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A Study of Some Multi-expert Recognition Strategies for Industrial Applications: Issues of Processing Speed and Implementability

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Abstract

Multiple expert decision combination strategies have been used extensively in designing very powerful classifiers for various image processing tasks. These approaches are generally very successful in enhancing the recognition performance of a system, but tend to be costly in terms of implementation and execution, making their application in real time processing environments difficult. This paper investigates the implications in terms of processing speeds and other implementability issues in relation to the incorporation of these multiple expert decision combination approaches in system design. It is demonstrated that selection of a particular multiple expert approach for a particular task domain is influenced by both the achievable recognition performance and the overall execution speed in terms of system throughput. A performance-cost profile has also been proposed to visualise and select the optimal decision combination approach for a specific task domain.

1 Introduction

In recent years, multiple expert decision combination strategies have been applied very successfully to the recognition of handwritten and printed characters. Various such approaches have been proposed, ranging from relatively simple to very complicated methods (Suen *et al.*[1, 2], Rahman and Fairhurst[3, 4], Ho *et al.*[5], Kittler *et al.*[6] etc.). In most cases, these approaches enhance the overall recognition performance of the system, but this enhancement is often achieved at the price of additional structural and implementation complexity. This arises because of the introduction of additional logic and increased processing requirements, and in most cases the overall system processing speed is reduced.

In a real-time application (e.g. in many industrial or commercial environments), the processing speed of a system can be a factor as important as the attainable recognition performance. In most cases involving multiple expert decision combination strategies, the design emphasis has concentrated on achieving the highest recognition performance, and the implications concerning execution speed (in terms of system throughput, for example) have often been ignored, making commercial exploitation of these schemes difficult. In this paper, the performance of various established multiple expert recognition strategies has been investigated in relation to the implications of processing speed and implementability in this type of environment.

2 Selected Multiple Expert Decision Combination Methods

A range of multiple expert decision combination methods have been selected in order to investigate processing speed and implementability issues in the context of multiple expert decision combination strategies as applied to the character recognition task, by way of a specific example. These methods include the following:

- The Aggregation Method (Ho *et al.*[5], Hull *et al.*[7]),
- The Ranking Method (Mazurov *et al.*[8] and Ho *et al.*[5]),
- The Behaviour Knowledge Space Method (Huang and Suen[9]),
- The Majority Voting Scheme (Kittler and Hatel[10]).

- Serial Combination Method (Rahman and Fairhurst[11]),
- Parallel Combination Method (Rahman and Fairhurst[12]) and,
- Hybrid Combination Method (Rahman and Fairhurst[13]).

3 Selected Independent Experts

To compare the performances of different multiple expert configurations, it is important to have a group of experts which have comparable inter-expert performance indices, but which, at the same time, use different types of features and classification criteria. The following experts were chosen in order to provide a basis for the exploration of the implementation of various integrated multiple expert systems.

- *Binary Weighted Scheme(BWS):* This employs a technique based on *n-tuple* sampling or memory network processing[14]. The image array is divided into a certain number of samples, each consisting of a fixed number of pixels. Each of these samples is connected to a memory element, which in turn computes a single valued Boolean function.
- *Frequency Weighted Scheme(FWS):* This is similar to the *BWS*, but in this case the memory elements calculate the relative frequencies of the sampled features, thereby indicating the probability distribution of the group of points or *n-tuples*[15].
- *Multi-layer Perceptron Network(MLP):* This is the standard multilayer perceptron neural network structure, employing the standard error backpropagation algorithm[16].
- *Moment-based Pattern Classifiers(MPC):* These statistical algorithms make use of the *n* th order mathematical moments derived from the binarised patterns. Different discriminating functions may be used to identify possible cluster formation[17]. Among these are the Euclidean Distance, the Mahalanobis Distance and the Maximum Likelihood Discriminator.

4 Selected Database

A database has been chosen for all the experiments presented in this paper containing samples of handwritten characters (0..9, A..Z, with no distinction made between the characters '1/I' and '0/O') (Rahman and Fairhurst[13]). Some typical examples from this database are presented in

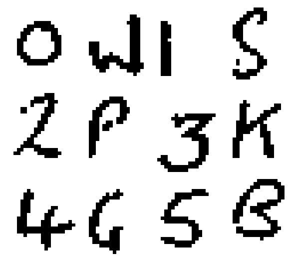

Figure 1: Some typical examples from the reference handwritten database

Figure 1. Each class has 300 samples, each having the resolution of 24X16 pixels. The training used 200 randomly selected samples per class and the testing was carried out on the rest of the samples.

