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Image segmentation based on kernel fuzzy C means clustering using edge detection method on noisy images

Saritha A K, MTech Student,MES College of Engineering

Ameera P.M, Assistant Professor,MES College of Engineering.

Abstract— **Classical fuzzy C-means (FCM) clustering is performed in the input space, given the desired number of clusters. Although it has proven effective for spherical data, it fails when the data structure of input patterns is non-spherical and complex. In this paper, a novel kernel-based fuzzy C-means clustering algorithm (KFCM). Its basic idea is to transform implicitly the input data into a higher dimensional feature space via a nonlinear map, which increases greatly possibility of linear separability of the patterns in the feature space, then perform FCM in the feature space. Another good attribute of KFCM is that it can automatically estimate the number of clusters in the dataset. A survey on clustering algorithms and emphasis on kernel based FCM is provided , since through a nonlinear map it wisely increases the linear separability of data points. Hence KFCM provide a suitable solution for segmenting images into subimages. The numerically complex level set method for extracting boundaries has paved a way for proposing Canny Edge Detection Algorithm for accurate results and reduction of computational complexity**.

Index Terms—**KFCM, FCM, Level Sets, Fuzzy Sets.**

I. INTRODUCTION

Image segmentation is one of the image processing applications in which input is an image and output will be attributes or parts of that image. Segmentation refers to the process of partitioning a digital image into multiple regions (sets of pixels). It is one of the most fundamental problems in computer vision has interested many researches throughout the years. As the use in computers increase through the years, reliable image segmentation is needed in more and more application, in the industrial, medical and personal fields. Segmentation has a number of applications from daily life and computer vision operations. Some of the practical applications ofimage segmentation are, location of tumours and other pathologies, measure tissue volumes, computer-guided surgery and diagnosis of anatomical structure in medical images, locate objects in satellite images (roads, forests etc.), face recognition, iris recognition, fingerprint recognition, traffic control systems, brake light detection, machine vision, crop disease detection in agricultural images etc.

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First Author name, *Saritha A K, Computer Science, MTech Student, MES College of Engineering, kuttipuram,9962228565*

Second Author name,*Ameera P M,Computer Science, Assistant Professor, MES College of Engineering, ,*

Most of the image processing application uses segmentation as a preliminary step. Some applications depends heavily on the initial models obtained as the result of the segmentation. The output of the application will be qualitative and quantitative if and only if the output of the segmentation is so. The ideal goal of segmentation is to identify the semantically meaningful components of an image and thus to simplify or change the representation of an image into more meaningful and easier to analyse. Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions results after segmentation are significantly distinguishable based on the same characteristic. Image segmentation is an important image processing, and it seems everywhere if there is a need to analyze what inside the image. For example, in order to find if there is a chair or person inside an indoor image, it may need image segmentation to separate objects and analyze each object individually to check what it is. Image segmentation usually serves as the pre-processing before image pattern recognition, image feature extraction and image compression. Researches of it started around 1970, while there is still no robust solution, so want to find the reason and see what to do to improve it.

There are several types of images, namely, light intensity (visual) images, range image (depth image), nuclear magnetic reasonance image (commonly known as magnetic reasonance image(MRI)), thermal image and so on. Light intensity (LI) images, the most common type encountered in daily life, represent the variation of light intensity on the scene. Range image (RI) on the other hand is a map of depth information at different points on the scene. In a digital LI image the intensity is quantized, while in the case of RI the depth value is digitized. Hundreds of segmentation techniques are availiable in literature, but there is no single method which can be considered good for all images, nor are all method equally good for a particular type of image. Moreover algorithms developed for one class of image (say ordinary intensity image) may not always be applied to other classes of images (MRI/RI). There are many challenging issues like, the development of unified approach to image segmentation which can probably be applied to all kinds of images. Even the selection of an appropriate technique for a specific type of image is a difficult problem. Up to now, to the knowledge of authors there is no universally accepted method of quantification of segmented output.

2 Image segmentation categories

Extensive work has been done in the field of image segmentation. Traversing the huge amount of existing techniques, it could be helpful if could categorize them into groups. Edge based segmentation, Probability based image segmentation, Cluster based image segmentation, Graph cut segmentation, Quad tree method, Thresholding, Region growing and shrinking method are some examples.

