SPATIAL FUZZY C-MEAN SOBEL ALGORITHM WITH GREY WOLF OPTIMIZER FOR MRI BRAIN IMAGE SEGMENTATION

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Dedicated to my beloved family especially my parents, my wife, and my supportive supervisors –Prof. Dr. Habibollah Bin Haron and Associate Prof. Dr. Subariah Ibrahim. Thank you very much for being supportive, helpful and understanding.

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ABSTRACT

Segmentation is the process of dividing the original image into multiple sub regions called segments in such a way that there is no intersection between any two regions. In medical images, the segmentation is hard to obtain due to the intensity similarity among various regions and the presence of noise in medical images. One of the most popular segmentation algorithms is Spatial Fuzzy C-means (SFCM). Although this algorithm has a good performance in medical images, it suffers from two issues. The first problem is lack of a proper strategy for point initialization step, which must be performed either randomly or manually by human. The second problem of SFCM is having inaccurate segmented edges. The goal of this research is to propose a robust medical image segmentation algorithm that overcomes these weaknesses of SFCM for segmenting magnetic resonance imaging (MRI) brain images with less human intervention. First, in order to find the optimum initial points, a histogram based algorithm in conjunction with Grey Wolf Optimizer (H-GWO) is proposed. The proposed H-GWO algorithm finds the approximate initial point values by the proposed histogram based method and then by taking advantage of GWO, which is a soft computing method, the optimum initial values are found. Second, in order to enhance SFCM segmentation process and achieve higher accurate segmented edges, an edge detection algorithm called Sobel was utilized. Therefore, the proposed hybrid SFCM-Sobel algorithm first finds the edges of the original image by Sobel edge detector algorithm and finally extends the edges of SFCM segmented images to the edges that are detected by Sobel. In order to have a robust segmentation algorithm with less human intervention, the H-GWO and SFCM-Sobel segmentation algorithms are integrated to have a semi-automatic robust segmentation algorithm. The results of the proposed H-GWO algorithms show that optimum initial points are achieved and the segmented images of the SFCM-Sobel algorithm have more accurate edges as compared to recent algorithms. Overall, quantitative analysis indicates that better segmentation accuracy is obtained. Therefore, this algorithm can be utilized to capture more accurate segmented in images in the era of medical imaging.

ABSTRAK

Segmentasi adalah proses pembahagian imej asal kepada pelbagai sub kawasan yang dipanggil segmen agar tidak terdapat pertembungan antara dua kawasan. Dalam imej perubatan, segmentasi sukar untuk diperoleh kerana persamaan keamatan antara pelbagai kawasan dan kehadiran hingar dalam imej perubatan. Salah satu algoritma segmentasi yang paling popular adalah Min-C Kabur Ruang (SFCM). Walaupun algoritma tersebut mempunyai prestasi yang baik dalam imej perubatan namun menghadapi dua isu. Masalah pertama adalah kurangnya strategi yang tepat bagi langkah pengawalan titik yang perlu dijalankan sama ada secara rawak ataupun secara manual oleh manusia. Masalah kedua SFCM adalah terdapatnya sudut bersegmen yang tidak tepat. Matlamat kajian ini adalah untuk mencadangkan algoritma segmentasi imej perubatan yang teguh yang mengatasi kelemahan SFCM tersebut untuk pembahagian imej pengimejan resonans magnet (MRI) otak dengan kurang campur tangan manusia. Pertama, untuk mencari titik permulaan yang optimum, algoritma berdasarkan histogram bersamaan dengan Pengoptimum Musang Kelabu (H-GWO) dicadangkan. Algoritma H-GWO yang dicadangkan akan mencari anggaran nilai titik permulaan menggunakan kaedah berdasarkan histogram yang dicadangkan dan kemudian mengambil manfaat daripada GWO yang merupakan kaedah pengiraan lembut, nilai awal optimum yang ditemukan. Kedua, dalam usaha untuk meningkatkan proses segmentasi SFCM dan mencapai ketepatan paling tinggi bagi sudut bersegmen, algoritma pengesanan sudut yang dinamakan Sobel telah digunakan. Oleh itu, algoritma hibrid SFCM-Sobel yang dicadangkan tersebut pertamanya, mendapatkan pinggir bagi imej asal menggunakan algoritma pengesanan pinggir Sobel dan akhirnya memanjangkan sudut bagi imej bersegmen SFCM kepada pinggir yang dikesan oleh Sobel. Dalam usaha untuk mencapai algoritma segmentasi teguh dengan kurang campur tangan manusia, algoritma segmentasi H-GWO dan SFCM-Sobel disepadukan untuk mendapatkan algoritma segmentasi separa automatik yang teguh. Keputusan algoritma H-GWO yang dicadangkan menunjukkan titik permulaan yang optimum dapat dicapai dan juga imej bersegmen bagi algoritma SFCM-Sobel mempunyai pinggir yang lebih tepat berbanding algoritma semasa. Secara keseluruhan, analisis kuantitatif menunjukkan bahawa segmentasi ketepatan yang lebih baik telah diperolehi. Oleh itu, algoritma tersebut boleh digunakan untuk memberikan gambaran pembahagian yang lebih tepat bagi imej dalam era pengimejan perubatan.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ACO	-	Ant Colony Optimization
ANN	-	Artificial Neural Network
BCFCM	-	Bias-Corrected Fuzzy c-Mean
CFM	-	Charged Fluid Model
CLAHE	-	Contrast Limited Adaptive Histogram Equalization
CSF	-	Cerebrospinal Fluid
CT	-	Computed Topography
DC	-	Dice Coefficient
EnFCM	-	Enhanced FCM
FCM	-	Fuzzy c-Mean
FGFCM	-	Fast Generalized Fuzzy c-Means
FLICM	-	Fuzzy Local Information c-Means
FN	-	False Negative
FP	-	False Positive
FPSO	-	Fuzzy Particle Swarm Optimization
GA	-	Genetic Algorithm
GM	-	Gray Matter
GMAC	-	Global Minimization by Active Contour
GVF	-	Gradient Vector Flow Snake
GWO	-	Grey Wolf Optimizer
H-GWO	-	Histogram Based Gray Wolf Optimizer
IBSR	-	Internet Brain Segmentation Repository
IFCM	-	Intuitionistic Fuzzy c-Means
IIFCM	-	Improved Intuitionistic Fuzzy c-Means
ImFCM	-	Improved Fuzzy C-Means
INU	-	Intensity None Uniformity
JS	-	Jaccard Similarity

