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# Fuzzy Segmentation of Cervical Cytology Image using Level set algorithm

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**Abstract**. Due to the low resolution and low contrast, image segmentation in medical profession is a very tough task. When the photos are distorted by noise, outlier and other artifacts, the performance further declines. In order to overcome the abovementioned problem, a new technique is proposed in this paper. This paper proposes a method for cervical cytology image segmentation based on Fuzzy c-means and the Level set algorithm. The current study has begun its work with a median filter with a fuzzy level set method to segment cervical cytology images. An image of cervical cytology was used as an input image. A median filter and fuzzy c-means were applied to the image to abstract image noise and generate image clusters, respectively. The image clusters displayed the initial and final cluster centres. Following separation and extraction of white matter from grey scale images, the proposed level set method was used for segmentation of cervical images. The fuzzy c-means were sensitive to the initial cluster centre. A new fuzzy level set algorithm can directly evolve from the initial segmentation by spatial fuzzy clustering. The results are also used to estimate the level set algorithm's controlling parameters. Additionally, the fuzzy level set algorithm benefits from locally regulated evolution. Such enhancements make level set manipulation easier and lead to more reliable segmentation. When compared to techniques described in prior studies, this approach fared well in segmenting cervical pictures The accuracy of the proposed method is 94%

**Keywords:** Fuzzy-c-means, Spatial fuzzy clustering, Level set method, controlling parameters

## 1 Introduction

The primary goal of cervical image segmentation is to divide the image into different anatomical structures, thus separating components such as nucleus from cytoplasm from their background. Because of the low resolution and low contrast, computerized cervical image segmentation is a tricky problem. Furthermore, the presence of noise and artifacts as a result of instrumental limitations, reconstruction algorithms, and patient movements frequently complicates the task. There is no universal algorithm for cervical image segmentation as of yet. The benefits and drawbacks of an algorithm frequently vary depending on the problem under investigation.

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Most medical imaging segmentation results in grey scale images. Consider a medical image I(x,y) in which x(A[1,Nx]) and y(A[1,Ny]) are spatial indices and the pixel i(x,y) quantifies the intensity of the pixel. The goal of image segmentation is to find a set of subclasses Sk where

$$\cup S_k = I \quad (1)$$

$$S_k \cap S_j = \Phi \quad (2)$$

The indices k and j fall within the range [1,K], where K is the number of subclasses. Eq.(1) emphasizes the importance of complete image segmentation. Eq(2) requires that it be non-overlapping.

Segmentation is nothing more than the splitting of a digital image into segments or pixels sets, in which pixels are grouped similarly according to different criteria, such as texture, intensity or color, to identify items and borders within a defined image [1].

For cervical image segmentation, many algorithms have been proposed, including graph cut, edge detection, and clustering [2, 28]. The goal of cervical image segmentation is to separate the nucleus from the cytoplasm in the cervical image. The segmentation results are processed by extracting a set of image segments, regions, or contours. A pixel in a region has several characteristics in common, such as contrast, texture, colour, grayscale [3], and so on. Fuzzy C-Means [4,5, 26, 27], an iterative algorithm, is essential in cervical image segmentation. FCM's performance in medical image segmentation has significantly improved. In medical image segmentation, there are two powerful concepts to consider. The first is pixel classification, and the second is variational boundary tracking [2]. The main one is that the intensities of the pixels in each subclass are nearly constant, which is true for anatomical structures with similar physiological properties. Such algorithms can unearth multiple components at the same time, but they are vulnerable to environmental factors.

On the other hand, methods that use variation boundaries rely on both intensity and spatial information. Therefore, a subclass must be akin and enclosed in a variation boundary. However, neither of these methods is universally robust when it comes to medical image segmentation because of intrinsic noise and artifacts [6,7,8,9]

The use of dynamic implicit interfaces and partial differential equations [PDEs] for level set methods has been demonstrated to be effective for cervical image segmentation [10,11,12,25].