A. *Edge based Segmentation*

Edge based segmentation is also known as contour based image segmentation. Edge detection significantly reduces the amount of data and filters out useless information, while preserving the important structural properties in an image. In this type, the objects are selected by means of edges. Edge detection refers to the process of identifying and locating sharp discontinuities in an image. The discontinuities are abrupt changes in pixel intensity which characterize boundaries of objects in a scene. Edges are detected using a combination of operators for intensity gradient, texture discontinuities and color variation etc. Supplementary processing step must follow to combine edges in to edge chains. Edge chains are used in the segmentation process. Canny's edge detector is a good example.

B. *Clustering based Segmentation*

Clustering method are usually iterative methods to partition an image into a number of clusters or groups. The initial clusters has to be re order to make it include only similar characteristics at the end of the operations. K-means clustering is an example clustering method. The basic algorithm or operations picks K cluster centers, either randomly or based on some heuristic. Then assign each pixel in the image to the cluster that minimizes the distance between the pixel and the cluster center. Re-compute the cluster centres by averaging all of the pixels in the cluster .Repeat steps 2 and 3 until convergence is attained (e.g. no pixels change clusters). This algorithm is guaranteed to converge, but it may not return the optimal solution. The quality of the solution depends on the initial set of clusters and the value of K. When the number of clusters is fixed to k, k-means clustering gives a formal definition as an optimization problem: find the k cluster centers and assign the objects to the nearest cluster center, such that the squared distances from the cluster are minimized.

C. *Quadtree Representation*

Quad tree method considers image to be segmented as a tree. The root of the tree represents the whole image. If the image at root is found non-uniform (not homogeneous), then it is split into four son-squares (the splitting process). This process continues recursively until no further splits or merges are possible or all sub trees are homogeneous. Conversely, if any son-squares are homogeneous, they can be merged (the merging process). The QT structure allows to divide an image within a complete tree representation, including neighbouring information. This spatial information can be further used by a merging strategy which joins the QT leaves using color and edge information.

D. *Thresholding*

Thresholding is the simplest way of doing image segmentation. It is a technique which bands some range of values and permits other range. The key parameter in the thresholding process is the selection of threshold value. If a single threshold value is used, it is called a global thresholding. Adaptive threasholding uses different threshold values for different parts of the image. A task well suited to local adaptive thresholding is segmenting text from the image. During the thresholding process, individual pixels in an image are marked as "object" pixels if its value is greater than the threshold and as "background" pixels otherwise.A task well suited to local adaptive thresholding is the segmentation of text from the image. Iit is clear that the adaptive segmentation gives a better result than global segmentation for text extraction

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E. *Graph Cut based Segmentation*

A graph cut is the process of partitioning a directed or undirected graph into disjoint sets. Adopting this technique to images will break the image into disjoint regions. Graph-based image segmentation techniques generally represent the image in terms of a graph G = (V,E) where vertices are used to represent pixels. There will be edges in between vertices according to the nature of image. Edges in the set E connect certain pairs of neighbouring pixels and it represent the similarity between pixels. A weight is associated with each edge based on some property of the pixels that it connects, such as their image intensities.

F. *Probability based Segmentation*

Probability based image segmentation model is also known as Bayesian model of image segmentation. This method calculates the maximum a posteriori probability of each pixel. This involves the use of inferred probabilities rather than observed probabilities. Hence it involves the use of conditional probability as in any other case of Bayesian model.There are known Quantities and unknown quantities in Bayesian model.There will be probability associated with each of it. The probability of the known quantities are referred to as observed probability, where as the probability of unknown quantities are referred to as inferred probability. According to Bayesian model, inferred probabilities are calculated from the observed probabilities. This property is found to be very useful in the case of images, because neighbouring pixels possesses a large amount of similarity if they belong to same object. That is , it is possible to infer or calculate the value of a pixel if its neighbouring pixel value is given. For example, if a pixel is found to be red, there is a high probability that its neighbouring pixel is of having red or its similar color.

