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Improved Entropy based Fuzzy Classifier in Handwritten Gesture Recognition

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Abstract

Many Fuzzy classifiers have been developed to identify the handwritten gestures. Handwritten gestures various from person-to-person and with mood and time .Since these rule-based classifiers which are incremental in nature, a large number of rules are generated for unseen inputs.Thus, the size of the rule base rises exponentially ,further introducing rule overfitting and misclassification error. The problem of rule base explosion has been handled by an Entropy based classifier which keeps only most promising rules in the rule base ,based on the threshold value.In this paper,we have shown experimentally that the efficiency of this entropy based classifier can be further improved by considering more linguistic variables or linguistic values or a combination of both..

Introduction

Research on gesture recognition has many motivations, most of which are related to improving the interface between computers and humans. In order to convey a message to a recipient ,human make gestures ,such as waving hand. These gestures can be used to communicate with a computer system ,if it can identify these gestures. Similarly, handwritten gestures can be used to communicate with pen-based devices like PDAs by associating commands with each gesture. If the pen-based interface device can identify and recognize a set of gestures, it can respond appropriately. Thus a handwritten gesture recognition system helps to bridge the gap between human and computer communication.

Classification is a data mining function that assigns items in a collection to target categories or classes. The goal of classification is to accurately predict the target class for each case in the data. Classification techniques has its roots in many applications areas, and have become the basic tool for almost any pattern recognition task. Rule based pattern classification algorithms may also give such additional insight. As the name suggests, rule based algorithms consists of a set of rules that perform the mapping from feature to class space. Since the rules are typically written in an “if-then” fashion, they can be inspected by the user which might lead to some useful findings.The main problem with the classifier is that it needs a large data sample to predict the resultant class efficiently.It is practically difficult to have such large number of data samples for all the classes.Therefore, an incremental or evolving classifier[1] is required which considers unseen classes and integrates them in the classification process .This evolving classifier has the advantage that it is dynamic in nature and the recognition system starts to learn from scratch which allows adding unseen classes without destroying the already learned ones.The disadvantage of the above mentioned incremental classifier is that as the recognition system recognizes classes, the size of the rule base is expanding exponentially.

Gesture recognition system has found its roots in many applications such as visual surveillance.To make gesture classification tractable for machine learning, and to improve classification performance it is an essential requirement to select good features. *Bayesian* scores and *Shannon's entropy* are available for columns that contain discrete and discretized data. In this work, we are using Shannon’s Entropy Method. By comparing the features of an unknown gesture with the existing ones stored in the database, it is possible to identify the type of the gesture examined.

Abdullah Almaksour Eric Anquetil [1] has proposed a hand written gesture recognition system which is able to efficiently classify basic signs gestures for handwritten gesture recognition application. For gesture classification and recognition, algorithms as well as fuzzy logic sets are used. A self adaptive Handwritten Gesture Classifier suffers from problems of rules overfitting, because there is a great possibility of addition of new rules in rule set for unseen inputs and most of the times these new rules are distinguished from the existing one. Ultimately, we get a huge set of rules which suffers from the problem of overfitting and rule base explosion. In this work, we have used an ANFIS *(Adaptive-Network-based Fuzzy Inference System)* [2], [3] method from Fuzzy Logic [4] for the task of classification. Fuzzy rule-base classification systems tend to generate simple if-then rules that can thus also be interpreted by the user. But rule-base classifiers are prone to rule explosion. Since the number of generated rules increases exponentially with the number of attributes and with the number of partitions for each attribute, the basic fuzzy classifier suffers (as do many other approaches) from the curse of dimensionality, hence giving rule bases that contains large numbers of rules.However , it is possible to arrive at a compact yet well performing rule base through an optimisation approach

Section 2 gives a brief description of the related work . Data collection is explained in section 3. Section 4 discusses the proposed approach and experimental results. Section 5 provides the conclusion and future work.

Background and related work

Abdullah Almaksour [1] has built an evolving fuzzy classifier for handwritten gesture recognition system which is built from scratch and starts learning only from few data.The incremental learning algorithm is given in [15].It is specified by the following criteria :

- it should be able to learn additional information from new data
- it should not require access to the original data that is used to train the classifier
- it should preserve the previously acquired knowledge; i.e; it should not suffer from significant loss of learned knowledge.
- it should also be able to able to integrate new unseen classes that gets introduced with new data.