Clinical radiologist and even engineering practitioners are frequently overwhelmed by increased computational requirements and sophisticated control parameter guidelines [13]. The current state of the art research is geared toward promoting control while improving the nature of segmentation.

Many hybrid intelligence systems have been developed that use fuzzy clustering to facilitate level set segmentation [14,15]. In summary, the algorithms utilized in the previous two articles use fuzzy clustering based on picture intensities for initial segmentation and then apply the level set technique for object refining by tracking boundary variation.

Section II describes the spatial fuzzy clustering and image segmentation concepts in detail. Level set method is outlined in Section III. Section IV portrays the level set method in detail and along with the algorithm. Results and Discussion are covered in Section V. Section VI discusses the performance analysis of the system. Finally, conclusion is covered in Section VII.

## 2 Spatial Fuzzy Clustering and Image Segmentation

The centroid and extent of each subclass are adaptively appraised in fuzzy clustering to limit a pre-defined cost function. As a result, accepting fuzzy clustering as a type of flexible thresholding makes sense. The fuzzy-c-means (FCM) computation is one of the most widely used in fuzzy clustering and has been widely applied to clinical problems [4,5,15].

The classic FCM method divides N items into K groups (K N) based on their attributes N which approaches the number of picture pixels Nx x Ny in medical image segmentation. The centroid of each cluster and the affiliations of N items are desirable results. The goal of standard K-means clustering is to keep the cost function as small as possible.

$$j = \sum_{m=1}^{N} \sum_{n=1}^{N} || i_n - v_m ||^2 \quad (3)$$

where n in denotes a specific picture pixel, $V_m$ denotes the mth cluster's centroid, and ||,|| denotes the norm. A K-means algorithm's optimum outcome maximizes inter-cluster variation while minimizing intra-cluster variation. Every object in K-Means clustering can only belong to one of the K clusters. An FCM, on the other hand, uses the membership function mn to express the degree of membership of the nth object to the mth cluster, which is appropriate for medical picture segmentation because physiological tissues are rarely homogeneous.

$$\left[ j = \sum_{n=1}^{n} \sum_{m=1}^{C} \mu_{mn}^{l} \quad \||| i_n - v_m \||^2 \right] \tag{4}$$

where l(>1) is a parameter that controls the fuzziness of the segmentation that results. The following constraints apply to the membership functions.

$$\left[ j = \sum_{n=1}^{n} \sum_{m=1}^{C} \mu_{mn}^{l} = 1 \mid \right] 0 \leq \mu_{mn} \leq 1 \sum_{n=1}^{N} \mu_{mn} < 1 \tag{5}$$

Iteratively, the membership functions *mn* the centrodies *nm* are modified.

The typical FCM algorithm is optimized by assigning high membership values to pixels close to their centroid and low membership values to pixels far away.

The lack of spatial information is one of the issues with the traditional FCM algorithm in image segmentation. Because image noise and artefacts frequently degrade FCM segmentation performance, incorporating spatial information into an FCM would be appealing. Cai et al. [5] devised a generalised FCM algorithm that incorporates local intensity and spatial information using a similarity factor. In contrast to the prior weighing described above, morphological processes can be used to provide spatial restriction during the post-processing stage [9]. Chuang et al [4] present a new spatial FCM [24] technique in which spatial data is directly included into fuzzy membership functions.

$$\mu_{mn} = \frac{\mu_{mn}^{p} h_{mn}^{q}}{\sum_{k=1}^{C} \mu_{kn}^{P} h_{kn}^{q}} \tag{6}$$

Where p and q are two parameters controlling the respective contribution

The variable $h_{mn}$ includes spatial information by

$$h_{mn} = \sum_{k \varepsilon Nn} \mu_{nk} \tag{7}$$

where $N_n$ denotes a local window centered around the image pixel n. The weighted $\mu_{mn}$ and the centroid $V_m$ are updated usual according to Eqs. 6 and 7.

