Weighted Average SIFT Algorithm for Fast Pancreas Detection and Pathology Analysis from Abdominal CT Scans

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Abstract – Analyzing the medical image in image processing is the most important research area. Capturing the image are analyzed to identify different medical imaging problems is the common factor in this field. Robust organ segmentation is a prerequisite for computer-aided diagnosis (CAD), quantitative imaging analysis, pathology detection and surgical assistance. Some of the organs in the human body have high anatomical variability, so segmentation of such organs is very complex. The proposed system segments the pancreas with the considerations of spatial relationships of splenic, portal and superior mesenteric veins with the pancreas. The proposed system uses macro super-pixels for fast and deep labeling and segmentation process. The proposed system is an automated bottom-up approach for pancreas segmentation with the consideration of spatial relationships with the veins in abdominal computed tomography (CT) scans. The earlier work on organ segmentation achieved only low accuracies when comparing to organs like the heart or liver. In this paper a complete self learning deep analysis method is presented for pancreas segmentation along with the pathology information's. This utilizes the abdominal computed tomography (CT) scans as input. The method developed a segmentation technique by sorting image patches at different resolutions and cascading super-pixels. With the method of decay of CT slice images into a set of disjoint boundary- safeguard superpixels, by using the computation of pancreas class likelihood maps via opaque patch classification by using Super-pixel classification by grouping both strength and likelihood features to form observed statistics in pouring random forest frameworks and at last effortless connectivity based post-processing were done. These were done in image histogram, spatial and texture features. The method generates dynamic cascaded and macro super-pixel segmentation information's by classifying image patches at different resolutions. For Fast organ detection Weighted average SIFT algorithm is proposed.

Index Terms – Image Processing, Segmentation, CT images, Pancreas detection.

1. INTRODUCTION

Image segmentation is a solution to a number of computer vision problems. In a Large number of applications (in image processing, computer vision, and computer graphics), segmentation plays a fundamental role. Image Segmentation has a wide range of applications such as automated detection and classification of cancerous cell; identification of crops from remotely sensed data and vision guided automobile assembly [1]. It has become increasingly important in a variety of fields such as video coding, computer vision & medical imaging as well as biometrics, pattern recognition, Image analysis and so on[2]. By considering these important applications of segmentation, this research work has motivated to select the segmentation topic [3]. In image segmentation process, the image is divided into its constituent parts, which is going to discuss in this section. Image segmentation approaches can be broadly grouped into the five different categories such as Region Based Methods, Edge Based Methods, Thresholding or Histogram based techniques, Morphology based and Hybrid Techniques [4][5]. Image segmentation algorithms are generally based on the two basic concepts that are similarity and discontinuity with respect to the intensity values.

Region Based Methods:

The principal approach in similarity based partitioning, an image is partitioned into regions that are similar according to the set of predefined criteria and the principal approach behind the second approach is to partition images based on the abrupt changes in the intensity values. Region based methods are based on continuity. These techniques divide the entire image into sub regions depending on some rules like all the pixels in one region must have the same gray level. Edge detection is an important issue for complete understanding of an image. The most usual classical methods search for several ways to perform an approximation to the local derivatives and they marks the edge by searching the maximum of these derivatives. In this section, discussion about all techniques is given.

Edge or Boundary based Technique:

Segmentation Methods based on Discontinuity find for abrupt changes in the intensity value. These methods are called as Edge or Boundary based methods. An edge is a vector variable with two components magnitude and orientation, where x Edge magnitude – gives the amount of the difference between pixels in the neighborhood (the strength of the edge). x Edge orientation- gives the direction of the greatest change, which presumably is the direction across the edge Edge detection is the problem of fundamental importance in image analysis. According to John canny there are three criterions should be well taken care of while edge detection. One is High probability of marking the real edge point and low probability of marking non edge points second one is the points marked as edge points should be as close as possible to the center of the true edge There should be only one response to a single edge i.e. double line for edges should not be detected Edge detection techniques are generally used for finding discontinuities in gray level images. Edge detection is the most common approach for detecting meaningful discontinuities in the gray level. Image segmentation methods for detecting discontinuities are boundary based methods. It reduces the complexity of image allowing more costly algorithms like object recognition, object matching, object registration or surface recognition from stero-images to be used.