LoG	-	Laplacian of Gaussian
LSM	-	Level Set Algorithm
MOO	-	Multi-Objective Optimization
MR	-	Magnetic Resonance
MRF	-	Markov Random Field
MSLSM	-	Multi-Resolution Stochastic Level Set Method
PCM	-	Possibilistic c-Means Clustering
PSO	-	Particle Swarm Optimization
RFCM	-	Robust Fuzzy c-Mean Algorithm
ROI	-	Region of Interest
SA	-	Simulated Annealing
SFCM	-	Spatial Fuzzy C-means
SOM	-	Self-Organizing Maps
SPF	-	Signed Pressure Fore
TP	-	True Positive
TS	-	Tabu Search
WM	-	White Matter

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Overview

The use of Magnetic Resonance (MR) and Computed Topography (CT) images has increased widely for treatment planning, medical analysis and clinical studies. MR images with high level of accuracy show three dimensional information of human soft tissues and unlike X-ray images, no radiation is needed to scan an MR image. Therefore, MR images have become more popular among other formats like CT and X-ray.

The use of computers is almost necessary to help radiological experts to diagnose patients by analyzing MR images. Most of these computer applications use segmentation algorithms to divide image volume into tissue types. In image processing a process in which the boundaries are located to distinguish different regions in an image is called image segmentation. This process is applicable in different applications such as geographical and medical imaging, robot vision and object recognition. (Bezdek *et al.*, 1993, Wells *et al.*, 1996, Xu *et al.*, 2000).

In general, segmentation is the process that divides an image based on its properties such as the grayscale level or color to similar regions (Gonzalez and Woods, 2004, Pal and Pal, 1993). Segmentation algorithms can be categorized into three groups namely boundary-based, region-based and hybrid (Ciesielski and Udupa, 2010). In boundary-based methods, regions are classified by identifying the edges among regions. Snakes (Kass *et al.*, 1987) which is one of the known boundary-based methods, draws contour lines around different regions by minimizing a cost function. The second group which is region based algorithms detects different regions based on the level of homogeneity of the regions. The simplest and fastest algorithm in this group is intensity thresholding. A threshold value simply can categorize the original image into two groups namely background and foreground. Otsu's method (1979) is an intensity thresholding algorithm which finds threshold value automatically by analyzing the histogram of the image. In case that there exist more than two regions in the original image then more than one threshold is used for the segmentation process and this method is called multilevel thresholding. Hybrid algorithms which are the third group combine two or more segmentation algorithms in order to overcome the shortcomings of other algorithms.

A region based segmentation algorithm called Fuzzy c-Mean (FCM) which was first proposed by Bezdek (1981) is used as the basis of the medical image segmentation algorithm in this research. This method is the most powerful and the best known fuzzy segmentation algorithm (Cai *et al.*, 2007, Shen *et al.*, 2005, Siyal and Yu, 2005). FCM is an enhancement of hard K-means algorithm. In hard K-means, each pixel of the image is assigned to only one region while in FCM, pixels of the image are assigned to different regions according to a degree of membership.

In this research the advantages and disadvantages of using FCM in terms of point initialization and segmentation accuracy are fully analyzed by implementing the algorithm in MATLAB. The method proposed in this thesis is trying to overcome the shortcomings of FCM algorithm and to achieve accurate results in a shorter time.

1.2 Background of the Problem

The use of image segmentation has increased in medical image analysis. It is difficult to achieve medical image segmentation because of complexity of the tissue/organ, significant amount of noise and weak boundary in image that is caused by equipment and operator. Boundary leakage is another common problem which occurs when the boundary among tissues is blur, therefore image segmentation algorithm considers both tissues as one region mistakenly (Li *et al.*, 2011a).

Recently several image segmentation algorithms are investigated to achieve more accurate algorithms. Discontinuity and similarity approaches are widely used to run the majority of segmentation algorithms (Richard and Rafael, 2008). Based on the abrupt changes in the image, the discontinuity approach locates the partitions. In order to detect abrupt changes, intensity value of edges must be evaluated. On the other hand, by evaluating the level of similarity for each region in the original image, it is possible to locate partitions in the second approach. Since brain tissue has complex intensity distributions and the boundary between different regions are not sharp, choosing a proper segmentation algorithm is challenging. According to Verma *et al.* (2016), clustering based algorithms are considered as the most efficient algorithms for MRI brain segmentation. FCM as a clustering based segmentation algorithm has some problematic issues (Cai *et al.*, 2007). The main problem of this method is that noisy images highly reduce the quality of segmentation because in standard FCM, spatial context between pixels are not considered because the clustering is running based on the characteristics of the image pixels itself only (Wang *et al.*, 2008). In order to overcome this problem and to achieve better segmentation of images, various FCM extension algorithms are proposed by many researchers (Cai *et al.*, 2007, Chuang *et al.*, 2006, Ma and Staunton, 2007, Siyal and Yu, 2005, Wang *et al.*, 2008).

Modifying the objective function is mostly utilized to increase the robustness of FCM against noise. For this purpose, Pham (2001) proposed a robust Fuzzy c-Mean algorithm (RFCM). By setting a parameter to control the trade-off between sharpness and smoothness of the image, Pham incorporated the smooth membership function. A similar approach called Bias-Corrected Fuzzy c-Mean (BCFCM) was presented by Ahmed *et al.* (2002). By modifying the objective function, he introduced a term allowing the labeling of the pixel to be influenced from the labels in its immediate neighborhood. Moreover, in order to control the effect of the neighbor term a parameter was set. The FCM method was simplified by Zhang and Chen (2004). They replaced the original Euclidean distance function with kernel induced distance metric. Shen *et al*. (2005) proposed improved fuzzy c-means clustering. In this method, the features of the neighborhood pixels were used by using a degree of attraction and this value was optimized by a neural network. These methods had modified the FCM by adding more equations to the objective function which leads to computation and time complexity issues and losing the FCM continuity (Shen *et al.*, 2005).