3. Emergence of Clustering

A good strategy to produce meaningful segments is to fuse segmentation results and edge outputs. The incorporation of psycho-visual phenomena may be good for light intensity images but not applicable for range images. Actually semantics and pror information of the type of images are crucial to the solution of the segmentation problem. According to Pavlidis (visual) image segmentation is a problem of psycho-physical preception, therefore not susceptible to purely ananlytical solution. Any mathematical problem be supplemented by heuristics which involve semantic information about the class of images under consideration. One may attempt to extract the segments in a variety of ways. Broadly, there are two approaches namely classical approach and fuzzy mathematical approach. Under the classical approach there are segmentation techniques based on thresholding, edge detection, relaxation and semantic and syntactic approaches. In addition to these, there are certain other methods which do not fall clearly in any one of the above classes. Similarly the fuzzy mathematical approach also has methods based on edge detection, thresholding and relaxation.

The relevance of fuzzy set set mathematical approach has been addressed in the literature. It is seen that the concept of fuzzy sets can be used at the feature level representing an input pattern as an array of membership values denoting the degree of possession of certain properties and in representing linguistically phrased input features; at the classification level in representing multiclass membership of an ambigous pattern, and in providing an estimate (or a representation) of missing information in terms of membership values. In other words fuzzy set theory may be incorporated in handling uncertainities (arising from deficiencies of information: the deficiencies may result from incomplete, imprecise, ill defined, not fully reliable, vague, contradictory information) in various stages of segmentation.

A gray tone image possess ambiguity within pixels due to the possible multi-valued levels of brightness in the image. This indeterminacy is due to inherent vagueness rather than randomness. Conventional approaches to segmentation consist of segmenting the image into meaningful regions, extracting their edges and skeletons. Since the regions in an image are not always crisply defined, uncertainity can arise within every phase of the process. Thus it is convenient, natural and appropriate avoid commiting to a specific (hard) decision segmentation technique likewise the thresholding, edge detection, graph cut etc, by allowing the segments or contours to be fuzzy subsets of the image, the subsets are characterised by the possibility(degree) to which each pixel belongs to them. Similarly, for describing and interpreting ill-defined structural information in a pattern, it is natural to de_ne primitives and relations among them using fuzzy sets.

II. LITERATURE SURVEY

Clustering has long been a popular approach to unsupervised pattern recognition. The fuzzy c-means (FCM) algorithm [1], as a typical clustering algorithm, has been utilized in a wide variety of engineering and scientific disciplines such as medicine imaging, bioinformatics, pattern recognition, and data mining. Since the original FCM uses the squared- norm to measure similarity between prototypes and data points, it can only be effective in clustering 'spherical' clusters. And many algorithms are derived from the FCM in order to cluster more general dataset. Most of those algorithms are realized by replacing the squared-norm in the object function of FCM with other similarity measures.

A. *Clustering based Segmentation*

In general, cluster analysis refers to a broad spectrum of methods which try to subdivide a data set X into c subsets (clusters) which are pairwise disjoint, all nonempty, and reproduce X. via union. The clusters then are termed a hard (i.e., nonfuzzy) c-partition of X. Many algorithms, each with its own mathematical clustering criterion for identifying "optimal" clusters, are discussed in the excellent monograph of Duda and Hart (1973). A significant fact about this type of algorithm is the defect in the underlying axiomatic model that each point in X is unequivocally grouped with other members of "its" cluster, and thus bear no apparent similarity to other members of X. One such manner to characterize an individual point's similarity to all the clusters was introduced in 1965 by Zadeh (1965). The key to Zadeh's idea is to represent the similarity a point shares with each cluster with a function (termed the membership function) whose values (called memberships) are between zero and one. Each sample will have a membership in every cluster, memberships close to unity signify a high degree of similarity between the sample and a cluster while memberships close to zero imply little similarity between the sample and that cluster. The history, philosophy, and derivation of such mathematical systems are documented in Bezdek (1981). The net effect of such a function for clustering is to produce fuzzy c-partitions of a given data set. A fuzzy c-partition of X is one which characterizes the membership of each sample point in all the clusters by a membership function which ranges between zero and one. Additionally, the sum of the memberships for each sample point must be unity.

