CHAPTER 5: A FOURTH ORDER PDE BASED FUZZY C-MEANS APPROACH FOR SEGMENTATION OF MICROSCOPIC BIOPSY IMAGES IN PRESENCE OF POISSON NOISE FOR CANCER DETECTION

In this chapter we proposed a fourth order partial differential equation (FPDE) based nonlinear filter adapted to Poisson noise (AFPDE) with fuzzy c-means (FCM) segmentation method. This method is capable of effectively reducing the blocky artifacts while achieving good tradeoff between Poisson noise removals with edge preservation of the microscopic biopsy images. The proposed approach is tested on breast cancer microscopic data set with ROI segmented ground truth images. The microscopic biopsy data set contains 31 benign and 27 malignant images of 896×768. The region of interest (ROI) selected ground truth of all 58 images are also available for this data set Finally, the result obtained from proposed approach is compared with the results of popular segmentation algorithms; fuzzy c-means, color k-means, texture based segmentation, and total variation fuzzy c-means (TVFCM) approaches. The experimental results shows the proposed approach is providing better results in terms of various performance measures such as Jaccard coefficient, dice index, Tanimoto coefficient, area under curve (AUC), accuracy, true positive rate (TPR), true negative rate (TNR), false positive rate (FPR), false negative rate (FNR), random index (RI), global consistency error (GCE), and variance of information (VoE) as compared to other segmentation approaches used for cancer detection.

5.1 Introduction

Cancer is a leading health problem in the most part of the world. Majority of new cases of breast, prostate, lungs, and colorectal cancer are estimated continuously. Segmentation of microscopic biopsy images for cancer detection is typical task due to its complex nature. The cellular components of the microscopic biopsy images are segmented on the basis of intensity, color, shape, and texture features. The microscopic biopsy has several segmentation issues and challenges like high quality segmentation with low computational cost, accurate segmentation cell and nuclei. There is several image segmentation approaches reported in literature for microscopic biopsy images (Cisneros, F. J. *et al*., 2011) but most of the segmentation algorithms have their limitations in terms of segmentation accuracy and computational cost. Color k-means (Luccheseyz, L., & Mitray, S. K. 2001), fuzzy c-means (FCM) (Bunyak, F., Hafiane, A., & Palaniappan, K. 2011) total variation fuzzy c-means (TVFCM) (He, Y. *et al.,* 2012) and texture based segmentation (Jain, A. K., & Farrokhnia, F., 1990) have very rich literature and every approach has its own advantages and disadvantages. When, there no training data set is available in the microscopic biopsy image analysis then features vectors are extracted from local properties. Thresholding approaches are roughly categorised into local global and adaptive thresholding approach. The adaptive thresholding is the most popular approach for creating the binary images (Kumar, R., & Srivastava, R., 2015). The computational complexities of thresholding approaches are low, but its losses the colour information of microscopic biopsy images. Therefore, it does not use alone for the segmentation of microscopic biopsy images. The combination of thresholding with clustering based approaches may be used for the segmentation of microscopic biopsy

images. The watershed algorithm (Jain, A. K., & Farrokhnia, F., 1990, November) is region-based image segmentation approach. It was originally proposed by (Beucher, S.,& Meyer, F., 1992) It is a popular segmentation method coming from the field of mathematical morphology. A visual appearance of original and ground truth microscopic biopsy images is shown in figure 5.1.

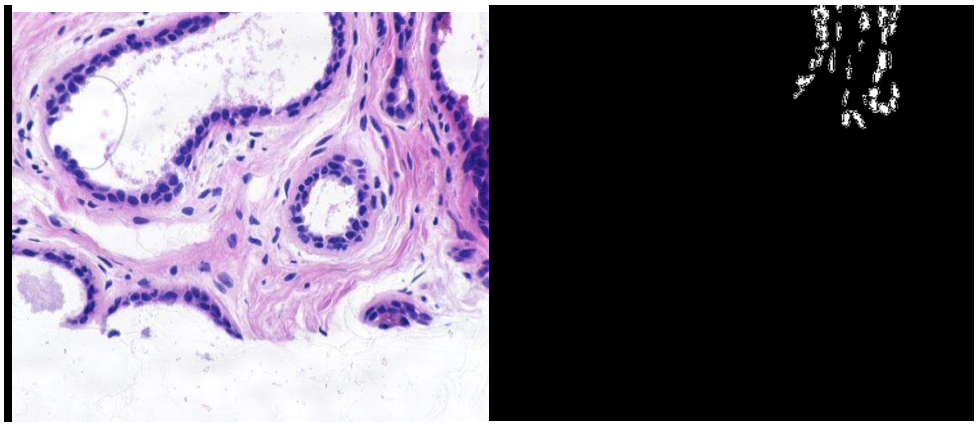

Figure 5.1: Original (left) and ROI segmented ground truth (right) microscopic biopsy image