Spatial FCM (SFCM) was proposed by Chuang *et al*. (Chuang *et al.*, 2006). This algorithm could resolve FCM noise issue by making modification to FCM objective function and considering the intensity values of neighborhood pixels. However good segmentation may not be achieved due to presence of noise in neighborhood pixels. Fast generalized Fuzzy c-means (FGFCM) was proposed by Cai (Cai *et al*., 2007). In this algorithm, a new image was constructed by utilizing a similarity measure which combines gray-level and spatial local information. In these methods, at least one parameter exists to control the tradeoff between the original image feature and spatial constraint (β in (Pham, 2001), α in (Ahmed *et al*., 2002, Zhang and Chen, 2004)) while selection of these parameters are hard and were done by trial and error (Wang *et al*., 2008). A fuzzy local information c-means (FLICM) was proposed by Krinidis and Chatzis (Krinidis and Chatzis, 2010) to solve the problem of parameter setting in FCM based algorithms. This algorithm also takes advantage of gray-level and spatial local information.

In order to accelerate the image segmentation, enhanced FCM (EnFCM) was proposed by Szilagyi (SziláGyi *et al*., 2012). In this algorithm, first a linearly weighted sum image is pre-calculated and finally FCM algorithm is performed to histogram of the new image. Intuitionistic fuzzy c-means (IFCM) algorithm, one of the variants of FCM which incorporates the advantage of intuitionistic fuzzy sets theory, was found suitable for image segmentation (Jiang *et al.*, 2013). It could handle the uncertainty but since it did not incorporate any local spatial information it was sensitive to noise. Verma (Verma *et al.*, 2016) presented an algorithm called an improved intuitionistic fuzzy c-means (IIFCM). This algorithm considers the local spatial information in an intuitionistic fuzzy way.

In spite of the amount of recent works to modify the FCM, there are still some drawbacks in the algorithms such as lacking of a proper strategy for the initial point placement and the sensitivity to noise (Benaichouche *et al*., 2013). For more clarification both issues are discussed in the following subsections.

1.2.1 Initial Point Optimization

Regardless of FCM noise issue which is enhanced by SFCM technique, in FCM based approaches, the number of regions as well as the initial points location values must be determined in advance (Kao *et al.*, 2014). Initial point values can be randomly determined and standard SFCM algorithm fails to have a proper strategy for this case (Benaichouche *et al.*, 2013). Because the accuracy of the segmentation process is highly depended on the point initial values therefore, random selection of these points cannot guarantee reasonable accuracy. As such the optimum values for these points are required.

In order to overcome the initialization issue of FCM, recently a hybrid algorithm of particle swarm optimization (PSO) which is a technique of population based clustering with FCM namely (PSO+FCM) was proposed by researchers (Benaichouche *et al.*, 2013, Krishnapuram and Keller, 1993b, Liu *et al.*, 2008, Samadzadegan and Naeini, 2011, Wang *et al.*, 2007, Zhang *et al.*, 2011). For enhancing the spectral characteristics of features for clustering, Liu Hanli *et al* (Liu *et al.*, 2008) used the PSO-FCM on the image data to enhance the accuracy of wetland extraction. Farhad *et al* (Samadzadegan and Naeini, 2011) used PSO-FCM with four iterations to the particles in the swarm for every eight generations such that the fitness value of each particle was improved. The result of using PSO-FCM on hyperspectral data, in two spaces data and feature showed its higher ability in segmentation than fuzzy clustering (Samadzadegan and Naeini, 2011). PSO also was used by Zhang *et al.* (Zhang *et al.*, 2011) as an initialization step in possibilistic c-means clustering (PCM) (Krishnapuram and Keller, 1993b) to find the best possible position of cluster centers. Wang *et.al* (Wang *et al.*, 2007) proposed a hybrid fuzzy clustering algorithm named QPSO+FCM which FCM was incorporated into quantum-behaved PSO. The QPSO has less parameters and higher convergent capability of the global optimizing than PSO algorithm. Therefore, the iteration algorithm was replaced by the QPSO based on the gradient descent of FCM, that makes the algorithm to have a strong global searching capacity and avoids the local minimum problems of FCM and in a large degree avoid depending on the initialization values.

Although it is possible to find the optimum initial position values by PSO and QPSO but the resulted values are not always optimized because both of them are trapped into local optimal solution and fail to find the global best value (Liu *et al.*, 2005, Noel and Jannett, 2004). Further using soft computing technique to find the optimum initial points takes a long time to achieve the desired results and in some cases the algorithm must be repeated multiple times to get the optimized results.

1.2.2 Blur Boundaries Issue

Since the incorporation of spatial constraints into the classification, blurs some details; therefore, high contrast pixels that usually represent boundaries between the objects should not be included in the neighborhood (Gondal and Khan, 2013). Also according to Chuang (Chuang *et al.*, 2006), SFCM algorithm with a higher spatial weighting parameter shows a better smoothing effect. However, the possible disadvantage of SFCM is the blurring of some of the finer details.

1.3 Problem Statement

There are two main drawbacks in SFCM segmentation algorithm. The first problem is that there is the lack of a proper strategy for the point initialization step and point initialization must be performed manually or randomly in the SFCM algorithm. Although algorithms such as QPSO or PSO based are proposed to overcome this issue however using of these algorithms are not suitable because they can fall into local optimal solution and also performing such algorithms are a time intensive tasks. The second problem of SFCM is causing of blur boundaries in the segmented images. This issue is mainly caused by spatial weighting parameter used in SFCM algorithm.

1.4 Objective of the Thesis

According to problems stated in the previous section, the main objectives of this thesis are as follows:

i. To evaluate and compare the performance of FCM, SFCM and K-means in segmentation of medical brain images.

ii. To propose enhanced SFCM segmentation algorithm based on edge-detected image using edge detection Sobel operator that is called SFCM-Sobel Segmentation Algorithm.

iii. To propose histogram-based GWO algorithm to determine the optimum values for initial points.

1.5 Scope of the Thesis

In this study, the scope of the proposed algorithm is mainly based on the following items:

i. The desired format of the medical image datasets is Analyze and minc for IBSR and BrainWeb datasets respectively.

ii. The proposed method uses the basic concept of FCM method.

iii. The performance of the proposed algorithm is evaluated based on quantitative measures including Dice Coefficient, Jaccard Index, Sensitivity and Precision.

iv. The visual language used for coding is MATLAB.