B. *K means clustering algorithm*

K-means (MacQueen, 1967)[8] is one of the simplest unsupervised learning algorithms that solve the well known clustering problem. The procedure is simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. The main idea is to define k centroids, one for each cluster. These centroids shoud be placed in a cunning way because, different location causes different result. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the _rst step is completed and an early groupage is done. At this point re-calculate k new centroids as barycenters of the clusters resulting from the previous step. After these k new centroids, a new binding has to be done between the same data set points and the nearest new centroid. A loop has been generated. As a result of this loop the k centroids change their location step by step until no more changes are done. In other words centroids do not move any more. Finally, this algorithm aims at minimizing an objective function, in this case a squared error function The algorithm is composed of the following steps:

1.Place K points into the space represented by the objects that are being clustered.
2.The points represent initial group centroids.
3.Assign each object to the group that has the closest centroid.
4. When all objects have been assigned, recalculate the positions of the K centroids.
5.Repeat the above steps until the centroids no longer move.

This produces a separation of the objects into groups from which the metric to be minimized can be calculated Disadvantages include its dependent on initialization, can deal only with clusters with spherical symmetrical point distribution, and deciding K poses a problem.

C.*Fuzzy C means Algorithm*

Fuzzy c-means (FCM)[8] is a method of clustering which allows one piece of data to belong to two or more clusters. This method (developed by Dunn in 1973 and improved by Bezdek in 1981) is frequently used in pattern recognition. It is based on minimization of the following objective function:

$$J_m(U,V) = \sum_{i-1}^{c} \sum_{j-1}^{n} v_{ij}^{m} \left\| x_i - c_j \right\|^2$$

where m is any real number greater than 1, V_{ij}^{m} is the degree of membership of x_i in the cluster j, x_i is the of d-dimensional measured data,c_j is the d-dimension center of the cluster. Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership V_{ij}^{m} and the cluster centers c_j by:
This iteration will stop when , where is a termination criterion between 0 and 1, whereas k are the iteration steps and N is the total number of clusters. This procedure converges to a local minimum or a saddle point of Jm .Finally, this algorithm aims at minimizing an objective function, in this case a squared error function.

D. *Kernel based Fuzzy C means Algorithm*

The basic idea of KFCM[4] is to first map the input data into a feature space with higher dimension via a nonlinear transform and then perform FCM in that feature space. Thus the original complex and nonlinearly separable data structure in input space may become simple and linearly separable in the feature space after the nonlinear transform.
Define a nonlinear map as:

$$\phi x \longrightarrow \phi(x) \in F$$

where *X* denotes the data space and *F* is the transformed feature space with higher even infinite dimensions The KFCM[4] minimizes the following objective function.

$$J_m(U,V) \equiv \sum_{i-1}^{c} \sum_{k-1}^{n} v_{ik}^{m} \left\| \phi(x_i) - \phi(v_i) \right\|^2$$

where "c" denotes the number of cluster centers and "n" denote the number of datapoints. V_{ik}^{m} determines the fuzzy membership of pixels and "m" defines the fuzzification exponent.
The kernel function is defined as follows:

$$K(x,y) \equiv \exp(-\|x-y\|^2 / 2\alpha^2)$$

Kernel induced new metric in the data space is defined as following

$$d(x,y)\Delta\|\phi(x)-\phi(y)\| \equiv \sqrt{2(1-K(x,y))}$$

.

The image for segmentation is provided as input. Mostly, the number of successive centers and results of fuzzy c-means and other soft clustering depends on initial centers of clusters. In general the clustering algorithms choose the initial centers in random manner, which are affecting the results of clustering.

1.Providing the kernels for the input image.
2. Evaluation of memberships of pixels .
3. Evaluation of successive centers.
4.Repeat the steps iteratively until no new cluster centers are found.

