Brain image segmentation using semi-supervised clustering

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A R T I C L E   I N F O

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Sym-index
I-index
MS-index

A B S T R A C T

The objective of brain image segmentation is to partition the brain images into different non-overlapping homogeneous regions representing the different anatomical structures. Magnetic resonance brain image segmentation has large number of applications in diagnosis of neurological disorders like Alzheimer diseases, Parkinson related syndrome etc. But automatically segmenting the MR brain image is not an easy task. To solve this problem, several unsupervised and supervised based classification techniques have been developed in the literature. But supervised classification techniques are more time consuming and cost-sensitive due to the requirement of sufficient labeled data. In contrast, unsupervised classification techniques work without using any prior information but it suffers from the local trap problems. So, to overcome the problems associated with unsupervised and supervised classification techniques, we have proposed a new semi-supervised clustering technique using the concepts of multiobjective optimization and applied this technique for automatic segmentation of MR brain images in the intensity space. Multiple centers are used to encode a cluster in the form of a string. The proposed clustering technique utilizes intensity values of the brain pixels as the features. Additionally it also assumes that the actual class label information of 10% points of a particular image data set is also known. Three cluster validity indices are utilized as the objective functions, which are simultaneously optimized using AMOSA, a modern multi-objective optimization technique based on the concepts of simulated annealing. First two cluster validity indices are symmetry distance based Sym-index and Euclidean distance based I-index, which are based on unsupervised properties. Last one is a supervised information based cluster validity index, Minkowski Index. The effectiveness of this proposed semi-supervised clustering technique is demonstrated on several simulated MR normal brain images and MR brain images having some multiple sclerosis lesions. The performance of the proposed semi-supervised clustering technique is compared with some other popular image segmentation techniques like Fuzzy C-means, Expectation Maximization and some recent image clustering techniques like multi-objective based MCMOClust technique, and Fuzzy-VGAPS clustering techniques.

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1. Introduction

The major challenge in analyzing MR brain images is to classify the pixels of images into homogeneous regions. This type of problem is termed as clustering/segmentation problem (Gonzalez & Woods, 2001). The success of medical imaging system depends on proper segmentation of images. MR images have large number of applications in solving several neurodegenerative disorders like Alzheimer diseases, Parkinson related syndrome etc. To solve these problems, several unsupervised and supervised based classification techniques have been developed (Bhandarkar & Zhang, 1999; Saha & Bandopadhyay, 2009). Most of the clustering techniques rely on some similarity/dissimilarity criteria of data points by using which points are assigned to different clusters. They evolve the partition matrix 𝑈(𝑋) of size 𝑁 × 𝑘 in such a way that 𝑈 = [𝑢𝑖𝑗], 1 ≤ 𝑖 ≤ 𝑇, where, 𝑢𝑖锺 takes value “0” if pattern 𝑥锺 does not belong to cluster 𝐶锺(𝑖 = 1, . . . , 𝑇), and can take value “1” if pattern 𝑥锺 belongs to cluster 𝐶锺(𝑖 = 1, . . . , 𝑇). Unsupervised classification techniques do not take into account any kind of supervised information (Gath & Geva, 1989; Kwan, Evans, & Pike, 1999). They are used to partition the pixels based on some internal characteristics (Suckling, Sigmundsson, Greenwood, & Bullmore, 1999). Thus obtained partitioning may not be perfect always. Supervised classification techniques require large amount of labeled information to generate the models which are further utilized for classifying some unknown pixels (Pedrycz & Waletzky, 1997). But it is both time consuming
and costly to generate huge amount of labeled information. In recent years a new classification technique, namely semi-supervised classification (Ebrahimi & Abadeh, 2012; Handl & Knowles, 2006), is developed to solve the difficulties of both supervised and unsupervised classification techniques. It utilizes the advantages of both supervised and unsupervised classification. Here some small amount of labeled data and a huge collection of unlabeled data are used. The available labeled data is used to fine-tune the obtained partitionings. Several approaches have been developed to solve this type of semi-supervised classification problem. Literature survey shows that semi-supervised classification techniques are more powerful as compared to supervised or unsupervised classification techniques for solving different real-life problems (Saha et al., 2012).

In the current paper, the automatic MR brain image segmentation problem is posed as a multiobjective optimization (MOO) problem. Here we need to determine the number of clusters and the corresponding partitioning automatically from the given MR images using the search capability of any MOO based technique. During the clustering process, we have also assumed that some labeled information is also available. Thus the clustering problem is treated as a semi-supervised classification problem and a MOO based framework is developed to solve this problem. The proposed technique, namely Semi-MriMOO, utilizes a recently proposed simulated annealing based MOO technique, namely AMOSA (Bandyopadhyay, Saha, Maulik, & Deb, 2008), as the underline optimization strategy. Three objective functions are used to quantify the goodness of the obtained partitionings. These are simultaneously optimized using AMOSA (Bandyopadhyay et al., 2008). First two objective functions are some internal indices for cluster validity based on unsupervised properties of image data sets. These are: symmetry distance based Sym-index (Bandyopadhyay & Saha, 2008), and Euclidean distance based I-index (Maulik & Bandyopadhyay, 2002). Last one is an external index of cluster validity, Minkowski Score or MS-index (Ben-Hur & Guyon, 2003) based on supervised information or prior information of data set (Alok, Saha, & Ekbal, 2012; 2014). This basically checks the compatibility of the obtained partitioning and the available supervised information. A new encoding schema is used to represent clusters in the form of a string. Clusters are divided into multiple small sub-clusters. Centers of these small clusters are then encoded in the form of a string. In the current paper, assignment of points to different clusters is done using the popular Euclidean distance. Different new perturbation operations are defined, and as supervised information, we have assumed that class labels of only 10% data points are available. The segmentation results obtained by the proposed Semi-MriMOO clustering technique for different brain MR images are analyzed quantitatively and visually. Those are further compared with the results obtained by some recent or popularly used clustering techniques like Fuzzy C-means (Bezdek, 1981), Expectation Maximization (Jain, Murty, & Flynn, 1999), MCMOClust (Saha & Bandyopadhyay, 2007) and Fuzzy-VGAPS (Saha & Bandyopadhyay, 2007) clustering techniques.