1.6 Significance of the Thesis

The significant of this thesis can be divided into two fields including segmentation algorithm and medical. The significant of the thesis in terms of segmentation algorithm is that the proposed algorithm can determine the optimized initial point values for segmentation process of the medical image automatically. Moreover, the blurred area around the edges is further enhanced. Therefore, the quality of the final segmentation result is getting improved. In this thesis, the large number of cases are processed in a short time having the almost same accuracy. The segmentation process utilizing the method presented in this thesis becomes easier with less human intervention. The significant of the project in terms of medical field is that treatment planning by medical expert will be easier because the brain relate diseases such as Alzheimer can be found out by measuring brain White Matter (WM) region using segmentation algorithm.

1.7 Organization of the Thesis

This thesis consists of six chapters. In Chapter 1, introduction, problem background, problem statement, objectives, scopes and significant of the thesis are presented. In Chapter 2, a background about image segmentation, segmentation algorithm techniques, soft computing algorithms including PSO and GWO and finally edge detection algorithms are presented and compared. In Chapter 3, a research methodology related to development of the method to design an enhanced SFCM based medical image segmentation is presented. The research framework of the project is also presented in this chapter.

In Chapter 4, besides the evaluating of K-means, FCM and SFCM segmentation algorithms, the framework of proposed enhanced SFCM segmentation algorithm that is based on Sobel edge detection is presented. The goal of this framework is to achieve higher accuracy around the edges of the SFCM segmented image. This framework consists of three main phases namely SFCM segmentation, Sobel edge detection and SFCM-Sobel segmentation. Finally, the results of proposed

SFCM-Sobel based algorithm is compared with conventional segmentation algorithms.

In Chapter 5, the analysis of initial point selection of SFCM and its impact on the segmentation result are presented. The hybrid histogram based GWO algorithm is also presented. The result of the proposed algorithm is demonstrated and compared with SFCM-Sobel with manual initialization.

In Chapter 6, the conclusion and summary of the research work is illustrated. The summary of the research including objectives, methodology and results are presented. Finally, the future work and possible limitations of the current research is also provided.

REFERENCES

Aboutanos, G. B. and Dawant, B. M. (1997). Automatic brain segmentation and validation: image-based versus atlas-based deformable models. *Medical Imaging*, 299-310.

Ahmed, M. N., Yamany, S. M., Mohamed, N., Farag, A. A. and Moriarty, T. (2002). A modified fuzzy C-means algorithm for bias field estimation and segmentation of MRI data. *IEEE Transactions on Medical Imaging,* 21**,** 193-199.

Al-Sultan, K. S. and Fedjki, C. A. (1997). A tabu search-based algorithm for the fuzzy clustering problem. *Pattern Recognition,* 30**,** 2023-2030.

Al-Tamimi, M. S. H. and Sulong, G. (2014). A review of snake models in medical MR image segmentation. *Jurnal Teknologi,* 69**,** 101-106.

Anbeek, P., Vincken, K. L., van Osch, M. J. P., Bisschops, R. H. C. and van der Grond, J. (2004). Probabilistic segmentation of white matter lesions in MR imaging. *Neuroimage,* 21**,** 1037-1044.

Antonie, M. L., Zaiane, O. R. and Coman, A. (2001). Application of data mining techniques for medical image classification. *Multimedia Data Mining*, 94-101.

Baker, K. R., Xu, L., Zhang, Y., Nevitt, M., Niu, J., Aliabadi, P., Yu, W. and Felson, D. (2004). Quadriceps weakness and its relationship to tibiofemoral and patellofemoral knee osteoarthritis in Chinese: The Beijing osteoarthritis study. *Arthritis & Rheumatism,* 50**,** 1815-1821.

Bell, Z. W. (1989). A Bayesian/Monte Carlo segmentation method for images dominated by Gaussian noise. *IEEE Transactions on Pattern Analysis and Machine Intelligence,* 11**,** 985-990.

Bello, M. G. (1994). A Combined Markov Random-Field and Wave-Packet Transform-Based Approach for Image Segmentation. *IEEE Transactions on Image Processing,* 3**,** 834-846.

Benaichouche, A., Oulhadj, H. and Siarry, P. (2013). Improved spatial fuzzy c-means clustering for image segmentation using PSO initialization, Mahalanobis distance and post-segmentation correction. *Digital Signal Processing,* 23**,** 1390-1400.

Beolchi, L. and Kuhn, M. H. (1995). *Medical Imaging - Analysis of Multimodality 2D/3D Images.* IOS Press.

Bezdek, J. (1981). *Pattern recognition with fuzzy objective function algorithm.* New York: Plenum Press.

Bezdek, J. C., Ehrlich, R. and Full, W. (1984). FCM: The fuzzy c-means clustering algorithm. *Computers & Geosciences,* 10**,** 191-203.

Bezdek, J. C., Hall, L. O. and Clarke, L. P. (1993). Review of Mr Image Segmentation Techniques Using Pattern-Recognition. *Medical Physics,* 20**,** 1033-1048.

Bong, C. and Rajeswari, M. (2012). Multiobjective clustering with metaheuristic: current trends and methods in image segmentation. *IET image processing,* 6**,** 1-10.

Bouman, C. A. and Shapiro, M. (1994). A Multiscale Random-Field Model for Bayesian Image Segmentation. *IEEE Transactions on Image Processing,* 3**,** 162-177.

Cai, W. L., Chen, S. C. and Zhang, D. Q. (2007). Fast and robust fuzzy c-means clustering algorithms incorporating local information for image segmentation. *Pattern Recognition,* 40**,** 825-838.

Canny, J. (1986). A computational approach to edge detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence***,** 679-698.

Caselles, V., Catté, F., Coll, T. and Dibos, F. (1993). A geometric model for active contours in image processing. *Numerische mathematik,* 66**,** 1-31.

Caselles, V., Kimmel, R. and Sapiro, G. (1997). Minimal surfaces based object segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence,* 19**,** 394-398.

Chan, T. F. and Vese, L. A. (2001). Active contours without edges. *IEEE Transactions on image processing,* 10**,** 266-277.

Chang, H.-H. and Valentino, D. J. (2006). Image segmentation using a charged fluid method. *Journal of Electronic Imaging,* 15**,** 1-16.

Chang, H.-H. and Valentino, D. J. (2008). An electrostatic deformable model for medical image segmentation. *Computerized Medical Imaging and Graphics,* 32**,** 22-35.