The presented paper combines an incremental clustering algorithm with a fuzzy adaptation method in [1], in order to learn and maintain the handwritten gesture recognition system. The self-adaptive nature of this system allows it to start its learning process with few learning data, to continuously adapt and evolve according to any new data, and to remain robust when introducing a new unseen class at any moment in the life-long learning process. The format of the fuzzy implications and the reasoning algorithm are used, for the method of identification of a system using its input-output data, as shown in [5]. The learning procedure and its architecture underlying ANFIS is presented in [6].It is a fuzzy inference system implemented in the framework of adaptive networks. Takagi-Sugeno (TS) is based on a novel learning algorithm [7] that recursively updates TS model structure and parameters.It applies new learning concept to the TS model called Evolving Takagi-Sugeno model (ETS). An online evolving fuzzy Model (efM) approach [8] to modeling non-linear dynamic systems, in which an incremental learning algorithm is used to build the rule-base. The rule-base is evolved when "new" information is available by creating a new rule or deleting an old rule depending upon the proximity and potential of the rules, and the maximum number of rules to be used in the rule-base. Various works have been done using maximum entropy approach [9], [10], [11].In [16] , a self adaptive gesture fuzzy classifier is built which uses maximum entropy model for preserving most promising rules and removing redundant rules from the rule set, based on interestingness.But , this classifier has considered only three features .As we increase the number of linguistic variables or number of linguistic values or a combination of both, the accuracy will further increase.

In Statistical modeling, given the sample, which represents an incomplete state of knowledge about the process, the modeling problem is to parlay this knowledge into a representation of the process. After that, we can use this representation to make predictions about the future behavior about the process.

Maximum Entropy Model

There are different types of fuzzy information measures. A number of methods have been proposed to combine the fuzzy set theory and its application to the entropy concept for fuzzy information measurements. The entropy concept, as a relative degree of randomness, has been used to measure the fuzziness in a fuzzy set or system[17]. Let us consider a random process that produces an output value y, a member of a finite set Y. In generating y, the process may be influenced by some contextual information x, a member of a finite set X.

Our task is to construct a stochastic model that accurately represents the behavior of the Random process. The model is the method of estimating the conditional probability, that a given context x, the process will produce an output y. The probability that the model assigns to y in context to x is denoted by $p(y|x)$. The conditional probability distribution provided by the model is denoted by $p(y|x)$. We will denote by P the set of all conditional probability distributions. Thus a model, $p(y|x)$ is just an element of P. Here, we have considered y as class and x as feature i.e.

y *= {Snail, Right Circle, Right Arrow}*
x *= {Time offset , Duration, Trace Points, Age Factor}*

Training Data

To study the process, we observe the behavior of the Random process for some time collecting a large number of samples $(x1,y1), (x2,y2), (x3,y3)\ldots\ldots(xN,yN)$ [12]. We can summarize the Training sample in terms of its Empirical probability distribution p~, defined by

$$p\sim(x,y) \equiv \quad (1/N) * \text{number of times that } (x,y) \text{ occurs in the sample} \qquad (1)$$

Statistics, Features and Constraints

Our goal is to construct a statistical model of the process that generated the train-ing sample *(x,y).* The building blocks of this model will be a set of statistics [13] of the Training sample. For example, Indicator function of a context feature *f*,

$$f(x,y) = \begin{cases} 1 \text{ if } y = \text{Snail and Duration follows Very High} \\ 0 \text{ otherwise;} \end{cases} \qquad (2)$$

The expected value of *f* with respect to the *empirical distribution,* is exactly the statistics we are interested in. we denote this expected value by

$$p\sim(f) \equiv \sum_{x,y} \sim(x,y)f(x,y) \qquad (3)$$

We call such a function, a Feature function or a Feature for short. When we discover any statistic to be useful, we can acknowledge its importance by constraining the expected value that the model assigns to the corresponding feature function *f*. The expected value of *f* with respect to the *conditional probability p (y|x).*

$$p(f) \equiv \sum_{x,y} p\sim(x)p(y|x)f(x,y) \qquad (4)$$

where, p~*(x)* is the Empirical Distribution of *x* of the training sample. We constrain this expected value to be same as the expected value of *f* in the training sample. i.e

$$p\sim(f) = p(f) \qquad (5)$$

We call the requirement in (2.5) as a *Constraint Equation* or *Constraint***.** On combining (2.3), (2.4) and (2.5), we get the following equation.

$$\sum_{x,y} p\sim(x,y)\, f(x,y) \equiv \sum_{x,y} p\sim(x)p(y|x)\, f(x,y) \qquad (6)$$

Maximum Entropy Principle

Given n feature functions f_i, we want *p (y|x)* to maximize the entropy measure

$$H(p) \equiv -\sum_{x,y} p\sim(x)p(y|x)\, f(x,y) \qquad (7)$$

To select a model from a set *C*, of allowed probability distributions, choose the model $p^* \epsilon C$ with Maximum Entropy *H (p):*

$$P^* = \underset{p^* \epsilon C}{argmax} H(p) \qquad (8)$$

Where, It can be shown that *p** is always well defined; that is there is always a unique model *p** with maximum entropy in any constrained set *C*.