The contributions of the current paper are as follows:

- To the best of our knowledge this is the first work where a semi-supervised based approach in multiobjective optimization framework is proposed to automatically segment the brain images.
- Semi-supervised clustering is solved using a multiobjective optimization framework.
- A new encoding strategy is proposed to represent the partitions in the form of a solution.
- A set of internal and external cluster validity indices are used as the objective functions.
- Search capability of a simulated annealing based multiobjective optimization technique, AMOSA, is utilized to automatically determine the appropriate partitioning from different brain images.
- Effectiveness of the proposed technique is shown for segmenting several normal brain images and also brain images with multiple sclerosis lesions. Results are compared with several popular and recent image segmentation techniques. Experimental results and a thorough analysis of those results clearly demonstrate the effectiveness of the proposed technique.

2. Literature review

In recent years there have been several attempts to solve the brain image segmentation problem (Klauschen, Goldman, Barra, Meyer-Lindentro, & Lundervold, 2009; Ortiz, Górriz, Ramirez, Salas-Gonzalez & Llamas-Elvira, 2013). In Portela, Cavalcanti, and Ren (2014), authors have proposed clustering based semi-supervised classification technique to segment the MR brain images. Initially K-means clustering technique is applied on randomly selected MR brain slices. Thereafter, these clusters are labeled by human experts in terms of gray matter(GM), white matter(WM) and cerebrospinal fluid(CSF). Thereafter, some statistical measures of these clusters are computed. Finally, labeled information and statistical measures are given as initial parameters to Gaussian Mixture Model (GMM) to classify the remaining MR brain image slices. In Zhang, Dong, Clapworthy, Zhao, and Jiao (2010), authors have proposed semi-supervised spectral clustering technique to segment the MR brain images. In this approach instance level constraints like must-links and cannot-links are generated based on randomly selected subset of voxels from the same slice. Further, this supervision is also provided in spectral clustering to segment the remaining slices of MR brain images. Nearest neighbor strategy is applied for segmenting images to overcome the computation complexity of spectral clustering. In Ortiz, Górriz, Ramirez, and Salas-Gonzalez (2014), authors have proposed Self-Organizing Maps(SOMs) and Genetic Algorithm(GA) based unsupervised clustering technique to segment the MR brain images. The whole process is divided into two modules. First module includes the preprocessing, feature extraction, feature selection based on genetic algorithm(GA), and voxel clustering using self-organizing maps(SOMs). Second module basically explores the entropy gradient clustering on extracted features. The obtained clustering solutions are validated using two cluster validity indices like DBI (Davies & Bouldin, 1979) and DUNN (Dunn, 1974). In Ortiz et al. (2013), authors have proposed self-organizing map (SOM) based two clustering techniques to segment the MR brain images. In the first approach, the relevant information is extracted from the whole volume histogram using SOM to classify the voxels. Second approach is divided into four stages including preprocessing, first and second order feature extraction, genetic algorithm based feature selection and finally mapped units are clustered using self-organizing map (SOM). The first approach is a fast procedure and the second approach is more robust under noisy and bad intensity conditions. In Li, Ogumbona, deSilva, and Attikiouzel (2011), authors have proposed a semi-supervised maximum posteriori probability (ssMAP) based segmentation technique for MR brain image data sets. The main intuition behind this algorithm is to exploit the incomplete training or labeled data. Due to the presence of homogeneity in images, performing proper segmentation becomes infeasible. Furthermore, authors have introduced second order polynomial function to handle with in-homogeneity to achieve maximum posterior probability estimation. In Song, Huang, Ma, and Hung (2011), authors have proposed semi-supervised classification technique inspired by Adaboost. Here, nearest neighbor algorithm is applied on unlabeled data to obtain first pseudo class label information.
Thereafter, these class labeled data is used to train the classifier to predict the class labels for unlabeled data.

In Saha and Bandyopadhyay (2011), authors have proposed a multiobjective based clustering technique (MCMOClust) utilizing simulated annealing based optimization technique, AMOSA (Bandyopadhyay et al., 2008), as the underline optimization strategy. Two objective functions are simultaneously optimized in this study. The first one is the Euclidean distance based XB-index (Xie & Beni, 1991), which measures the total compactness of the partitioning. Second one is the point symmetry distance based Sym-index (Bandyopadhyay & Saha, 2008), which measures the total symmetry present in the partitioning. Again, center based encoding is used to represent the partitionings. Here one cluster is divided into multiple sub-clusters. In Saha and Bandyopadhyay (2007), authors have proposed fuzzy point symmetry based genetic clustering technique (Fuzzy-VGAPS) to automatically segment the MR brain image data sets. The assignment of points to different clusters is done based on the point symmetry distance (Bandyopadhyay & Saha, 2007). Here, cluster centers are encoded in variable length chromosomes. In Saha and Bandyopadhyay (2009), authors have proposed multi-seed based variable length genetic clustering technique (MCVGAPS) to automatically segment the MR brain image data sets. Here each cluster is divided into several small sub-clusters, thereafter, centers of these sub-clusters are encoded in a string to represent the whole clustering. In this approach, assignment of points to different clusters is done in a similar way as proposed in Saha and Bandyopadhyay (2007). Thereafter, point symmetry based objective function, Sym-index (Bandyopadhyay & Saha, 2008), is optimized to obtain the optimal partitioning results. In Saha, Maulik, Bandyopadhyay, and Piewczynski (2010), authors have proposed differential evolution based crisp clustering to segment the multi-spectral magnetic resonance image data sets. Here, assignment of points to different clusters is done based on the Euclidean distance. In order to show the effectiveness of the proposed clustering technique (DECC), it is applied on several T1-weighted, T2-weighted, proton density normal and MS lesion magnetic resonance image data (DECC), it is applied on several T1-weighted, T2-weighted, proton density normal and MS lesion magnetic resonance image data sets. To evaluate the obtained partitioning results, some internal or external validity indices are utilized. In Mukhopadhyay, Maulik, and Bandyopadhyay (2009), authors have proposed multi-objective based fuzzy clustering technique using NSGA-II as the underline optimization strategy. Three objective functions, XB index (Xie & Beni, 1991), PBM index (Maulik & Bandyopadhyay, 2002) and Jm measure (Bezdek, 1981) are simultaneously optimized. Again for the purpose of encoding, center based representation is used. Thereafter, cluster ensemble method is utilized to combine the set of non-dominated solutions obtained from the final Pareto front. In order to theoretically differentiate our proposed approach from the other existing approaches, in Table 1 we have summarized all the existing approaches.