Thresholding based Techniques:

Thresholding is one of the most important approaches to image segmentation. Suppose that the gray-level histogram corresponds to an image, f(x, y), composed of light objects on a dark background. Furthermore, suppose that the object and background pixels have gray levels grouped into two dominant modes. One obvious way to extract the objects from the background is to select a threshold T that separates these modes. Then, at any point (x, y) for which f(x, y) > T is called an object point; otherwise, the point is called a background point. If three or more dominant modes characterize the image histogram (for example, two types of light objects on a dark background), it is sometimes possible to segment the image by multilevel thresholding.

This is generally less reliable than its single-level thresholding. Great care must be taken with illumination because it plays a crucial role in establishing the shape of the histogram in the resulting image. Once derivative is calculated, the next stage is to apply a threshold, to determine where the results suggest an edge is present. The lower the threshold, the more lines will be detected, and the results become increasingly susceptible to noise, and also to picking out irrelevant features from the image. Conversely a high threshold may miss subtitle lines, or sections of lines. A commonly used compromise is thresholding with hysteresis. This method uses multiple thresholds to find edges, now by using the upper threshold to find the start of a line. Once have a start point, trace the edge's path through the image pixel by pixel, marking an edge whenever above the lower threshold criteria is satisfied. The process should stop marking our edge only when the value falls below lower threshold. This approach makes the assumption that edges are likely to be in continuous lines, and allows us to follow a faint section of an edge that have previously seen, without meaning that every noisy pixel in the image is marked down as an edge. In Image Segmentation, the image is composed of a number of constant intensity objects in a well-separated background. The image histogram is usually considered as being the sample probability density function (PDF) of a Gaussian mixture and, thus, the segmentation problem is reformulated as one of parameter estimation followed by pixel classification.

Morphology Based Techniques:

Morphology is biological term refers to study of form and structure, in imaging, the term is not used so generically. Morphological operators often take a binary image and a structuring element as input and combine them using a set operator (intersection, union, inclusion, complement). They process objects in the input image based on characteristics of its shape, which are encoded in the structuring element. The mathematical details are explained in Mathematical morphology.

Usually, the structuring element is sized 3×3 and has its origin at the center pixel. It is shifted over the image and at each pixel of the image its elements are compared with the set of the underlying pixels. If the two sets of elements match the condition defined by the set operator (e.g. if set of pixels in the structuring element is a subset of the underlying image pixels), the pixel underneath the origin of the structuring element is set to a pre-defined value (0 or 1 for binary images). A morphological operator is therefore defined by its structuring element and the applied set operator.

Hybrid Techniques:

The aim of this technique is to offer an improved solution to the segmentation problem by combining techniques of the previous categories. Most of them are based on the integration of edge and region based methods. There are two ways the edge and region integration can be performed. There are two ways we can integrate the region based and edge based techniques. x Perform edge detection on the input image then region detection on the output from the first step; this gives us the finally segmented output image. In some hybrid techniques the image is initially partitioned into regions using surface curvature sign and, then, a variable-order surface fitting iterative region merging process is initiated.

While in some, the image is initially segmented using the region-based, split-and-merge technique and, then the detected contours are refined using edge information. Initial image partition is obtained by detecting ridges and troughs in the gradient magnitude of image through maximum gradient paths connecting singular points. Then, region merging is applied through the elimination of ridges and troughs via similarity/dissimilarity measures. The aim of this technique is to offer an improved solution to the segmentation problem by combining techniques of the previous categories.

2. PROBLEM DEFINITIONS

The overview of the problem in the current pancreas segmentation is presented in this section. Segmentation method of organ can be divided into two categories: top-down and bottom-up methods. In top-down methods, a-priori knowledge such as atlas(es) and/or shape models of the organ are generated and incorporated into the framework via learning based shape model fitting or volumetric image registration. In bottom-up methods, segmentation is performed by local image similarity grouping and growing or pixel, super pixel/super-voxel based labeling. In previous segmentation approaches report low accuracies. It is suitable for well studied organs such as liver and heart. It does not scale up easily to large datasets. Existing algorithm creates over fitting problem and hence not accurate result of data. Several existing algorithms have surveyed in [6], finally a new technique is proposed to overcome the existing issues.

3. PROPOSED SYSTEM METHODOLOGY

3.1 INTRODUCTION:

This section presents a study and analysis of feature extraction techniques for fast pancreas detection from the vein spatial relationships that are investigated on CT images for detection of pancreas. Features like color, texture, shape and spatial information are common for various image processing applications. Out of these, texture analysis has been effectively used in many applications in image processing which extracts and quantifies features based on local patterns in images. Literature has shown analysis on brain CT images for the detection of pathology based on their texture properties. It has given promising results in segmentation of pancreas from CT which has potential to perform analysis as performed by experts in terms of diagnostic accuracy. Mainly for medical image processing applications, segmentation of images based on textural feature methods give more reliable and desired results compared to segmentation based on only gray level values. Therefore, texture-based analysis is widely used in analysis of medical images.