Chou, P. B. and Brown, C. M. (1990). The Theory and Practice of Bayesian Image Labeling. *International Journal of Computer Vision,* 4**,** 185-210.

Chuang, K. S., Tzeng, H. L., Chen, S., Wu, J. and Chen, T. J. (2006). Fuzzy c-means clustering with spatial information for image segmentation. *Computerized Medical Imaging and Graphics,* 30**,** 9-15.

Chunming, L., Chenyang, X., Changfeng, G. and Fox, M. D. (2005). Level set evolution without re-initialization: a new variational formulation. *IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2005. CVPR 2005,* 1**,** 430-436.

Ciesielski, K. C. and Udupa, J. K. (2010). Affinity functions in fuzzy connectedness based image segmentation I: Equivalence of affinities. *Computer Vision and Image Understanding,* 114**,** 146-154.

Cobzas, D., Birkbeck, N., Schmidt, M., Jagersand, M. and Murtha, A. (2007). 3D variational brain tumor segmentation using a high dimensional feature set. *11th International Conference on Computer Vision***,** 1-8.

Coleman, G. B. and Andrews, H. C. (1979). Image segmentation by clustering. *Proceedings of the IEEE,* 67**,** 773-785.

Das, S., Abraham, A. and Konar, A. (2009). *Metaheuristic clustering.* Springer.

Davatzikos, C. A. and Prince, J. L. (1995). An Active Contour Model for Mapping the Cortex. *IEEE Transactions on Medical Imaging,* 14**,** 65-80.

de Ridder, D., Duin, R. P. W., Verbeek, P. W. and van Vliet, L. J. (1999). The applicability of neural networks to non-linear image processing. *Pattern Analysis and Applications,* 2**,** 111-128.

Defigueiredo, M. T. and Leitao, J. M. N. (1992). Bayesian-Estimation of Ventricular Contours in Angiographic Images. *IEEE Transactions on Medical Imaging,* 11**,** 416-429.

Dong, J. W., Zhang, S. and She, L. H. (2008). A knowledge-based segmentation method integrating both region and boundary information of medical images. *Bmei 2008: Proceedings of the International Conference on Biomedical Engineering and Informatics, Vol 1***,** 797-801.

Dubes, R., Jain, A., Nadabar, S. and Chen, C. (1990). MRF model-based algorithms for image segmentation. *10th International Conference on Pattern Recognition,* 1**,** 808-814.

Duda, R. O., Hart, P. E. and Stork, D. G. (2012). *Pattern classification.* John Wiley & Sons.

El-Dahshan, E.-S. A., Mohsen, H. M., Revett, K. and Salem, A.-B. M. (2014). Computer-aided diagnosis of human brain tumor through MRI: A survey and a new algorithm. *Expert systems with Applications,* 41**,** 5526-5545.

Gering, D. T., Nabavi, A., Kikinis, R., Hata, N., O'Donnell, L. J., Grimson, W. E. L., Jolesz, F. A., Black, P. M. and Wells, W. M. (2001). An integrated visualization system for surgical planning and guidance using image fusion and an open MR. *Journal of Magnetic Resonance Imaging,* 13**,** 967-975.

Golland, P., Grimson, W. E. L., Shenton, M. E. and Kikinis, R. (2000). Small sample size learning for shape analysis of anatomical structures. *Medical Image Computing and Computer-Assisted Intervention - Miccai 2000,* 1935**,** 72-82.

Gondal, A. H. and Khan, M. N. A. (2013). A review of fully automated techniques for brain tumor detection from MR images. *International Journal of Modern Education and Computer Science (IJMECS),* 5**,** 55-61.

Gonzalez, R. C. and Woods, R. E. (1987). Digital image fundamentals. *Digital Imaging Processing Second Edition, Addison-Wesley Publishing Company***,** 52-54.

Gonzalez, R. C. and Woods, R. E. (2004). *Digital image processing.* Pearson Education.

Gordillo, N., Montseny, E. and Sobrevilla, P. (2013). State of the art survey on MRI brain tumor segmentation. *Magnetic resonance imaging,* 31**,** 1426-1438.

Gorelick, L., Galun, M., Sharon, E., Basri, R. and Brandt, A. (2006). Shape representation and classification using the poisson equation. *IEEE Transactions on Pattern Analysis and Machine Intelligence,* 28**,** 1991-2005.

Guttmann, C., Weiner, H., Hsu, L., Khoury, S., Orav, E., Hohol, M., Ahn, S., Kikinis, R. and Jolesz, F. (1998). The natural course of relapsing-remitting and chronic progressive multiple sclerosis. *International Society for Magnetic Resonance in Medicine,* 2**,** 1327.

Guttmann, C. R. G., Kikinis, R., Anderson, M. C., Jakab, M., Warfield, S. K., Killiany, R. J., Weiner, H. L. and Jolesz, F. A. (1999). Quantitative follow-up of patients with multiple sclerosis using MRI: reproducibility. *Journal of Magnetic Resonance Imaging,* 9**,** 509-518.

Ho, S., Bullitt, E. and Gerig, G. (2002). Level-set evolution with region competition: automatic 3-D segmentation of brain tumors. *16th International Conference on Pattern Recognition, 2002,* 1**,** 532-535.

Izakian, H. and Abraham, A. (2011). Fuzzy C-means and fuzzy swarm for fuzzy clustering problem. *Expert Systems with Applications,* 38**,** 1835-1838.

Jain, R., Kasturi, R. and Schunck, B. G. (1995). *Machine vision.* McGraw-Hill New York.

Jiang, H., Zhou, X., Feng, B. and Zhang, M. (2013). A new intuitionistic fuzzy c-means clustering algorithm. *Proceedings 2013 International Conference on Mechatronic Sciences, Electric Engineering and Computer (MEC)***,** 1116-1119.

Juneja, M. and Sandhu, P. S. (2009). Performance evaluation of edge detection techniques for images in spatial domain. *International Journal of Computer Theory and Engineering,* 1**,** 614.

Kao, Y., Chen, M.-H. and Hsieh, K.-M. (2014). Combining PSO and FCM for Dynamic Fuzzy Clustering Problems. *Swarm Intelligence Based Optimization.* Springer. 1-8.

