# Pancreas Segmentation using Level-set Method based on Statistical Shape Model

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As Computer Aided Diagnosis (CAD) was widely used in medical field, it was necessary to be studied deeply, especially in image segmentation. The complex anatomy structure around the pancreas made segmentation of pancreas become more difficult. In this paper a new method for medical image segmentation was proposed which used level-set method based on statistical shape model to solve above problem and improve the performance of segmentation. The level-set method was used firstly to obtain the segmentation result of the pancreas from CT images. Then some anatomical information was added into segmentation process by using a better shape of the interest object obtained by statistical shape model. Several experiments were carried out to demonstrate the validation of our proposed algorithm, and the level-set and region-grow methods were chosen as the contrast algorithm. We also gave quantitative results which showed that our method had a good robustness and better precise of segmentation than other methods.

**Key words:** Computer aided diagnosis, image segmentation, pancreas, level-set, statistical shape model.

According to the survey of World Health Organization (WHO), the pancreatic cancer ranks 9th in cancer ranking of the world and the death rate (5-year survival below 5%) is 6th (Ghaneh *et al*., 2007). Since pancreatic cancer is one of the most difficult cancer to treat and the most dangerous malignancies, whose malignant degree is extremely high, illness development quickly and easily to transfer, it is vital to discover and treat at early stage. Computed Tomography (CT) is an effective tool for detection of cancers.

There are two main reasons lead to the fact that segmentation of pancreas in CT is difficult for human. The first one is the complex anatomy structure around the pancreas. Pancreas is an organ outside peritoneal, hidden in the retroperitoneal and its shape is irregular. Thus, to distinguish it from some other organs around it, such as small bowel, becomes very hard. Another reason is individual difference, since the shape of pancreases of different people is not same which increases the difficulty of pancreas segmentation[1]. So far, there exist a few publications on pancreas segmentation. Shimizu(Shimizu *et al*., 2007) *et al*. proposed a simultaneous segmentation framework for 12 organs including pancreas based on a combination of atlas-guided segmentation and level-sets. The result is that evaluation on 10 non-contrast CT scans showed an average overlap of 32.5% for the pancreas. However, the algorithm would need major revisions to make it applicable to contrast enhanced CT (Shimizu *et al*., 2009). The authors later proposed a pancreas segmentation system using 3-phase contrast enhanced CT data. Firstly, they register 3 CT phases to a common space through a landmark based deformable registration with a certain patient

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chosen as reference. Secondly, a rough segmentation can be obtained through patient-specific probabilistic atlas guided segmentation. An intensity based classifier is used together with morphological operations for final segmentation. This algorithm was the winner of the medical image processing competition in Japan in the category pancreas(Magjarevic *et al.*, 2009). It evaluated on 20 cases and showed an average Jaccard index of 57.9%. But it needs 3-phase CT and more signal information is available to guide segmentation. Kitasaka *et al.*(Kitasaka *et al.*, 2008) presented a sophisticated automated pancreas segmentation algorithm, but it suffered from low segmentation accuracy due to large variations in the location and shape of the pancreas.

This paper proposes an algorithm using level-set method based on statistical shape model. This algorithm incorporates two main ideas for pancreas segmentation. The first idea is to utilize level-set method to segment pancreas from CT image. The advantage of the level set method is that one can perform numerical computations involving curves and surfaces. However, when the image contrast is low or when the object boundary is not distinct, level-set method could not get satisfactory outcome. Since the general shape, location and orientation of an anatomical structure of interest is typically known a priori in medical imaging applications, we use statistical shape models (SSMs) to form it. The level-set method based on statistical shape model improves the segmentation precision greatly. To validate the performance, we show the results of applying the algorithm to CT image and discuss the effectiveness of this approach.

The rest of the paper is organized as follows. Section 2 gives some related algorithm and the new algorithm for pancreas segmentation is introduced in Section3. In Section 4, we explain the results of applying the proposed algorithm and discuss its effectiveness. Finally, the conclusion is given in Section 5.

**Related algorithm**

In this section, we would introduce two related algorithms including level-set and statistical shape model. The proposed method is based on these related algorithms.