Organ segmentation is a prerequisite for a computer-aided diagnosis (CAD) system to detect pathologies and perform quantitative analysis. For anatomically high-variability abdominal organs such as the pancreas, previous segmentation works report low accuracies when comparing to organs like the heart or liver. In this paper, a fully-automated bottom-up method is presented for pancreas segmentation, using abdominal computed tomography (CT) scans. Segmentation of CT scans is an important and challenging task in medical diagnostics. CT images often differ in quality and vary in noise levels, which make recognition of target object for segmentation a difficult task. FCNN can learn, if provided with sufficient dataset, how to segment objects in low quality and noisy CT scans. Since image segmentation is in the forefront of image processing, it is crucial to have a good understanding of it. Image segmentation is one of the most commonly used operations in image analysis. A fundamental challenge in image segmentation lies in determining which performance evaluation techniques to be used for comparing the various techniques. Also several studies have indicated the importance of preprocessing and post processing in case of image segmentation and found to have given better results. However, the frameworks created till today do not apply in case of CT pancreas with vein image (having any type of edges and lines). Hence, this research work concentrates not only on segmentation of Medical images but also on unifying it under one roof. Thus it gives a combined or a unified Framework of segmentation which can take as input different types of pancreas and medical images.

3.2 Research Contributions:

Robust organ segmentation is a prerequisite for computer-aided diagnosis (CAD), quantitative imaging analysis, pathology detection and surgical assistance. Some of the organs in the human body have high anatomical variability, so segmentation of such organs is very complex. To overcome the above problems, a set of algorithm and techniques are developed in the proposed work.

- The proposed system segments the pancreas with the considerations of spatial relationships of splenic, portal and superior mesenteric veins with the pancreas.
- The proposed system uses macro super-pixels for fast and deep labeling and segmentation process.
- The proposed system is a self learning mechanism with the improvement of bottom-up approach for pancreas segmentation with the consideration of spatial relationships with the veins in abdominal computed tomography (CT) scans.
- The method generates dynamic cascaded and macro super-pixel segmentation information's by classifying image patches at different resolutions.
- Fast organ analysis is performed by the weighted average scalable invariant feature transform WA-SIFT algorithm.
- Finally the pathology detection is performed over the segmented organs. With the size and other features, the pathology information's are gathered.

3.3. WA-SIFT ALGORITHM PROCESS

The system proposed paper contains four steps in the implementation:

1) The Decomposition of CT sliced images into a set of disjoint boundary-preserving super-pixels. This step in the proposed

implementation increases the segmentation accuracy in CT images.

2) The analysis of the abdomen scan images to detect the pancreas class probability, and effective method is used. This maps the organ via dense patch labeling method;

3) Macro-Super pixel classification by pooling both intensity and probability features to form empirical statistics in cascaded random forest frameworks; and

4) Finally, a Simple connectivity based post-processing is performed to improve the quality.

Dense image patch labeling is conducted using three methods:

1. Efficient gradient-boosted trees Method (GBM) on image histogram, location and texture feature.
2. With the method of decay of CT slice images into a set of disjoint boundary- safeguard superpixels, by using the computation of pancreas class likelihood maps via opaque patch classification by using Super-pixel classification by grouping both strength and likelihood features to form observed statistics in pouring random forest frameworks and at last effortless connectivity based post-processing were done. So super pixel and Random Forest (RF) mechanisms are used.
3. Weighted Average SIFT algorithm

GBM can offer a bigger edge. GBM is a boosting method, which builds on weak classifiers. The idea is to add a classifier at a time, so that the next classifier is trained to improve the already trained collection. Notice that for RF each iterations the classifier is trained independently from the rest. The aim of the proposed system with RF is to classify medical images. RF algorithms are currently one of the top performing algorithms for medical data classification and regression of pathology detections. This allows fast image classification through parallel processing.

a. Data preprocessing

Preprocessing is a stage where the requirements are typically obvious and simple, such as removal of artifacts from images or eliminating of image information that is not required for the application. For example, in one application this needed to eliminate borders from the images that have been digitized from image. Another example of preprocessing step involves a robotics gripper that needs to pick and place an object ; for this reduce a gray-level image to binary (two-valued) image that contains all the information necessary to discern the object ‘s outlines. The data processing task is also one of the criteria which must be taken care in the process of images from the dataset. The image data input to extracting algorithm need not be in proper format and is hence not suitable for processing image efficiently. In such a case, this need to see the data is in proper format so that it is suitable for processing.