## 3 Level Set Method

Moving bends and surfaces with arch-based speeds are used in a significant variety of PDEs used in image processing. The level set strategy [21] was incredibly persuasive and beneficial in that area. The basic idea is to think of bends and surfaces as zero-level configurations of a higher-dimensional hyper-surface. This approach provides more precise mathematical use as well as the ability to manage topological changes without difficulty.

It basically means that the closed bends in a two-dimensional surface are perceived as a three-dimensional space's consistent surface. The surface is represented by the smoothing capacity (x,y,t), whereas the bends are represented by the arrangement of definition (x, y, t) 0. As a result, the progression of a bend can be transformed into the progression of a three-dimensional level set capacity. Given a level set of work (x, y, r0), the zero level of which corresponds to bent The entire surface can be divided into an inward district and an outer locality of the bend with the bend as the limit. By all accounts, define a Signed Distance Function (SDF).

# 4 A New Fuzzy Level Set Algorithm

Both the FCM and level set techniques are general-purpose computational models that may be used to situations of any size. However, when applied to a medical image, this technique fully utilizes both algorithms' advantages for increased performance. It starts its journey with spatial fuzzy clustering.

A FCM with spatial restrictions is used to find the approximate outlines of interest in a cervical cytology image. The enhanced level set method uses Equ 16's flexible initialization to handle FCM findings directly for evolution.

Suppose the component of interest in an FCM result is

$$R_k: [\, r_k = \mu_n \Phi_0(x,y) = -4\varepsilon(0.3 - B_k)\,,\ n = x + N_y + y].$$

Then the level set function is initiated where ε is a constant which regulates the Dirac function [7]. The Dirac function is then defined as follows

$$\delta_0(X) = \begin{cases} 0 & |x| > \varepsilon \\ \frac{1}{2\varepsilon}[1+\cos(\frac{\pi x}{\varepsilon})], & |X| \le \varepsilon \end{cases} \qquad (8)$$

$B_k$ is a binary image obtained from

$B_k = R_k \geq b_0$

Where $b_0$ ($\varepsilon(0,1)$) is adjustable threshold. Spatial fuzzy clustering $B_k$ can be approximate the component of interest which can be adjusted by $b_0$

Level set methods are coupled with a number of controlling parameters that can vary from case to case.

The following are some of the governing parameters that control level set segmentation.

| Parameter | Significance |
|---|---|
| $\varsigma$ | Controlling the gradient strength of initial level set function |
| $\varepsilon$ | Regulator for Dirac function $\delta(\Phi)$ |
| $\sigma$ | Controlling the spread of Gaussian smoothing function |
| $\mu$ | weighting coefficient of the penalty term |
| $\lambda$ | coefficient of the contour length for smoothness regulatin |
| $\nu$ | Artificial balloon force |
| $\tau$ | Time step of level set evolution |
| T | maximum iteration of level set evolution |

A longer time step τ may speed up the evolution of the level set, but it also increases the possibility of border leakage. If the starting $\Phi_0$ is outside the component of interest, it is critical to choose a positive ν, and vice versa.

Apart from that, the trial-and-error method has recommended numerous rules of thumb for effective set segmentation [16,17,20]. For example, for stable evolution, the product of the time step and penalty coefficient ( $\tau$ x $\mu$) must be less than 0.25, and the parameter value of $\varsigma$ should be bigger than 2ε The greatest value of $\varsigma$ slows down the progression of the level set. However, a larger λ frequently results in smoother contours, and a larger speeds up the evolution of the level set.

Given the initial level set function $\Phi_0$ from spatial fuzzy clustering Eq 20, it is convenient to estimate the length l and the area z by

$$l = \int \delta(\phi_0)\,dxdy$$

$$x = \int H(\phi_0)dxdy \qquad (9)$$

where the Heaviside function $H(\Phi_0)$ is defined as

$$H(\Phi_0) = \begin{cases} 1, & (\Phi_0) \geq 0 \\ 0, & (\Phi_0) < 0 \end{cases} \qquad (10)$$

We notice that when the Component of Interest is large, the level set evolution is faster. The ratio $\varsigma = x/l$ will likewise be significant in this situation. As a result, assigning the time step $\tau$ as $\varsigma$ in the suggested fuzzy level set technique seems fair. The punishment coefficient will be calculated as $\mu = 0.2 / \varsigma$

Because for steady evolution, their product ( $\tau$ x $\mu$) should be less than 0.25. The genuine boundaries will be approximated by the starting level set function $\Phi_0$ generated via fuzzy clustering eq (20). As a result, the comparatively conservative $\lambda$

$\lambda = 0.1\varsigma$ is used to keep topological changes under control.