**Level-Set**

Level-set is introduced by Osher and Sethian(Osher *et al.*, 1988) and becomes popular in computer vision and image analysis by Malladi *et al.*( Malladi *et al.*, 1995). Level-set is a numerical method for tracking the evolution of contours and surfaces. The main idea is setting the contour as zero level-set of a higher dimensional function called level-set function $\psi(\mathbf{X}, \mathbf{t})$ instead of manipulating the contour directly. The function is then evolved under control of a differential equation. The evolving contour can be obtained by extracting the zero level-set $\Gamma((\mathbf{X}), \mathbf{t}) = \{\psi(\mathbf{X}, \mathbf{t}) = 0\}$ from output. The main advantages of level-set is arbitrarily complex shapes can be modeled and topological changes. Using image-based features such as mean intensity, gradient and edge in the governing differential equation can execute image segmentation. It can make use of a generic level-set equation to compute the update to the solution $\psi$ of the partial differential equation.

$$\frac{d}{dt}\psi = -\alpha A(\mathbf{x}) \cdot \nabla \psi - \beta P(\mathbf{x})|\nabla \psi| + \gamma Z(\mathbf{x})\kappa|\nabla \psi| \quad ...(1)$$

*Et al*A is an advection term, *P* is a propagation term, and *Z* is a spatial modifier term for the mean curvature $\kappa$. The constants $\alpha, \beta$ and $\gamma$ weight the relative influence of each of the terms on the movement of the interface.

For level-set segmentation method, it requires two images as input, one is an initial model $\psi(\mathbf{X}, \mathbf{t} = 0)$ and another is a feature image which is either the image to be segmented or some preprocessed version. And it needs to give the contour which represents the isosurface $\Gamma$ in the initial model. Finally, the contour representing the surface is the zero level-set of the output image.

**Statistical shape models**

Statistical shape models (SSMs) have already been firmly established as a robust tool using in medical images segmentation(Heimann *et al.*, 2009). And best-known methods in this area are the Active Shape models (ASMs) which were introduced by Cootes *et al.*( Cootes *et al.*, 1995) and Active Appearance models (AAMs) also introduced by Cootes *et al.*( Cootes *et al.*, 2001). In order to describe all of the allowed statistical variation of some general shape, active shape model is developed. The model is formed by using

a training set of objects that are already segmented either manually or by some other automatic or semi-automatic method. The variation among the set of these previously segmented shapes is used to describe the variation of the shape model and therefore the training set needs to be a good representation of the overall distribution of allowable shapes.

During process of building active shape model, principal component analysis (PCA) is used to decompose the large variation in the shapes into a set of variables that describe the majority of variation. The basic steps of PCA include aligning the training images, finding some corresponding landmarks, computing covariance matrix of these landmarks, and finally finding the determinate of the covariance matrix.

The first step of PCA is to align the training image. The training images are registered with the first training image using a similarity transform that includes rotating, scaling, and translating. The mean image can be computed after the first iteration. From this set of transformed, registered training images, a mean model is made by taking the mean of each pixel in the training set.

$$\overline{I} = \frac{\sum_{i=1}^{N} I_i}{N} \qquad ...(2)$$

*Et al* $N$ stands for the numbers of training images and $I$ stands for the image intensity.

In shape model construction, it always uses a set of landmarks along the outline of shape to represent the shape. Landmarks are a set of points $(x,y)$ in the training images that describe the outline of the shapes. Each image should have the same number of landmarks and they should be corresponding to the same location on the general shape. The $N$ landmarks are represented by variables $\mathbf{X_0, X_1, ..., X_{n-1}}$. Each training image is subtracted from the mean image so that the data is normalized for PCA.

$$I'_i = I_i - \overline{I} \qquad ...(3)$$

Then the $n \times n$ covariance matrix is computed. The size of the covariance matrix is equal to $N^2$ *et al* $N$ is number of landmarks.

$$Cov = \begin{pmatrix} Cov_{x_1 x_1} & \cdots & Cov_{x_1 x_{n-1}} \\ \vdots & \ddots & \vdots \\ Cov_{x_{n-1} x_1} & \cdots & Cov_{x_{n-1} x_{n-1}} \end{pmatrix} \qquad ...(4)$$