Kass, M., Witkin, A. and Terzopoulos, D. (1987). Snakes: active contour models. *International Journal of Computer Vision 1***,** 321–331.

Kecman, V. (2001). *Learning and soft computing: support vector machines, neural networks, and fuzzy logic models.* MIT press.

Kennedy, J. (2010). Particle swarm optimization. *Encyclopedia of Machine Learning.* Springer. 760-766.

Kennedy, J. and Eberhart, R. (1995). Particle swarm optimization. *IEEE International Conference on Neural Networks,* 4**,** 1942-1948.

Kichenassamy, S., Kumar, A., Olver, P., Tannenbaum, A. and Yezzi, A. (1995). Gradient flows and geometric active contour models. *Fifth International Conference on Computer Vision***,** 810-815.

Krinidis, S. and Chatzis, V. (2010). A Robust Fuzzy Local Information C-Means Clustering Algorithm. *IEEE Transactions on Image Processing,* 19**,** 1328-1337.

Krishnapuram, R. and Keller, J. M. (1993a). A possibilistic approach to clustering. *Fuzzy Systems, IEEE Transactions on,* 1**,** 98-110.

Krishnapuram, R. and Keller, J. M. (1993b). A possibilistic approach to clustering. *IEEE Transactions on Fuzzy Systems,* 1**,** 98-110.

Kumar Rai, R., Gour, P. and Singh, B. (2012). Underwater image segmentation using clahe enhancement and thresholding. *International Journal of Emerging Technology and Advanced Engineering,* 2**,** 118-123.

Kumar, S., Ray, S. K. and Tewari, P. (2012). A hybrid approach for image segmentation using fuzzy clustering and level set method. *International Journal of Image, Graphics and Signal Processing,* 4**,** 1.

Kupinski, M. A. and Giger, M. L. (1998). Automated seeded lesion segmentation on digital mammograms. *IEEE Transactions on Medical Imaging,* 17**,** 510-517.

Law, A. K., Lam, F. and Chan, F. H. (2002). A fast deformable region model for brain tumor boundary extraction. *Proceedings of the Second Joint on Engineering in Medicine and Biology, 2002. 24th Annual Conference and the Annual Fall Meeting of the Biomedical Engineering Society EMBS/BMES Conference, 2002,* 2**,** 1055-1056.

Law, Y. N., Lee, H. K. and Yip, A. M. (2008). A multiresolution stochastic level set method for Mumford–Shah image segmentation. *IEEE transactions on image processing,* 17**,** 2289-2300.

Lefohn, A. E., Cates, J. E. and Whitaker, R. T. (2003). Interactive, GPU-based level sets for 3D segmentation. *International Conference on Medical Image Computing and Computer-Assisted Intervention***,** 564-572.

Lei, W. K., Li, B. N., Dong, M. C. and Vai, M. I. (2007). AFC-ECG: An adaptive fuzzy ECG classifier. *Soft Computing in Industrial Applications: Recent and Emerging Methods and Techniques,* 39**,** 189-199.

Leventon, M. (2000). *Statistical Models for Medical Image Analysis.* PHD Thesis, Massachusetts Institute of Technology.

Li, B. N., Chui, C. K., Chang, S. and Ong, S. H. (2011a). Integrating spatial fuzzy clustering with level set methods for automated medical image segmentation. *Computers in Biology and Medicine,* 41**,** 1-10.

Li, B. N., Chui, C. K., Ong, S. H. and Chang, S. (2009). Integrating FCM and Level Sets for Liver Tumor Segmentation. *13th International Conference on Biomedical Engineering, Vols 1-3,* 23**,** 202-205.

Li, C., Huang, R., Ding, Z., Gatenby, J. C., Metaxas, D. N. and Gore, J. C. (2011b). A level set method for image segmentation in the presence of intensity inhomogeneities with application to MRI. *IEEE Transactions on Image Processing,* 20**,** 2007-2016.

Li, C., Kao, C.-Y., Gore, J. C. and Ding, Z. (2008). Minimization of region-scalable fitting energy for image segmentation. *IEEE transactions on image processing,* 17**,** 1940-1949.

Liu, B., Wang, L., Jin, Y.-H., Tang, F. and Huang, D.-X. (2005). Improved particle swarm optimization combined with chaos. *Chaos, Solitons & Fractals,* 25**,** 1261-1271.

Liu, H., Pei, T., Zhou, C. and Zhu, A.-X. (2008). Multi-temporal MODIS-data-based PSO-FCM clustering applied to wetland extraction in the Sanjiang Plain. *International Conference on Earth Observation Data Processing and Analysis***,** 72854Z-72854Z-11.

Lloyd, S. (2006). Least squares quantization in PCM. *IEEE Trans. Inf. Theor.,* 28**,** 129-137.

Lobregt, S. and Viergever, M. A. (1995). A Discrete Dynamic Contour Model. *IEEE Transactions on Medical Imaging,* 14**,** 12-24.

Lombaert, H., Yiyong, S., Grady, L. and Chenyang, X. (2005). A multilevel banded graph cuts method for fast image segmentation. *Tenth IEEE International Conference on Computer Vision, 2005. ICCV 2005,* 1**,** 259-265 Vol. 1.

Lorensen, W. E. and Cline, H. E. (1987). Marching cubes: A high resolution 3D surface construction algorithm. *SIGGRAPH Comput. Graph.,* 21**,** 163-169.

Lorenzo-Valdes, M., Sanchez-Ortiz, G. I., Elkington, A. G., Mohiaddin, R. H. and Rueckert, D. (2004). Segmentation of 4D cardiac MR images using a probabilistic atlas and the EM algorithm. *Medical image analysis,* 8**,** 255-265.

Luo, S. (2006). Automated medical image segmentation using a new deformable surface model. *International Journal of Computer Science and Network Security,* 6**,** 109-115.

Luo, S., Li, R. and Ourselin, S. (2003). A new deformable model using dynamic gradient vector flow and adaptive balloon forces. *APRS Workshop on Digital Image Computing***,** 9-14.

Ma, F., Wang, W., Tsang, W. W., Tang, Z., Xia, S. and Tong, X. (1998). Probabilistic segmentation of volume data for visualization using SOM-PNN classifier. *Proceedings of the 1998 IEEE symposium on Volume visualization***,** 71-78.

