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An Adaptive FCM with Incremental Learning For Human Activity Recognition

K. Nanthini
Student, Department of CSE
Kongu Engineering College
Perundurai, Erode-638052
Tamil Nadu, India

R. Manjula Devi
Assistant Professor, Department of CSE
Kongu Engineering College
Perundurai, Erode-638052
Tamil Nadu, India

Abstract: **Fuzzy Logic is a multi-valued logic where the truth values lies between zero and one. In any system there are two phases namely the training (learning) phase and the testing phase. In the training or learning phase the data samples are given as input to the system for training the fuzzy system, to classify the inputs according to the characteristics of the problem. In the testing phase the data instances are given as input to check whether the system classifies correctly. To improve the training speed of the fuzzy system the number of instances introduced to the epochs must be adjusted. The fuzzy system, when introduced with a set of new input patterns, the fuzzy system must be able to easily learn additional information from new samples to improve its recognition accuracy and must be independent of the previously trained data. This work aims to improve the training speed of the network, where, Adaptive Skipping method is applied. Thus the number of instances introduced to the epochs for training the fuzzy system is reduced. To train the new input patterns, Incremental Adaptive Fuzzy C-Means Learning approach is used. This method does not require the whole dataset with old and new dataset to train the fuzzy system but trains only the new data with previously used conditions. So, the system can easily adapt to the new input patterns and can also reduce the training time. Thereby the overall training time is reduced and new input samples are trained easily.**

Keywords: Clustering analysis, Fuzzy Clustering, Fuzzy C-Means (FCM), Human Activity Recognition, Incremental Learning.

I.INTRODUCTION

Artificial Neural Network (ANN) is a mimic of human brain. Every ANN is composed of collection of neurons arranged in layers namely input layer, hidden layer and output layer. GA is a search heuristic that mimics the process of natural selection. This heuristic is routinely used to generate useful solutions to optimization and search problems. Genetic algorithms are used in the applications like bioinformatics, phylogenetics, computational science, engineering, economics, chemistry, manufacturing, arithmetic, physics, pharmacometrics and other fields. FL is a multi-valued logic where the truth values lies between zero and one. Here FL is used for classification purpose. Fuzzy Classification is the process of grouping elements into a fuzzy set whose membership function is defined by the truth value of a fuzzy propositional function. Classification is the process of grouping individuals having the same characteristics into a set. A classification corresponds to a membership function that indicates whether an individual is a member of a class.

Every system has two phases namely the training phase and the testing phase. The training phase is used to train the fuzzy system by making the system learn from the experience to perform a task. At the testing phase, the fuzzy system is given with a data instance and processes it to produce an output. If the fuzzy system has correctly learnt, it should be able to generalize and produce the actual output.

Compared to the testing phase, the training phase is important because the fuzzy system can acquire the knowledge from this phase to enhance its performance. The factors that are to be considered during the training phase include the time taken to train the fuzzy system and the ability to train the new incoming data. The time taken for training the fuzzy system with the large dataset may consume large amount of time. This can be resolved using adaptive skipping method. In the real-time scenario, the data samples may arrive periodically. So, the fuzzy system must be able to gain knowledge from the new data without accessing the new data and without losing its previously acquired knowledge. This can be done by using the incremental learning approach.

Adaptive skipping (AS) method is used to speed up the training time with maintaining the generalization process. This method is done by skipping the correctly classified samples for specific number of epochs, where the training time of the large dataset could be reduced.

An incremental learning (IL) algorithm is defined as the acquisition of new input samples periodically. By using this incremental algorithm, the fuzzy system has the ability to learn from new information whenever the information becomes available. A fuzzy system should be able to use any new training data to improve its performance, without using the previous data. This can also be used to accommodate new classes of data that are introduced with the new data.

In incremental learning, whenever a new input is given to the system, the new inputs are trained without affecting the previous knowledge. To train the new inputs the conditions used in training the previous data are used to improve the training speed of the fuzzy system. The adaptive method is incorporated in the incremental method where the numbers of instances are reduced to speed up the training of the fuzzy system.

