, but their functions and performances are not the same. In spite of all the efforts, none of the proposed operators are fully satisfactory in real world cases. Applying different operators to a noisy image shows that, the second derivative operators exhibit better performance than classical operators, but require more computations because the image is first smoothed with a Gaussian function and then the gradient is computed. Since it is not necessary to find the accurate locations of the edges, and due to its simplicity, the Sobel operator for calculating the discontinuity and the magnitude of the gradient at location (x, y) are used for their measurement.

Step 2: Compute the standard deviation

By assuming, that the signals are ergodic, the standard deviation $v^k_{x,\ y}$ describes the contrast within a local image window, and is calculated for a pixel component $P^k_{\ x,\ y}$ (k=H, S).

Step 3: Compute the pixel-level color feature

In this paper, we define the local homogeneity of image pixel as the pixel-level color feature. Homogeneity is largely related to the local information extracted from an image and reflects how uniform a region is. It plays an important role in image segmentation since the result of image segmentation would be several homogeneous regions. We define local homogeneity as a composition of two components: standard deviation and discontinuity of color component.

Image pixel's texture feature representation

Texture is one common feature used in image segmentation. It is often used in conjunction with color information to achieve better segmentation results than possible with just color alone. To obtain the image pixel's texture feature, we apply the Gabor filter to the image, and extract the local energy, local gradient and local second moment of the filter responses, which are regard as the pixel texture features.

The main steps of image pixel's texture feature extracting procedure developed can be described as follows.

Step 1: Color space transformation

For texture feature extraction purposes, we use the CIE L*a*b* representation of the color image because this color space can control color and intensity information independently. In this paper, the texture feature is extracted from the L* component, this is because that the L* component closely matches human perception of lightness.

Step 2: Applying the Gabor filter to the L* component

We use Gabor filter decomposition of L* component with 6 orientation and 2 scale sub bands, for most researches have used 4 to 6 orientation sub bands to approximate the orientation selectivity of the human visual system. Since the images are fairly small, we found that a 2 level decomposition is adequate. Out of those we use only the 6 orientation and 2 scale bands.

Step 3: Local energy extraction

Let $G_{m,\ n}(x,\ y)$ represent the Gabor sub band coefficient at location (x, y) that corresponds to the m (m=1.0, 2.0) scale and n (n =0 , 30, 60, 90, 120, 150) orientation. The local energy $E_{\ x,y}$ is defined as the maximum (in absolute value) of the 12 coefficients at location (x, y), which is one pixel texture feature at location (x, y).

Step 4: Local gradient extraction

The gradient is an important measure of image features. The gradient is a vector, whose components measure how rapid pixel value are changing with distance in the x and y direction. The gradient value will be small when the domain is smooth and large when the pixel is in edge regions. In this paper, we use $G_{\ x,\ y}$ to denote the maximum of the 12 gradient magnitudes at location (x, y), which is another pixel texture feature at location (x, y)

Step 5: Local second moment matrix extraction

To characterize the texture patterns, we also utilize texture features based on the second moment matrix , which has been used in numerous works on image processing. The second moment matrix can be thought of as a covariance matrix of a two-dimensional random variable, or, with a mechanical analogy, as the moment of inertia of a mass distribution in the plane. Its eigen-values represent the amount of ''energy'' in the two principle directions in a neighborhood. When one Eigen value is larger than the other, the local neighborhood possesses a dominant orientation and can be characterized as 1D texture. When the Eigen values are comparable, there is no preferred orientation. When both Eigen values are negligible in magnitude, the local

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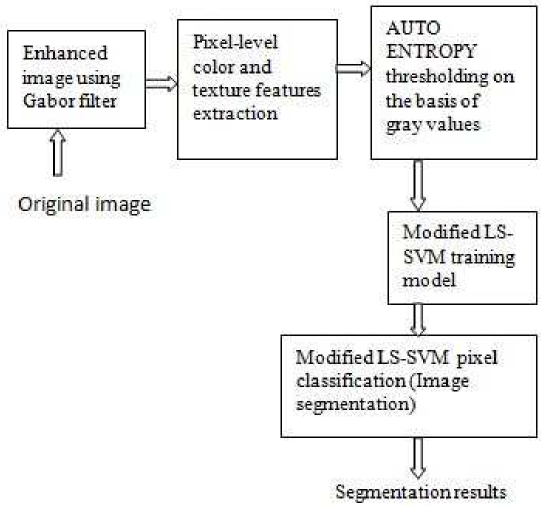
neighborhood is approximately a constant intensity and can be characterized as low contrast.

