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Variable Variance Adaptive Mean-Shift and possibilistic fuzzy C-means based recursive framework for brain MR image segmentation

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ABSTRACT

Segmentation of brain MR image tissues has been a challenge because of the embedded nonlinear bias field acquired during the image acquisition process. This problem is further compounded due to the presence of noise. In order to deal with such issues, we have proposed a Variable Variance Adaptive Mean-Shift (VVAMS) algorithm which not only removes noise but also reinforces the clustering attribute by its mode seeking ability. We have formulated the problem for jointly estimating the bias field, tissue class labels and noise free pixels. Since, all the parameters are unknown and interdependent it is hard to obtain optimal estimates. In this regard, we have proposed a recursive framework to obtain the estimates of the parameters, which are partial optimal ones. In the first step of the recursion, the possibilistic fuzzy clustering algorithms has been applied to determine different clusters and bias field. These clusters are noisy and hence in the second step of the recursion, VVAMS algorithm has been applied on each cluster to eliminate noise and reinforce the modes of the clusters. These two steps constitute one combined iteration. Theoretically, the recursive framework is supposed to converge after large number of recursions but in practice it converges after a few iterations. This proposed scheme has successfully been tested with 50 biased noisy slices from Brainweb database and some real brain MR image data from IBSR database. The results have been quantitatively evaluated by percentage of misclassification, Rand Index, *t*-test, fuzzy partition coefficient (V_{pc}), fuzzy partition entropy (V_{pe}) and Tanimoto index. The quantitative evaluations of the tissue class labels demonstrate the superiority of proposed scheme over the existing methods.

1. Introduction

The problem of segmentation of brain Magnetic Resonance (MR) image has been addressed by different researchers yet it remains as a challenge because of the presence of a slowly varying nonlinear field, called the bias field (Ahmed, Yamany, Mohamed, & Farag, 2002; Aparajeeta, Nanda, & Das, 2016; Sing, Adhikari, & Basu, 2015) and noise. This bias field is embedded with the image during the acquisition process of MR imaging. The problem is further compounded because of the presence of noise of varying strength. Therefore, hybrid approaches need to be contrived to simultaneously estimate bias field and obtain segmentation under noisy environment.

In this regard, many new approaches have been proposed based on the fuzzy and possibilistic notions. Specifically, Fuzzy C-means (FCM) algorithm (Bezdek, 1980) has been extensively used to model the uncertainty of the data and successfully used for clustering. FCM and its variants have also been employed for MR image segmentation. It has been found that the performance of the FCM algorithm deteriorates in the presence of noise. Ahmed et al. (2002) proposed a modified FCM to estimate the bias field and to obtain segmentation. They have incorporated the neighborhood information (Ahmed et al., 2002) to estimate the bias field and achieve segmentation concurrently. Several modified approaches of FCM have been proposed to effectively take care of bias field and noise (Aparajeeta et al., 2016; Ji, Liu, Cao, Sun, & Chen, 2014; Ji, Sun, & Xia, 2011). In order to improve upon the performance under noisy scenario, Possibilistic C-means (PCM) algorithm has been proposed (Krishnapuram & Keller, 1993). Even though PCM takes care of noise and intensity inhomogeneity to some extent, the major bottleneck is the result of coincident clusters, which is detrimental for accurate classification of tissue

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classes. This problem has been circumvented by the Possibilistic Fuzzy C-means (PFCM) approach proposed by Pal, Pal, Keller, and Bezdek (2005).

Although, several modified FCM and PCM algorithms have been proposed, development of an efficient algorithm for accurate tissue classification of MR image under noisy environment is a challenge. In literature, the notion of mean-shift has been used in a wide variety of situations for simultaneously removing noise and seeking the modes of a distribution for clustering (Cheng, 1995). Adaptive Mean-Shift (AMS) algorithm, an improved version of mean-shift, has successfully been used to obtain segmentation of MR images (Mayer & Greenspan, 2009). AMS takes care of noise but is not potential enough to yield accurate tissue classification of MR data. Therefore, this research work aims to address the above issues in a new recursive framework exploring the potential attributes of the notion of mean-shift and modified PFCM algorithm.

In this paper, attempts have been made to estimate the bias field, and obtain segmentation of the MR image under noisy environments. The presence of noise in such a situation makes the estimation of tissue classes of White Matter (WM), Gray Matter (GM) and Cerebro Spinal Fluid (CSF) a hard task. The presence of noise affects the estimation of cluster centers and hence the clusters. Besides, the data could be sparse and dense. Determination of cluster centers in a data set having sparse and dense data together with noise is a challenging task. In order to deal with such issues, we have proposed VVAMS algorithm. This algorithm not only eliminates noise but also seeks the cluster center. This accelerates the possibilistic fuzzy algorithm to yield the accurate fuzzy partitions. The problem has been formulated as a joint estimation problem of bias field, image labels and noise free tissue classes. All the above parameters are unknown and the accuracy of estimation of bias field and class labels depends on the availability of the noise free data. This is hard because both are unknown and interdependent. Hence, a recursive framework has been proposed to achieve the estimation of bias field, tissue class labels and eliminate the noise simultaneously. In the first part of the recursion, the modified PFCM algorithms (Aparajeeta et al., 2016) have been applied on the whole image to obtain the estimate of the bias field, cluster prototype, fuzzy membership and typicality measure. This generates the necessary fuzzy partitions. In the second part of the recursion, the noise has been filtered and the mode seeking ability has been reinforced by the proposed Variable Variance Adaptive Mean-Shift (VVAMS) algorithm that has been applied on each fuzzy partitions obtained in the previous recursion. Thus one combined iteration estimates all the necessary parameters but the estimates are not optimal because of lack of convergence.