Type of Expert	Optimum Recognition Rate	
	Digit Classes %	Digit + Upper Case Letters %
BWS	88.18	72.05
FWS	92.36	79.39
MPC	90.50	80.00
MLP	92.17	81.07

Table 1: Performance comparison of the different experts

5 Relative Overall Performance

Before an attempt is made to combine multiple experts using the various approaches considered in this paper, the performances of the individual experts on the selected database must be evaluated. Table 1 presents the performance of the various individual experts.

Table 2, on the other hand, presents the comparative performances of the various multiple expert approaches. It is observed that decision combination always produces a performance enhancement. The degree of enhancement depends on the decision combination strategy adopted. It is also observed that the enhanced performance is in no way dependent on the modification of the participating individual experts in the multiple expert framework, rather, it is the way in which the individual decisions are combined which is most important.

6 Implications Concerning Processing Speed

So far the discussion has been concentrated on evaluating the various approaches in terms of overall recognition performance and it has been demonstrated that application

Type of Algorithm	Overall Performances Digit Classes %	Digits Plus Upper Case %
Aggregation Method	92.92	81.85
Ranking Method	94.11	82.51
Behaviour Knowledge Space Method	94.56	83.86
Majority Voting Scheme	93.42	82.34
Serial	93.31	82.77
Parallel	94.43	84.72
Hybrid Single Stage	93.41	83.19
Hybrid Two Stage	96.8	84.91

Table 2: Performance comparison among different configurations

of multiple expert approaches is very effective in enhancing system performance. Unfortunately, this enhancement is achieved at a price. In this section, possible implications of the incorporation of the additional complexities in the various multiple expert approaches in terms of the processing speed is explored.

It is noted that most of the selected decision combination methods are parallel in nature. In these cases, the cooperating experts receive the input characters as a complete set and evaluate them separately. Although conceptually this evaluation occurs concurrently and independently, in practice the constraints of serial software implementation makes the implementation scenario much less attractive. In a serial implementation using standard software techniques (not using a parallel implementation) these methods become very expensive as far as the processing speed or throughput is concerned.

When comparing issues relating to speed, a fair basis for comparison is to consider configurations having the same number of participating cooperating experts. An illustrative case is chosen here, where four independent experts are unified in a single framework utilising various decision combination strategies. Table 3 presents the comparative throughput values of the selected multiple expert decision combination approaches. The values presented here are the average throughput, expressed in terms of characters per second (cps), achieved by these configurations in recognising the test characters, having a resolution of 16X24 pixels, excluding the time for file handling. Although it is clear

Type of Algorithm	Processing Speed
BWS	2174 cps
FWS	2128 cps
MPC	542 cps
MLP	10 cps
Aggregation Method	9 cps
Ranking Method	8 cps
Behaviour Knowledge Space Method	7 cps
Majority Voting Scheme	8 cps
Serial	32 cps
Parallel	9 cps
Hybrid Single Stage 1 Similar Pair	41 cps
Hybrid Single Stage 2 Dissimilar Pairs	22 cps
Hybrid Two Stage 1 Similar Pair	39 cps
Hybrid Two Stage 2 Dissimilar Pairs	21 cps

Table 3: Comparison among different configurations: Processing time

that multiple expert configurations have a relatively lower throughput with respect to the individual experts, there are some cases where the combined structures are faster than the experts working alone. This is especially true for the case of the neural network expert (MLP) which has an extremely low throughput. This is possible because of the unique way the data is distributed into separate channels based on its characteristics. This controlled data-flow ensures that the data is properly split up into smaller groups before being processed by various experts, enabling each expert in the hierarchy to process only a fraction of the total input characters, making the overall processing faster.

The throughput values cited in Table 3 and elsewhere in this paper are related to various implementations implemented in C running on a SPARC IPX platform and hence represent a serial implementation (a standard software implementation). A parallel implementation (involving multiple processing units and exploitation of parallel software implementation) is expected to enhance the speed considerably (Rahman and Fairhurst[18]).