Modified LS-SVM based segmentation using low level features:

Modified LS-SVM based segmentation using color and texture features proposed a methodology which is explained below:

General methodology of our work is as under:



Flowchart of Proposed Algorithm

Proposed Algorithm Steps

Step I: Browse the original image.

Step II: Enhance image using Gabor filter.

Step III: Applying segmentation process using modified LS-SVM.

(a) Extraction of low-level features (color & texture).

(b) Both features are used as input in modified LS-SVM training model.

(c) Training samples are selected using auto entropy thresholding.

(d) Finally, the color image is segmented with the trained modified LS-SVM pixel classification model.

Quality metrics

When modified LS-SVM pixel classification segmentation results are computed, these are compared with performance matrices of both earlier and modified LS-SVM. These matrices are:

a) ER: The segmentation Error Rate Average Normal Precision (ER) presents the ratio of misclassified image pixels over the total image pixels.

Error rate can be defined as: $ER=N_f + N_m \backslash N_t * 100\%$

Where N_f is the number of false-detection image pixels, N_m denotes the number of miss-detection image pixels, and N_t is total number of images pixels.

b) LCI: The Local Consistency Index (LCI) measures the degree of overlap of the cluster associated with each pixel in one segmentation and its ‘‘closest’’ approximation in the other segmentation.

Let S and S’ be two segmentations of an image $X =(x_1, x_2 \ldots x_n)$ consisting of N pixels. For a given pixel x_i, consider the classes (segments) that contain x_i in S and S’. $C(S, x_i)$ and $C(S', x_i)$ denote the sets of pixels respectively. Then, the local refinement error (LRE) is defined at point x_i as:

$LRE(S, S', x_i) = |C(S, x_i) \backslash C(S', xi)| \backslash |(C(S, x_i)|$

where \ denotes the set differencing operator.

Local Consistency Error (LCE) allows for different directions of refinement in different parts of the image:

$LCE(S, S') = 1\backslash N \min \{LRE (S, S', x_i), LRE(S', S, xi)\}$

and LCI = 1 – LCE.

c) BCI: The Bidirectional Consistency Index (BCI) gives a measure that penalizes dissimilarity between segmentations in proportion to the degree of overlap.

Consider a set of available ground-truth segmentations $\{S_1, S_2, \ldots, S_K\}$ of an image. The Bidirectional Consistency Error (BCE) measure matches the segment for each pixel in a test segmentation S_{test} to the minimally overlapping segment containing that pixel in any of the ground-truth segmentations and BCI = 1-BCE.

Results and Comparison of Performance

This section shows the results of different techniques and compares the quality of segmented images. Overall, the proposed color image segmentation scheme reached competitive results as it gives relatively good results in terms of some segmentation indices for natural images, and the best subjective segmentation quality for most natural images compared to some state of the art segmentation algorithms. The main contribution of the proposed scheme are using novel pixel-level color and texture features, introducing the Auto entropy thresholding for initialization and training sample selection, and replacing LS-SVM with modified LS-SVM for better classification efficiency. Following are the results (snapshots of results) of modified LS-SVM algorithm for the proposed technique with its performance matrices.

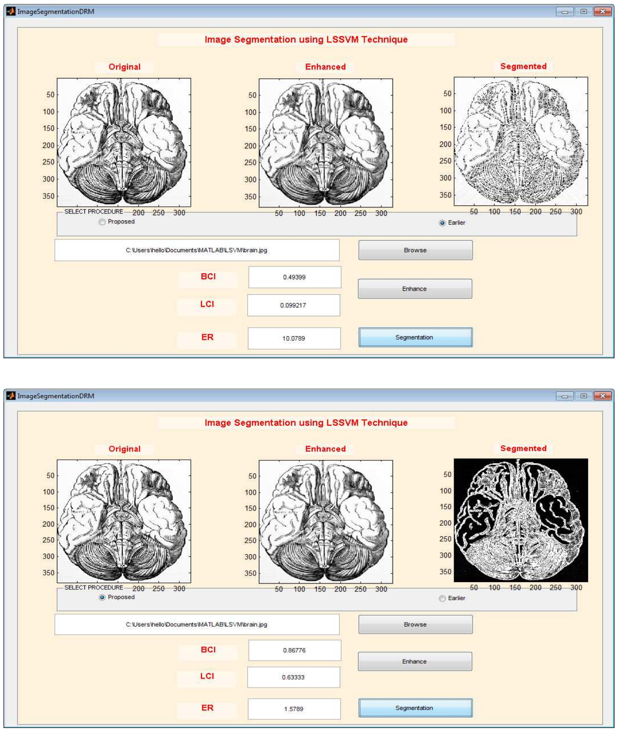


Fig 5.1 (a) CT image of brain by earlier LS-SVM segmentation (b) Proposed LS-SVM segmentation

