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A Novel Framework for Image Segmentation with De-Oversegmentation Technique

B.V.Kasar S.S.Sherekar Dr. V. M. Thakare

Abstract **:- Image segmentation is an important processing step in many image, video and computer vision applications. Extensive research has been done in creating many different approaches and algorithms for image segmentation, but it is still difficult to assess whether one algorithm produces more accurate segmentations than another, whether it be for a particular image or set of images, or more generally, for a whole class of images. This paper focused on some of the segmentation technologies i.e Improved AFCM Method, Interactive Image Segmentation, Multichannel pulse coupled Neural Network and MDS based multi-resolution. These segmentation methods are analysed with their parameters it gives efficient result but it produces slight over segmentation in the results due to the textured patterns of grassland and rough surface of rocks and cause noise in the image produced. So we will propose, De-Over segmentation method to reduce these problems. Segmentation can be used for object recognition, occlusion boundary estimation within motion or stereo systems, image compression, image editing, or image database look-up.**

Keywords – **Segmentation for M-FISH with IAFCM Method, Interactive Segmentation Method, Multichannel pulse coupled Neural Network and MDS based multi-resolution.**

I. INTRODUCTION

One of the most important operations in Computer Vision is segmentation. The aim of image segmentation is the domain-independent partition of the image into a set of regions which are visually distinct and uniform with respect to some property, such as grey level, texture or colour and second aim to enhanced image segmentation techniques. The problem of segmentation has been, and still is, an important research field and many segmentation methods. Dynamic background is done by using image segmentation of video. Segmentation of video with dynamic background has been an important research topic in intelligent surveillance and human-machine interface technologies. For the segmentation need the Images. But the images are either in form of black and white or colour. Colour images are due to the grey level. As the grey level contrast changes the colour of colour image also changes.

Basically the segmentation is divided in three categories-

1) Region-based segmentation
2) Boundary-based segmentation
3) Edge-based segmentation

In this paper, discusses four methods i.e Improved AFCM Method, Interactive Image Segmentation Multichannel pulse coupled Neural Network and MDS based multi-resolution.

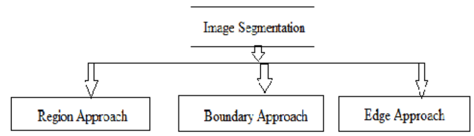

Fig1: Image Segmentation Approach

II. BACKGROUND

Multicolour fluorescence *in situ* hybridization (M-FISH) is a combinatorial labelling technique that was developed for the analysis of human chromosomes. The detection of chromosomal abnormalities depends on accurate pixel-wise classification techniques. Even though many attempts have been made to automate image analysis procedure, the reliability of the diagnosis technique has not reached the level for clinical use due to a number of factors that include non-homogeneity of staining, variations of intensity levels within and between image sets, and emission spectral overlaps between fluorophores. The sizes of the misclassified regions are often larger than the actual chromosomal rearrangements or lost, which often lead to incorrect interpretation by cytogeneticists. To improve the detection of chromosomal abnormalities for clinical diagnosis, accurate segmentation and classification algorithms an adaptive fuzzy c-means (AFCM) algorithm is developed and applied to the classification of M-FISH images[1].Despite many years of research, unsupervised image segmentation techniques without human interaction still do not produce satisfactory results. Fully automated segmentation is an ill-posed problem due to the fact that there is neither a clear definition of a correct segmentation nor an objective measure of the goodness of a segment. To perform interactive segmentation on the image has no seed at the trunk of the tree, a typical interactive segmentation method would fail to segment it as part of the tree. The reason that the trunk and leaves have very different colour components, and therefore, there was no sufficient cue for the seeds on the leaves to influence the segmentation decisions on the trunk [2]. The MPCNN is comparable to those of other image segmentation algorithms for the segmentation of noisy images while its parallel neural circuits improve the speed of processing drastically as compared with the sequential-code-based counterparts. A typical PCNN is a 2-D or 3-D array of neurons with one-to-one pixel-to-neuron. Including its complex dynamics and multiple interneuron coupling, the computation will be undoubtedly time consuming for colour images if executed in sequential codes. Then, some modified PCNNs applied to multichannel image fusion and real-time path planning. A model named M-PCNN is reported to perform medical image fusion. An improved PCNN model to perform colour image segmentation and circumvent the aforementioned problems of conventional PCNN. But MPCNN produces slight over segmentation in the results due to the textured patterns of grassland and rough surface of rocks [3]. The scalable MDS task directly as an optimization problem and used a (multi-resolution) sub sampling and interpolation schemes which exploit the important features of a (textured) natural image, i.e. the inherent spatial dependencies between spatial neighbouring samples. In this application, these inherent spatial dependencies between (spatial) neighbouring samples allow us to define a multi-resolution representation of the data in order to construct approximate coarser versions of the original optimization problem and to used the solution of the coarser version of this optimization to obtain a good initial guess that guides and accelerates the solution of finer versions. These dimensionality reduction methods can create a visual and logical representation of a large data document set in a low-dimensional space that is most expressive and thus leads to an easier interpretation of a large text corpus[4].Image segmentation is generated by the most probable explanation inference of the true states of both region and edge nodes from the updated BN. Besides the automatic image segmentation, the proposed model can also be used for interactive image segmentation. While existing interactive segmentation (IS) approaches often passively depend on the user to provide exact intervention, we propose a new active input selection approach to provide suggestions for the user's intervention[5].