In this chapter, a fourth order PDE based FCM segmentation model is introduced by improving the basic FCM algorithm. The proposed approach is able to solve the problem of blocky effect and edge preservation with multiplicative noise removal on the stage of segmentation. It incorporate both de-noising and segmentation approach in single package. The experimental results show that proposed approach is simple, efficient and reliable for the segmentation of microscopic biopsy images.

The rest part of this chapter is organized as follows: In the section second, related works of segmentation of microscopic biopsy images are reported. In section third, investigation of the general model for fourth order PDE based FCM segmentation is presented as methods and models. The section four represents, the results and discussions derived from proposed approach, and finally section five provides the conclusion and future works.

5.2 Related works

A thresholding based Fuzzy c-means approach for the cell nuclei segmentation of breast microscopic biopsy images is proposed by (Yasmeen *et al.,* 2013). The specificity and sensitivity obtained by this approach is 83.16% and 95.49 % respectively. A blood vessel segmentation using watershed based approach is presented by (Rodríguez *et al.,* 2005) .The number of blood vessels present in an image is easily identified by this approach. The results obtained by the approach are compared with manual segmentation of blood vessels with 10% false positive and 0 % false negative. Automated cell nuclei segmentation for breast tissues is presented by (Georgeet *et al*., 2013) the circular Hough transform is proposed for the cell, and nuclei segmentation form breast microscopic biopsy. The noisy circles and blood cells are extracted by Otsu's thresholding and the fuzzy c-means approach. The corresponding sensitivity, and specificity obtained is 95.49 %, and 83.16 % respectively. Xu, J. *et al., (*2010) presented a weighted normalized cut active contour model for segmentation of 60 microscopic biopsy of prostate cancer. Total accuracy obtained by weighted normalized cut active contour model is 84%. Sertel, O. *et al,.* (2009) proposed a component wise thresholding approach for segmentation of neroblastic(NB) biopsy imagesThe sensitivity, and false positive rate obtained by this approach are 81.14%, and 12.2% respectively. Demir, C. *et al.,* (2005), presented object graph approach for the segmentation of colon gland microscopic images and average accuracy obtained by this approach is 85 % . Kong, H *et al.,* (2011) presented supervised color-texture segmentation of cell and nuclei of follicular lymphoma and total error rate reprted in this approach is 5.25%. Basavanhally, A. *et al.,* (2011) presented color gradient based active contour model (CGAC) and hieratical normalized cut approach for the

segmentation of cell and nuclei of H&E strain microscopic biopsy of breast tissue. The average reported accuracy in this chapter is 86%. Tosun, A *et al.,* (2011) proposed a graph run length matrix based approach for the segmentation of microscopic biopsy images of breast sample. In this chapter 150 images were taken for testing and experimentation purpose. The average accuracy, specificity, and sensitivity obtained by this approach are 94.7%, 95.2% and 92 % respectively

5.3 Methods and Models

In this chapter, a hybrid approach for segmentation of microscopic biopsy images in presence of Poisson noise is proposed. This section is divided into three sub-sections. Sub-section 5.3.1, presents the analysis of a fuzzy C-means segmentation approach and examines its limitations for its applicability in the proposed application i.e. segmentation of microscopic biopsy images in presence of noise specifically Poisson noise. Sub-section5.3.2 presents the concepts of a proposed model for the restoration and enhancement of microscopic biopsy images in presence of Poisson noise. The proposed model for this task is based on a fourth order PDE based nonlinear filter adapted to Poisson noise and hereafter termed as adaptive Fourth order PDE based filter (AFPDE). Sub-section 5.3.3 presents the proposed model for the segmentation of microscopic biopsy images in the presence of Poisson noise.

5.3.1 Fuzzy c-means Segmentation (FCM)

FCM segmentation approach is developed by, (Trivedi, M. M., & Bezdek, J. C. 1986). It depends upon the strength of association of particular pixel elements for suitable segmentation of microscopic biopsy images. FCM is robust to blurring, easy to implement, and sensitive to the noise but have the limitation that it does

not work properly in presence Poisson noise. FCM only needs the intensity of the image, the spatial context, and boundary conditions of the microscopic biopsy images are not considered in FCM (Srivastava, S. *et al.,* 2014).Mathematically, the fuzzy means is represented as:

$$J(u, c_1, c_2 \ldots c_n) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{m} d_{ij}^{2} \tag{5.1}$$

Where, J is cost function or performance index for membership matrix u , c_i is centroid of the fuzzy cluster i, $d_{ij} = \|c_i - x_j\|$ is the Euclidian distance between ith centroid c_i of the cluster and jth data point, and $m \in (1, \infty)$ is a weighting exponent.