After finding the determinate of the covariance matrix by using PCA, we can get a set of eigenvalues and corresponding eigenvectors. Suppose the $t$ largest eigenvalues $\lambda_i$ are retained in a matrix $\mathbf{\phi} = (\varphi_1 | \varphi_2 | ... | \varphi_t)$ .All of the training images can be reconstructed by combining a linear combination of the eigenvectors and a mean image.

$$I = \overline{I} + \mathbf{\phi} b \qquad ...(5)$$

is a vector of $t$ elements containing the model parameters, computed by following equation.

$$b = \mathbf{\phi}^T (I - \overline{I}) \qquad ...(6)$$

To fit the model to a set of points, the values of $b$ are often constrained to lie within the ranges $\pm m \sqrt{\lambda_i}$ , *et al* $m$ is between two and three. The number $t$ of eigenvalues to retain is chosen so as to explain a certain proportion of the variance in the training shapes, usually ranging from 90% to 99.5%.

**Proposed new algorithm**

In this paper, the new algorithm which combines level-set and statistical shape model is proposed. The algorithm has three inputs: feature image, initial model and statistical shape model. The statistical shape model which includes some anatomical information is an additional shape-influenced term in the driving partial differential equations of level-set.

**Getting feature image**

The potential image is set as feature image which is to be as the speed term used in the differential equation. The potential image can be getting by following these steps. First, to smooth the input image using edge-preserving filter; then the magnitude of its gradient is computed; and after that the potential image can be get from the output of sigmoid function. The flowchart of getting feature image can be described as Fig. 1.

The disadvantage of image smoothing is that it tends to blur away the sharp boundaries in the image that help to distinguish between the anatomical structures. Even in the case *et al* smoothing does not obliterate boundaries, it tends to distort the fine structure of the image and thereby changes subtle aspects of the anatomical shapes. Perona and Malik(Perona *et al*., 1990)
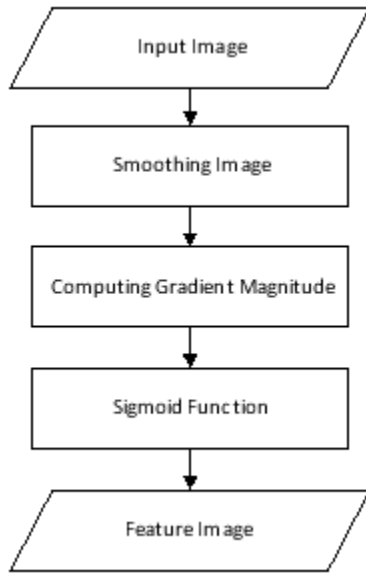
**Fig. 1**. The flowchart of getting feature image

introduced an alternative to linear-filtering that they called anisotropic diffusion. The motivation for anisotropic diffusion is that a Gaussian smoothed image is a single time slice of the solution to the heat equation, which has the original image as its initial conditions.

$$\frac{\partial g(x,y,t)}{\partial t} = \nabla \cdot \nabla g(x,y,t) \qquad ...(8)$$

Thus the solution to *et al* $g(x,y,0) = f(x,y)$ is the input image, is $g(x,y,t) = G(\sqrt{2t}) \otimes f(x,y)$, *et al* $G(\sigma)$ is the Gaussian distribution with standard deviation .There is a variable conductance which depends on the differential structure of the image in anisotropic diffusion. Therefore, this variable conductance can be formulated to limit the smoothing at edges in images. It can also use a modified curvature diffusion equation (MCDE). MCDE does not exhibit the edge enhancing properties of classic anisotropic diffusion, which can under certain conditions undergo a negative diffusion which can enhance the contrast of edges. The MCDE equation is shown as follow:

$$f_t = |\nabla f| \nabla \cdot c(|\nabla f|) \frac{\nabla f}{|\nabla f|} \qquad ...(9)$$

And the conductance modified curvature term is shown as follow.

$$\nabla \cdot \frac{\nabla f}{|\nabla f|} \qquad ...(1)$$

The function $c(\nabla f)$ is a fuzzy cutoff that reduces the conductance at areas of large $|\nabla f|$.