The rest of the paper is organized as follows. In Section 2, related works are reviewed. Section 3 describes the Problem Definition. Section 4 elaborates the proposed work. Section 5 deals with the results and the discussions employed on Human Activity Recognition dataset. Finally Section 6 concludes the paper and gives the future work that can be incorporated in the FCM for human recognition system.

II.RELATED WORK

A. Incremental Learning

Polikar et al (2001) proposed an algorithm for incremental training of neural network (NN) pattern classifiers. The proposed algorithm enables supervised NN paradigms, such as the multilayer perceptron (MLP), to accommodate new data, including examples that correspond to previously unseen classes. Furthermore, the algorithm does not require access to previously used data during subsequent incremental learning sessions, yet at the same time, it does not forget previously acquired knowledge. The incremental learning algorithm as one that meets the following criteria as 1.It should be able to learn additional information from new data, 2.It should not require access to the original data, used to train the existing classifier, 3.It should preserve previously acquired knowledge, 4. It should be able to accommodate new classes that may be introduced with new data.

Muhlbaier et al (2009) proposed an algorithm that describes an efficient incremental learning of multiple new classes with significantly few classifiers. To do so, the algorithm introduced dynamically weighted consult and vote(DW-CAV), a novel voting mechanism for combining classifiers: individual classifiers consult with each other to determine which ones are most qualified to classify a given instance, and decide how much weight, if any, each classifier's decision should carry.

He et al (2011) proposed an adaptive incremental learning framework for the stream of data that appear over a specific amount of time. This algorithm is capable of learning from continuous raw data, accumulating experience over time, and using such knowledge to improve future learning and prediction performance.

Wong et al (2011) proposed an algorithm on Radial Basis Function (RBF) with incremental learning method based on orthogonal least square method. It is designed to accommodate new information without retraining the initial network. In our proposed method, the selection of the regressors for the new data is done locally, hence avoiding the expensive reselecting process. In addition, it accumulates previous experience and learns updated new knowledge of the existing groups to increase the robustness of the system.

Pang et al (2011) proposed an incremental algorithm for incrementally learning the threshold-based classifiers. Threshold-based classifier is a simple and powerful pattern classification tool, which is frequently used in applications of object detection and recognition. A threshold-based classifier is associated with a unique one-dimensional feature. A properly selected threshold and a binary sign corresponding to the feature govern the classifier. Here, the learning process is generally done in a batch manner. The batch algorithms are not suitable for sequentially incoming data because of the limitation of storage and prohibitive computation cost. To deal with sequentially incoming data, this proposed incremental algorithm is used.

Cavalin et al (2012) proposed the LoGID (Local and Global Incremental Learning for Dynamic Selection) framework, the main goal of which is to adapt hidden Markov model-based pattern recognition systems during both the generalization and learning phases. Given that the base line system is composed of a pool of base classifiers, adaptation during generalization is performed through the dynamic selection of the members of this pool that best recognize each test sample. This is achieved by the proposed K-nearest output profiles algorithm, while adaptation during learning consists of gradually updating the knowledge embedded in the base classifiers, by processing previously unobserved data. This phase employs two types of incremental learning: local and global. Local incremental learning involves updating the pool of base classifiers by adding new members to this set. The new members are created with the Learn++ algorithm. Global incremental learning, in contrast, consists of updating the set of output profiles used during generalization process.

Lu et al (2012) proposed an Incremental Complete Linear Discriminant Analysis (ICLDA) method which can accurately update the discriminant vectors of Complete Linear Discriminant Analysis (CLDA) when new samples are inserted into the training set. The complete linear discriminant analysis algorithm has been proven to be an effective tool for face recognition. The CLDA method can make full use of the discriminant information of the training samples. However, the implementation of CLDA may not suitable for incremental learning problem. Thus, the ICLDA approach has been used for incremental learning ability.

B) Clustering Algorithms

Data clustering is the process of dividing data elements into classes or clusters so that items in the same class are as similar as possible, and items in different classes are as dissimilar as possible. **Fuzzy clustering** is a class of algorithms for cluster analysis in which the allocation of data points to clusters is fuzzy. In fuzzy clustering, every point in the cluster has a degree to indicate its importance rather than belonging to just one cluster.