E. *Level set Method for extracting boundaries*

The level set method was invented by Osher and Sethian to hold the topology changes of curves. A simple representation is that when a surface intersects with the zero plane to give the curve when this surface changes, and the curve changes according with the surface changes. The heart of the level set method is the implicit representation of the interface. To get an equation describing varying of the curve or the front with time.

$$\phi(x,y,t) \equiv 0$$

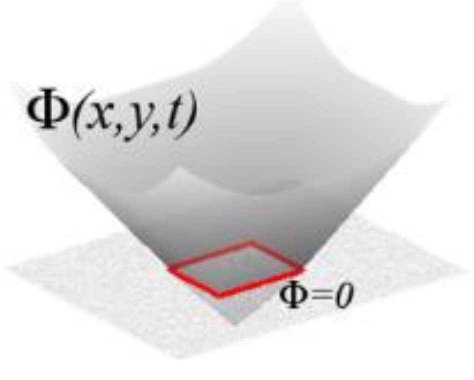

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Figure 2.1: Here the zero level set of the surface is a square

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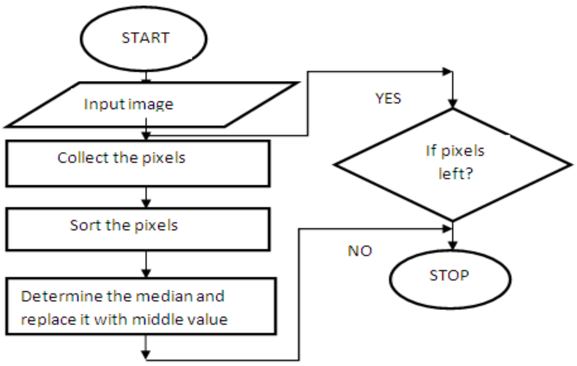
Here a new method to transform the algorithm. The original image was partitioned with KFCM, and the controlled action of the edge indicator function was increased. The result of KFCM segmentation was used to obtain the initial contour of level set method. With the new edge indicator function, results of image segmentation showed that the improved algorithm can exactly extract the corresponding boundaries. Under the same computing proposal, the average time cost was lower. Alternatively the KFCM clustering is sensitive to noise; some redundant boundaries were appeared in the candidates. Consecutively to solve this problem, the method of edge detection is proposed.

III .Kernel Fuzzy C Means Clustering using Level Set Method

The design phase consist of the following sections. Denoising the input image before it is segmented out by KFCM. The original image is partitioned into subimages with fuzzy boundaries through KFCM. At the end of image segmentation level set method is initiated and an edge indicator function extracts of boundaries for furthur processing.

A. *Denoising the image*

First of all the input image is underwent denoising. There are many filters availiable in doing the process. Order statistics filters are nonlinear spatial _lters whose response is based on the ordering the pixels contained in the image area encompassed by the filter, and then replacing the value of the center pixel with the value determined by the ranking result.The best known example of this category is the median filter, which, as its name implies ,replaces the value of a pixel with the median of the gray level values in the neighbourhood of that pixel. Median filters are quite popular because for certain type of random noise, they provide excellent noise reduction capabilities.



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Kernel induced new metric in the data space is defined as following

