A Fine Grained Parallel Fuzzy Segmentation Algorithm on Reconfigurable Mesh Computer

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Abstract

In this paper, we propose a fast parallel algorithm for data classification, and its application for Magnetic Resonance Images (MRI) segmentation. The presented classification method is based on a parallel fine grained fuzzy C-means algorithm. It is implemented on a polymorphic SIMD machine to sort out the different components of a brain image. The use of the massively parallel architecture in the classification domain and particularly for the fuzzy classification is introduced to improve the complexities of the corresponding algorithms. The proposed algorithm is assigned to be implemented on a massively parallel machine, which is the Reconfigurable Mesh Computer (RMC). The brain image of size (m x n) to be processed must be stored on the RMC of the same size, one pixel per Processing Element (PE). Some interesting results are obtained in terms of accuracy and efficiency analysis of the proposed method, thanks to the reconfiguration ability of the used computational model.

Keywords: Parallel Programming, Image Segmentation, Brain MRI image, Parallel Classification, Fuzzy C-means, Massively Parallel Algorithm
1. Introduction

Magnetic Resonance (MR) imaging has been widely used in brain exploration, due to its excellent soft tissue contrast, non-invasive behavior, high spatial resolution and easy slice selection at any orientation. However, accurate and fast tools for cerebral MR images processing are of great interest for many brain manipulations such as analysis, interpretation, diagnostics, and examination of the progression of brain disorders such as Alzheimer’s disease, multiple sclerosis or schizophrenia, and neurosurgical operation planning [1]. MRI segmentation can be considered as an Image processing problem or a pattern recognition one. Actually, the massively parallel architectures are known as the high performance computational models. They have demonstrated their effectiveness in terms of supporting the most complex parallel algorithms such as Fuzzy C-Means algorithms [1]. In [2], the authors have discussed the need of parallel methods to speed up clustering algorithms. They have implemented their parallel FCM on a parallel architecture named “Red hat based cluster”. This later is assigned to be implemented on a parallel computer of Single Program Multiple Data (SPMD) model using MPI tool. The proposed algorithms, in the literature, have been investigated as: Decision tree induction [3], Fuzzy rule based classifiers [4] [5], neural networks [6], association rules mining [7] and clustering [2] [8].

In this paper, we propose a massively parallel algorithm for fuzzy classification (fuzzy c-means) and its application to the MRI cerebral images. The proposed algorithm is assigned to be implemented on a SIMD structure which is an \((n \times n)\) massively parallel Reconfigurable Mesh Computer (RMC). The proposed fine grained parallel algorithm requires computational model of the same size \((n \times n)\) as the image, where each pixel \((i, j)\) is associated to it corresponding processing element PE \((i, j)\). To validate the proposed method, we use an emulation platform of the RMC architecture [9], [10] where the developed parallel program is performed.

This paper is organized as follows: Section 2 presents the parallel segmentation fuzzy c-means algorithm, and the obtained segmentation results are presented in section 3 where. The complexity analysis of the parallel fuzzy c-means program and its improvement are discussed in the next section 4. Finally, the last section gives some concluding remarks on this work.

2. Parallel Fuzzy Segmentation Algorithm

The computational model that will support the proposed Parallel FCM is the Reconfigurable Mesh Computer (RMC) of same size \(n \times n\) as the input MRI image. It is a massively parallel machine having \(n^2\) Processing elements (PEs) arranged on a 2-D matrix. It is a Single Instruction Multiple Data (SIMD) structure, in which each PE \((i, j)\) is localized in row \(i\) and column \(j\) and has an identifier defined by \(ID= n \times i + j\). Like any processor, each processing element (PE)
of the RMC can execute a set of instructions relating to the arithmetic and logical operations. The concerned operands can be the local data of a PE or the data arising on its communication channels after data exchange operation between the PEs. The PE can also carry out the bridge configurations in order to establish connections between two or more communication channels.
Fuzzy C-means (FCM) is a clustering technique that employs fuzzy partitioning such that a data point can belong to all classes with different membership grades between 0 and 1.
The aim of FCM is to find the final values of the C cluster centers (centroids) in the data set \(X = \{x_1, x_2, \ldots, x_N\}\) that minimize the following dissimilarity function:

\[
J(U, V_1, V_2, \ldots, V_C) = \sum_{i=1}^{C} J_i = \sum_{i=1}^{C} \sum_{j=1}^{N} u_{ij}^m d_{ij}^2(v_i, x_j)
\]