To find the minimum cost function given by equation (5.1), the following conditions given in the equation (5.2) and equation (5.3) must be satisfied:

$$ci = \frac{\sum_{j=1}^{n} u_{ij}^{m} x_j}{\sum_{j=1}^{n} u_{ij}^{m}} \tag{5.2}$$

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}} \right)^{2/(m-1)}} \tag{5.3}$$

Where, u_{ij} is the degree of membership function, c_i is the centroid of fuzzy cluster i , d_{ij} is the Euclidian distance between ith centroid (c_i) of the cluster and jth data point ,and m $\in [(1,\infty)]$ *is a weighting* exponent, u is the membership matrix, $u = \left[u_{ij} \right]$, and the value of u ranges between 0 and 1,($0 < u \leq 1$), and the

summation of degrees of belongingness of a data point to all clusters or partitions is always equal to unity. But, in the case of Poisson noise, FCM is not performing well.

To make the FCM algorithm more robust with respect to noisy data, TVFCM were proposed by (You, Y. L., & Kaveh, M., 2000) The TVFCM algorithms, which are more robust with respect to the noise (He, Y. *et al*., 2012) suggests minimizing instead of the FCM functional the following TV regularization functional

$$J(u, c_1, c_2 \ldots c_n) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} J_i + \sum_{k=1}^{c} TV(u_{ij}) \tag{5.4}$$

$$\sum_{i=1}^{c} (u_{ij}) = 1 \qquad \forall j, = 1 \ldots\ldots n \tag{5.5}$$

The TV functional is separately applied to the different leveling vectors $u_j \in \mathbb{R}^n, \quad j = 1 \ldots . c$, j (He, Y *et al*., 2012) Alternatively a coupled TV functional as suggested in (Lellmann, J. *et al,* 2009) is as follows:

$$\sum_{j=1}^{n} (\left|\nabla u_1(j)\right|^2 + \ldots . + \left|\nabla u_c(j)\right|^2)^{\frac{1}{2}} \tag{5.6}$$

The chapter proposed by (Lellmann, J. *et al.,* 2009) uses coupled TV functional and only takes care of enhancement and restoration of image corrupted with Gaussian noise but in the case of Microscopic biopsy images the dominating noise is Poisson noise. Also the use of TV functional produces blocking artifacts in enhanced leading to inaccurate segmentation results which further affects the accuracy of diagnosis of the disease.

To deal with the above mentioned issues associated with the method presented in (Lellmann, J. *et al.,* 2009) here in this chapter we propose to couple a fourth order partial differential equation (FPDE) based nonlinear filter adapted to Poisson noise (AFPDE) with fuzzy c-means (FCM) segmentation method. This method is capable of effectively reducing the blocky artifacts while achieving good tradeoff between Poisson noise removals with edge preservation of the microscopic biopsy images.

5.3.2 Adaptive fourth order PDE based filter adapted to Poisson noise (AFPDE)

The working details of AFPDE are given as follows:

In microscopic biopsy images, the noisy image g belongs to noisy photon count that follows the Poisson distribution. The statistical model in these systems reads

$$g = Poisson\ (A_j + b) = Poisson\ (z) \tag{5.7}$$

where, $Poisson\ (A_j + b)$ is an independent variable which is random vector with Poisson parameter vector z. The Probability density function (PDF) of data u_0 corrupted by Poisson noise (Srivastava R., *et. al*., 2012) is given as equation (5.8**)**

$$p\left(\frac{j}{g}\right) = \frac{\Pi_{i=1}^{n}\left([A_j]_i + b_i\right)\cdot e^{-\left([A_j]_i + b_i\right)}}{g\,!} \tag{5.8}$$

In general if we substitute $u_0 = g$ and $u \approx (A_j + b)$, where, u_0 is the observed initial image and u is the estimated /restored image then Poisson PDF reads

$$p\left(\frac{u}{u_0}\right) = \left(\frac{e^{-u}.u^{u_0}}{u_0!}\right) \tag{5.9}$$