$$d(x,y) \Delta \|\phi(x) - \phi(y)\| \equiv \sqrt{2(1-K(x,y))}$$

.
FCM is effective only in clustering those crisp, spherical, and non-overlapping data. When dealing with non-spherical shape and much overlapped data, such as the Ring dataset , FCM cannot always work well. In this paper, the kernel method [3][5] to construct the nonlinear version of FCM, and propose a kernel-based fuzzy C-means clustering algorithm (KFCM). The basic ideas of KFCM is to first map the input data into a feature space with higher dimension via a nonlinear transform and then perform FCM in that feature space. Thus the original complex and nonlinearly separable data structure in input space may become simple and linearly separable in the feature space after the nonlinear transform. So we desire to be able to get better performance. Another merit of KFCM is, Unlike the FCM which needs the desired number of clusters in advance, it can adaptively determine the number of clusters in the data under some criteria.The image for segmentation is provided as input. Mostly, the number of successive centers and results of fuzzy c-means and other soft clustering depends on initial centers of clusters. In general the clustering algorithms choose the initial centers in random manner, which are affecting the results of clustering.
1.Providing the kernels for the input image.
2.Evaluation of memberships of pixels using the equation for computing
3.Evaluation of successive centers.
4.Repeat the steps iteratively until no new cluster centers are found.
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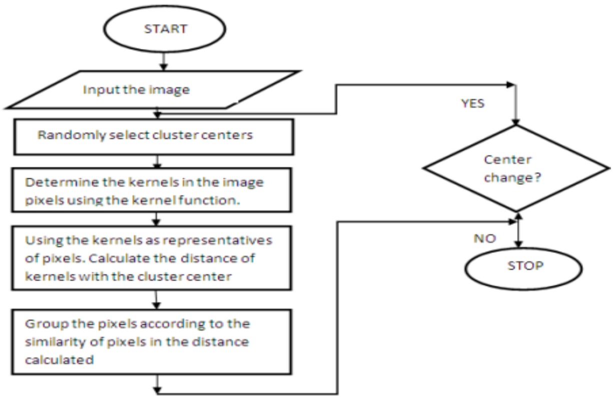

C. *Level set Method for extracting boundaries*

The level set method was invented by Osher and Sethian to hold the topology changes of curves. A simple representation is that when a surface intersects with the zero plane
to give the curve when this surface changes, and the curve changes according with the surface changes. The heart of the level set method is the implicit representation of the interface. To get an equation describing varying of the curve or the front with time.

$$\phi(x, y, t) \equiv 0$$

The general idea behind the level set method is to apply a function *f(p; t)* to the space the interface inhabits, where *p* is a point in that space, *t* a point in time. The function is initialized at *t* = 0, and then a scheme is used to approximate the value of *f(p; t)* over small time increments.

The first step in applying the level-set method is to pick a mesh, or a grid of points that covers the image. Level set methods have been shown to be versatile, robust, accurate, and e_cient tech-niques for a wide class of problems in etching, deposition, and photolithography development. They work by embedding the propagating front as the zero level set of a higher dimensional function, whose equation of motion resembles a Hamilton-Jacobi equation. This initial value partial di_erential equation is then solved using technology borrowed from the numerical solutions of hyperbolic conservation laws. The resulting techniques are able to handle sharp corners and cusps in the propagating solution, as well as topological changes, and three-dimensional effects. By employing fast narrow band adaptive techniques, the computational labor is the same as other methods,with the advantages of increased accuracy and robust modeling.

The drawback to level set techniques is that they require considerable thought in order to construct appropriate velocities for advancing the level set function. Nonetheless,
the reward is highly versatile techniques for a wide class of complex problems. In general, the finer the mesh, the more accurate the level set method. However, digitized image puts a limit on how fine a mesh is used. Since the image consists of several thousand pixels, the mesh must be at least as coarse as the individual pixels, and optimally even coarser. Once a mesh is chosen, the next step is to initialize the value of *(p; t)* at each point of the mesh
.

The function is defined as follows.
For any point p in the mesh, f(p; t) = d where d is the distance from the point p to the curve at the time(t = 0). The positive sign is used if the point p is outside the closed curve; the negative sign is used if the point p is inside the closed curve. Thus the name of the level-set method is explained: at any time t0, the evolving curve corresponds to the locus of all points p such that f(p; t_0) = 0, and that locus is a level curve of the function. The locus of all points p such that f(p; t_0) = c, contour around the original curve, where c is an arbitrary positive or negative constant. An edge indicator function is utilised. The original image is partitioned with KFCM, and controlled action of the edge indicator function was increased to exactly the boundaries.

III. PROPOSED SYSTEM : REPLACEMENT OF LEVEL SET METHOD BY EDGE DETECTION METHOD

The original image was partitioned with KFCM, and the controlled action of the edge indicator function was increased. The result of KFCM segmentation was used to obtain the initial contour of level set method. With the new edge indicator function, results of image segmentation showed that the improved algorithm can exactly extract the corresponding region of interest. Under the same computing proposal, the average time cost was lower. Alternatively the KFCM clustering is sensitive to noise; some redundant boundaries were appeared in the candidates. Consecutively to solve this problem, the method of edge detection is proposed.