After getting the smoothing image, it requires to compute the magnitude of the image gradient at each pixel location. The computational process is equivalent to first smoothing the image by convolving it with a Gaussian kernel and then applying a differential operator. The value of $\sigma$ is decided by us.

Here using a sigmoid function since it offers a good deal of control parameters which can be customized to shape a nice speed image.

$$I' = (Max - Min) \cdot \frac{1}{\left(1 + e^{-\frac{I-\beta}{\alpha}}\right)} + Min \qquad ...(11)$$

In the above equation, $I$ is the intensity of the input pixel, $I'$ is the intensity of the output pixel, *Min, Max* are the minimum and maximum values of the output image, $\alpha$ defines the width of input intensity range and $\beta$ defines the intensity around which the range is centered.

**Getting initial model**

The initial model should be set after obtaining feature image. It is necessary to provide a seed point from the contour which will be expanded. And the distance parameter is also needed. Then we can get initial level-set by using seed point and the distance. The procedure is described in Figure 2. However, the number of seed points is not limited and it can also give a set of seed points. A good set of seed points increases the chances of segmenting a complex object without missing parts. The use of multiple seeds also helps to reduce the amount of time needed by the front to visit a whole object and hence reduces the risk of leaks on the edges of regions visited earlier. For example, when segmenting an elongated object, it is undesirable to place a single seed at one extreme of the object since the front will need a long time to propagate to the other end of the object. Placing several seeds along the axis of the object will probably be the best strategy to ensure that the entire object is captured early in the

expansion of the front. One of the most important properties of level sets is their natural ability to fuse several fronts implicitly without any extra bookkeeping. The use of multiple seeds takes good advantage of this property
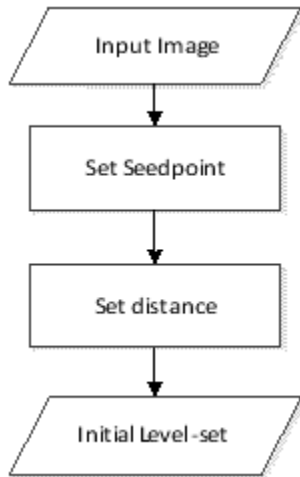


**Fig. 2.** The procedure of getting initial level-set

**Shape model construct and estimate**

To support SSM, the general level set equation (1) is extended to incorporate a shape guidance term

$$\xi(\psi^*(\mathbf{x}) - \psi(\mathbf{x})) \qquad \qquad ...(7)$$

*et al* $\psi^*$ is the signed distance function of the "best-fit" shape with respect to a shape model. The new term has the effect of driving the contour towards the best-fit shape. The scalar $\xi$ weights the influence of the shape term in the overall evolution. In general, the best-fit shape is not known ahead of time and has to be iteratively estimated in conjunction with the contour evolution.

When the feature image and initial model are gotten, the next step is to construct and estimate shape model. A statistical shape model can be described use a mean signed distance and the first *t* principal components modes that have been mentioned before. Here the best-fit shape estimation problem is reformulated as a minimization problem *et al* the cost function is to be optimized. The cost function is composed of four terms: contour fit, image fit, shape prior and pose prior. Contour fit measures the likelihood of seeing the

current evolving contour for a given set of shape/ pose parameters. This is computed by counting the number of pixels inside the current contour but outside the current shape.

Image fit measures the likelihood of seeing certain image features for a given set of shape/pose parameters. This is computed by assuming that (1 - edge potential) approximates a zero-mean, unit variance Gaussian along the normal of the evolving contour. Image fit is then computed by computing the Laplacian goodness of fit of the Gaussian:

$$\sum (G(\psi(\mathbf{x})) - |1 - g(\mathbf{x})|)^2 \qquad ...(13)$$

*et al G* is zero-mean, unit variance Gaussian and    is the edge potential feature image. In this paper, pose parameters are supposed that have the uniform distribution and hence they do not have contribution to the cost function. The left parameters are shape parameters. Since we assumed the principal modes have already been normalized, we set the distribution to zero mean and unit variance.