This paper introduces four segmentation methods i.e. Segmentation of M-FISH Images for Improved Adaptive Fuzzy C-means Clustering Algorithm, Interactive Image Segmentation Using Dirichlet Process Multiple-View Learning, Multichannel pulse coupled Neural Network and MDS based multi-resolution and these are organizes as follows. Section 1 Introduction. Section 2 discusses Background. Section 3 discusses previous work done. Section 4 discusses various methodologies. Section 5 discusses attributes and parameters and how these are affected on images. Section 6 Proposed methodology and outcome result possible. Finally section 7 Conclude this paper and Section 8 shows Future scopes.

III. PREVIOUS WORK DONE

In research literature, a number of empirical evaluations are performed, comparing the relative performance of different methods [1][2][3]. An improved AFCM classification method (IAFCM) with a new objective function, which yields better background compensation and results in improved chromosome segmentation and classification. In IAFCM algorithm, the regularization term uses the approximation of the first-order derivative with a filter, which could preserve the shape of the gain filed while suppressing noise. In addition, the IAFCM algorithm avoids solving large differential equations and gives much faster computational speed. In order to evaluate the performance of the algorithm compared it with FCM, AFCM, Otsu's method, and reported region-based method for M-FISH image segmentation and classification algorithm used by the same database [1]. The important method of Interactive segmentation framework has Drichlet Process Mixture Models (DPMMs). The extended model DMVL used multiple views in image segmentation, for parameter learning and inference. This model provides a natural framework for handling partially labelled data in interactive image segmentation. The learning algorithm, which uses a Markov chain with states consisting of the component indices for data $c_1, \ldots, c_n$ and component parameters $\{\phi_c\}$, where $c \in \{c_1, \ldots, c_n\}$ [2]. In Table I, summarize likelihood functions $L(q)$ and priors $\pi(q)$ that are used for updating parameter, where stands for parameters, as detailed in the first column of the table. Object detection and recognition are natural capabilities of human beings. To detect object from images used Multi Channel Pulse Coupled Neural Network (MPCNN) method.

TABLE I
SUMMARY OF LIKELIHOOD FUNCTIONS AND PRIORS USED FOR OUR MODEL. THEY ARE USED IN THE PARAMETER UPDATE STAGE OF THE MAIN MCMC ALGORITHM