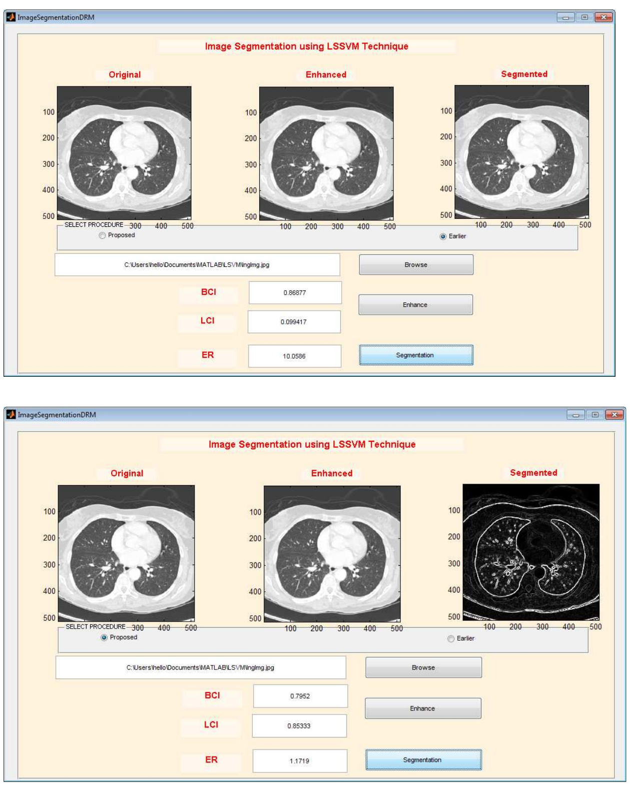
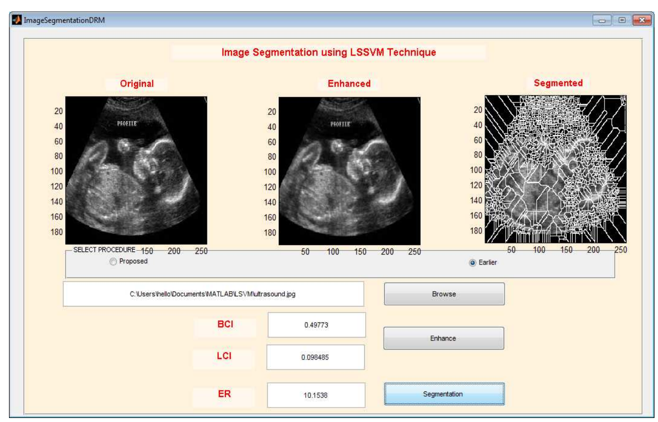


Fig 5.2 (a) Lung image segmentation by earlier LS-SVM (b) Proposed LS-SVM

Table1. Comparative results of various medical images

S. NO.	Medical test image name	Earlier LS-SVM segmentation			Proposed LS-SVM segmentation		
		ER	LCI	BCI	ER	LCI	BCI
1.	CT image of brain	10.0789	0.099217	0.49300	1.5789	0.63333	0.86776
2.	Lung image	10.0586	0.099417	0.86877	1.1719	0.85333	0.7952
3.	Ultrasound image	10.1538	0.098485	0.49773	3.0769	0.325	0.4475
4.	Hand image	10.1145	0.098888	0.49577	2.2901	0.43667	1.227
5.	Medical image	10.1181	0.098833	0.49595	2.3622	0.42333	1.159