The cost function has $t+3$ parameters. The first    are the principal component multipliers, followed by the 2D rotation parameter (in radians) and the x- and y- translation parameters (in mm). We need to carefully scale the different types of parameters to compensate for the differences in the dynamic ranges of the parameters.

**The whole procedure of the algorithm**

Combining three steps described above, we can get the final algorithm. Put the feature image, initial level-set and statistical shape model together. Compute cost function after level-set evolving. Comparing cost function with termination criteria, if the ending condition is satisfied, the final output image can be obtained. We take Root Mean Square(RMS) error as a measure criterion, and the iteration will stop at the time of the RMS error between two images during the iterations are below the small value which is set manually. The procedure of the proposed algorithm is shown in the Figure 3.

**Experimental results and analysis**

In this section, at first, the experimental data is introduced. Then the result of new algorithm should be showed as follow. We also give some discussions in allusion to the proposed algorithm.
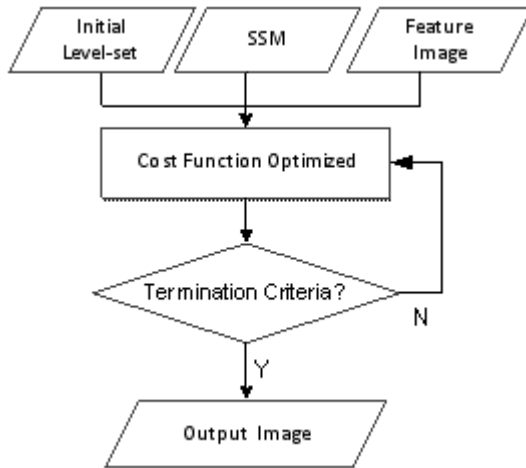
**Fig. 3** The flowchart of the new algorithm

**Experimental data**

The experimental data can divide into two parts. The first part is training data which is used

to build statistical shape model and it includes 36 abdomen CT data with resolution of 512x512. The training data has already been segmented by manually and they are all binary images. Another part is input image which will be segmented by the new algorithm which proposed in this paper. This part includes about 30 image data. And these images are all gray-level images. Experiments are carried out in a computer with Intel processor of 3.40GHz and memory of 8GB.

## RESULTS

We choose two images from 36 input images to give the experimental results in Figure 4. (a) and (b) stand for original images, the green contours are results of manual segmentation in (c) and (d), and in (e) and (f) the red contour are the result of proposed algorithm.
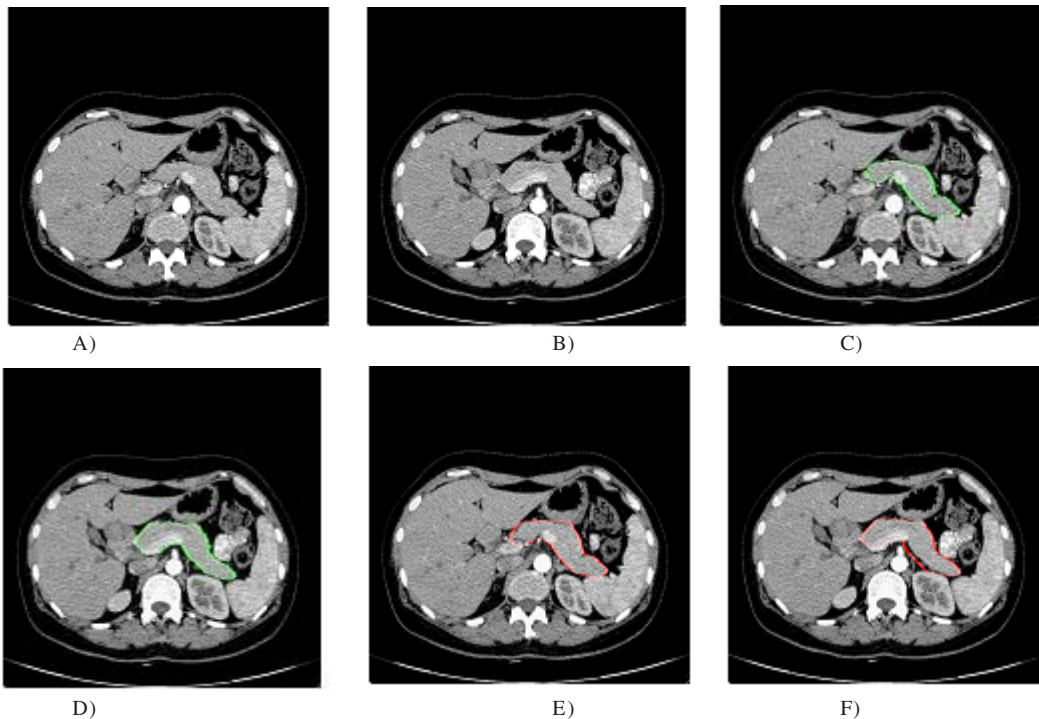