In the level set algorithm, the balloon force $\nu$ serves two purposes. The level set function's moving direction is determined by its sign, which is positive for shrinkage and negative for expansion. Second, the larger the level set, the faster it evolves. The controlling parameter $\nu$ is established as a global constant in the conventional level set algorithm. The level set function appears to be faster or slower depending on $\Phi$ the method. Furthermore, while going across the boundary of interest, the level set function should automatically change its orientation. The initial FCM segmentation is shown to be very beneficial in regularizing level set evolution as a quantitative.

The degree of membership of each picture pixel $\mu_k$ is used as the distance to the specific component of interest $R_k$ in the new fuzzy level set approach. The use of an augmented balloon force to pull or push the dynamic interface towards the object of interest is proposed.

$$G(R_{k.}) = 1- 2 R_k \qquad (11).$$

$G(R_{k.})$ [ $\in(-1,1)$] is the resulting balloon force matrix, which has a variable pulling or pushing force at each image pixel. In other words, regardless of its initial position, the level set function will be drawn to the object of interest. The evolutionary equation Eq. 17 is thus rewritten as

$$\xi(g,\phi) = \lambda\delta(\phi)div(g\frac{\nabla\phi}{|\nabla\phi|}) + gG(R_k)\delta(\phi) \qquad (12)$$

The proposed enhancement achieves several practical benefits. The balloon force can now be derived from spatial fuzzy clustering directly. Moreover, level set evolution is now adapted to the distance to the genuine object. Once approaching the object, the level set function will automatically slow the evolution down and will become totally dependent on the smoothing term. Since a conservative $\lambda$ is adopted here, level set evolution stabilizes automatically. For robust segmentation, we can choose large iteration of evolution T.

The proposed upgrade has a number of practical advantages. The balloon force may now be easily calculated using spatial fuzzy clustering. Furthermore, level set evolution has been adjusted to account for the distance between the genuine object and the user. When you get close to the object, the level set function will automatically slow down the evolution and become completely reliant on the smoothing term. Because a cautious approach $\lambda$ is used here, level set evolution stabilizes on its own. We can choose a big iteration of evolution T for robust segmentation.

The proposed method Pseudo code is given below

1. Read the image
2. Convert into grayscale image
3. Use a grey threshold value to convert into a binary image.
4. Using median filter to remove noise
5. Use a weighted membership function with spatial limitations to do FCM segmentation.

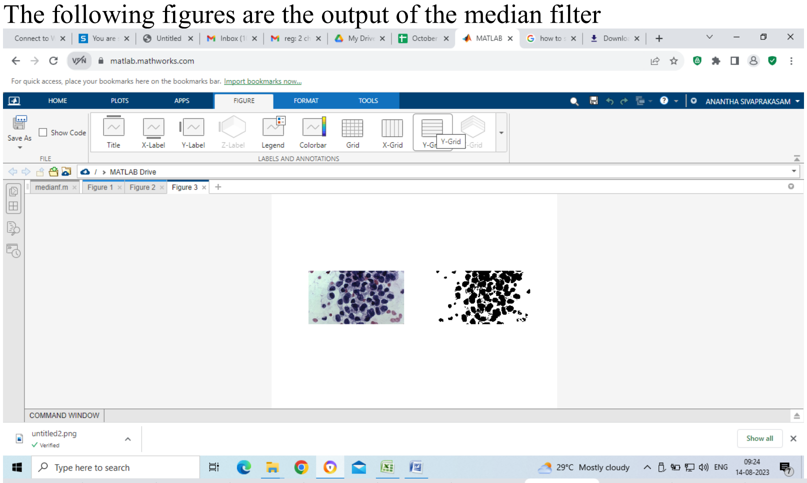
6. Use spatial limitations to improve level set segmentation.
7. Show the image that has been segmented