Kernel fuzzy c-means (KFCM) was used to generate an initial contour curve which overcomes leaking at the boundary during the curve propagation. Firstly, KFCM algorithm computes the fuzzy membership values for each pixel. On the basis of KFCM the edge indicator function was redefined. Using the edge indicator function the segmentation of medical images which are added with salt and pepper noise was performed to extract the regions of interest for further processing. The results of the above process of segmentation showed a considerable improvement in the evolution of edge detection method.

A. *Canny Edge Detection Algorithm*

The purpose of edge detection in general is to significantly reduce the amount of data in an image, while preserving the structural properties to be used for further image process-ing. Several algorithms exists, and this worksheet focuses on a particular one developed by John F. Canny (JFC) in 1986 [2]. Even though it is quite old, it has become one of the standard edge detection methods and it is still used in research [3] [1]. The aim of JFC was to develop an algorithm that is optimal with regards to the following criteria:
1. Detection: The probability of detecting real edge points should be maximized while the probability of falsely detecting non-edge points should be minimized. This corresponds to maximizing the signal-to-noise ratio.

2. Localization: The detected edges should be as close as possible to the real edges.

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3. Number of responses: One real edge should not result in more than one detected edge

The algorithm runs in 5 separate steps:

1. Smoothing: Blurring of the image to remove noise.
2. Finding gradients: The edges should be marked where the gradients of the image has large magnitudes.
3. Non-maximum suppression: Only local maxima should be marked as edges.
4. Double thresholding: Potential edges are determined by thresholding.
5. Edge tracking by hysteresis: Final edges are determined by suppressing all edges that are not connected to a very certain (strong) edge.

Each step is described in the following subsections

B. *Smoothing*

It is inevitable that all images taken from a camera will contain some amount of noise. To prevent that noise is mistaken for edges, noise must be reduced. Therefore the image is first smoothed by applying a Gaussian filter. The kernel of a Gaussian filter with a standard deviation of 1.4.

C. *Finding Gradients*

The Canny algorithm basically _nds edges where the grayscale intensity of the image changes the most. These areas are found by determining gradients of the image. Gradients at each pixel in the smoothed image are determined by applying what is known as the Sobel-operator. First step is to approximate the gradient in the x- and y-direction respectively by applying the kernels.

The gradient magnitudes (also known as the edge strengths) can then be determined as an Euclidean distance measure by applying the law of Pythagoras. It is sometimes simpli_ed by applying Manhattan distance measure to reduce the computational complexity. The Euclidean distance measure has been applied to the test image. The computed edge strengths are compared to the smoothed image.

D. *Non Maximum Suppression*

The purpose of this step is to convert the blurred edges in the image of the gradient magnitudes to sharp edges. Basically this is done by preserving all local maxima in the gradient image, and deleting everything else. The algorithm is for each pixel in thegradient image:

1. Round the gradient direction to nearest 45, corresponding to the use of an 8-connected neighbourhood.
2. Compare the edge strength of the current pixel with the edge strength of the pixel in the positive and negative gradient direction. if the gradient direction is north compare with the pixels to the north and south.
3. If the edge strength of the current pixel is largest; preserve the value of the edge strength.If not, suppress (i.e. remove) the value.

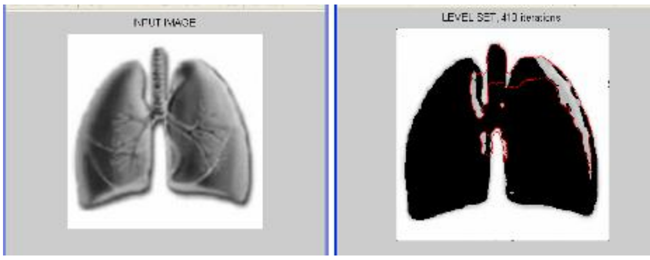
E. *Double Thresholding*

The edge-pixels remaining after the non-maximum suppression step are (still) marked with their strength pixel-by-pixel. Many of these will probably be true edges in the image, but some may be caused by noise or color variations for instance due to rough surfaces. The simplest way to discern between these would be to use a threshold, so that only edges stronger that a certain value would be preserved. The Canny edge detection algorithm uses double thresholding. Edge pixels stronger than the high threshold are marked as strong; edge pixels weaker than the low threshold are suppressed and edge pixels between the two thresholds are marked as weak. The effect on the test image with thresholds of 20 and 80.