Data Collection

The SIGN-ON LINE DATABASE has been considered for the experiments. The SIGN On-Line Database contains data collected from 20 writers. The collection contains a unistroke on-line handwritten gestures that were collected on PDAs, Tablet PCs and whiteboards. The data collection was performed at the Synchromedia laboratory (ETS, Montreal, Canada) and by the Imadoc team (Irisa laboratory, Rennes, France). In total, 17 classes of gestures were collected. From [16], we can see the 17 gesture classes.Each gesture is described by a set of 21 features. The dataset and additional information on the data collection protocol can be found in [14].

Experimental Results

We propose an experimental setup for self adaptive gesture fuzzy classifier which uses maximum entropy principle for preserving most promising rules and removing the redundant rules from the rule set, based on interestingness. The analysis of the result is done and shown by doing the comparison between the training and checking error, before pruning g and after pruning of the rules .

Evaluation

We have tested the whole database containing the 17 gestures, but here we have shown the result for the 3 gestures (for the sake of simplicity),

- Class A = *Spiral*
- Class B = *Circle Right*
- Class C = *Right Arrow*

The dataset consist of the 21 features, but among all the 21 features, we have considered 3 features; *(i) Duration (ii) Trace points (iii) Age factor iii)Time offset.*

The main focus of our experiments is to find the performance before pruning of the rules in the beginning and the performance after pruning of the rules, on the stability and the recovery speed of the performance when introducing new unseen classes, in order to reduce the problem of overfitting and limit the database.

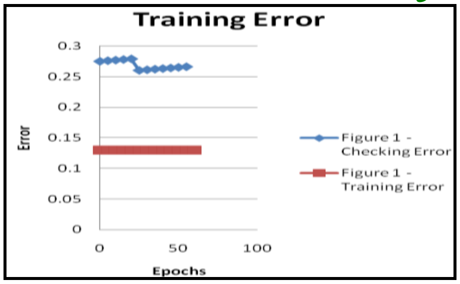

Fig. (i) Before rule pruning

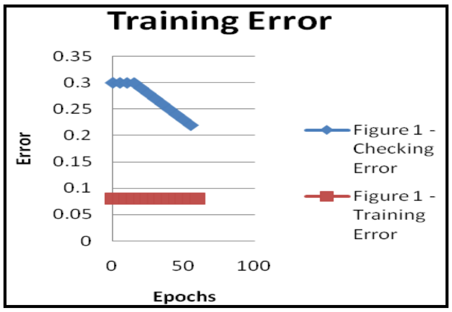

Fig. (ii) [16] After rule pruning Using centroid method considering only 3 features

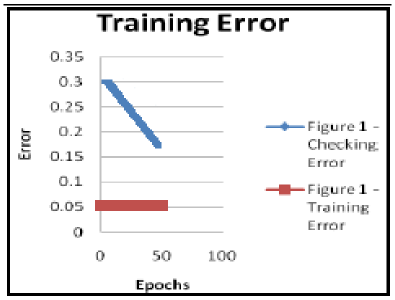

Fig. (iii) After rule pruning using centroid method considering 4 features

As shown in figure (i) and (ii),it can be concluded from [16] that , before pruning the rules and after pruning of the rules (considering 3 features),the training error and checking error rate Decreases by 40%, for constant output. From fig (iii) it can be seen that the performance increases further when number of features have been increased to 4.

Conclusion and Future Work

In handwritten gesture recognition systems, we presented an improved fuzzy based gesture classifier which considered 4 features and used maximum entropy principle for keeping most promising rules and removing redundant rules from the rule set. Experimental results show the effectiveness of the approach with respect to reduction of overfitting, which further reduces the misclassification error, and hence limits the database. For future work, this approach can be applied to other datasets of other fields. Also, some other concepts may also be applied to compute interestingness in the fuzzy system, instead of maximum entropy.

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