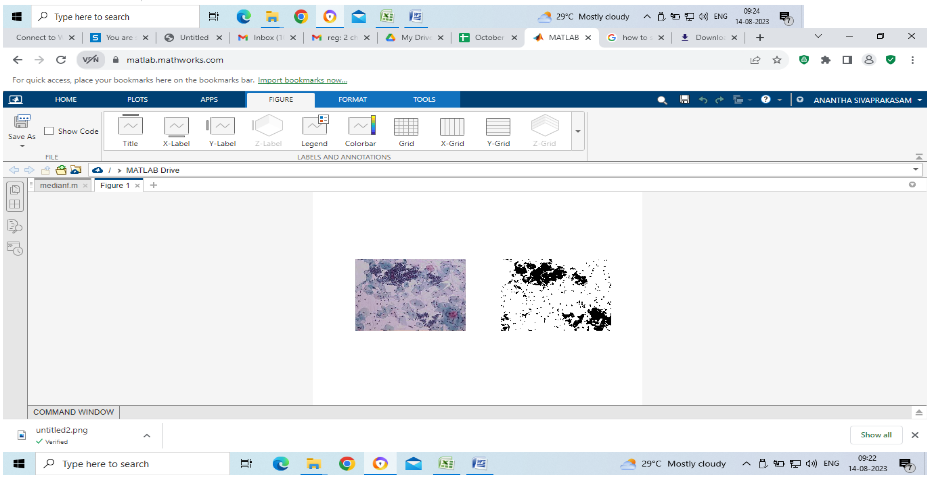
# 5 Results and Discussion

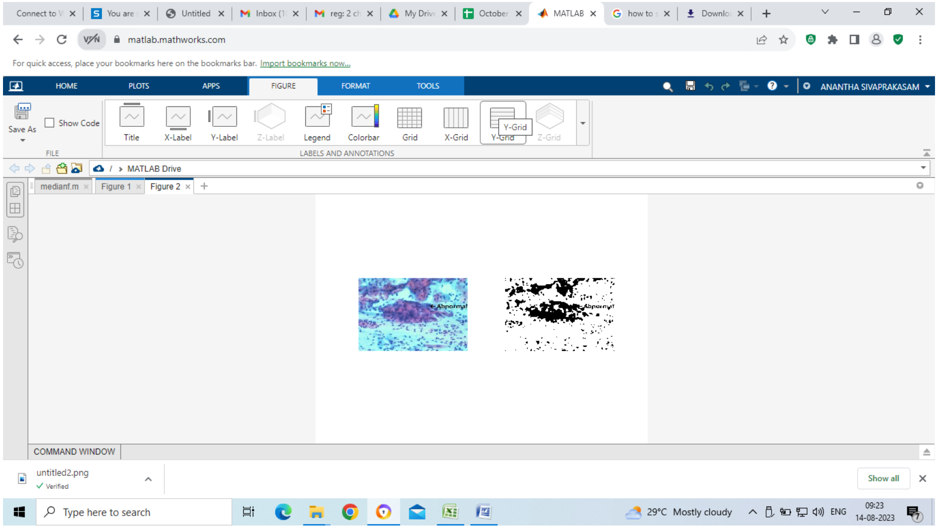
A range of cervical cytology pictures were used to evaluate this approach. The given image is first converted into grayscale and then into binary images using the grey threshold value in this process. Use the median filter to remove the noise. FCM is then used to segment the picture using weighted membership and spatial constraints. Finally, the image is segmented using a spatially constrained improved Level set technique. The experiment result used 3 clusters as well as 4 clusters. The outcomes can be found to be positive. The MatLab 2014a version was used to create this system.