It is seen that the serial approach, and some of the hybrid approaches (Table 3), are faster than the other selected approaches. This shows that the efficient ordering of the class-directed separation algorithm implemented as part of the hybrid combination approach actually makes the overall system more efficient in terms of processing speed in addition to providing enhanced recognition performance. This also implies that contrary to what might be expected, employing additional experts and incorporating additional *a priori* information does not necessarily generate a slower system. On the contrary, proper ordering of the experts in the overall hierarchy and making sure that the way the experts communicate with each other reflect the characteristics of the data and the inter-relation of cooperating experts can lead to successful implementation of very powerful multiple expert decision combination frameworks.

7 Issues Concerning Implementability

So far, discussions about the implications of incorporating multiple expert decision combination strategies in terms of execution speed (throughput) have been presented. In a practical industrial application, the two most important issues related to a successful implementation are the processing speed and the overall recognition performance. In this respect, it is useful to consider the implications of the implementation of the more complex multiple expert configurations in terms of processing speed and achievable recognition performance.

Table 4 presents an overview of system performance with respect to the recognition of the digit classes from the selected database by adopting the various decision combination strategies. Information about the processing time associated with different types of classifier combination schemes in addition to the recognition performance achieved has been presented. The different configurations have been ranked from 0 to 9 with respect to the processing speed (0 = fastest, 9 = slowest). This Table forms the basis of the following discussion.

As is clearly seen from Table 4, serial approaches are very fast with respect to the other approaches (especially the parallel approaches). As already pointed out, required processing time is a major index in selecting a particular system in many practical situations. If a very fast system is required, then the serial systems should be preferred over the other configurations. If the time constraint is not severe, then parallel systems are often a better choice than serial systems, because of their higher accuracy in terms of recognition performance. On the other hand, if ultimate classification performance is of paramount interest, then the more sophisticated hybrid systems might be adopted.

Type of Algorithm	Overall Performance	Processing Speed (cps)	Rank
BWS	88.18	2174	0
FWS	92.36	2128	1
MPC	90.50	542	2
MLP	92.17	10	8
Aggregation Method	92.92	9	10
Ranking Method	94.11	8	11
Behaviour Knowledge Space Method	94.56	7	13
Majority Voting Scheme	93.42	8	12
Serial	93.31	32	5
Parallel	94.43	9	9
Hybrid Single Stage 1 Similar pair	93.12	41	3
Hybrid Single Stage 2 Dissimilar pairs	93.41	22	6
Hybrid Two Stage 1 Similar pair	95.10	39	4
Hybrid Two Stage 2 Dissimilar pairs	96.70	21	7

Table 4: Comparison among different configurations with respect to the processing time

However, the ultimate choice of a particular classifier combination should be defined by both the recognition performance achieved and the processing time required to achieve that performance. Figure 2 demonstrates how a decision in this respect can be reached by use of a performance-cost profile for different classifier combinations. In this case, the percentage recognition achieved by the classifier combinations is plotted along the x-axis and the processing times with respect to characters processed per second are plotted along the y-axis. The rankings assigned to the different classifier combinations (Table 4) are plotted along the z-axis. A parametric surface is constructed by projecting these performance values along the z-axis which then gives a 3-D surface of preference. The balance between the performance-cost indicators has to be obtained by selecting the optimum for a given task, as the ultimate choice of a particular type of configuration must be governed by the requirements of a

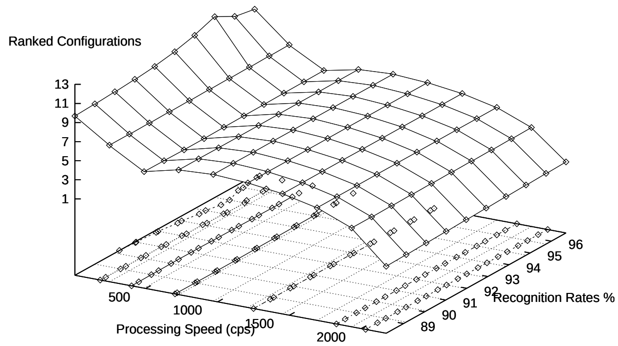

Figure 2: Profile of processing time vs. percentage recognition rate on the digit classes

particular task domain.

8 Conclusion

Processing time and implementability issues concerning the incorporation of multiple expert decision combination approaches in system design have been investigated. It has been demonstrated that selection of a particular multiple expert approach to a particular task domain is influenced by both the achievable recognition performance and the overall execution speed in terms of system throughput. A performance-cost profile has also been proposed to visualise and select the optimal decision combination approach for a specific task domain.

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