Bezdek proposed Fuzzy C-means that is applicable to a wide variety of geostatistical data analysis problems. This method generates fuzzy partitions and prototypes for any set of numerical data. These partitions are useful for corroborating known substructures or suggesting substructure in unexplored data. The clustering criterion used to aggregate subsets is a generalized leastsquares objective function. Features of this program include a choice of three norms (Euclidean, Diagonal, or Mahalonobis), an adjustable weighting factor that essentially controls sensitivity to noise and acceptance of variable number of clusters.

Pedrycz (1998) proposed a Conditional Fuzzy Clustering in the Design of RBF Neural Networks. This paper deals with the design of the neural networks, especially with the layer composed of RBF's, using the techniques of fuzzy clustering. The main idea of conditional clustering whose objective is to develop clusters preserving homogeneity of the clustered patterns with regard to their similarity in the input space as well as their respective values assumed in the output space.

Pedrycz (2008) developed a concept of dynamic data granulation realized in presence of incoming data organized in the form of so-called data snapshots. For each of these snapshots a structure is reveals by running fuzzy clustering. The proposed algorithm of adjustable FCM exhibits a number of useful features which directly associate with the dynamic nature of the underlying data: (a) the number of clusters is adjusted from one data snapshot to another in order to capture the varying structure of patterns and its complexity, (b) continuity between the consecutively discovered structures is retained, viz the clusters formed for a certain data snapshot are constructed as a result of evolving the clusters discovered in the predeceasing snapshot. The cluster splitting is guided by conditional FCM while cluster merging involves two neighbouring prototypes. The criterion used to control the level of information granularity throughout the process is guided by a reconstruction criterion which quantifies an error resulting from pattern granulation and de-granulation. Numeric experiments provide a suitable illustration of the approach.

III.PROBLEM DEFINITION

The limitation of the existing methods is that the training phase consumes a large amount of time for large datasets which may affect the training rate. In order to improve the speed of the training in the training phase the adaptive skipping method is introduced. This adaptive skipping method skips the correctly clustered samples for specific number of iterations, which improves the training speed without affecting its generalization accuracy.

When a new set of input patterns are introduced to the present network, all the input patterns are retrained instead of training only the new input patterns. In order to retrain the whole network, the Incremental training is employed. The Incremental Learning process does not require the previously trained dataset to train the newly incoming data but trains the new data with the previously used conditions for clustering and is capable of adding new activities.

The training speed can be improved using the adaptive skipping method and the newly introduced dataset must be trained without retraining the whole dataset. The Adaptive FCM with Incremental Learning is used to improve the training time and to train the new dataset without using the previously trained dataset but with the previously used conditions to cluster the data instances.

IV.PROPOSED WORK

The paper proposes the fuzzy clustering with incremental learning capability for the daily human activities such as sitting, standing, walking, walking upstairs, walking downstairs and lying. The activities recorded for the dataset are proposed in [3]. In hard clustering the data samples can be assigned to only one cluster but in fuzzy clustering a single data sample may correspond to more than one cluster. In fuzzy clustering method each data point in the cluster is given with a membership degree to mark its importance in the cluster. The most widely used clustering algorithm is Fuzzy C-Means (FCM) algorithm which is used to cluster the data instances initially. The Adjustable Fuzzy Clustering (AFC) algorithm is employed for the human activity recognition for incorporating the incremental learning capability in the Human Activity Recognition system.

A) Adjustable Fuzzy Clustering

The Adjustable Fuzzy Clustering (AFC) is an improvement over the FCM algorithm. The Human Activity Recognition dataset is initially clustered using the FCM algorithm. The main limitation of the FCM algorithm is the lack of ability to learn incrementally. To make the algorithm learn incrementally the AFC algorithm uses the previously used conditions to cluster the new data of the existing activities into the existing clusters or the new clusters are formed in the case of new activities.