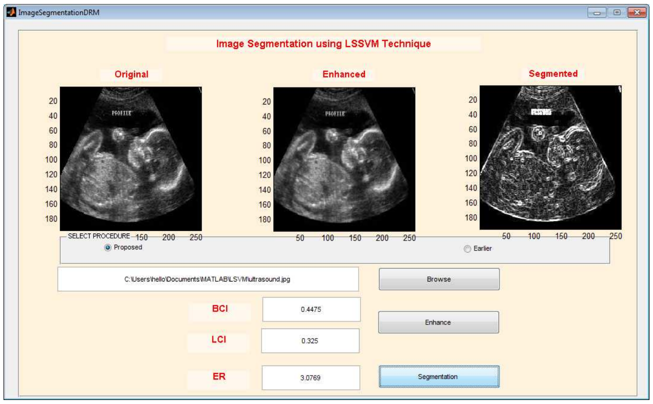
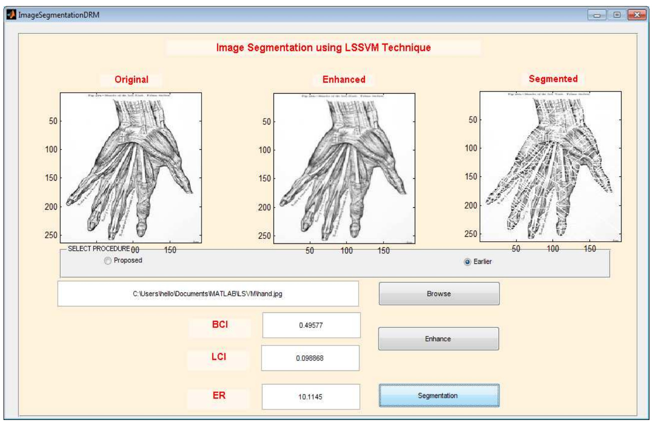


Fig 5.3 (a) Ultrasound image by earlier LS-SVM segmentation (b) Proposed LS-SVM segmentation



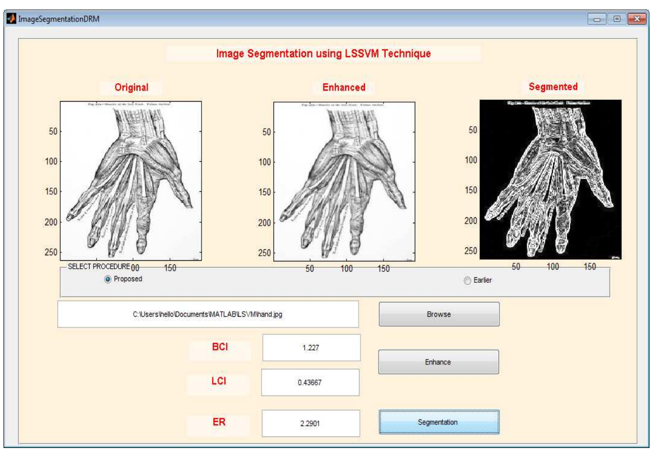


Fig 5.4(a) Hand medical image by earlier LS-SVM segmentation (b) Proposed LS-SVM segmentation

Above Table1 is the Comparison table of ER, LCI, BCI achieved on the earlier & modified LS-SVM segmentation.
It is clearly shown that error rate value of various medical images become high to low while LCI and BCI values are low to high. It means the proposed method gives much more better results than earlier. It decreases the error rate and improves the LCI and BCI.

Conclusion

In this paper, we discuss and presented the modified LS-SVM approach which is a powerful method for image segmentation. In this research, a very simple and accurate image segmentation system has been implemented for the grey scale images based upon thresholding segmentation using modified LS-SVM approach.

The first objective of this paper was to propose an algorithm which is simple and effective for image segmentation based upon thresholding. This approach is accurate, simple as well as recent one.

The second objective of the paper was to compare the proposed method with existing state-of-art techniques. In this paper, work result of LS-SVM is compared with modified LS-SVM. ER, LCI and BCI performance matrices have been used for calculating results to compare quantitatively these techniques. Experimental results show that proposed method performs well than the earlier LS-SVM in terms of quality as well as limitation of over segmentation. The proposed method increases the quality significantly, while preserving the important details or features. This also gives the better results in terms of visual quality.
For future work, the other stages of LS-SVM may be improved to find out the better results. This technology can be tried to merge with a new method DRM (dynamic region merging) to access the user for interactive segmentation. Other performance metrics can be used to judge the performance of this algorithm. And further improvements can also be done in the algorithm to improve the quality as well as it can be compared with different recent techniques. This method will be very useful for segmentation as well as for efficient retrieval purposes.

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