Chapter 2

MRI Brain Image Segmentation Using Interactive Multiobjective Evolutionary Approach

Anirban Mukhopadhyay
University of Kalyani, India

ABSTRACT

The problem of image segmentation is frequently modeled as a problem of clustering the pixels of the images based on their intensity levels. In some recent studies, multiobjective clustering algorithms, where multiple cluster validity measures are optimized simultaneously for yielding robust clustering solutions have been proposed. It has been observed that the same set of validity measures optimized simultaneously do not generally perform well for all image datasets. In view of this, in this article, an interactive approach for multiobjective clustering is proposed for segmentation of multispectral Magnetic Resonance Image (MRI) of the human brain. In this approach, a human decision maker interacts with the multiobjective evolutionary clustering technique during execution in order to obtain the final clustering, the suitable set of validity measures for the input image, as well as the number of clusters by employing a variable-length encoding of the chromosomes. The effectiveness of the proposed method is demonstrated on many simulated normal and MS lesion MRI brain images.

INTRODUCTION

Image segmentation refers to the procedure of separating the pixels of an image into multiple non-overlapping, homogeneous and meaningful regions (Gonzalez, 1992). These regions are generally strongly associated with the objects in the image. Segmentation plays a vital role for analysis of medical images in computer-aided diagnosis and therapy. Automatic segmentation of MRI brain images into different tissue classes, such as gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF) is very important in clinical study and neurological pathology. Further, the quantization of GM and WM region volumes may be of major interest in understanding different neurological disorders and diseases.

DOI: 10.4018/978-1-5225-0058-2.ch002

The problem of segmentation of MRI brain images in different tissue classes is often posed as clustering the image pixels in the intensity space (Mukhopadhyay, 2009a, 2011). Clustering (Jain,1988) is a popular unsupervised pattern classification technique that partitions a set of n objects into K groups based on some similarity/dissimilarity metric where the value of K may or may not be known *a priori*. Unlike hard clustering, a fuzzy clustering algorithm produces a $K \times n$ membership matrix $U(X) = [u_{kj}]$, $k = 1,\ldots,K$ and $j = 1,\ldots,n$, where u_{kj} denotes the membership degree of pattern x_j to cluster C_k. For probabilistic non-degenerate clustering $0 < u_{kj} < 1$ and $\sum_{k=1}^{K} u_{kj} = 1$, $1 \le j \le n$ (Bezdek, 1981). Due to the inherent noisy nature of MRI images, fuzzy clustering is more appropriate in segmentation of MRI imagery.

Different types of clustering algorithms such as Fuzzy C-means (FCM) (Suckling, 1999), Expectation Maximization (EM) algorithm (Zhang, 2001), and Genetic Algorithm (GA) based clustering (Bhandarkar, 1999) have been widely used for the purpose of MRI image segmentation. Though genetic algorithms (Goldberg, 1989) have been previously used in data clustering problems (Maulik, 2003, 2000), most of them use a single objective to be optimized, which is hardly equally applicable to all kinds of data sets. Optimization of multiple cluster validity measures in parallel helps deal with various properties of the clustering and leads to better solutions and an improved robustness towards the different data characteristics. In this view, in recent years, we have proposed several multiobjective clustering algorithms for the purpose of image segmentation and other applications. (Bandyopadhyay, 2007; Mukhopadhyay, 2009a; Maulik, 2009; Mukhopadhyay, 2011). Unlike single objective optimization, in multiobjective optimization (MOO) (Deb, 2001;Coello, 2006), search is performed over multiple objective functions which are usually conflicting in nature. The final solution set contains different non-dominated solutions, such that no solution can be improved further on any one objective without causing a degradation of the same in another.

The existing GA-based multiobjective clustering methods encode a potential clustering solution in a chromosome and optimize in parallel more than one (usually two or three) cluster validity measures that are chosen before the start of execution (Mukhopadhyay, 2015). However, it has been observed that these predefined set of objectives (validity measures) may not work equally well for all images. This is because the performance of the cluster validity measures depends on the image properties and the inherent clustering structure. Hence it may be beneficial to develop some technique to evolve the most suitable set of validity measures during the execution of the algorithm instead of choosing them *a priori*. Motivated by this, a novel interactive multiobjective variable string-length GA-based fuzzy clustering (IMOVGAC) technique is proposed here for segmentation of MRI brain imagery. The proposed algorithm periodically interacts with a human decision maker (DM) while executing and adaptively learns from the DM choices to obtain the most suitable set of validity measures along with the final clustering. Moreover, IMOVGAC is able to evolve the number of clusters automatically with the help of variable chromosome-length encoding policy.

The proposed IMOVGAC technique is applied on several simulated T1-weighted, T2-weighted and proton density-weighted normal and MS lesion MRI brain images. Superiority of the proposed method over several existing clustering algorithms K-means (Jain, 1999), Fuzzy C-means (FCM) (Bezdek, 1981), Expectation Maximization (EM) clustering (Jain,1999), hierarchical average linkage clustering (Jain, 1999), single objective variable string length genetic fuzzy clustering (SVGA) (Maulik, 2003), multiobjective fixed chromosome length genetic fuzzy clustering (MOGA) (Bandyopadhyay, 2007) and

Related Content