For the image data u_0 being generated from the model described in equation (5.7) where, PDF is described by equation (5.9). The maximum likelihood estimation of u is obtained by minimizing $p\left(\frac{u}{u_0}\right)$ with respect to u subject to the constraint $u \geq 0$.Alternatively we can calculate the maximum likelihood estimate (Srivastava, S, *et al*, 2012) of u_0 by minimizing the negative log likelihood of Poisson PDF is given by equation (5.10)

$$U_{ML} = \arg\min\left\{-\ln p\left(\frac{u}{u_0}\right)\right\} = \arg\min_{u\geq 0}\{u - u_0 \ln u\} \tag{5.10}$$

The maximum likelihood estimate of u assuming Poisson noise reads .

$$U_{ML} = \frac{u_0 - u}{u} \tag{5.11}$$

If point spread function (PSF) A is ill conditioned, the solution of equation (5.10) given by equation (5.11) can be noise computed and further regularization may be required. For doing so the following optimization problem can be formulated in the Bayesian setting using maximum posterior approach (MAP).

By casting the problem in a variational framework the solution of the best estimate of u is given by Gibbs equation. The Gibbs prior model is bound on energy function which is defined in terms of squared gradient norm of the image related to the fourth order based Partial differential equation (PDE)(Srivastava, S. *et al.* 2012) The Gibbs prior model reads

$$p(u) = \exp(-\lambda \cdot E(u)) \tag{5.12}$$

Where, energy functional is defined by

$$E(u) = \arg \min_{\Omega} \int Lp\left(\frac{u}{u_0}\right) + \lambda \phi\left(\left\|\nabla u\right\|\right) d\Omega \tag{5.13}$$

In the case of fourth order based PDE:

$$\varphi\left(\left\|\nabla u\right\|\right) = \left\|\nabla^2 u\right\|^2 \tag{5.14}$$

Then, the corresponding energy function that defines the prior or second term in proposed framework reads

$$E(u) = \arg \min_{\Omega} \int L\ p\left(\frac{u}{u_0}\right) + \lambda \left(\left\|\nabla^2 u\right\|^2\right) d\Omega \tag{5.15}$$

To minimize the Poisson noise from microscopic biopsy images, the Euler – Lagrange minimization technique combined with gradient decent approach is used to minimize the energy functional given by equation (5.15) and this operation leads to a nonlinear PDE based filter adapted to Poisson noise, which reads (Srivastava, S, *et al*., 2012)

$$\frac{\partial u}{\partial t} = L' p\left(\frac{u}{u_0}\right) + \lambda \nabla^2 \left(c\left\|\nabla^2 u\right\|\right) \nabla^2 u \tag{5.16}$$

$$\frac{\partial u}{\partial t} = \frac{u_0 - u}{\lambda\, u} + \lambda \nabla^2 \left(c\left\|\nabla^2 u\right\|\right) \nabla^2 u \tag{5.17}$$

Where

$$c\left\|\nabla^2 u\right\| = \frac{1}{1 + \left\lceil \left\| \frac{\nabla^2 u}{k} \right\| \right\rceil^2} \tag{5.18}$$

Where k>0 and is a gradient threshold that differentiate homogeneous areas and regions of contour and edges. Therefore for the best result the value of k should be determined positively according to the application in hand, rather than fixing it to a constant value throughout the various iterations of the PDE till its convergence. Hence, to make the proposed scheme over all adaptive in nature, the adaptive value of k is (Srivastava, S. *et al*., 2012)

$$k = \frac{\sqrt{\sigma_n^2}}{\mu} = \frac{stddev(u_{ij})}{mean(u_{ij})} \tag{5.19}$$

5.3.3 Proposed Method for segmentation of microscopic biopsy image in presence of Poisson noise

The proposed method is defined as follows:

Here, we define the restoration and segmentation framework as follows:

$$J(u, c_1, c_2 \ldots c_n) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} J_i + \sum_{k=1}^{c} AFPDE(u_{ij}) = J1 + J2 \tag{5.20}$$

The basic objective is to minimize this cost functional defined by equation (5.20).

Where AFPDE is the adaptive fourth order based PDE (i.e. a fourth order nonlinear PDE based filter adapted to Poisson noise). The first part in the cost function defined in equation (5.20) is given by equation (5.1) and performs FCM based segmentation while the second part acts as smoothing function or prior and is responsible for reduction of Poisson noise and enhancement of microscopic biopsy image.