<table>
<thead>
<tr>
<th>Author</th>
<th>Approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>Portela et al. (2014)</td>
<td>Single objective based semi-supervised approach; K-means to generate labeled data; GM classifier</td>
</tr>
<tr>
<td>Ortiz et al. (2014)</td>
<td>Feature selection; genetic algorithm (GA); voxel clustering; self-organizing maps (SOMs); entropy gradient based clustering; cluster validity indices: DBI and DUNN</td>
</tr>
<tr>
<td>Ortiz et al. (2013)</td>
<td>Unsupervised approach; feature extraction; histogram; classifier; self-organizing maps (SOMs)</td>
</tr>
<tr>
<td>Ortiz et al. (2013)</td>
<td>Unsupervised approach; feature extraction; second order; feature selection; genetic algorithm; clustering; self-organizing maps (SOMs)</td>
</tr>
<tr>
<td>Zhang et al. (2010)</td>
<td>Semi-supervised approach; supervision: must-link and cannot-link; clustering; spectral clustering</td>
</tr>
<tr>
<td>Saha et al. (2010)</td>
<td>Differential evolution based crisp clustering (DECC); assignment of points: Euclidean distance; cluster validation: internal and external validity indices</td>
</tr>
<tr>
<td>Saha and Bandyopadhyay (2007)</td>
<td>Fuzzy genetic clustering technique (Fuzzy-VGAPS); assignment of points: point symmetry distance; encoding: variable length chromosomes.</td>
</tr>
<tr>
<td>Saha and Bandyopadhyay (2011)</td>
<td>Multiobjective based clustering technique (MCMOClust); optimization technique: AMOSA; objective functions: XB-index and Sym-index; center based encoding</td>
</tr>
<tr>
<td>Saha and Bandyopadhyay (2009)</td>
<td>Multi-seed based variable length genetic clustering technique (MCVGAPS); assignment of points: point symmetry distance; objective functions: Sym-index</td>
</tr>
<tr>
<td>Li et al. (2011)</td>
<td>Semi-supervised approach; second order polynomial function; maximum posterior probability estimation</td>
</tr>
<tr>
<td>Mukhopadhyay et al. (2009)</td>
<td>Multiobjective based fuzzy clustering technique; optimization technique: NSGA-II; objective functions: XB index, PBM index and Jm measure; center based encoding; cluster ensemble method</td>
</tr>
<tr>
<td>Song et al. (2011)</td>
<td>Semi-supervised classification technique; class labeled data: nearest neighbor algorithm; classifier</td>
</tr>
<tr>
<td>Proposed</td>
<td>Multiobjective based semi-supervised clustering technique (Semi-MrMOO); optimization technique: AMOSA; multi-center based encoding; objective functions: 1-index, Sym-index, MS index; supervision: 10% labeled data; selection of single optimum solution: minimum MS index value</td>
</tr>
</tbody>
</table>

Table 1: Comparative analysis of different approaches.

Framework for solving the problem of automatic partitioning of MR brain images. Also most of the clustering techniques fail due to the overlapping nature of the clusters. In order to deal with this problem, in our proposed approach, we have used different objective functions based on different data intrinsic properties like: cluster compactness and cluster separation. In order to encode different types of structures including connected, symmetrical and hyperspherical shaped clusters, clusters are divided into multiple small sub-clusters. Centers of these small clusters are then encoded in the form of a string. This helps the proposed algorithm to determine clusters having any shape, size or convexity. Different new perturbation operations are defined. Perturbation operations used are capable of updating the sub-cluster centers corresponding to a particular center, increasing the number of whole clusters encoded in the string or decreasing the number of whole clusters encoded in a string. A set of internal and external cluster validity indices are used as the objective functions. Search capability of a
simulated annealing based multiobjective optimization technique, AMOSA, is utilized to automatically determine the appropriate partitioning from different brain images. Here only 10% labeled information is used as supervision to solve the semi-supervised clustering problem. Finally, this is the first attempt to develop semi-supervised clustering technique in MOO framework to segment the MR brain image data sets.

3. Proposed framework for MR brain image segmentation

In the current paper in order to automatically segment magnetic resonance brain images, a multiobjective semi-supervised clustering technique is proposed. The proposed technique uses the search capability of AMOSA (Bandyopadhyay et al., 2008), a modern multiobjective optimization technique based on the concepts of simulated annealing to automatically determine the appropriate partitioning from MR brain image data sets. The proposed technique is a semi-supervised clustering technique; it utilizes some amount of labeled information. In the current paper we have assumed that for 10% data points actual class labels are known. This information is used as the supervised information in the proposed semi-supervised clustering technique. The flow chart of the proposed algorithm is shown in Fig. 1.