Parameters q	Likelihoods $L(q)$	Priors $\pi(q)$
μ^i, Σ^i	$p(\mathbf{x}_j^i) \propto \frac{1}{(2\pi)^{k/2}\|\Sigma^i\|^{1/2}} e^{-\frac{1}{2}(x-\mu^i)'(\Sigma^i)^{-1}(x-\mu^i)}$	$\mu^i \sim \mathcal{N}(0, I)$, $\log(diag(\Sigma^i)) \sim \mathcal{N}(0, I)$
α^i, β^i	$p(y_j\|\mathbf{x}_j^i) = \frac{\exp(\alpha_{y_j}^i + \mathbf{x}^T \beta_{y_j}^i)}{\sum_{k=1}^J \exp(\alpha_k^i + \mathbf{x}^T \beta_k^i)}$	$\alpha^i \sim \mathcal{N}(0, I)$, $\beta^i \sim \mathcal{N}(0, I)$
τ, v	$p(y_j\|\mathbf{x}_j^1, \mathbf{x}_j^2) = \frac{\exp(\tau_{y_j} + \mathbf{g}^T v_{y_j})}{\sum_{k=1}^J \exp(\tau_k + \mathbf{g}^T v_k)}$	$\tau \sim \mathcal{N}(0, I)$, $v \sim \mathcal{N}(0, I)$

This method has implemented for colour image segmentation . MPCNN method improves the speed of segmentation drastically as compared with its sequential-code based counterparts. In contrast to sequential algorithms, the salient point of the MPCNN is parallel-oriented design. This drastically reduces its time complexity. In the segmentation algorithm, seed selection, local linking, and region merging by linking are designed in parallelism. These computations can be completed in constant time. To calculate the sizes and mean color for all the regions, it takes $O(n)$, where O is the Landau notation and n *is* the total number of pixels in an image. Therefore, the total time complexity for the MPCNN segmentation algorithm is $O(n)$[3]. An efficient course to fine multi-resolution framework for Multidimensional Scaling (MDS) demonstrate performance on a large scale nonlinear dimensionality reduction and embedding problem in a texture feature extraction step for the unsupervised image segmentation problem, this segmentation Procedure applied on the Berkley image database. There are two different types of texture features to characterize a textured region, and since there has no reason why these two texture clues are interrelated, separately reduce the dimensionality of the color and the gradient magnitude feature vectors. This strategy allows the MDS algorithm to more easily find a nonlinear manifold. Moreover, since the color features seem more important than the gradient magnitude clues to characterize a texture region, also use twice as much weight by searching for them in a nonlinear manifold with two times more dimensions. Finally, construct a low-dimensional representation with three dimensions; this allows us to visualize this low-dimensional representation as a three-channel image [4].

IV. EXISTING METHODOLOGIES

Many image segmentation methods have been implemented over the last several decades. There are different methodologies that are implemented for image segmentation , Segmentation of M-FISH images, Interactive image Segmentation, MPCNN, MDS based multi-resolution. The IAFCM algorithm used a new objective function with a different regulation term, which appears to be more effective in controlling the shape of the gain field this method called as Improved Adaptive Fuzzy C-Means (IAFCM). An IAFCM segmentation algorithm is introduced and applied to the classification of M-FISH images. Both AFCM and the IAFCM seeking an optimum gain field that can compensate the background intensity in homogeneity. The classification of the 24 classes of chromosomes is realized by two steps: First, segmented each of the five channels into two clusters (background and foreground); Second, employed the combinatorial labelling technique to assign the class labels to each pixel. Thus, for the segmentation stage, NC = 2, tolerance U = 0.01, and tolerance G = 0.1. The initialization of this improved FCM algorithm does not need special treatment.

Second Segmentation technique is Interactive image segmentation. The base algorithm based on generative modelling using Dirichlet processes, which shown to be powerful in many recent applications in computer vision. The resulting framework referred to as **Dirichlet process multiple-view learning** (DPMVL), which provides systematic. The **smoothed DPMVL** (sDPMVL) expected to refine the resulting object boundaries and thus leads to better segmentation performance.

IAFCM Algorithm:
1) Initialize g_i with 1 ($i = 1, \ldots, N$) and cluster centers c_k ($k = 1, \ldots,$ NC) with random values within the image intensity, where NC is the number of clusters.
2) Update the membership function u_{ik} by using (10).
3) Update the cluster centers C_k by using (11).
4) Calculate the gain field g_i by using (14).
5) Update the gain field g_i by using (13).
If the maximum change of u_{ik} < tolerance U and the maximum change of g_i < tolerance G, break. Otherwise, go to step 2).