The first term in equation (5.20) is as follows which is the functional for FCM algorithm as explained in section 5.1.

$$J1 = \arg\min\left[\sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m} d_{ij}^{2}\right] \tag{5.21}$$

Here, FCM algorithms work iteratively through the two conditions as mentioned in section 5.3.1 until there is no more improvement over the segmentation result. The main requirement of this algorithms is number of clusters should be known in advance.

The second term in equation (5.20) is the adaptive FPDE (AFPDE) as explained in section 5.3.2 and is responsible for Poisson noise reduction from segmented image in each iteration obtained by minimizing the cost functional of FCM segmentation method given by equation (5.21). The solution of functional J2 obtained after its minimization as discussed in section 5.3.2 is as follows:

$$\frac{\partial u}{\partial t} = \left(\frac{u_0 - u_{ij}}{\lambda u_{ij}} + \lambda\nabla^2\left(c\left\|\nabla^2 u_{ij}\right\|\right)\nabla^2 u_{ij}\right) \tag{5.22}$$

The overall combined process of segmentation and restoration may be written as follows:

$$\frac{\partial u_{ij}}{\partial t} = \arg\min\left[\sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{m} d_{ij}^{2}\right] + \left(\frac{u_0 - u_{ij}}{\lambda u_{ij}} + \lambda\nabla^2\left(c\left\|\nabla^2 u_{ij}\right\|\right)\nabla^2 u_{ij}\right) \tag{5.23}$$

Using finite difference scheme, the above equation (5.24) may be discretized as:

$$\frac{u_{ij}^{n+1} - u_{ij}^{n}}{\Delta t} = \arg\min\left[\sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{n} d_{ij}^{2}\right] + \left(\frac{u_0 - u_{ij}^{n}}{\lambda u_{ij}^{n}} + \lambda\nabla^2\left(c\left\|\nabla^2 u_{ij}^{n}\right\|\right)\nabla^2 u_{ij}^{n}\right) \tag{5.24}$$

$$u_{ij}^{n+1} = u_{ij}^{n} + \Delta t\left[\arg\min\left[\sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij}^{n} d_{ij}^{2}\right] + \left(\frac{u_0 - u_{ij}^{n}}{\lambda u_{ij}^{n}} + \lambda\nabla^2\left(c\left\|\nabla^2 u_{ij}^{n}\right\|\right)\nabla^2 u_{ij}^{n}\right)\right] \tag{5.25}$$

Where u_0 is the initial input image and u_{ij}^n is the processed image obtained in nth iteration and u_{ij}^{n+1} is the image obtained in current (n+1)th iteration. Δt is the grid constant set to 0.25 for stability reasons and λ is the regularization parameter that makes a balance between Poisson likelihood (data fidelity) term and the fourth order PDE based prior during the restoration process. It was also determined adaptively as discussed in section 5.3.2.

The working of the proposed model is illustrated in Figure 5.2.

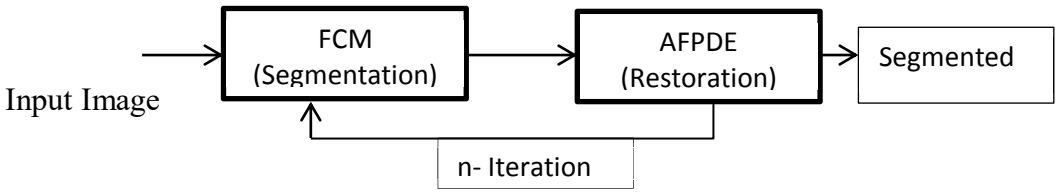

Figure 5.2: An iterative process performs AFPDEFCM for segmentation of microscopic biopsy images

The pseudo code for AFPDEFCM algorithm:

Begin
for n=1 : n iterations
step1: Use FCM segmentation to segment the image and call the equation no. (22).
Step 2: Use AFPDE to remove the noise present, if any during segmentation process and call the equation no (23).
Step 3: Repeat step1 and step2, until SNR does not further increment for segmentation of image.
End

The general proposed mathematical model as described in equation (5.26), for the FCM segmentation of microscopic biopsy images in presence of Poisson will reduce to following model if no Poisson noise is present in the image i.e. only additive Gaussian noise is present:

$$u_{ij}^{n+1} = u_{ij}^{n} + \Delta t \left[\arg\min \left[\sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{n} d_{ij}^{2} \right] + \lambda \nabla^{2} \left(c \left\| \nabla^{2} u_{ij}^{n} \right\| \right) \nabla^{2} u_{ij}^{n} \right] \quad (5.27)$$