3.1. Encoding of a state and initialization of archive members

In semi-MrMOO, the states of AMOSA comprise of some real numbers. Here multiple centers are used to represent a partitioning as done in Saha and Bandyopadhyay (2013).

These real numbers in fact indicate the locations of the centers of the clusters. Hence the modern MOO technique AMOSA can automatically determine the proper set of cluster coordinates and the respective partitionings of the data items. Suppose a state comprises of encoded centers of \(K\) partitions, and let us assume that each cluster is decomposed into \(C\) number of small sub-clusters. Then the length of that state will be \(K \times C \times F\), where \(F\) is the number of features present in the data set. Let a particular state hold 2 whole clusters (i.e., \(K = 2\)), each whole cluster is further partitioned into 10 different sub-clusters (\(C = 10\)), and the number of features present in a data set, \(F = 2\). So \(j\)th subcluster of \(i\)th cluster is represented by \(c_{ij} = (c_{xij}, c_{yij})\). Then the entire state will look like \((c_{x11}, c_{y11}, c_{x12}, c_{y12}, \ldots, c_{x10}, c_{y10}, c_{x21}, c_{y21}, \ldots, c_{x20}, c_{y20})\). Here, \(K_i = (\text{rand}(K_{\text{max}} - 1)) + 2\), where \(K_i\) is the total number of whole clusters encoded in the string \(i\) of the archive. Here \(K_{\text{max}}\) represents the higher limit of the cluster number and \(\text{rand()}\) is a function which returns an integer. So number of initial clusters can vary in the range of 2 to \(K_{\text{max}}\). Minimum distance based criteria is used for assigning points to different clusters. After forming the initial partitions, \(C\) number of sub-cluster centers are chosen.

![Fig. 1. Flow chart of the proposed algorithm.](image-url)
for each cluster. These sub-cluster centers are then encoded in the string to represent a particular partitioning. Hence, a string comprises of total $C \times K$ number of encoded centers.

3.2. Assignment of points

Here, we have considered each sub-cluster as a separate cluster for the allocation process. Now, assume that, each state comprises of $K$ number of whole clusters and each cluster is further partitioned into $C$ number of sub-clusters. For the assignment point of view, minimum Euclidean distance based criterion is considered. A particular point $y_j$ is allocated to the $(v, t)$th sub-cluster where

$$v(t) = \text{argmin}\{d_c(z_p, y_j)\}, \text{ for } p = 1 \ldots K, n = 1 \ldots C.$$ 

$z_p$ is the $n$th sub-cluster center of $p$th cluster. $d_c(z_p, y_j)$ denotes the Euclidean distance between the point $y_j$ and the cluster center $z_p$. Thereafter, the partition matrix can be formulated as follows:

$$\Xi((v - 1) \times C + t)[j] = 1 \text{ and } \Xi[c][j] = 0, \text{ } \forall c = 1 \ldots K \times C \text{ otherwise.}$$

3.3. Objective functions used

Three objective functions are considered for the purpose of optimization. First two objective functions are based on some natural characteristics of the data sets, and known as internal cluster validity indices. Last one measures the similarity of the obtained sub-clusters with the available supervised information. This is also called an external index of cluster validity. The used three objective functions are Sym-index (Bandyopadhyay & Saha, 2008), I-index (Maulik & Bandyopadhyay, 2002) and Minkowski index (Ben-Hur & Guyon, 2003). Sym-index and I-index are based on point symmetry and Euclidean distance based computations, respectively. Minkowski index counts the agreement between obtained clustering solution and ground truth information based solution.

3.3.1. Minkowski index

Minkowski index (Ben-Hur & Guyon, 2003) is based on supervised information, which validates the quality of obtained partitioning based result on given true solution. Let true solution be $T$, and obtained clustering solution be $U$. To define Minkowski index, some parameters are evaluated, denoted by $n_{11}$, $n_{01}$, and $n_{10}$. Where, $n_{11}$ is the total number of pairs of data points situated in the same cluster of $T$ and $U$. $n_{01}$ signifies the total number of pairs of pixels which are contained only in same cluster of $U$. $n_{10}$ signifies the total number of pairs of pixels which are contained in the same cluster of $T$ but in different cluster of $U$. So, Minkowski index can be defined as follows:

$$MS(T, U) = \sqrt{\frac{n_{01} + n_{10}}{n_{11} + n_{10}}}. \tag{1}$$

The minimum value of Minkowski index ensures the true partitioning result. For each string Minkowski index value is calculated over 10% data points for which class label information is known. This is then used as the third objective function.

3.3.2. Other steps

To evaluate the three objective functions, whole partitioning is generated after joining the sub-cluster centers. After merging operation is over, the values of these three objective functions for each string are calculated. The multiple objectives corresponding to a particular string are:

$$\text{obj} = \{\text{Sym}(K), I(K), MS(T, U)\},$$

where Sym$(K)$, I$(K)$, and MS$(T, U)$ denote, respectively, the obtained value of Sym-index, I-index and MS-index. To optimize these three objective functions simultaneously, AMOSA is utilized as the background optimization strategy. Three types of mutation operations have been used.

1. In order to perturb each individual cluster center, we have used Laplacian distribution, $p(e) \propto e^{-\frac{|\mu|}{\delta}}$, where the scaling factor $\delta$ sets the magnitude of perturbation to generate a new value for that particular position. The position for perturbation is denoted by $\mu$. We have kept scaling factor $\delta$ equal to 1.0. The newly generated value is used to replace the old value. This perturbation operation is applied to all dimensions independently. In order to change the feature combination, binary mutation is applied.