Algorithm 1: IAFCM Method

The two complementary features of a super pixel, image appearance feature represented by mean RGB colour values at constituent pixels and boundary feature represented by the diffusion signature vector. To start with salient boundaries in an image described by assigning boundary probabilities to image pixels. To characterize the overall boundary constraints, Diffusion Signatures is introduced as feature vectors for each vertex and derived by a diffusion process on the graph. The other technique was PCNN model, confined to the processing of gray-scale images. The processing of colour images can be considered as a special case of this multichannel image processor. Then use the acronym MPCNN for the multichannel PCNN. One of the key differences between the MPCNN and the conventional PCNN is that the latter uses the pixel intensity to implement the coupling of pulses while the MPCNN utilizes the feature vectors.

The segmentation technique is MDS-Based Multiresolution Nonlinear Dimensionality Reduction Model Method used for noise-robust image segmentation. An efficient coarse-to-fine multi-resolution framework for the MDS technique especially suited for large-scale dimensionality reduction problems such as those occurring during the texture feature extraction step in (texture) image segmentation or (more generally) occurring in large-scale high-dimensional clustering application [3].An important ingredient of the MDS algorithm, the choice of the distance measure which will be used in the optimization problem. In this context, one benefit of the MDS method over the other nonlinear dimensionality reduction models has its ability to be very flexible in the choice of this distance measure. By comparison, LLE and its variants involve writing each data point as a linear combination of its neighbours and, in the Euclidean case; this step is simply a least-squares problem, but a computationally costly problem for other distance measures[4].

V. Analysis And Discussion

In chromosome classification with M-FISH imaging, image segmentation is one of the most important steps. In order to increase the classification accuracy, image segmentation has to be improved, which would otherwise significantly affect the subsequent classification accuracy. In segmented M-FISH images method, the classification of the 24 classes of chromosomes is realized by two steps: first, segmented each of the five channels into two clusters; second, employed the combinatorial labelling technique to assign the class labels to each pixel. Thus, for the segmentation stage, NC = 2, tolerance U = 0.01, and tolerance G = 0.1. The initialization of this improved FCM algorithm does not need special treatment. According to the combinatorial labelling technique that was developed for the analysis of human chromosomes, once images of each channel were correctly segmented, the classification could be easily performed by the use of the binary combination. The DAPI channel image is first segmented with the IAFCM algorithm to generate a chromosome mask. The mask is applied to all other five channels so that the same background (i.e., non-chromosome regions) is identified. After image segmentation, each pixel in an M-FISH image set labelled as $xi = [xi\ 1, xi\ 2, xi\ 3, xi\ 4, xi\ 5]$, where $xij \in \{0,1\}$, $i = 1, 2, \ldots, N$; $j = 1, \ldots, 5$; and N is the number of pixels in the image. For example, pixels that are labelled as [0, 0, 0, 0, 1] will be set as class 1; pixels that are labelled as [0, 0, 0, 1, 0] will be set as class 2, etc. Fig. 3 gives an example of the segmentation stage of M-FISH images for each channel. In Fig.4, pixels of the green circled chromosome (see fig.4 (e) and 4 (f)] will be assigned as class 1 since they are labelled as [0, 0, 0, 0, 1] [1].

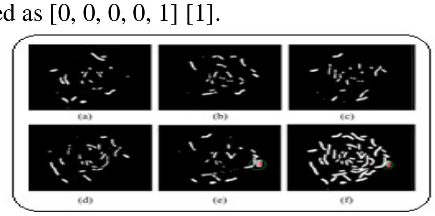

Fig.2. Segmentation of M-FISH images at each channel. (a)–(e) Segmentation results for channels (1)–(5); (f) segmentation result of the DAPI channel.