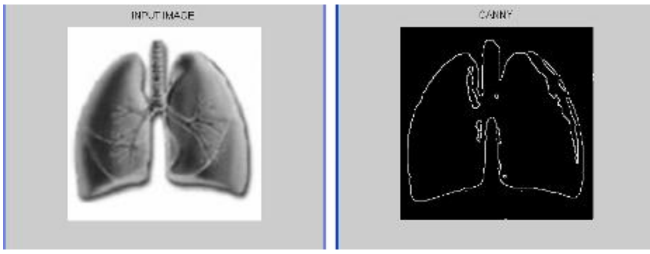
F. *Edge Tracking by Hysterisis*

Strong edges are interpreted as certain edges, and can immediately be included in the final edge image. Weak edges are included if and only if they are connected to strong edges. The logic is of course that noise and other small variations are unlikely to result in a strong edge (with proper adjustment of the threshold levels). Thus strong edges will (almost) only be due to true edges in the original image. The weak edges can either be due to true edges or noise/color variations. The latter type will probably be distributed independently of edges on the entire image, and thus only a small amount will be located adjacent to strong edges. Weak edges due to true edges are much more likely to be connected directly to strong edges.

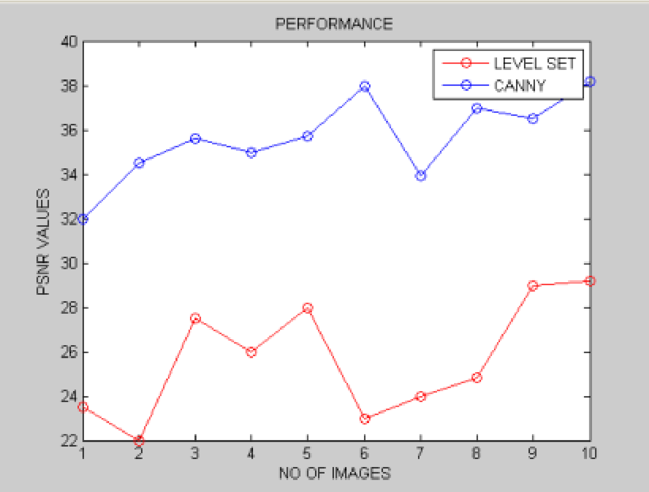
IV. RESULTS



Level set method with 410 iterations



Canny Edge Detection Method.



Canny Edge Detection with higher SNR .

V. DISCUSSION

The original image was partitioned with KFCM, and the controlled action of the edge indicator function was increased. The result of KFCM segmentation was used to obtain the initial contour of level set method. With the new edge indicator function, results of image segmentation showed that the improved algorithm can exactly extract the corresponding boundaries. Under the same computing proposal, the average time cost was lower. Alternatively the KFCM clustering is sensitive to noise; some redundant boundaries were appeared in the candidates. Consecutively to solve this problem, the method of edge detection is proposed.

Edge detection method as a modification to the level set method for extracting boundaries from the KFCM segmented image. The observation is that the boundaries are more accurate , as well as numerical processing involved in level set method is avoided and number of iterative steps reduced, hence time consumption is reduced. The purpose of edge detection in general is to significantly reduce the amount of data in an image, while preserving the structural properties to be used for further image processing.

VI. CONCLUSIONS

A new metric to replace the Euclidean norm in fuzzy c-means algorithm in the original space and then derive an new method of the fuzzy c-means algorithm. The results of experiments using the new metric could be able to be used for the segmentation of low contrast images and medical images. The method can have advantages of no reinitialization, automation, and reducing the number of iterations. The validity of new algorithm should be verified in the process of exacting details of images. In the future research, noise was added in images prior information on the object boundary extraction such as boundary, shape, and size, would be further analyzed. At the same time, the performance of image segmentation algorithms would be improved .

VII. REFERENCES

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