2. This type of mutation is used to reduce the number of clusters which is encoded in a particular string. We select a cluster center randomly and it is then deleted from the given string. In this case again to change the feature combination, binary mutation is used.

3. This type of mutation is used to increase the number of clusters encoded in a particular string. We randomly select a point from the given data set and it is encoded in the string as the new center. In this case again to change the feature combination, binary mutation is used.

If any string is selected for mutation then any of the above mentioned mutation types is applied with uniform probability.

3.3.3. Selection of single best optimum solution

In MOO, the final Pareto optimal front consists of a set of non-dominated solutions (Deb, 2011). Each solution is responsible for providing some partitioning information for a given data set. Each non-dominated solution is equally important and none of these dominates others. But, sometimes from user’s point of view, selection of a single best solution is needed. In the current paper we have used MS index value for selecting the single best optimum solution from final Pareto optimal front. We have calculated Minkowski index over 10% data points for which class label information is known for each solution on the final Pareto front. Finally we have selected the solution with the lowest value of Minkowski index. The use of 10% labeled data helps to evaluate the goodness of each solution with respect to ground truth information.

4. Discussion and experimental results

Here for MR brain images three bands are available: T1-weighted, T2-weighted and proton density weighted. This brain image data set can be downloaded from Brainweb database (brainWeb, 2013). The parameters for this brain image data set are: 1mm slice thickness, 3% noise and 20% intensity non-uniformity. The size of the image is $217 \times 181 \times 181$. It consists of 181 different z planes. In the current paper we have executed the proposed algorithm on the intensity values corresponding to the pixels on a given z plane. We have executed our proposed algorithm on total seven z planes. The proposed Semi-MriMOO algorithm is executed with the following parameter combinations: $T_{\text{min}} = 0.01$, $T_{\text{max}} = 10$, $SL = 50$, $HL = 40$, $\alpha = 0.8$, and iter = 15. Here $K$ is varied from $K = 2$ to $K_{\text{max}}$. As per given ground truth information, there are total 10 classes present in the image. Number of available classes varies along the different z planes. In order to compare the performance of the proposed technique with some recent and popularly used techniques, Fuzzy C-means (Bezdek, 1981), Expectation Maximization(EM) (Jain et al., 1999), multi-objective based MCMOClust
Table 2
Comparative analysis of obtained cluster number with MS index value for different clustering techniques applied on normal brain images for different $z$ planes. Here OR, OB indicate the actual and obtained clusters, respectively.

<table>
<thead>
<tr>
<th>$z$ plane</th>
<th>OR MS for OB</th>
<th>MCMOClust</th>
<th>Fuzzy-VGAPS</th>
<th>Semi-MriMOO</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OB MS FCM EM</td>
<td>OB MS</td>
<td>OB MS</td>
<td>OB MS</td>
</tr>
<tr>
<td>1</td>
<td>6 8 0.7254 1.022</td>
<td>8 0.6571</td>
<td>9 0.6989</td>
<td>6 0.5631</td>
</tr>
<tr>
<td>2</td>
<td>6 9 0.6502 0.8332</td>
<td>9 0.6382</td>
<td>9 0.6287</td>
<td>6 0.5694</td>
</tr>
<tr>
<td>5</td>
<td>6 8 0.7209 0.7955</td>
<td>9 0.5769</td>
<td>9 0.6281</td>
<td>6 0.5983</td>
</tr>
<tr>
<td>10</td>
<td>9 8 0.7162 0.7732</td>
<td>8 0.7001</td>
<td>8 0.7233</td>
<td>8 0.6417</td>
</tr>
<tr>
<td>36</td>
<td>9 9 0.8912 0.9857</td>
<td>9 0.8263</td>
<td>8 0.8468</td>
<td>9 0.8123</td>
</tr>
<tr>
<td>72</td>
<td>10 9 0.8933 0.7055</td>
<td>9 0.5769</td>
<td>8 0.5965</td>
<td>8 0.5796</td>
</tr>
<tr>
<td>108</td>
<td>9 9 0.7945 0.5767</td>
<td>9 0.5081</td>
<td>9 0.5266</td>
<td>8 0.5038</td>
</tr>
<tr>
<td>144</td>
<td>9 8 0.5912 0.7823</td>
<td>8 0.5433</td>
<td>6 0.3356</td>
<td>7 0.3161</td>
</tr>
</tbody>
</table>

Fig. 2. Actual partitioning of MR normal brain images shown on different planes (a) $z_1$, (b) $z_2$, (c) $z_5$, (d) $z_{10}$, (e) $z_{36}$, (f) $z_{72}$, (g) $z_{108}$ and (h) $z_{144}$.

Results show that for different $z$ planes the proposed Semi-MriMOO clustering technique performs the best compared to other clustering techniques in terms of obtained number of clusters and also MS indices. The MS index values attained by the proposed technique are lower than those obtained by other recent techniques.

The original MR brain images projected on different $z$ planes like, $z_i (i = 1, 2, 5, 10, 36, 72, 108$ and $144$) are shown in Fig. 2(a)–(h), respectively. The obtained best partitioning solutions (here the best partitioning is the one which corresponds to the minimum value of MS index over all the solutions of the final Pareto optimal front) provided by the Semi-MriMOO clustering technique for MR brain image data sets on different $z$ planes like $z_i (i = 1, 2, 5, 10, 36, 72, 108, 144)$ are shown in Fig. 3(a)–(h), respectively. The obtained segmentation results again prove the superiority of the proposed
Semi-MriMOO clustering technique. It can be easily visualized that the proposed Semi-MriMOO clustering technique attains the near optimal partitionings from all the MR images. The obtained lowest MS index values provided by Semi-MriMOO clustering technique ensure the true partitioning results. Obtained Pareto optimal fronts after execution of Semi-MriMOO clustering on different z planes of MR normal brain images, $z_i$ ($i = 1, 2, 5, 10, 36, 72, 108, 144$) are shown in Fig. 4(a)–(h), respectively. Again, box plots of the MS index values corresponding to different non-dominated solutions obtained after execution of semi-supervised clustering technique, Semi-mriMOO, on normal images of brain corresponding to different z planes are shown in Fig. 8(a)–(h), respectively.