In **Interactive segmentation** method, used super pixels in place of pixels for computational efficiency, such that a super pixel, which roughly contains 15 pixels, assumed the smallest unit for labelling. Generate boundary fragments by thresholding a boundary probability map at its 60th percentile of nonzero values. The boundary fragments with junctions were broken into smaller ones so that they contain simple curves for generating diffusion signatures. Used fixed distributions for the base distribution G_0 on properly normalized data, i.e., $\mu_i \sim \mathcal{N}(0,1), \log(\sigma_i^2) \sim \mathcal{N}(0,1)$, $\alpha_j \sim \mathcal{N}(0,1), \beta_j \sim \mathcal{N}(\mathbf{0},I), \tau_i \sim \mathcal{N}(0,1)$, and $\upsilon_i \sim \mathcal{N}(\mathbf{0},I)$. Where I was an identity matrix. The numbers of MCMC iterations $T_0 = T = 100,$ the number of auxiliary components

$m = 5$, $L = 200$, and $\epsilon = 0.2$. to measure the goodness of segmentation, compute the *error rate* as the percentage of wrongly labelled pixels in the original unlabelled region [2]. To investigate the noise resistance of MPCNN is analysed by adding the salt-and-pepper noise with various noise densities. The *F*-measure values of the MPCNN approach as compared with JSEG and SRG. The results show that the MPCNN's resistibility to salt-and-pepper noise is comparable to SRG and JSEG. The impact of the parameters of the region-merging phase. As the performance of object detection has direct dependence on the quality of the segmentation phase, these parameters also have impact to the object-detection phase [3]. The two internal parameters of MDS segmentation algorithm are thus ***K***, i.e., the number of classes of *K* means, and regularization parameter ξ. These two parameters controlling the resolution in the spatial and range domains and ξ). In this method, PRI results for the different algorithms, the distribution of the PRI measure over the 300 images of the Berkeley image database. To be impartial and for comparison, illustrate the results of simplest segmentation algorithm **MD2S***K*-means [K=11 | ξ=0.4] by showing the same segmented images, in which the best existing segmentation algorithm, in the PRI score. [4].

Segmentatio nTechniques	Advantages	Disadvantages
Segmentation of M-FISH images for Improved AFCM Method	To improve the detection of chromosomal abnormalities for clinical diagnosis, accurate segmentation and classification algorithms have to be developed.	The Gap algorithm used in IAFCM method, performed significantly worse on the single-object data set due to over fragmentation.
Interactive Segmentation Method	DPMVL is more flexible as it directly addresses the interaction between the two complementary views.	The DPMVLs method was much less sensitive to the distortion in labelling contours than the random walk approach.
Multichannel pulse Coupled Neural Network	The MPCNN improves the speed of segmentation drastically as compared with its sequential-code-based counterparts.	competitive for the other techniques this segmentation produced of noisy images.
MDS-Based Multiresolutio n Nonlinear Dimensionalit y Reduction Model	It improve Accurate and noise-robust image segmentation to more easily find a nonlinear manifold	MDS algorithm requires too much computing when applied to all pixels of the image

Table 1: Comparison between IAFCM, Interactive Segmentation, MPCNN, MDS based Multi-resolution Method.

VI. Proposed Methodology

Image segmentation is the important step in image analysis and processing mechanism. Several proposed algorithms have faced the problem of over segmentation. A new propose De-over-segmentation method overcome the over segmentation of an image. The propose method is effective approach of digital image segmentation with watershed algorithm for reducing over segmentation problem. The implementation is actually intended for digital colour image processing. In mathematical morphology, the watershed algorithm is a tool for segmentation of a query image in its original version. In this method there are four parts: First, if image is RGB then convert to Gray-scale image and apply Gaussian smoothing operator to image. Second, apply integrated marker based watershed algorithm with hybrid medina filter. Finally, to overcome over segmentation using BFS method and get segmented result.