5.4 Results and discussions

MATLAB 2013b is used for implementation of the algorithms. PC equipped with Intel Core i7-3770 CPU @ 3.40GHz, with 2GB RAM memory and windows7 operating system is used for experimental purpose. The microscopic biopsy data set contains 31 benign and 27 malignant images of 896×768. The ROI (region of interest) selected ground truth of all 58 images are also available for this data set (http://www.bioimage.ucsb.edu/images/stories/BioImage/research/Benchmark/BREAST_CANCER/BreastCancerCell_dataset.tar.gz). For testing and experiment purpose, the various segmentation algorithms are compared with proposed frame work for cell and nuclei segmentation from microscopic biopsy. The Jacard, Tanimoto and dice similarity coefficients are calculated for measuring of the similarity of the pixels between segmented and ground truth images. The measuring matrices accuracy, true positive rate, true negative rate, false positive rate and false negative rate, and area under curve (AUC) were calculated from true positive, true negative false positive and false negative, and receiver operating characteristic (ROC) curve. The parameters RI, GCE and VI are measuring matrices for check the goodness of segmentation using supervised learning approach where ground truth image (GT) is required.

Table5.1 to Table 5.3 and Figure 5.3 to Figure 5.7 shows the comparisons of popular segmentation approaches with proposed approach (AFPDEFCM) for the segmentation of microscopic biopsy images. The obtained results of proposed approach are compared with, color k-means, fuzzy c-means, TVFCM, and texture based segmentation approaches.

Table 5.1: Comparison of proposed segmentation method with other standard methods in terms of Jaccard Index, Dice Coefficient, and Tanimato Coefficient performance measures

Segmentation Method	**Performance Measures**		
	Jaccard	**Dice**	**Tanimoto**
Color k means	0.494357	0.640071	0.494357
FCM	0.502415	0.660864	0.502415
TVFCM	0.530086	0.684207	0.530086
Texture based	0.195247	0.324119	0.195247
AFPDEFCM	**0.566755**	**0.716681**	**0.566755**

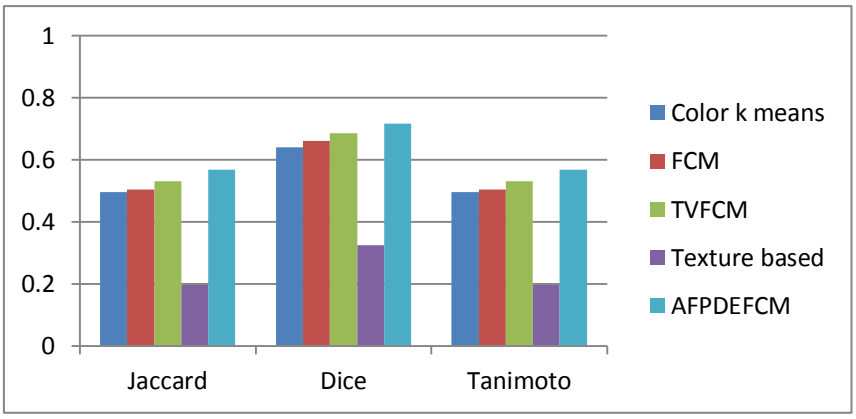

Figure 5.3: Comparison of proposed segmentation method with other standard methods in terms of Jaccard Index, Dice Coefficient, and Tanimato coefficient performance measures

From Table 5.1 and Figure 5.3 following observations are made for segmentation of microscopic biopsy images of breast tissues:

In the case of color k-means approach, the average values of Jaccard Index, Dice coefficient, and Tanimoto coefficient are, 0.494357, 0.640071, and 0.494357 respectively.

In the case of FCM approach, the average values of Jaccard Index, Dice coefficient, and Tanimoto coefficient are 0.502415, 0.660864, and 0.502415 respectively.

In the case of TV FCM approach, the average values of Jaccard Index, Dice coefficient, and Tanimoto coefficient are 0.530086, 0.684207, and 0.530086 respectively.

In the case of Texture based segmentation approach, the average values of Jaccard Index, Dice coefficient, and Tanimoto coefficient are 0.195247, 0.324119 and 0.195247 respectively.

In the case of proposed AFPDEFCM approach, the average values of Jaccard Index, Dice cofficient, and Tanimoto coefficient are 0.566755, 0.716681 and 0.566755 respectively.

Jaccard, Dice and Tanimoto coefficients are used to compare pixel wise similarity and diversity between two images. All these parameters state that the proposed approach is performing better in all aspects.