Next, Semi-mriMOO clustering technique is applied on simulated MR brain images with multiple sclerosis lesions obtained from Brainweb database (brainWeb, 2013). These images have three bands: T1-weighted, T2-weighted and proton density weighted. The parameters for this brain image data set are 1mm slice thickness, 3% noise and 20% intensity non-uniformity. The size of the image is $217 \times 181 \times 181$. It consists of 181 different z planes. We have executed our proposed algorithm on different image data sets available at total seven z planes. As per ground truth information, there are total 11 classes present in the image. Number of available classes varies along the different z planes. The ground truth information is available to us. Table 3 shows the number of clusters obtained by multi-objective based MCMOClust technique (Saha & Bandyopadhyay, 2011), Fuzzy-VGAPS clustering technique (Saha & Bandyopadhyay, 2007) and the proposed Semi-MriMOO clustering technique (here a single solution is selected which exhibits the lowest MS index value for the 10% data for which the actual class labels are known). The Minkowski Score values obtained by different clustering techniques like Fuzzy C-means (Bezdek, 1981), Expectation Maximization (EM) (Jain et al., 1999), multi-objective based MCMOClust technique (Saha & Bandyopadhyay, 2011), Fuzzy-VGAPS clustering technique (Saha & Bandyopadhyay, 2007) and our proposed Semi-MriMOO clustering technique are reported in Table 3. Results show that for different z planes the proposed Semi-MriMOO clustering technique performs the best compared to other clustering techniques. The MS index values attained by the proposed technique are lower than those obtained by other recent techniques. The original brain images having multiple sclerosis lesions projected on different z plane like, $z_i$ ($i = 1, 2, 5, 10, 36, 72, 108$ and $144$) are shown in Fig. 5(a)–(h), respectively. The obtained best partitioning solutions (here the best partitioning is the one which corresponds to the minimum value of MS index over all the solutions of the final Pareto optimal front) provided by the Semi-MriMOO clustering technique for MR brain images having multiple sclerosis lesions projected on different z planes like $z_i$ ($i = 1, 2, 5, 10, 36, 72, 108, 144$) are shown in Fig. 6(a)–(h), respectively. These figures again illustrate visually that our proposed Semi-MriMOO clustering technique attains the near optimal partitionings for most of the image data sets. Obtained Pareto optimal fronts after execution of Semi-MriMOO clustering technique on different MR brain images with multiple sclerosis lesions for planes $z_i$ ($i = 1, 2, 5, 10, 36, 72$) are shown in Fig. 7(a)–(f), respectively. The obtained MS index values reveal that our proposed Semi-mriMOO clustering technique works well for both MR normal brain images and MR brain images with multiple sclerosis lesions. The experimental results show the usefulness of the proposed Semi-MriMOO clustering technique. Note that MCMOClust is
Fig. 4. Pareto optimal fronts obtained by Semi-MriMOO algorithm after execution on normal images of brain for different planes (a) z1, (b) z2, (c) z5, (d) z10, (e) z36, (f) z72, (g) z108 and (h) z144.

Table 3

Comparative analysis of obtained cluster number with MS index values for different clustering techniques applied on different images of brain having some multiple sclerosis lesions for different z planes. Here OR, OB denote the actual and obtained number of clusters, respectively.

<table>
<thead>
<tr>
<th>z plane</th>
<th>OR</th>
<th>MS for OB</th>
<th>MCMOClust</th>
<th>Fuzzy-VGAPS</th>
<th>Semi-MriMOO</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OB</td>
<td>FCM</td>
<td>EM</td>
<td>OB</td>
<td>MS</td>
</tr>
<tr>
<td>1</td>
<td>6</td>
<td>7</td>
<td>0.6512</td>
<td>0.6333</td>
<td>7</td>
</tr>
<tr>
<td>2</td>
<td>6</td>
<td>8</td>
<td>0.7201</td>
<td>0.7343</td>
<td>8</td>
</tr>
<tr>
<td>5</td>
<td>6</td>
<td>9</td>
<td>0.7211</td>
<td>0.7334</td>
<td>9</td>
</tr>
<tr>
<td>10</td>
<td>7</td>
<td>7</td>
<td>0.7245</td>
<td>0.7367</td>
<td>7</td>
</tr>
<tr>
<td>36</td>
<td>9</td>
<td>9</td>
<td>0.9089</td>
<td>1.012</td>
<td>9</td>
</tr>
<tr>
<td>72</td>
<td>11</td>
<td>9</td>
<td>0.7665</td>
<td>0.6567</td>
<td>9</td>
</tr>
<tr>
<td>108</td>
<td>10</td>
<td>9</td>
<td>0.7912</td>
<td>0.7025</td>
<td>9</td>
</tr>
<tr>
<td>144</td>
<td>9</td>
<td>9</td>
<td>0.7123</td>
<td>0.7634</td>
<td>9</td>
</tr>
</tbody>
</table>

A multiobjective based clustering technique recently developed for MR image segmentation. But our proposed Semi-MriMOO clustering technique outperforms this technique for segmenting different MR brain images. This proves the utility of using 10% labeled information in the framework of Semi-MriMOO clustering technique. Use of this labeled information helps the proposed technique to further fine-tune the obtained partitionings. Our proposed Semi-MriMOO also outperforms some popular image segmentation techniques like Fuzzy C-means (Bezdek, 1981) and Expectation Maximization (EM) (Jain et al., 1999).