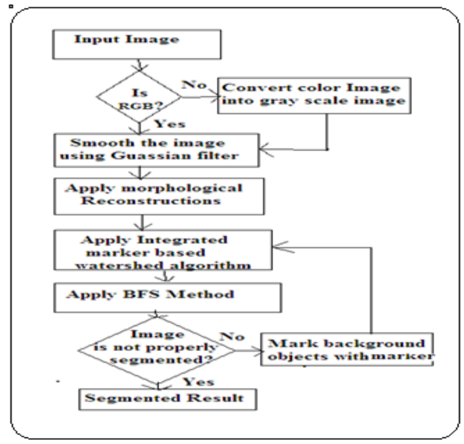

Fig 3 : Framework for De-Over segmentation Method

Outcome Possible Result

The propose algorithm provides better results than existing algorithm especially in case of noisy images and also reducing the over segmentation but it might decrease speed.

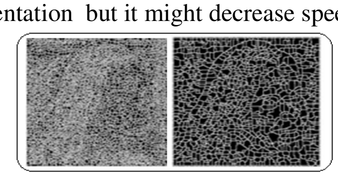

Fig 4: (a) Input image b) Segmented Image

VII. Conclusion

In this paper, examined the breadth of existing methods that objectively evaluate image segmentation. First focused on full range of segmentation evaluation methodologies, and discussed the advantages among each others. This advantage is crucial to general-purpose segmentation applications, such as those embedded in real-time systems, where a large variety of images with unknown content and no ground truth need to be segmented. The objective of this paper is a comparative study of four of the most frequently used strategies to perform segmentation based on region and boundary information. These methods produces slight over segmentation in the results so De-Over-segmentation proposes method will be implementing to overcome this drawback. This algorithm becomes more useful when salt and pepper noise is present in the images.

FUTURE SCOPE

In future we will work, to improve speed and complexity.

REFERENCES

[1] Hongbao Cao, Hong-Wen Deng, and Yu-Ping Wang, “Segmentation of M-FISH Images for Improved Classification of Chromosomes With an Adaptive Fuzzy C-means Clustering Algorithm,” *IEEE Transactions On Fuzzy Systems*, VOL. 20, NO. 1, PP. 1-8, FEBRUARY 2012.

[2] Lei Ding, Alper Yilmaz, and Rong Yan, “Interactive Image Segmentation Using Dirichlet Process Multiple-View Learning,” *IEEE Transactions On Image Processing*, VOL. 21, NO. 4, PP. 2119-2129, APRIL 2012.

[3] Max Mignotte, “MDS-Based Multiresolution Nonlinear Dimensionality Reduction Model for Color Image Segmentation,” *IEEE Transactions On Neural Networks*, VOL. 22, NO. 3, PP. 447-460, MARCH 2011.

[4] Hualiang Zhuang, Kay-Soon Low,” Multichannel Pulse-Coupled-Neural-Network-Based Color Image Segmentation for Object Detection”, *IEEE Transactions On Industrial Electronics*, VOL. 59, NO. 8, PP. 3299-3308, AUGUST 2012.

[5] Lei Zhang,” A Bayesian Network Model for Automatic and Interactive Image Segmentation ”, *IEEE Transactions On Image Processing*, VOL.20, NO. 9, PP. 2582-2593, Sept. 2011.

[6] Sheng Liu, “A Resegmentation Approach for Detecting Rectangular Objects in High-Resolution Imagery”, *IEEE Transactions On Geoscience and Remote Sensing Letters*, VOL. 8, NO. 4, PP. 621 - 625, July 2011.

[7] Deren Li, Guifeng Zhang, Zhaocong Wu, Lina Yi**,** ” An Edge Embedded Marker-Based Watershed Algorithm for High Spatial Resolution Remote Sensing Image Segmentation”, *IEEE Transactions On Image Processing*, VOL. 19, NO. 10, PP. 2781 - 2787, OCT 2010.

[8] Bo Peng,, Zhang, D.,Zhang, D, “Automatic Image Segmentation by Dynamic Region Merging”, *IEEE Transactions On Image Processing*, VOL. 20, NO. 12, PP. 3592 - 3605, DEC 2011.

[9] Lulu Xu, Huaxiang Lu,” Automatic Morphological Measurement of the Quantum Dots Based on Marker-Controlled Watershed Algorithm”, *IEEE Transactions On Nanotechnology*, VOL. 12, NO. 1, PP. 51-56, JAN 2013.