Table 5.2: Comparison of proposed segmentation method with other standard methods in terms of segmentation accuracy, TPR, FPR and FNR

Segmentation Method	**Accuracy**	**TPR**	**TNR**	**FPR**	**FNR**
Color k means	0.980405	0.778945	0.992789	0.007211	0.221055
FCM	0.983846	0.529358	0.998609	0.001391	0.470642
TVFCM	0.986982	0.704835	0.995515	0.004485	0.295165
Texture based	0.966093	0.245813	0.991565	0.008435	0.754187
AFPDEFCM	**0.99038**	**0.626727**	**0.99763**	**0.00237**	**0.373273**

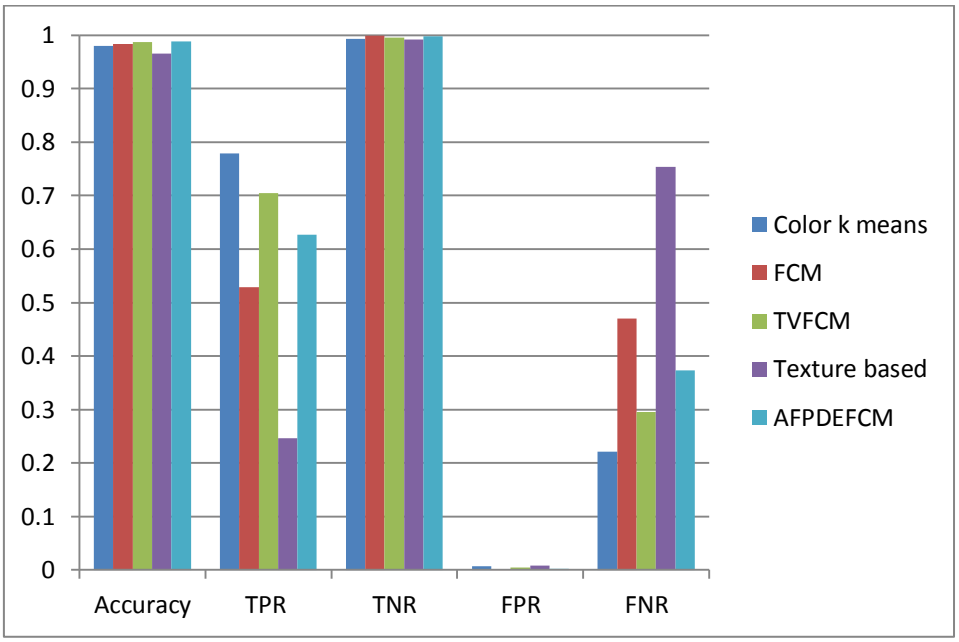

Figure 5.4: Comparison of proposed segmentation method with other standard methods in terms of segmentation accuracy, TPR, FPR and FNR

From Table 5.2 and Figure 5.4 following observations are made for segmentation of microscopic biopsy images of breast tissues:

In the case of color k-means approach, the average values of, accuracy, TPR, TNR, FPR, and FNR are 0.980405, 0.778945, 0.992789, 0.007211 and 0.221055 respectively.

In the case of FCM approach, the average values of accuracy, TPR, TNR, FPR, and FNR are 0.983846, 0.529358, 0.998609, 0.001391 and 0.470642 respectively.

In the case of TV FCM approach, the average values of accuracy, TPR, TNR, FPR, and FNR are 0.986982, 0.704835, 0.995515, 0.004485 and 0.295165 respectively

In the case of texture based segmentation approach, the average values of accuracy, TPR, TNR, FPR, and FNR are 0.966093, 0.245813, 0.991565, 0.008435 and 0.754187 respectively

In the case of proposed AFPDEFCM approach, the average values of accuracy, TPR, TNR, FPR, and FNR, are 0.98838, 0.626727, 0.99763, 0.00237 and 0.373273 respectively.

Parameters used to compare the segmentation algorithm based on true positive, false positive, true negative and false negative values calculated from segmented and ground truth microscopic biopsy images. From Table 5.3 it is observed that, the proposed approach is performing better in terms of accuracy, true positive rate, and true negative rate as compared to other segmentation approaches. The area under curve obtained by proposed AFPDEFCM segmentation approach is 92.87.