Again to show the effectiveness of the proposed Semi-MriMOO, we have done region based comparative analysis on partitionings obtained by FCM, MCMOClust and Semi-MriMOO clustering techniques. From Table 2, we can easily see that the number of clusters determined by FCM, MCMOClust and Semi-MriMOO clustering techniques for MR normal image projected on z1 plane are $K = 8$, $K = 8$ and $K = 6$, respectively. Again minimum value of MS index attained by Semi-MriMOO is much better than those obtained by FCM and MCMOClust based approaches. In order to make some insightful conclusions, we have marked some regions in the partitionings obtained by Semi-MriMOO and FCM, respectively. Those are shown in Fig. 9(a) and (b), respectively. It can be easily observed that the regions A, C, G and I located in partitioning obtained by FCM (shown in Fig. 9(b)) are not proper as compared to the regions A, C, G and I located in partitioning obtained by Semi-MriMOO (as shown in Fig. 9(a)). Now consider region J (located in Fig. 9(a)). This is properly segmented in comparison with Fig. 9(b). Similarly, regions B, D, E, F, G and H as shown in Fig. 9(a) are also properly segmented in comparison with regions associated with Fig. 9(b). Similarly, we have marked 14 regions in the partitionings obtained by Semi-MriMOO and MCMOClust, respectively. Those are shown in Fig. 11(a) and (b), respectively. Regions marked as A, B, C, D, E, F, G, H, I, J, K, L, M and N are properly segmented in comparison with regions associated with Fig. 11(b).
Now, from Table 3, it can be easily revealed that the partitionings obtained by FCM, MCMOClust and Semi-MriMOO technique for MR brain image with multiple sclerosis lesions projected on z1 plane are having $K = 7$, $K = 7$ and $K = 5$ number of clusters, respectively. Again minimum value of MS index attained by Semi-MriMOO is much better than those obtained by FCM and MCMOClust clustering techniques, respectively. We have selected 22 regions from the partitionings obtained by FCM and Semi-MriMOO clustering techniques as shown in Fig. 10(b) and (a), respectively. Regions marked as A, B, C, D, E, F, G, H, I, J, K, L, M, N, O, P, Q, R, S, T, U and V in the partitioning obtained by Semi-MriMOO are shown in Fig. 10(a). These regions are properly segmented in comparison with regions marked as A, B, C, D, E, F, G, H, I, J, K, L, M and N in partitioning obtained by MCMOClust as shown in Fig. 12(b). After conducting the region based comparison, we can easily establish that the partitioning obtained by Semi-MriMOO technique is properly segmented in comparison with other existing clustering techniques.

4.1. Strengths and weaknesses of Semi-MriMOO clustering technique

The experimental results show that our proposed Semi-MriMOO clustering technique outperforms the clustering techniques like Fuzzy C-means (Bezdek, 1981), Expectation Maximization (EM) (Jain et al., 1999), multi-objective based MCMOClust technique (Saha & Bandyopadhyay, 2011), Fuzzy-VGAPS clustering technique (Saha & Bandyopadhyay, 2007). The uniqueness or strength of Semi-MriMOO clustering technique are as follows:

- Use of multiple centers per cluster helps the proposed technique to encode different shaped clusters well. Moreover this also helps to capture clusters having different sizes and densities. In MRI brain image data set several regions of varying sizes and densities exist. Thus automatic detection of these regions is a challenging task. The encoding used in the current paper helps to automatically detect these different shaped clusters well. The use of small sub-clusters for assignment of points to different clusters further helps to capture different shaped and different sized clusters which are always present in the MR brain images.
- Use of 10% labeled information helps the proposed algorithm to fine tune the obtained partitionings. In general all the existing techniques either are based on supervised concepts or unsupervised concepts. But the proposed technique is a combination of
these two different paradigms. Here first the entire unlabeled data is used for partitioning but later on the available small amount of supervised information helps to fine tune the obtained partitioning. This labeled information indeed helps the proposed approach to obtain the correct partition.

- Use of two different internal cluster validity indices which are based on some data properties helps the proposed technique to capture clusters having different shapes and sizes. While symmetry based cluster validity index helps to capture symmetrical shaped clusters well, the Euclidean distance based cluster validity index helps to capture some hyper-spherical shaped clusters. Thus the set of clusters captured by the proposed approach is a superset of the set of clusters captured by the existing partitioning techniques.

- Use of AMOSA helps to optimize the three objective functions simultaneously to determine a set of Pareto optimal solutions.
Fig. 8. Box plots of the obtained Minkowski score values corresponding to the nondominated solutions generated after execution of Semi-MriMOO technique on normal images of brain for different z planes (a) z1, (b) z2, (c) z5, (d) z10, (e) z36, (f) z72, (g) z108 and (h) z144.

Fig. 9. Comparison of partitioning obtained for MR normal brain images shown on z1 plane obtained by (a) Semi-MriMOO and (b) FCM algorithm.

Fig. 10. Comparison of partitioning obtained for MR Brain images with multiple sclerosis lesions shown on z1 plane obtained by (a) Semi-MriMOO and (b) FCM algorithm.
In general current literature on MOO supports the fact that AMOSA performs much better compared to other existing MOO based techniques. Thus use of AMOSA further helps to capture the optimal partitioning from these types of image data sets.

• Use of three different mutation operators helps to explore the search space efficiently and also to reach the global Pareto front in time.

But like any other existing approach of MR brain images, the current approach is also not flawless. There are some drawbacks of the current approach:

• Time complexity of the proposed technique is high due to optimization of multiple objective functions simultaneously.

• Archive initialization and obtaining dominance relationship are some time consuming processes. Thus some more efficient approach could have been explored to reduce the time complexity of non-dominance sorting. Use of some parallel approaches could also help in reducing the complexity of non-dominance sorting.