(1)

With the constraints:

\[
\sum_{i=1}^{C} u_{ij} = 1, \forall j = 1, \ldots, N
\]

(2a)

\[
0 < \sum_{j=1}^{N} u_{ij} < N, \forall i = 1, \ldots, C
\]

(2c)

Where:

- \(u_{ij}\): Membership of data \(x_j\) in the cluster \(V_i\);
- \(V_i\): Centroid of cluster \(i\);
- \(d_{(V_i, x_j)}\): Euclidian distance between \(i^{th}\) centroid \((V_i)\) and \(j^{th}\) data point \(x_j\);
- \(m \in [1, \infty]\): fuzzy weighting exponent (generally equals 2).
- \(N\): Number of data.
- \(C\): Number of clusters \(2 \leq C < N\).

To reach a minimum of dissimilarity function there are two conditions.

\[
V_i = \frac{\sum_{j=1}^{N} u_{ij}^m x_j}{\sum_{j=1}^{N} u_{ij}^m}, \quad u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{d_{ij}}{d_{kj}}\right)^{2(m-1)}}
\]

(3) (4)

The parallel algorithm, described in this section, is implemented in an RMC emulating framework [9] [10] using its XML based parallel programming language. The program code is performed on the MRI cerebral image as input data. Before its execution, we define in the initialization phase the number of classes by \(c = 3\). This means that the classes looked for in the image are the white matter, the gray matter and the cerebrospinal fluid. The background of the image is not considered by the algorithm. The proposed parallel algorithm is performed according to the following stages:
A. **Initialization procedure:**
   In this stage All the PEs of the RMC store in their data registers:
   - The gray level of the corresponding pixel \( x_j \)
   - The initial class centers \( V_i \)
   - The fuzzification parameter \( m \)

B. **For each iteration \( k \):**
   - The host broadcast the current class centers
   - Each PE computes the distances \( d(x_j, V_{i,k}) \) between its gray level \( x_j \) and the values of the \( c \) class centers. These values are stored in its \( c \) registers.
   - Each PE computes its membership degrees \( U_i \) to the clusters \( V_i \).
   - Each PE computes its local objective function \( J_i \).
   - All PEs participate in the parallel hierarchical summation to compute global objective function \( J \). This summation procedure was detailed in [10], it has a complexity of \( O(\log_2(n)) \) iterations. The Host PE will retrieve and retain the result of the summation \( (J) \).
   - The host computes the global cost function \( J \), the new class centers and sets up the iteration counter.
   - The host calculates the absolute value \( |J_k - J_{k-1}| \) and compares it with an arbitrary threshold \( S_{th} \).
     - If \( |J_n - J_{n-1}| < S_{th} \) then go to the end of procedure.
     - Else, loop the iteration \( k \).

C. **Membership decision :**
   - Labeling the different image components by assigning to each PE the index of the class to which it belongs.

3. **Results**

The input MRI image is the one of figure 1a); this image will be segmented to sort out its three components. The execution of the presented parallel program leads to the following results: The image of figure 1a) corresponds to a human brain slice, it is the original input image of the program. Figures 1b), 1c) and 1d) represent the three matters of the brain. They are named respectively the grey matter, cerebrospinal fluid and white matter.