**Fig. 4**. The segmentation results

**Analysis**

In this part, different methods are using to be compared with the proposed algorithm. Comparison algorithms are including region-grow

and level-set methods. Figure 5 shows the different results of these methods with an abdomen CT image. In Figure 5(a) the green contour is segmented pancreatic contour and (b) is the

corresponding segmented areas to (a). Other images have the same meaning as (a) and (b) and the only difference are obtained by using different methods. (c) And (d) are the results of region-grow method, (e) and (f) are using level-set method, at last, segmentation of our method is shown in (g) and (h). It is obvious to find that region-grow and level-set method are always leading to some areas cannot segment fully especially the inside of pancreas. Since the gray-value inside of pancreas is not uniform such as the value of some areas may be lower than filling conditions, it leads to the inside of pancreas is not segmented fully. However, our method can solve this problem well. Comparing
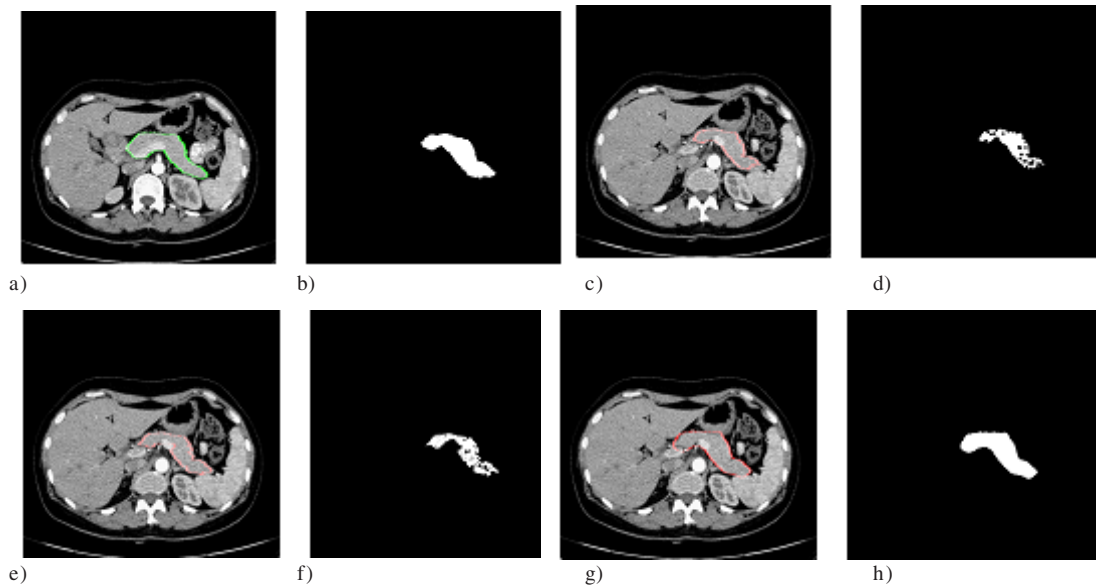


**Fig. 5.** The results of different algorithms

with other two methods, our method can segment the pancreatic fully and there are no holes in Figure 5(h). But in Figure 5(g) we can find that top right corner which pancreas is next to stomach appears slightly over-segmentation

Besides, we also give lots of quantitative results. The positive predictive value (*PPV*) (Heimann *et al.*, 2009) is used for result evolution.