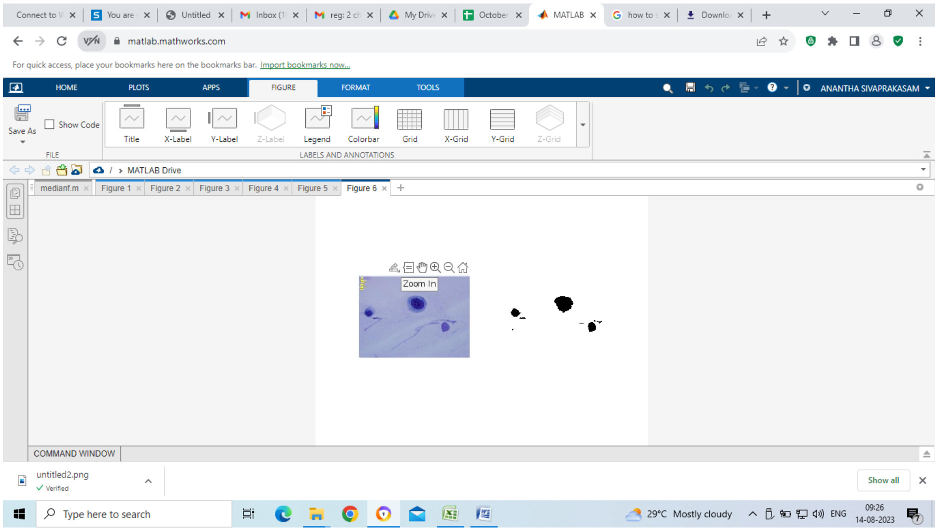
**Output**

The following figures are the output of the median filter

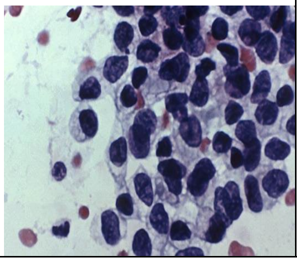
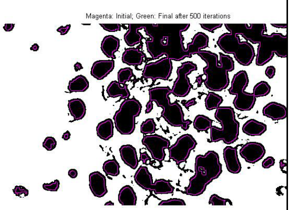
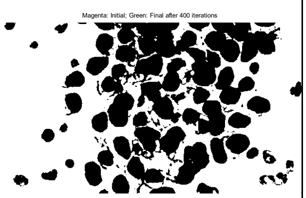


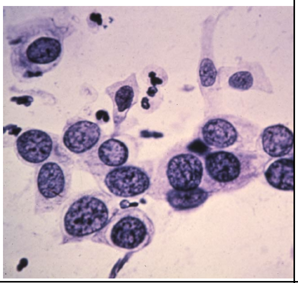
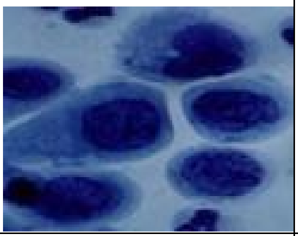
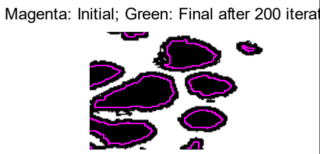
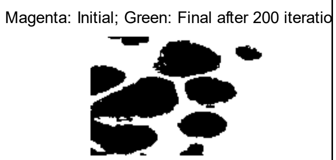
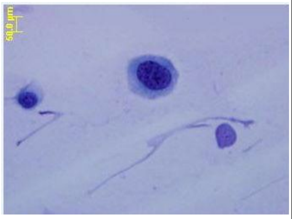
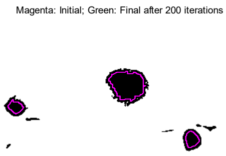
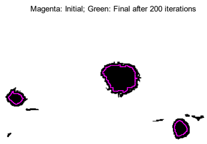
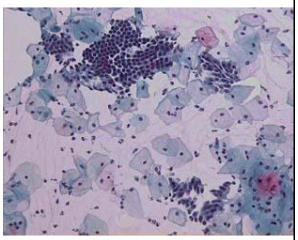
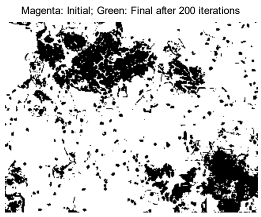
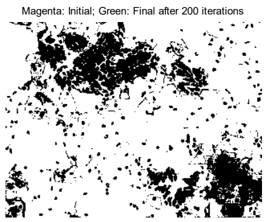
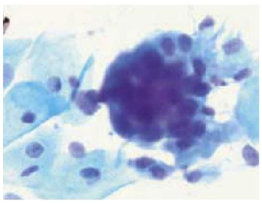
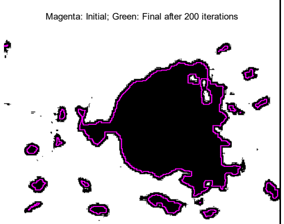
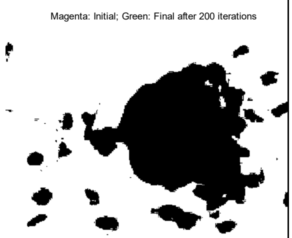