• Another drawback of AMOSA is the use of single linkage clustering approach to reduce the size of archive. Use of some unconstrained archive could help to avoid using time consuming clustering process.

• As the proposed technique needs to use some amount of labeled data as the supervised information, generating this labeled data would be difficult for some cases. Human annotators are required to generate the labeled data. This is both time consuming and cost sensitive process.

• Another drawback of the proposed technique is the use of same number of sub-clusters per cluster. It should vary depending on the size of clusters. For large cluster, number of sub-clusters should be more and in case of small sized cluster, number of sub-clusters should be less. Thus automatic determination of number of sub-clusters is also needed.

• In current work only two internal cluster validity index based objective functions are used. These objective functions capture two different data properties. But it can be easily extended to handle multiple objective functions capturing multiple data properties. The proposed approach can be easily extended to handle some connected structures from different data sets.

• Some parallel algorithms could be designed to accelerate the proposed Semi-MriMOO algorithm.

5. Conclusion

The current work deals with the application of a semi-supervised clustering technique for segmenting the MR brain images. Here a semi-supervised based clustering approach is developed using the search capability of a multiobjective simulated annealing based approach. In general the existing literature of MR brain image segmentation mostly used some supervised and unsupervised based techniques. In recent years a new paradigm named semi-supervised classification which is a half-way between supervised and unsupervised classification techniques is proposed. This new paradigm combines the usefulness of both supervised and unsupervised classification techniques. In recent years (Portela et al., 2014; Song et al., 2011), some single objective based semi-supervised clustering techniques are developed to segment the MR brain images. But in general it has been shown in the literature that multiobjective based approaches are more powerful com-
pared to single objective based techniques. Moreover multiobjective based approaches are also capable of detecting multiple solutions simultaneously on the final Pareto front. Depending on the user preference/domain specification, a particular solution can be picked up. Inspired by these observations, in the current paper we have developed a multi-objective based semi-supervised clustering technique. This is then applied for automatically segmenting the MR brain images.

Inspired by these observations, the current work focuses on developing a semi-supervised based approach for automatically segmenting the MR brain image data sets. These data sets contain clusters having different shapes and sizes; thus automatic determination of these structures from a given data set is very crucial. In the current approach i) a new encoding strategy to represent clusters ii) a new way of assigning image pixels to different clusters iii) new mutation operations iv) good combination of objective functions are used. Moreover the search capability of a popular simulated annealing based multiobjective based approach (AMOSA) is also used to simultaneously optimize multiple objectives. It has been found in the literature that AMOSA performs better than the existing other MOO based techniques for solving different benchmark problems. Thus the use of AMOSA as the underlining optimization technique further helps the proposed technique to capture optimal partitioning. The proposed approach is applied to retrieve the segmentation of normal MR brain images, and MR brain images with multiple sclerosis lesions, projected on different z planes. The segmentation results obtained by the proposed Semi-MriMOO clustering technique for different brain MR images are analyzed quantitatively and visually. Those are further compared with the results obtained by some recent clustering techniques like Fuzzy-C-means, Expectation Maximization, MCMOClust and Fuzzy-VGAPS. The proposed approach has many practical implications. It can be easily extended to further analyze some brain related diseases. As the proposed technique is capable of handling small clusters, it can be used to detect segments containing tumors. For example let us assume one normal brain image and a brain image with some tumors are given. We can first apply the proposed technique to automatically partition the given images. After that a thorough comparison of the obtained segments can easily identify the region containing the tumor. This has a large application in medical domain. As the accuracy of the proposed technique is much higher compared to the existing approaches, it can help in developing sophisticated imaging systems for medical domain. Now-a-days, another important area of medical research is the study of brain images of a patient having Alzheimer disease. Generally, Alzheimer affected brain has fewer tissue cells than a normal brain. The application of the proposed technique to automatically segment the brain image of the given patient would be the first stage of such kind of analysis. As the proposed system is capable of detecting small regions of high accuracy, the application of this system for detecting affected regions from brain images of the patient with this particular disease could be a new direction of research. In the next step, the obtained segmentation can be compared with the segmentation of normal brain images. This can provide us some insightful conclusions regarding the regions which need to be further studied to deal with such kind of diseases.

Several lessons are learnt during the experimental process of the proposed technique. It was observed that handling the MR brain images is a time-consuming process. As the segments present in the images are highly overlapping in nature, it would be better it we can some fuzzy rule based cluster assignments. Moreover as the sizes of the clusters vary over a range, fixing the number of sub-clusters per cluster is not a good idea. MR brain images contain clusters having different shapes, sizes and densities, thus in order to further improve the accuracy we need to automatically determine the number of sub-cluster centers per cluster using the search capability of AMOSA. In order to handle this variable length sub-cluster centers the proposed approach should be extended in future. The clustering process used in AMOSA to reduce the number of non-dominated solutions on the final Pareto front sometimes takes the maximum time. This further increases the complexity of the proposed approach. Use of unconstrained archive could be a good solution to get rid of this clustering process. Sometimes MR brain images contain some connected structures which are neither of symmetrical shaped or of hyperspherical shaped. In order to automatically detect them some connectivity based concepts could be used to develop some new cluster quality measures. The concepts like minimum spanning tree or relative neighborhood graph could be used to capture the connectivity. The addition of this objective function in the proposed approach could enrich the performance of the proposed approach. Selecting a single solution from the Pareto optimal front is another major concern, so we are also working towards the development of some novel methods to detect the single best solution from the final Pareto optimal front. Some clustering ensemble techniques could be used to combine the solutions obtained on the final Pareto front. Also, we would like to apply some more spatial information during segmentation of MR brain images. In the current study only intensity values are used as the features. In order to further improve the classification accuracy, some image related features could be used.

References