Theoretically the recursive algorithm is expected to converge to suboptimal solutions in large number of combined iterations, but in practice the combined algorithm has been found to converge in finite number of recursions. The proposed algorithm has successfully been tested on 50 number of different slices from Brainweb database and a few slices from IBSR database. Quantitative evaluations of the algorithm exhibited improved performance under noisy condition as compared to other existing approaches.

This paper is organized as follows. The related work to this problem has been presented in Section 2 and the proposed scheme has been explained with schematic diagram in Section 3. A brief background on AMS and fuzzy clustering has been presented in Section 4. Section 5 deals with the new recursive formulation for joint estimation while the proposed VVAMS scheme has been presented in Section 6. Implementation of the recursive framework has been discussed in Section 7 and the combined algorithm for the recursive formulation has been presented in Section 8. Section 9 deals with results and necessary discussions while the concluding remarks have been presented in Section 10.

2. Related work

In literature, K-means, FCM and PCM algorithms have been extensively used for clustering in spatial domain. FCM is the standard model to deal with the uncertainty present in the data. But in case of brain MR images, the problem is compounded due to low contrast among tissue classes and the presence of intensity inhomogeneity or bias field. During last decade, different modifications of FCM have been proposed to handle the bias field and noise present in brain MR images. The limitations of FCM may be attributed to the assumption of spatial independence of the data set. By and large, the modified FCMs take into account the spatial information to improve the potentiality of the fuzzy model. One of the modifications is by Pham (2001) who proposed a spatial model for fuzzy clustering, where, a penalty term has been added to the standard FCM model to encourage a pixel to be in the same class as its neighborhood. This resulted in more compact clusters while effectively taking care of the noise present in the data.

There are other variants of FCM which could handle noise and bias in MR image. One of such approaches is a multiview fuzzy clustering proposed by Wang and Chen (2017). This modified FCM has integrated the heterogeneous information underlying different views. Further, Ji et al. (2014) proposed a new spatial factor based on posterior and prior probabilities along with the spatial direction. This spatial factor restores the noise free image from the noisy data. It is known that in wide variety of algorithms, parameter tuning is cumbersome but crucial to produce effective results. To circumvent this problem, Guo, Wang, and Shen (2016) proposed a parameter auto tuning FCM with inhomogeneity penalty. As a further improvement in this direction, Sing et al. (2015) proposed a new fuzzy model which takes care of the noise and intensity inhomogeneity present in the data by incorporating a scale control spatial information in the fuzzy model. Based on this information, a local membership function for each pixel has been proposed. This reinforces the potentiality of the model that exhibits improved performance in the presence of noise and intensity inhomogeneity.

It is to be noted that FCM has limitation of handling noisy MR image. There has been conscious effort in this direction as a result of which different modifications of FCM have been proposed to handle the noise in MR image. Recently, Sarkar, Saha, and Maulik (2016) proposed a hybrid technique, called Rough Possibilistic Type-2 Fuzzy C-means clustering to take care of noise and uncertainties for accurate clustering. A hybrid segmentation algorithm known as Soft Fuzzy Rough C-means has been proposed by Namburu, kumar Samay, and Edara (2016) to handle uncertainty by defining lower and upper approximation. Besides, Benaichouche, Oulhadj, and Siarry (2016) have proposed a grayscale image segmentation algorithm based on multiobjective fuzzy clustering using a PSO metaheuristic. The multiobjective optimization approach optimizes two criteria i.e. region based and edge based. The region based fitness is the improved spatial FCM and the edge based fitness is based on the contour statistic which have been used to improve segmentation. Different hybrid techniques have been proposed by integrating FCM with Particle Swarm Optimization (PSO) to overcome the limitations of FCM (Filho, Pimentel, Souza, & Oliveira, 2015; Izakian & Abraham, 2011).

Besides FCM, mean-shift and AMS algorithms have been used for brain MR image segmentation. These algorithms are nonparametric and the segmentation accuracy greatly depends on proper choice of a kernel and appropriate bandwidth of the kernel. As far as kernel is concerned, Parzen (1962) has shown the possible estimates of probability density function and the corresponding modes, which are consistent and asymptotically normal. The use of generalized kernel approach for nonparametric estimation of probability density function has been investigated by Fukunaga and Hostetler (1975). The authors have used the Gaus-