Application of Modular Fuzzy Hypersphere and Hyperline Segment Neural Network for Handwritten Character Recognition

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This paper describes modular fuzzy hyperline segment and modular fuzzy hypersphere neural network with its learning algorithm, which are extensions of fuzzy hyperline segment neural network (FHSNN) and fuzzy hypersphere neural network\(^1\). The modular neural networks (MNN) offer higher degree of parallelism. Each module in MNN is exposed to the pattern of only one class and trained without overlap test and removal, leading to reduction in training time. Hence, each module captures peculiarity of only one particular class. Due to decrease in training time, the algorithm can be used for voluminous realistic database, where new patterns can be added on fly. The MNN is found superior in terms of generalisation and training time with equivalent testing time.

Keywords: Modular fuzzy hypersphere; Modular neural network; Training time

INTRODUCTION

The fuzzy neural networks (FNNs) have become very popular and being used in the pattern recognition applications. Basically, there are two main training strategies employed by FNNs, supervised and unsupervised learning. In supervised learning, class labels are provided with input patterns and the decision boundary between classes that minimizes misclassification is achieved. It is often referred to as pattern classification problem. In unsupervised learning, training patterns are unlabelled and cluster of the pattern are formed with suitable similarity measures, which is referred as clustering problem.

Many papers using FNN are reported on studies of pattern classification and clustering. Kwan and Cag have proposed four layer feed forward unsupervised FNN. Kulkarni and Sontakke\(^4\) have modified FNN to work under supervised environment, which is further extended by Patil, et al\(^5\), using selective aggregation operators. The modified FNN uses similarity measure and if the pattern is similar to already learned patterns of that class, then only it is accommodated by the neuron, otherwise new neuron of the pattern class is constructed. Patrick Simpson\(^5\) proposed supervised fuzzy min-max neural network (FMN) that utilizes fuzzy sets as pattern classes in which each fuzzy set is union of fuzzy set hyperboxes. Gabrys and Bargiela\(^6\) have proposed general fuzzy min-max neural network (GFN) for clustering and classification, which is an extension of FMN, with a fusion of supervised and unsupervised learning. Kulkarni, et al\(^1\) have proposed fuzzy HLS neural network (FHLSSN) and its performance is found superior than the FMN algorithm. Patil, et al\(^7\) have modified the membership function of FHLSSN algorithm that gives improved results. Patil, et al\(^8\) have proposed general fuzzy hyperline segment neural network (GFHLSNN), which is an extension of FHLSSN with a fusion of supervised and unsupervised learning.

In this paper, the MNN algorithms are presented, which are applied for rotation invariant handwritten character recognition. Ring and Zernike features are used as feature extraction methods. Its performance is also tested using Fisher Iris database. The MNN is found superior in terms of generalisation and training time with equivalent testing time.

THE TOPOLOGY

During training phase, \(K\) modules of FHLSSN or FHSNN are used, if database consists of patterns of \(K\) number of classes, as shown in Figure 1, in which each module is a simple two layer feed forward neural network that grows adaptively to meet the demands of the problem.

The first layer accepts the \(n\)-dimensional input pattern as it consists of \(n\) processing elements, one for each dimension of the pattern. Second layer consists of \(m\) processing nodes that are constructed during training. The connections from each first to second node represents the end points for that dimension, for a particular hyperline segment (HLS) or centre point and radius for a particular hypersphere. These are stored in a matrix for \(K\) modules that are present for \(K\) number of classes. Each module is trained with patterns of that class to which it represents. Hence, each module learns peculiarities of a single class.
Table 4: Timing analysis

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Training Time, s</th>
<th>Recall Time/Pattern, s</th>
<th>HBs/HSs/FSNs/HLSs</th>
</tr>
</thead>
<tbody>
<tr>
<td>FNN</td>
<td>1382.500</td>
<td>1.4252</td>
<td>992</td>
</tr>
<tr>
<td>MFNN</td>
<td>702.610</td>
<td>1.3848</td>
<td>963</td>
</tr>
<tr>
<td>FMN</td>
<td>435.450</td>
<td>1.4986</td>
<td>851</td>
</tr>
<tr>
<td>MFHSNN</td>
<td>200.320</td>
<td>0.3840</td>
<td>985</td>
</tr>
<tr>
<td>FHLSNN</td>
<td>42.461</td>
<td>0.5530</td>
<td>801</td>
</tr>
<tr>
<td>MFHLSNN</td>
<td>88.450</td>
<td>0.4930</td>
<td>858</td>
</tr>
</tbody>
</table>

respectively, to get 100% recognition rate for set 1. It can be observed that the MFHLSNN algorithm is computationally efficient as compared to the FNN, FMN and FHSNN algorithms.

CONCLUSIONS

The MNN has ability to learn the patterns faster than FNN, FMN, MFMN, FHSNN and FHLSNN because it creates/expand HLSs/HSs without any overlap test and its removal, which is a substantial overhead in the FMN, FHLSNN and FHSNN algorithms. Recognition rates with ring features are superior than Zernike features. The MFHLSNN algorithm gives better recognition rates for all the sets as compared to other algorithms. It can be observed that the MFHLSNN algorithm is computationally efficient as compared to the FNN, FMN and FHSNN algorithms. Thus, it can be used in voluminous realistic database recognition purposes where less training time is the prime demand.

REFERENCES