Table 5.3: Comparison of proposed segmentation method with other standard methods in terms of Random Index, GCE, and VoI performance measures

Segmentation Methods	**RI**	**GCE**	**VoI**
Color k means	0.971035	0.011173	0.104696
FCM	0.968331	0.016659	0.156123
TVFCM	0.978703	0.01377	0.118074
Texture based	0.934675	0.028149	0.278278
AFPDEFCM	**0.9771**	**0.01493**	**0.12623**

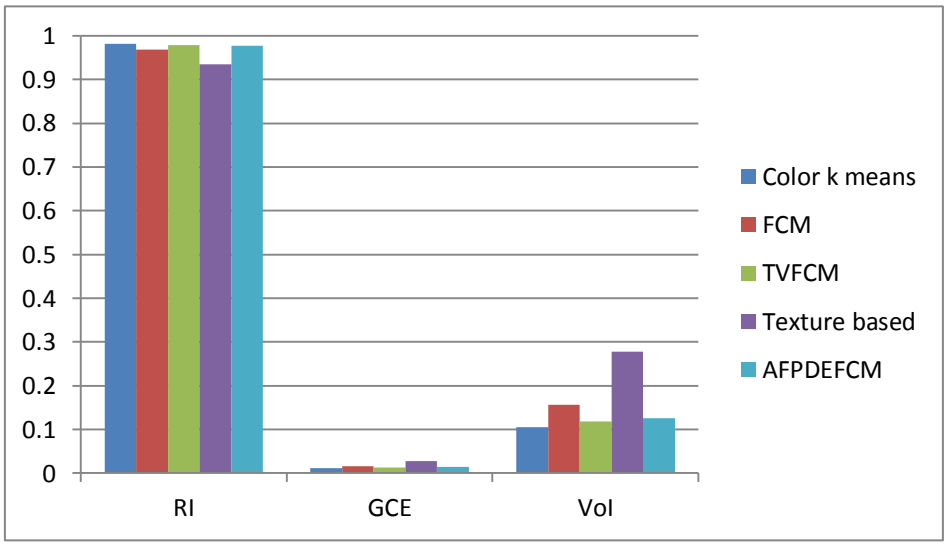

Figure 5.5: Comparison of proposed segmentation method with other standard methods in terms of Random Index, GCE, and VoI performance measures

From Table 5.3 and Figure 5.5 following observations are made for segmentation of microscopic biopsy images of breast tissues:

In the case of color k-means approach, the average values of are RI, GCE and VoI are 0.981035, 0.011173 and 0.104696 respectively.

In the case of FCM approach, the average values of RI, GCE and VoI 0.968331, 0.016659, and 0.156123 respectively.

In the case of TVFCM approach, the average values of RI, GCE and VoI are 0.978703, 0.01377 and 0.118074 respectively.

In the case of texture based segmentation approach, the average values of, RI, GCE and VoI are 0.934675, 0.028149 and 0.278278 respectively.

In the case of proposed AFPDEFCM approach, the average values, RI, GCE and VoI are 0.977102, 0.014934 and 0.12623 respectively.

From Table 5.3 Proposed approach is providing higher value of RI and lower values of GCE and VoI.

Thus From Figure 5.3, 5.4, and 5.5, it has been observed that, the proposed AFPDEFCM approach for segmentation of microscopic biopsy images performing better in terms of all measuring parameters of images segmentations.

5.5 Conclusion

In this chapter we propose to couple a fourth order partial differential equation (FPDE) based nonlinear filter adapted to Poisson noise (AFPDE) with fuzzy c-means (FCM) segmentation method. This method is capable of effectively reducing the blocky artifacts while achieving good tradeoff between Poisson noise removals with edge preservation of the microscopic biopsy images. The proposed approach is based on tissues level microscopic observations of cell and nuclei for breast biopsy images of benign and malignant tissue. For testing and experimentation purpose, 31 benign and 27 malignant images of 896×768 were taken from breast tissue dataset (http://www.bioimage.ucsb.edu/images). Finally, the ROI segmented image of microscopic biopsy was compared to ground truth images. The quantitative and qualitative evaluation of various segmentation approaches for all 58 sample images were performed. From Table 5.1-5.3, and Figure5.4-5.6, it was observed that the proposed AFPDEFCM approach is associated with larger value of accuracy, sensitivity, specificity, random index (RI), and smaller value of FPR, FNR, GCE, and VOI in comparison to other methods. The performance measured for microscopic biopsy of breast tissues dataset in terms of the Jaccard, dice, Tanimoto, accuracy, TPR, TNR, FPR, FNR, RI, GCE and VI are 0.566755, 0.716681, 0.566755, 0.98838, 0.626727, 0.99763, 0.00237, 0.373273, 0.977102, 0.014934 and 0.12623 respectively. Hence, we are

in position to conclude that, the proposed AFPDEFCM approach is performing better in terms of all parameters and it is suitable for the segmentation of microscopic biopsy images for cancer detection.

\