Ma, L. and Staunton, R. C. (2007). A modified fuzzy C-means image segmentation algorithm for use with uneven illumination patterns. *Pattern Recognition,* 40**,** 3005-3011.

Malladi, R., Sethian, J. A. and Vemuri, B. C. (1995). Shape modeling with front propagation: A level set approach. *IEEE transactions on pattern analysis and machine intelligence,* 17**,** 158-175.

Maulik, U. and Bandyopadhyay, S. (2000). Genetic algorithm-based clustering technique. *Pattern recognition,* 33**,** 1455-1465.

McCarley, R. W., Wible, C. G., Frumin, M., Hirayasu, Y., Levitt, J. J., Fischer, I. A. and Shenton, M. E. (1999). MRI anatomy of schizophrenia. *Biological Psychiatry,* 45**,** 1099-1119.

McInerney, T. and Terzopoulos, D. (1999). Topology adaptive deformable surfaces for medical image volume segmentation. *IEEE Transactions on Medical Imaging,* 18**,** 840-850.

McInerney, T. and Terzopoulos, D. (2000). *Deformable models.* Academic Press, Inc.

Mirjalili, S. (2015). How effective is the Grey Wolf optimizer in training multi-layer perceptrons. *Applied Intelligence***,** 1-12.

Mirjalili, S., Mirjalili, S. M. and Lewis, A. (2014). Grey wolf optimizer. *Advances in Engineering Software,* 69**,** 46-61.

Moh'd Alia, O., Al-Betar, M. A., Mandava, R. and Khader, A. T. (2011). Data clustering using harmony search algorithm. *Swarm, Evolutionary, and Memetic Computing.* Springer. 79-88.

Montagnat, J. and Delingette, H. (1997). Volumetric medical images segmentation using shape constrained deformable models. *CVRMed-MRCAS'97***,** 13-22.

Mumford, D. and Shah, J. (1989). Optimal approximations by piecewise smooth functions and associated variational problems. *Communications on pure and applied mathematics,* 42**,** 577-685.

Neumann, A. and Lorenz, C. (1998). Statistical shape model based segmentation of medical images. *Computerized Medical Imaging and Graphics,* 22**,** 133-143.

Ng, M. K. and Wong, J. C. (2002). Clustering categorical data sets using tabu search techniques. *Pattern Recognition,* 35**,** 2783-2790.

Niknam, T. and Amiri, B. (2010). An efficient hybrid approach based on PSO, ACO and k-means for cluster analysis. *Applied Soft Computing,* 10**,** 183-197.

Niknam, T., Amiri, B., Olamaei, J. and Arefi, A. (2009). An efficient hybrid evolutionary optimization algorithm based on PSO and SA for clustering. *Journal of Zhejiang University Science A,* 10**,** 512-519.

Noel, M. M. and Jannett, T. C. (2004). Simulation of a new hybrid particle swarm optimization algorithm. *Proceedings of the Thirty-Sixth Southeastern Symposium on System Theory***,** 150-153.

O'Donnell, L. (2001). *Semi-automatic medical image segmentation.* Citeseer.

Osher, S. and Sethian, J. A. (1988). Fronts propagating with curvature-dependent speed: algorithms based on Hamilton-Jacobi formulations. *Journal of computational physics,* 79**,** 12-49.

Otsu, N. (1979). A threshold selection method for grey-level histogram. *IEEE Syst. Man Cybern,* 9**,** 62–66.

Pal, N. R. and Pal, S. K. (1993). A Review on Image Segmentation Techniques. *Pattern Recognition,* 26**,** 1277-1294.

Pang, W., Wang, K.-p., Zhou, C.-g. and Dong, L.-j. (2004). Fuzzy discrete particle swarm optimization for solving traveling salesman problem. *The Fourth International Conference on Computer and Information Technology, 2004. CIT'04***,** 796-800.

Paulus, D., Wolf, M., Meller, S. and Niemann, H. (1999). Three-dimensional computer vision for tooth restoration. *Medical image analysis,* 3**,** 1-19.

Pham, D., Prince, J. L., Xu, C. Y. and Dagher, A. P. (1997). An automated technique for statistical characterization of brain tissues in magnetic resonance imaging. *International Journal of Pattern Recognition and Artificial Intelligence,* 11**,** 1189-1211.

Pham, D. L. (2001). Spatial models for fuzzy clustering. *Computer Vision and Image Understanding,* 84**,** 285-297.

Popuri, K., Cobzas, D., Jagersand, M., Shah, S. L. and Murtha, A. (2009). 3D variational brain tumor segmentation on a clustered feature set. *SPIE Medical Imaging***,** 72591N-72591N-10.

Prastawa, M., Bullitt, E., Ho, S. and Gerig, G. (2004). A brain tumor segmentation framework based on outlier detection. *Medical image analysis,* 8**,** 275-283.

Prescott, J. W., Pennell, M., Best, T. M., Swanson, M. S., Haq, F., Jackson, R. and Gurcan, M. N. (2009). An automated method to segment the femur for osteoarthritis research. *Annual International Conference of the IEEE on Engineering in Medicine and Biology Society***,** 6364-6367.

Qian, W. and Titterington, D. (1989). On the use of Gibbs Markov chain models in the analysis of images based on second-order pairwise interactive distributions. *Journal of Applied Statistics,* 16**,** 267-281.

Rafael, C. G. (2008). *Digital Image Processing (3rd Edition ed.).* Prentice Hall.

Rajapakse, J. C., Giedd, J. N. and Rapoport, J. L. (1997). Statistical approach to segmentation of single-channel cerebral MR images. *IEEE Transactions on Medical Imaging,* 16**,** 176-186.

Reddick, W. E., Glass, J. O., Cook, E. N., Elkin, T. D. and Deaton, R. J. (1997). Automated segmentation and classification of multispectral magnetic resonance images of brain using artificial neural networks. *IEEE Transactions on Medical Imaging,* 16**,** 911-918.

Richard, E. W. and Rafael, C. G. (2008). *Digital Image Processing.* New Jersey, Pearson Prentice Hall.

Samadzadegan, F. and Naeini, A. A. (2011). Fuzzy clustering of hyperspectral data based on particle swarm optimization. *2011 3rd Workshop on Hyperspectral Image and Signal Processing: Evolution in Remote Sensing (WHISPERS)***,** 1-4.