The following are original and segmented image using different clusters

| S .No. | Original Image | Segmented image using 3 cluster | Segmented image using 4 cluster |
|---|---|---|---|
| 1 |  |   |   |

| | | | |
|---|---|---|---|
| 2 |  |  |  |
| 3 |  |  |  |
| 4 |  |  |  |
| 5 |  |  |  |
| 6 |  |  |  |

Cervical cytology images are used in this study for investigations. There were 200 iterations in all. Initial spatial FCM produces the second column image. The final segmentation after 200 iterations with $\mu=0, \lambda=5, \nu = 1.5$ and $\tau=2$. is specified in the last column. In some images, the borders are clearly defined after 200 rounds, but in others, more than 200 iterations are required. This technique may be used to define the limits of any medical image. If iteration is more, ie 500, the robust segmentation result is obtained. But it is a time-consuming process.

This type of initialization is used by the majority of level set algorithms]7,23,24]. In medical imaging, however, the boundaries between physiological tissues are often blurry and fuzzy. Manual initialization is not a reliable option for level set segmentation due to image inhomogeneity and border leakage.

Fuzzy clustering can adaptively acquire the approximate borders of potential components of interest, making it a good place to start when segmenting an image. However, due to noise and abnormalities, the traditional FCM algorithm, which is solely concerned with intensity information, is not robust enough for cervical cytology picture segmentation. The enhanced spatial FCM tries to incorporate all of the intensity and spatial data. This spatial fuzzy clustering approach has been proven to be less vulnerable to various types of noise, making it a good choice for starting level set evolution for cervical image segmentation.

Because the implicit interface stabilizes as it approaches the genuine bounds, the new fuzzy level set technique has greater advantages. Furthermore, the nearly ideal regulating parameters may be automatically estimated from the result of spatial fuzzy clustering. All of them make level set segmentation easier in practices

# 6 Performance Analysis

Tanimoto and Jaccard Index methods are utilized to quantify segmentation performance in this quantitative investigation. The proposed method is compared against traditional segmentation methods in this paper.

## 6.1. Jaccard Index

The Jaccard Index [22], often known as the Jaccard similarity coefficient, is a metric used to compare sample sets' similarity and dissimilarity. The Jaccard coefficient is a measure of how similar two finite sample sets are. It compares the segmentation result to the ground truth in terms of region coincidence. It's calculated by dividing the size of the intersection by the size of the sample sets' union.

$$J(A,B)=\frac{|A\cap B|}{|A\cup B|}=\frac{|A\cap B|}{|A|+|B|-|A\cap B|} \tag{13}$$

J(A,B) = 1, If A and B are empty.