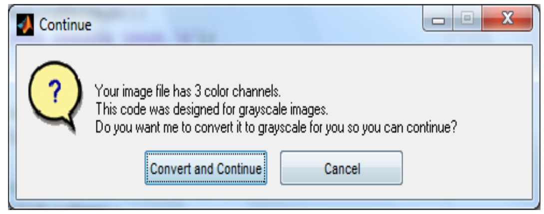

Figure 1.0 image formatting process when the input is a color channel.

The figure 1.0 shows the conversion message when the user uploads the color image as input. The data preprocessing process converts that into the grayscale image to continue the process. The process is the original image and edge detected image after the edge detection process done in the data pre-processing step. In this, canny and sobel edge detection algorithms are used. This case generally arrives when this try to mine the image using preprocessing algorithms. Different tools available to make preprocessing in the market and that have different formats for input which makes the user forced to transform the existing input dataset into the new format. This itself is very time consuming, laborious and has a chance of data loss as the data is to be entered manually into a new format to be supported by the tool. For this preprocessing the gradient-boosted algorithms were used to discover image histogram, location and texture feature. The gradient boosting tree method helps to classify the image with high quality output.

b. Filtering process:

Image filtering plays a very important role in enhancing the CT images and hence improving the performance of edge detectors. It aims to improve the image, remove the noise and enhances edges in such a way that the Framework improves the system performance. Some of these are presented in this section. Various image filters can be used for filtering the image so that it sharpens the image and improves the performance of the various operators. In the proposed Framework morphological filtering and used various combinations of these filters.

c. Feature extraction

Feature extraction helps to reduce the feature space which improves the prediction accuracy and minimizes the computation time. This process eliminates the irrelevant and noisy features without affecting the ground truth segmentation process. So, this process selects the subset of features that can achieve the best performance in terms of accuracy and computation time in pancreas detection. This process also applicable for the vein spatial analysis task too. It performs the Dimensionality reduction feature selection by the weighted feature selection method. Features are generally selected by search procedures. A number of search procedures have been proposed. In this work Gaussian Mixture Model Algorithm is proposed to select the optimal features. The selected optimal features are considered for classification. GMM classifiers have been utilized in various applications of computer vision and medical imaging. They are widely used in applications where data can be viewed as a combination of different populations mixed in varying proportions. Gaussian Mixture Model is supervised learning classification algorithm that can be used to classify a wide variety of N-dimensional signals. The GMM algorithm is a better method, which can be used for the classification of static images with less intense and accuracy. This is also suitable for and non-temporal pattern recognition process.

d. Super-pixel detection

Super-pixel-based WA-SIFT algorithm is proposed to obtain the organ surface. Instead of pixels, superpixels are considered as the basic processing units to construct a weighted super-pixel-based graph. The superpixels are labeled as the prostate or background by minimizing an energy function using graph cut based on the weighted Super-pixel based graph. Super-pixel representation is adapted to the local structure of the image where, small regions that results from conservative over segmentation, or super pixels, to be the elementary unit of any detection, categorization or localization scheme. Together on the surface, the existence of super pixels as the elementary units seems counterproductive, because aggregating pixels into groups requires a decision that is unrelated to the final task. However, Super-pixel aggregation captures the local redundancy in the data, and the aim is to minimize the risk of merging unrelated pixels. The proposed system finds the most appropriate pixels form the list of super-pixels. This will be applied into the WA-SIFT process to detect the pancreas.

e. Pancreas Segmentation

Segmentation is the process of dividing images into constituent sub-regions. Manual segmentation is possible but is a time-consuming task and subject to operator variability. Reproducing a manual segmentation result is difficult and the level of confidence ascribed suffers accordingly. Automatic methods are, therefore, preferable; however, significant problems must be overcome to achieve segmentation by automatic by using WA-SIFT algorithm. Accurate segmentation of pancreas from CT images is an essential part of clinical support. Many existing algorithms are specialized for the segmentation of healthy organs. The proposed system segments and detects the pancreas from the abdomen CT scan images with the region cover process. The detection contains a set of algorithms and process which is defined above.