In the Adjustable Fuzzy Clustering (AFC) the data samples are partitioned according to the activities to which they belong. Each activity containing a particular numbers of samples are clustered using the Fuzzy C – Means algorithm and the corresponding cluster centres, degranulation samples and the reconstruction error are calculated as described as mentioned below.

The AFC uses the centres for calculating the degranulation samples to find the reconstruction error. The reconstruction error is used to find whether the clusters are to be merged or to be spitted.

$$\mathrm{deg}=\sum_{h=1}^{H} u_h(w)^T v_h / \sum_{h=1}^{H} u_h(w)^T \tag{1}$$

where $u_h(w)$ is the membership degree of the data samples in the cluster, T is the fuzzifier value, H is the total number of clusters and v_h is the centre of the corresponding cluster.

The reconstruction criteria is calculated using difference between the degranulation samples and the data samples.

$$V_h = \sum_{w \in data} |w\text{-}\mathrm{deg}| \tag{2}$$

where w is the data samples and deg is the degranulation sample calculated for the corresponding data sample in the cluster.

The condition for the clusters to be merged or spitted is made according to the reconstruction criteria. If the reconstruction error is greater than the threshold value i.e., $\max(V_h)$>threshold value the cluster are spitted otherwise the clusters are merged when the reconstruction criteria is less than the threshold value i.e., $\max(V_h)$<threshold value. The new cluster centres and the membership degree for each data sample in the clusters are recalculated.

The new data samples can be of two types where the new data belong to the same activities or the data belong to the new activities. Whenever a new data sample of the existing activities are introduced to the Human Activity Recognition system the data samples are grouped to the corresponding cluster using the previous conditions such as centre and weight vectors. The second case corresponds to the data belonging to the new activity which is newly introduced. The new data for the new activity are clustered with the initial conditions as in FCM and the corresponding centres, membership functions, degranulation samples and the reconstruction criteria are calculated.

B) Overall Algorithm for Adaptive Adjustable Fuzzy Clustering

Step 1: Partition the dataset instances according to the activities to which they belong
Step 2: Apply the Fuzzy C – Means algorithm to cluster the dataset
Step 3: During the iteration process for each data instance a skipping factor is calculated
Step 4: If data sample is clustered correctly the skipping factor is incremented by one and respective data instance is skipped for that one iteration
Step 5: Otherwise the incorrectly grouped data instance is introduced to the next iteration
Step 6: Calculate the centre for the clusters and the membership degree of the each data sample in the cluster initially
Step 7: Calculate the degranulation samples and reconstruction criteria
Step 8: According to the degranulation sample the splitting mechanism and the merging mechanism are employed.
Step 9: If a new data sample is introduced belonging to the existing activity that data sample is grouped to the cluster using the previous conditions such as centre and membership function
Step 10: If the new data sample belonging to the new activity is introduced then the step 2 - 8 are followed

Adjustable Fuzzy Clustering is used to find the centres by clustering the data samples. The centres found in the AFC are used in the pattern layer of the Probabilistic Neural Networks as explained below.

C) Probabilistic Neural Networks

The Probabilistic Neural Network (PNN) consists of four layers namely the input layer, pattern layer, summation layer and decision layer. The working of the layers are as followed.

Input Layer : In the input layer the input is acquired from the user and forwarded to the pattern layer.

Pattern Layer : The pattern layer contains the neurons equal to the number of centres calculated using the AFC. This layer dot products the input with the centre obtained from the AFC instead of introducing the whole training data instances as the weights to this layer.

$$y_{m,k} = \exp[(x * w_{m.k} - 1)/\sigma^2] \qquad (3)$$

where x is the input from the user $w_{m,k}$ is the centre obtained from the AFC, m is the number of classes, k is the kth centre of the class and σ is the smoothing factor calculated as follows.

$$\sigma = 1/M \sum_{m=1}^{M} \frac{\sum_{i=1}^{K_m-1} \sum_{j=i+1}^{K_m} |w_{m,i} - w_{m,j}|}{(K_m-1)(K_m-2)} \qquad (4)$$

where M is the total number of classes and K_m is the total number of centre neurons belonging to one class, $w_{m,i}$ and $w_{m,j}$ are the centre neurons belonging to the particular class.