In order to evaluate the effectiveness features of the proposed program, we focused the study on the dynamic convergence analysis of the method. To do so, we present four cases of study. For each case we use the same input MRI image, but the initial class centers are changed. The obtained results are presented as follows:

- In the first case, the initial class centers are arbitrarily chosen as: \( (c_1, c_2, c_3) = (1, 30, 255) \). The algorithm converges to the final class centers \( (c_1, c_2, c_3) = (27.96, 102.39, 147.53) \) after 14 iterations.
In the second case, the initial class centers are arbitrarily chosen as: \((c_1, c_2, c_3) = (1, 2, 3)\). The algorithm converges to the same final class centers as in the first case, \((c_1, c_2, c_3) = (27.96, 102.39, 147.53)\), after 21 iterations.

In the third case, the initial class centers are arbitrarily chosen as: \((c_1, c_2, c_3) = (140, 149, 150)\). The algorithm converges to the same final class centers as in the first case, \((c_1, c_2, c_3) = (27.96, 102.39, 147.53)\), after 17 iterations.

In the fourth case, the initial class centers are chosen, using the a preprocessing parallel histogram computation procedure of [21, 22] that orients the class centers towards the histogram modes of the image. In this case, the initial values of the class centers are: \((c_1, c_2, c_3) = (23, 102, 150)\). For this case, we notice that the algorithm converges to the same final class centers as in the first case, \((c_1, c_2, c_3) = (27.96, 102.39, 147.53)\), after only 8 iterations.

![Figure 1. PFCM segmentation of an MRI brain image](image)

To illustrate this analysis we use the following figures 4, 5, 6 and 7, to show the curves of the different data, respectively, of the four cases and 5. Theses curves represent the dynamic changes of each class center.
Figure 4. Case 1: Dynamic changes of the class centres starting from values $(c_1, c_2, c_3) = (1, 30, 255)$

Figure 5. Case 2: Dynamic changes of the class centres starting from values $(c_1, c_2, c_3) = (1, 2, 3)$

Figure 6. Case 3: Dynamic changes of the class centres starting from values $(c_1, c_2, c_3) = (140, 149, 150)$

Figure 7. Case 4: Dynamic changes of the class centres starting from values $(c_1, c_2, c_3) = (23, 102, 150)$

4. Complexity Analysis

As shown in table 1, we can conclude that the proposed PFCM algorithm is more accurate than the PCM one. But its complexity remains greater than the one obtained in [13] and equal to these in [14].

<table>
<thead>
<tr>
<th>Reference</th>
<th>Algo.</th>
<th>Architecture</th>
<th>Bus width (bit)</th>
<th>Processors</th>
<th>Time complexity</th>
</tr>
</thead>
<tbody>
<tr>
<td>[13]</td>
<td>PCM</td>
<td>RMESH</td>
<td>$O(\log_2 N)$</td>
<td>$N$</td>
<td>$O(kM + \text{log}_2 \frac{N}{k} \text{ log}_2 N)$</td>
</tr>
<tr>
<td>[14]</td>
<td>PCM</td>
<td>RMESH</td>
<td>$O(\log_2 N)$</td>
<td>$N$</td>
<td>$O(kM + k \log_2 N)$</td>
</tr>
<tr>
<td>This paper</td>
<td>PFCM</td>
<td>RMESH</td>
<td>$O(\log_2 N)$</td>
<td>$N$</td>
<td>$O(kM + k \log_2 N)$</td>
</tr>
</tbody>
</table>
5. Conclusion

In this paper, we have presented a method for parallelizing the fuzzy c-means classification algorithm and its implementation on a massively parallel reconfigurable mesh computer. An application of this algorithm to the MRI images segmentation was considered. The elaborated program was performed on the reconfigurable mesh computer emulator. The obtained results show that, in little number of iterations, the algorithm converges to the same final class centers whatever their starting values. This is to proof its accuracy comparing to the well known C-mean algorithms. Hence, the parallel computation method is proposed essentially to reduce the complexity of the fuzzy clustering algorithms. Also it was shown that to enhance the effectiveness of this work, it is useful to improve the complexity of this algorithm by avoiding random initializations of the class centers.

References


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