In this work, a new pancreas segmentation and pathology detection method has been proposed which approximates intensity distribution of pancreas CT image using set of algorithms. As the approach is automated and unsupervised, there is no prior knowledge of background/foreground available; hence for estimation of parameters instead of using MRF, this use GBM-RF where segmentation is carried out in an unsupervised manner. the approach is modification of method suggested in the base paper, which doesn't detect the pathology and veins . The approach first optimizes initial conditions to be used by GBM-RF framework. When initial condition is very different than normal, the basic SIFT may give wrong results. So, to optimize initial conditions, WA-SIFT have been used to generate ground truth and for approximation of intensity distribution in each segment, a Gaussian Mixture Model has been used instead of single Gaussian component. Expectation maximization approach has used for learning parameter sets and label configurations of GBM-RF. The proposed CT image segmentation with pathology detection algorithm is given in the following Algo.1.0. Initial conditions in algorithm play very important role in final segmentation, mainly when initial conditions are far from ground truth. So, to ensure reasonably good initial parameter estimation, super pixel detection algorithm has been applied in this proposed algorithm. For each resultant segment, intensity distribution of pancreas tissues are estimated using Gaussian mixture models and parameterized with the mean, covariance and mixture weights from all component densities, represented as $\lambda = \{wi , \mu i , \sigma i \}$. The GMM model parameters have also been estimated using the WA-SIFT algorithm. In the E-step, we determine which data belongs to which Gaussian component, and in the M-step GMM parameters are recomputed. Model fitting is the process of estimating the unknown parameters. So, the problem is to define parameters and functional form of the GBM-RF model where the parameters are mean and standard deviation of each GMM. The main objective of the proposed algorithm is shown in Alg. 1.0 is to incorporate spatial information using GBM-RF in addition to intensity values and to get robust and accurate segmentation results. As parameters and class labels are unknown but dependent on each other, they are learned using MAP and WA-SIFT algorithm by maximizing probability of class labels and by minimizing total posterior energy. WA-SIFT algorithm starts with the current estimation, conditional expectation is calculated and then it maximizes this condition to get new estimate as explained. The process continues until it converges and no significant change in total energy observed or maximum WA-SIFT iterations are achieved.

Cystic pancreas segmentation is especially challenging due to its low contrast boundaries, variability in shape, location and the stage of the pancreatic detection. Decomposition of CT sliced images into a set of disjoint boundary-preserving superpixels; Computation of pancreas class probability maps via dense patch labeling. Macro-Super pixel classification by pooling both intensity and probability features to form empirical statistics in cascaded random forest frameworks and Simple connectivity based post-processing. Dense image patch labeling is conducted using three methods: Efficient gradient-boosted trees on image histogram, location and texture feature.

WA-SIFT algorithm has been proposed to solve this issue. GBM can offer a bigger edge. GBM is a boosting method, which builds on weak classifiers. Notice that for RF each iterations the classifier is trained independently from the rest.

Algorithm 3.1. Weighted average sift (WA-SIFT) algorithm

Step 1: Initialize a new WASIFT filter object by vl_dsift_new (or the simplified vl_dsift_new_basic).

Step2: Customize the descriptor parameters by vl_dsift_set_steps, vl_dsift_set_geometry, etc.

Step 3: Process an image by vl_dsift_process.

Step 4: Retrieve the number of keypoints (vl_dsift_get_keypoint_num), the keypoints (vl_dsift_get_keypoints), and their descriptors (vl_dsift_get_descriptors).

Step 5: Optionally repeat for more images.

Step 6: Delete the WASIFT filter by vl_dsift_delete.

Algorithm 1: WA-SIFT

Pathology detection:

The pancreas segmentation and the pathology detection process are explained by the following algorithm steps. This includes the image enhancement, histogram analysis, region based super-pixel detection etc.

Algorithm 2.0: Segmentation of CT pancreas images with pathology detection

Input: Pancreas CT images of different classes

Output: Segmented images and pathology detection

Steps:

1. Perform image enhancement by histogram normalization.

2. Perform initial intensity based grouping using pixilation depending upon number of groups specified as threshold. Also specify maximum number of iterations for vein and organ detection.

3. Estimate intensity distribution of CT pancreas image using Gaussian mixer model (GMM) with parameter set $\theta xi = (\mu xi , \sigma xi)$ 3, and fit GMM to the data generated in step 2.