Summation Layer : The Summation Layer consists of the neurons equal to the number of classes present in the dataset. The summation layer neuron summates the values from the pattern layer neurons that belong only to the class.

$$z_m = \frac{1}{(2\Pi)^{L/2}\sigma^L} \frac{1}{K_m} \sum_{k=1}^{K_m} y_{m,k} \qquad (5)$$

Where L is the dimension of the data set $y_{m,k}$ is the output of the summation layer.

Decision Layer : The decision layer consists of a single neuron which gets the inputs from the summation layer and decides to which the input neuron must be classified to.

$$\text{decision} = \arg\max_{m}\{p_m z_m | m=1,...,M\} \qquad (6)$$

Where p_m is the probability of the input belonging to one class where the value taken is 1/6.

The classification of the input pattern to a particular class is done through the Probabilistic Neural Network with the use of Adjustable Fuzzy Clustering technique to reduce the memory usage of the system and to reduce the computation speed of the human activity recognition system. Thus the system is capable of training the samples in a reduced time to improve the training speed of the human activity recognition system.

IV.RESULT AND DISCUSSION

The Adaptive Adjustable Fuzzy Clustering with Incremental Learning algorithm is used for the Human Activity Recognition dataset taken from the UCI machine repository. The data set consists of features using which the data samples are grouped into six clusters namely sitting, standing, walking, walking upstairs, walking downstairs and lying.

A. Five-Fold cross validation

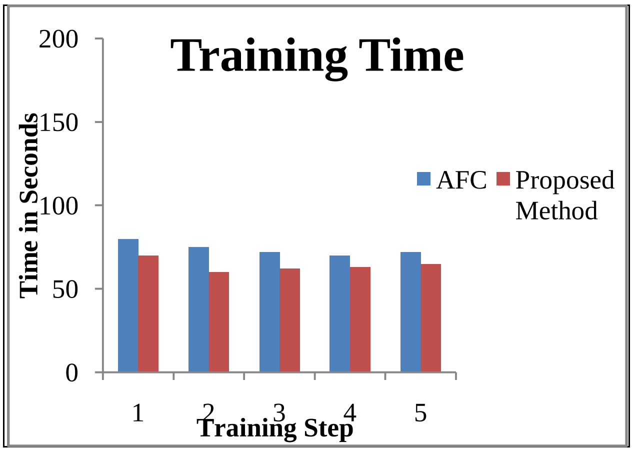

Fig.1

In this cross validation method the dataset is divided into five partitions say p_i where i correspond from 1 to 5. During the first validation process partitions p_1 to p_4 are used for training the human activity recognition system and the p_5 partition is used for testing the system. For the next validation process partitions p_1 to p_3 and p_5 are taken for training and the partition p_4 is used for testing. Likewise the iterations are continued for five times taking four partitions for training the system and the remaining one partition for testing the human activity recognition system.

The Fig.1 and Fig.2 shows the training and the testing time of the human activity recognition system respectively with the existing Adjustable Fuzzy Clustering method and the proposed Adaptive Adjustable Fuzzy Clustering. The results show that the training time and the testing time of the Human Activity Recognition system has been improved by using the Adaptive Skipping method.

V.CONCLUSION AND FUTURE WORK

Thus the regular human activities have been classified into six classes using the Adjustable Fuzzy Clustering algorithm. Development of any system consists of two phases namely the training phase and testing phase as described in the introduction. The training phase of any system consumes considerably large amount of time compared to the testing phase. The Human Activity Recognition system is incorporated with the incremental learning ability with the use of AFC algorithm where the training is also reduced to improve the performance of the overall system. The training time is improved using the adaptive skipping method without degrading the generalization accuracy. The results obtained are shown in the results and discussions section which are satisfactory.

The future work of this paper is to incorporate the Adaptive Adjustable Fuzzy Clustering for various datasets. This algorithm can also be tested using the unsupervised learning datasets to know the performance of the algorithm where the clustering can be used to cluster the data samples.

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