Sandor, S. and Leahy, R. (1997). Surface-based labeling of cortical anatomy using a deformable atlas. *IEEE Transactions on Medical Imaging,* 16**,** 41-54.

Shan, S., Sandham, W., Granat, M. and Sterr, A. (2005). MRI fuzzy segmentation of brain tissue using neighborhood attraction with neural-network optimization. *IEEE Transactions on Information Technology in Biomedicine,* 9**,** 459-467.

Sharma, N. and Aggarwal, L. M. (2010). Automated medical image segmentation techniques. *Journal of medical physics/Association of Medical Physicists of India,* 35**,** 3.

Shen, S., Sandham, W., Granat, M. and Sterr, A. (2005). MRI fuzzy segmentation of brain tissue using neighborhood attraction with neural-network optimization. *IEEE Transactions on Information Technology in Biomedicine,* 9**,** 459-467.

Siddiqi, K., Lauziere, Y. B., Tannenbaum, A. and Zucker, S. W. (1998). Area and length minimizing flows for shape segmentation. *IEEE Transactions on Image Processing,* 7**,** 433-443.

Siyal, M. Y. and Yu, L. (2005). An intelligent modified fuzzy c-means based algorithm for bias estimation and segmentation of brain MRI. *Pattern Recognition Letters,* 26**,** 2052-2062.

Songcan, C. and Daoqiang, Z. (2004). Robust image segmentation using FCM with spatial constraints based on new kernel-induced distance measure. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics,* 34**,** 1907-1916.

Sonka, M., Hlavac, V. and Boyle, R. (2014). *Image processing, analysis, and machine vision.* Cengage Learning.

SziláGyi, L., SziláGyi, S. M. and Benyó, B. (2012). Efficient inhomogeneity compensation using fuzzy c-means clustering models. *Computer methods and programs in biomedicine,* 108**,** 80-89.

Tu, Z. W. and Zhu, S. C. (2002). Image segmentation by data-driven Markov Chain Monte Carlo. *IEEE Transactions on Pattern Analysis and Machine Intelligence,* 24**,** 657-673.

Umamaheswari, J. and Radhamani, G. (2012). Hybrid Medical Image Segmentation based on Fuzzy Global Minimization by Active Contour Model. *International Journal of Computer Applications,* 39**,** 1-6.

Van Leemput, K., Maes, F., Vandermeulen, D. and Suetens, P. (1999). Automated model-based tissue classification of MR images of the brain. *IEEE Transactions on Medical Imaging,* 18**,** 897-908.

Verma, H., Agrawal, R. and Sharan, A. (2016). An improved intuitionistic fuzzy c-means clustering algorithm incorporating local information for brain image segmentation. *Applied Soft Computing,* 46**,** 543-557.

Vincken, K. L., Koster, A. S. E. and Viergever, M. A. (1997). Probabilistic multiscale image segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence,* 19**,** 109-120.

Wang, H., Yang, S., Xu, W. and Sun, J. (2007). Scalability of hybrid fuzzy c-means algorithm based on quantum-behaved PSO. *Fourth International Conference on Fuzzy systems and knowledge discovery, 2007. fskd 2007,* 2**,** 261-265.

Wang, J. Z., Kong, J., Lu, Y. H., Qi, M. and Zhang, B. X. (2008). A modified FCM algorithm for MRI brain image segmentation using both local and non-local spatial constraints. *Computerized Medical Imaging and Graphics,* 32**,** 685-698.

Wang, Y., Adali, T., Kung, S. Y. and Szabo, Z. (1998). Quantification and segmentation of brain tissues from MR images: A probabilistic neural network approach. *IEEE Transactions on Image Processing,* 7**,** 1165-1181.

Warfield, S. K., Nabavi, A., Butz, T., Tuncali, K., Silverman, S. G., Black, P. M., Jolesz, F. A. and Kikinis, R. (2000). Intraoperative segmentation and nonrigid registration for image guided therapy. *Medical Image Computing and Computer-Assisted Intervention - Miccai 2000,* 1935**,** 176-185.

Wells III, W., Grimson, W. E. L., Kikinis, R. and Jolesz, F. A. (1996). Adaptive segmentation of MRI data. *IEEE Transactions on Medical Imaging,* 15**,** 429-442.

Wells, W. M., Grimson, W. E. L., Kikinis, R. and Jolesz, F. A. (1996). Adaptive segmentation of MRI data. *IEEE Transactions on Medical Imaging,* 15**,** 429-442.

Wu, X., Spencer, S. A., Shen, S., Fiveash, J. B., Duan, J. and Brezovich, I. A. (2009). Development of an accelerated GVF semi-automatic contouring algorithm for radiotherapy treatment planning. *Computers in Biology and Medicine,* 39**,** 650-656.

Xie, K., Yang, J., Zhang, Z. and Zhu, Y. (2005). Semi-automated brain tumor and edema segmentation using MRI. *European Journal of Radiology,* 56**,** 12-19.

Xu, C. Y. and Prince, J. L. (1998). Snakes, shapes, and gradient vector flow. *IEEE Transactions on Image Processing,* 7**,** 359-369.

Xu, C. Y., Prince, J. L. and Pham, D. L. (2000). A survey of current methods in medical image segmentation. *Annu. Rev. Biomed. Eng***,** 315-337.

Yang, M.-S. and Tsai, H.-S. (2008). A Gaussian kernel-based fuzzy c-means algorithm with a spatial bias correction. *Pattern Recognition Letters,* 29**,** 1713-1725.

Yezzi, A., Kichenassamy, S., Kumar, A., Olver, P. and Tannenbaum, A. (1997). A geometric snake model for segmentation of medical imagery. *IEEE Transactions on medical imaging,* 16**,** 199-209.

Zhang, D. Q. and Chen, S. C. (2004). A novel kernelized fuzzy C-means algorithm with application in medical image segmentation. *Artificial Intelligence in Medicine,* 32**,** 37-50.

Zhang, J., Modestino, J. W. and Langan, D. A. (1994). Maximum-Likelihood Parameter-Estimation for Unsupervised Stochastic Model-Based Image Segmentation. *IEEE Transactions on Image Processing,* 3**,** 404-420.

Zhang, Y., Huang, D., Ji, M. and Xie, F. (2011). Image segmentation using PSO and PCM with Mahalanobis distance. *Expert Systems with Applications,* 38**,** 9036-9040.