4. Estimate the class labels $X*$ by super pixel estimation, which satisfies the following condition

$X* = \mathrm{argmaxx}\{P (Y |X , \theta)P (X)\}$

5. Update parameter set $\theta = \{\theta l \,|l\varepsilon L\}$ using WASIFT algorithm until it converges, where L is the set of all possible labels. Do class estimation and solve for $x*$ that minimizes the total posterior energy,

$X* = \mathrm{argminx}\{U (Y |X, \Theta) + U (X)\}$

$X* = \mathrm{argmaxx}\{P (Y |X , \theta)P (X)\}$

6. Repeat step 4 and step 5 till maximum group iterations reached or there is no significant change in the value of energy function, $U (Y |X, \theta) + U (X)$.

7. Check the threshold and define the pathology

8. End

4. RESULTS AND DISCUSSION

The major objective of the segmentation to separate pancreas from other organs is well obtained in all the experimental results. The results on sample images are visible from Figure 2.0 for both the set of experiments, one with the real pancreas and other with the simulated pancreas CT images.

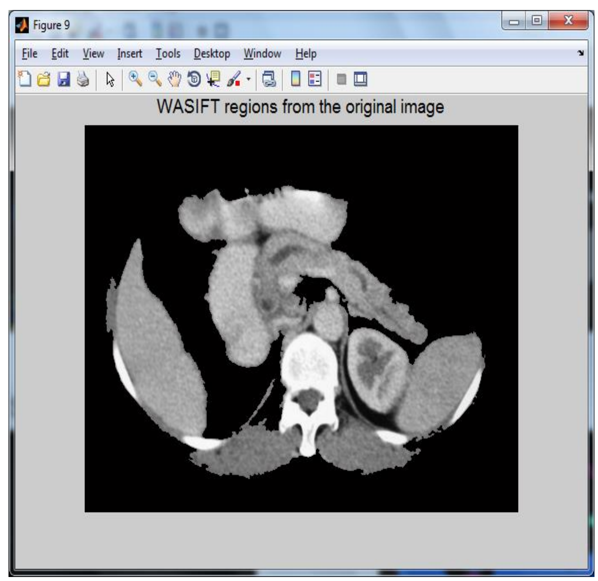

Figure 2.0 region detection from the original image

The segmented pancreas is found to be very close to the pancreas highlighted in the corresponding ground truth image is extracted. The segmentation results obtained using proposed method are found better than existing algorithm in terms of smoothness as seen visually and also based on quantification done based on similarity measures.

Table 1.0: Comparative analysis of results obtained based on similarity measures Jaccard, Dice and Tanimoto

Image from Dataset	Method	Pancreas Size (Area)-Experi-ment	Pancreas Size (Area)-Ground	Jaccard	Dice	Tanimoto
Dataset 1	Proposed Method	2086	1928	0.8007	0.8893	0.8007
	FCM-SC	904	1928	0.333	0.4996	0.333
Dataset 2	Proposed Method	892	768	0.5507	0.7102	0.5507
	FCM-SC	405	768	0.5097	0.6753	0.5097

Extracted pancreas area using proposed method is also very close to the ground truth compared to the FCM-SC approach as shown in Table 1.0. Plots of average values of similarity measures obtained for both the methods are shown in Figure 3.0 where results of proposed method are found to be better than other compared method. As observed from Table 1.0, major difference was observed in the results of TPR (sensitivity) for both the methods.

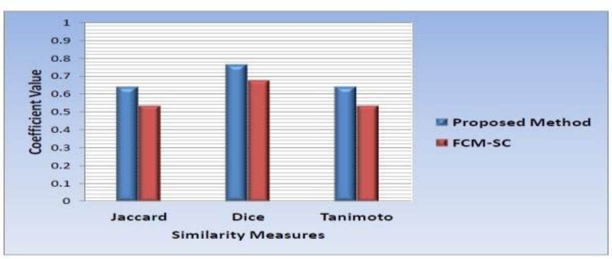

Figure 3.0 Plot of average values of similarity coefficients for proposed method and FCM-SC Method

5. CONCLUSION

From the analyses of the problem in medical data they were problem like image segmentation to solve the issue the proposed system segments the pancreas with the considerations of spatial relationships of splenic, portal and superior mesenteric veins with the pancreas. The proposed system uses macro super-pixels for fast and deep labeling and segmentation process. The proposed system is an automated bottom-up approach for pancreas segmentation with the consideration of spatial relationships with the veins in abdominal computed tomography (CT) scans. The method generates dynamic cascaded and macro super-pixel segmentation information's by classifying image patches at different resolutions. Fast organ detection and pathology analysis has been performed using WA-SIFT algorithm.

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