$0 \geq J(A,B) \leq 1$

The numerator |A∩b |measures the number of ground truth objects detected. The dominator |A∪B|| is a normalisation factor that limits the accuracy to [0.1]. The accuracy measure penalises the error for detecting irrelevant regions as foreground segments with this normalisation factor (false positives). This region-based measure is unaffected by minor variations in ground truth construction and combines accuracy and recall measurement into a single function. This metric contains both false positives and false negatives. This measure has no bias in segmentation that results in an excessively large or small number of segments.

## 6.2 **Tanimoto Coefficient**

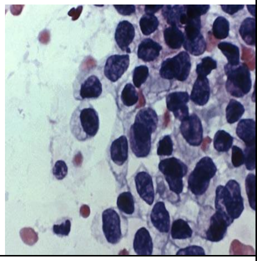
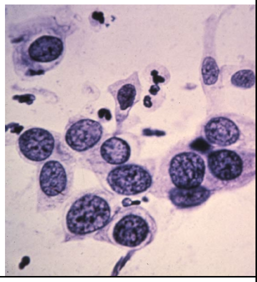
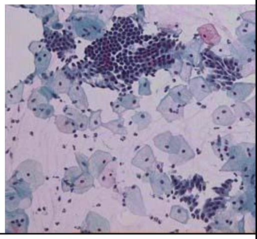
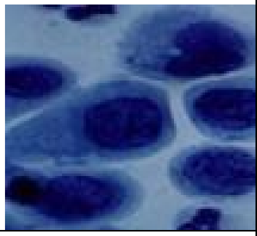
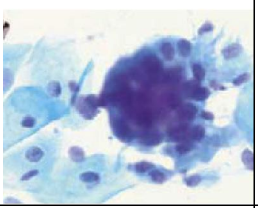
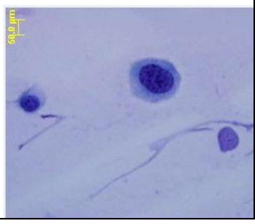
Tanimoto [23] is a similarity ratio calculated over bitmaps, where each bit of a fixed size array denotes the presence or absence of a feature in the image. The Tanimoto's ration is defined as the number of common bits divided by the number of set (i.e. nonzero) bits in both samples. The value range of the tanimoto is 0 to 1.

It's written in a mathematical format. If samples A and B are bitmaps, and Ai is the ith bit of A, $\wedge$ $\vee$ are bitwise and or operations, then Ts is the similarity ratio.

$$T_s\,(A,B)=\frac{\sum_i (A_i \wedge B_i)}{\sum_i A_i \vee B_i)} \tag{14}$$

Both Jaccard and Tanimoto's coefficient are same but it differs in terms of distance function.

The following table describes accuracy of the proposed method and traditional FCM method.

| Techniques | Proposed Method | | FCM |
|---|---|---|---|
| | Image | Accuracy | Accuracy |
| Tanimoto / Jaccard co-efficient value |  | .9525 | .9012 |
| |  | .9314 | .8990 |
| |  | .9314 | .8878 |
| |  | .9232 | .9012 |
| |  | .9525 | .9100 |
| |  | .9532 | .9155 |

# 7 Conclusion

For automated cervical image segmentation, a new fuzzy level set algorithm has been proposed. As the initial level set function, it employs fuzzy clustering. The improved FCM algorithm with spatial information can accurately approximate the boundaries of interest. As a result, level set evolution will begin in a region close to the true boundaries. Furthermore, the new algorithm automatically estimates the controlling parameters from fuzzy clustering. This process reduces the manual intervention. Finally, the level set equation is changed to include variable balloon forces, allowing the level set evolution to be regularized locally using spatial fuzzy clustering. In other works, the level set evolution automatically stabilizes once it approaches the true boundaries, which not only suppresses boundary leakages but also reduces the need for manual intervention. As a whole, accuracy of the proposed method outperformed than the previous method. The accuracy of the proposed method is average of 94%. All of these advancements result in a more robust algorithm for medical image segmentation. Different types of cervical images were used for performance analysis. The outcomes were found to be promising. In future, the overlapping cervical image can be taken and new hybrid algorithm can be developed to improve the accuracy of the segmentation.

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