*TP* stands for true positive which is the correct area and *FP* is false positive representing over-segmentation regions. The PPV ranges from 0 to 100%. And the higher value stands for better performance. Table 1 shows quantitative results of three methods. According to the table, we can

find that new method has a higher value standing for better segmentation performance than other else. Even if the accuracy is not reach to 90%, considering that the pancreas is a very small organ which is mapped to the given resolution, few misclassified pixels can account for a big overlap difference. And it still has some improving space.

### CONCLUSIONS

In this paper, a novel algorithm combining level-set with statistical shape model is proposed to get a better result in pancreas segmentation. The anatomical structure of interest such as general shape, location and orientation is added into the segmentation process to build statistical shape model. Several experiments demonstrate the validation of our proposed algorithm, and the level-set and region-grow methods are chosen as the contrast algorithm. Experimental results show that the proposed method has a good robustness and better precise of segmentation than other methods.

**Table 1.** The accuracy comparison about three methods

| Method | Accuracy |
|---|---|
| Region Growing Method | 59.79% |
| Level-Set Method | 63.22% |
| The Proposed Method | 83.72% |

Although the proposed method has some advantages than traditional method, it still suffers from several limitations. For example, the segmentation results are always existing slightly over-segmentation around boundary. The accuracy is improved but it could be improved much more. Therefore, many potential applications are existed for further research.

## ACKNOWLEDGEMENTS

## REFERENCES

1.  Cootes TF and Taylor CJ., Combining point distribution models with shape models based on finite-element analysis. *Image Vis. Comput.* 1995; **13**(5): 403–409.
2.  Cootes TF and Taylor CJ., Constrained active appearance models. In: Proc. IEEE ICCV, 2001; 1.
3.  Ghaneh P, Costello E, Neoptolemos JP., Biology and management of pancreatic cancer. *Gut*. 2007; **56**(8) : 1134–1152.
4.  Heimann T and Meinzer H., Statistical shape models for 3D medical image segmentation: a review. *Med. Image Anal.* 2009; **13**: 543–563.
5.  Heimann T. Ginneken BV, Styner M Arzhaeva Y, Aurich V., Comparison and Evaluation of Methods for Liver Segmentation from CT datasets. IEEE Transactions on. *Medical Imaging*. 2009; **28**(8): 1251–1265.
6.  Kitasaka T, Sakashita M, Mori K, Suenaga Y and Nawano S., A method for extracting pancreas regions from four-phase contrasted 3d abdominal ct images. *Int J Computer Assisted Radiology and Surgery*. 2008; **3** : 40.
7.  Magjarevic R, Shimizu A, Nawano S, Shinozaki K,and Tateno Y., Medical image processing competition in japan. World Congress on *Medical Physics and Biomedical Engineering*. 2009; **25**(4): 1814–1817.
8.  Malladi R, Sethian J, Vemuri B., Shape modeling with front propagation: A level set approach. IEEE Transactions on. *Pattern Analysis Machine Intelligence*. 1995; **17**(2) : 158–175.
9.  Osher S, Sethian JA., Fronts propagating with curvature-dependent speed: Algorithms based on Hamilton–Jacobi formulation. *Journal of computational physics*. 1988l; **79**: 12-49.
10. Perona P and Malik J., Scale-space and edge detection using anisotropic diffusion. IEEE *Transactions on. Pattern Analysis Machine Intelligence*. 1990; **12**(7) : 629–639.
11. Shimizu A, Ohno R, Ikegami T, Kobatake, H, Nawano S and Smutek D., Segmentation of multiple organs in non-contrast 3d abdominal images. *Int J Computer Assisted Radiology and Surgery*. 2007; **2**: 135–142.
12. Shimizu A, Kimoto T, Kobatake H, Nawano S and Shinozaki K., Automated pancreas segmentation from three-dimensional contrast-enhanced computed tomography. *Int J Computer Assisted Radiology and Surgery*. 2009; **5** : 85-98.