OFF-LINE HANDWRITTEN WORD RECOGNITION USING ENSEMBLE OF CLASSIFIER SELECTION AND FEATURES FUSION

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ABSTRACT

Handwritten recognition is a very active research domain that led to several works in the literature for the Latin Writing. The current systems tendency is oriented toward the classifiers combination and the integration of multiple information sources. In this paper, we describe two approaches for Arabic handwritten recognition using optimized Multiple classifier system MCS . The first rests on cooperation and selection of feature set in MCS studying the effect of fusion methods on global system performance The second one used Diversity measures and individual accuracy classifier for selecting the best set of classifier; its chooses among the classifier set the one with the best performance and adds it to the selected classifiers subset. The performance in our approach is calculated using three diversity measures based on correlation between errors. On two database sets using 10 different classifiers, we then test the effect of: the criterion to be optimized (diversity measures), and fusion methods (voting, weighted voting and Behavior Knowledge Space). The experimental results presented are encouraging and open other perspectives in the domain of classifiers selection especially speaking for Arabic Handwritten word recognition.

Keywords: *Arabic Handwritten word recognition, Classifiers set selection, Combination methods, Diversity measures, features extraction, BKS (behavior knowledge space).*

I. INTRODUCTION

The first observation concerning Arabian manuscript reveals the complexity of the task, especially for the used ensemble of classifiers.

For almost any real life pattern recognition application, a number of approaches and procedures may be used as a solution. After more than 20 years of continuous and intensive effort devoted to solving the challenges of handwriting recognition, progress in recent years has been very promising and are still of great interest [1] .

The problem of handwriting recognition can be classified into two main groups, namely off-line and on-line recognition, according to the format of handwriting inputs. In offline recognition, only the image of the handwriting is available, while in the on-line case temporal information such as pentip coordinates, as a function of time, is also available.

Many applications require off-line HWR capabilities such as bank processing, mail sorting, document archiving, commercial form-reading, office automation, etc. So far, off-line HWR remains an open problem, in spite of a dramatic boost of research [2]-[4] in this field and the latest improvement in recognition methodologies [4]-[6]

Studies in Arabic handwriting recognition, although not as advanced as those devoted to other scripts (e.g. Latin), have recently shown renewed interest [7]-[9] . We point out that the techniques developed for Latin HWR are not appropriate for Arabic handwriting because, Arabic script is based on an alphabet and rules distinct from those of Latin (cf. Section 2).

Since the word is the most natural unit of handwriting, its recognition process can be done either by an analytic approach of recognizing individual characters in the word or holistic approach of dealing with the entire word image as a whole.

The multiple classifier system has been shown to be useful for improving recognition rates [10]. In the literature, the use of MCS has been widely used for several pattern recognition tasks [11]-[15].

In other hand, in feature selection (i.e., forward or backward features selection), a part of the features is chosen as a new subset, while the rest is ignored. The neglected features still, however, may still contain useful information for discriminating data classes. To make use of this information, the combined classifier approach seems a reasonable solution.

In this paper we study, on one hand, the combinations efficiency based on feature selection/extraction. As well as analyzing conditions when combining classifiers on multiple feature subsets is more beneficial than exploiting a single selected feature set. On the other hand, one of the most important tasks in optimizing a multiple classifier system is to select a group of adequate classifiers from a pool of classifiers. These methods choose a small subset from a large set of candidate models. Since there are 2^L-1 possible subsets of L models. It is not reasonable to try all the possibilities unless the subset *L* is small [16] . Subset classifier selection methods also differ in the criterion they optimize. Additional to methods which directly optimize ensemble accuracy, *diversity* measures play an important role in selecting and explaining this classifiers sub set choice.

Diversity should therefore be regarded in a more general context than as a way of finding the best classifiers combination for a specific combination method. Optimally it should produce member classifier sets that are different from each other in a way that it benefits classifier combination, regardless of the used combination method [17]-[20]. In summary, these are three major topics associated with sub set classifier selection: set creation, set selection and classifier combination.

In this paper we propose two new approaches for Arabic handwritten recognition based on Multiple classifier systems. The first invests on the cooperation of several of features while proposing a family who selects the more discriminant; these wholes will be the input of MCS. The second proposes a progressive algorithm combining accuracy and diversity in classifier selection. Three combination methods are tested in the two proposed approaches (voting, weighted voting, and BKS (Behavior Knowledge Space)).

This paper is organized as follows: In the Section 2, we illustrate the adopted fusion method used in multiple classifier systems combination. We retail the two proposed approaches In Section 3 and 4, respectively. The databases used for the validation of the approaches and the experimental results are summarized in section 5.

2. COMBINATION METHODS

Combining multiple classifiers requires a uniform representation of their decisions with respect to an observation [20]. In order to assure the ability of the ensemble methods to combine the decisions of different types of classiffiers, we considered only methods that use a label for each classifier that indicates that the expert assigned the sample to the class represented by the corresponding label.

2.1. The voting methods

Initially, only the top choice of each classifier is considered. When multiple classifiers are combined using majority vote, we expect to obtain good results based on the belief that the majority of experts are more likely to be correct in their decision when they agree in their opinion. So if the decision of D classifiers are combined, and more than half of them decide that observation x belongs to class Ci, the ensemble decides that x €Ci. However, the word class that is most often on the first rank is the output of the combined classifier. These are broken by means of the maximum rule, which is only applied to the competing word classes [21]

2.2. Weighted voting

Here we consider again the top class of each classifier. In contrast with regular voting, a weight is assigned to each classifier. The class with the highest sum of the weights is the output of the combined classifier. The weights for the classifiers are calculated basing on the performance of the combined classifier on the training set.

In this framework, one of most common and effective strategy is the weighted majority vote rule [22], [23], according to which the votes of each classifier is weighted by using an estimate of its global reliability.

Such an estimate can be computed, for instance, by considering its recognition rate on a training set [10]. Independently on the way to compute the weights, it should be noted that they represent an average measure of the performance of a classifier on a training set. As a consequence, in the combining rule, the classifiers exhibiting higher recognition rates are much more important than other classifiers exhibiting worst performance, even if some sample may be more reliably classified by these latter.

2.3. Behaviour-knowledge space

Most fusion methods assume independence of the decisions made by individual classifiers. This is in fact not necessarily true and Behavior-Knowledge Space method (BKS) does not require this condition. It provides a knowledge space by collecting the records of the decisions of all classifiers for each learned sample.

If the decision fusion problem is defined as a mapping of K classifiers: e_1 ,..., e_K into M classes: c_1 ,..., c_M , the method operates on the K – dimensional space. Each dimension corresponds to an individual classifier, which can produce Ṃ1 crisp decisions, M class labels and one rejection decision. A unit of BKS is an intersection of decisions of every single classifier [24]-[26]. Each BKS unit contains three types of data: the total number of incoming samples: $T_{e1,...,eK}$, the best representative class: $R_{e1,...,eK}$, and the total number of incoming samples for each class: $n_{e1,...,eK}(m)$.

In the first stage of BKS method the training data are extensively exploited to build the BKS. Then the final classification decision for an input sample is derived in the focal unit where the balance is estimated between the current classifiers decisions and the recorded behavior Information [24].

3. APPROACH BASED ON FEATURES COOPERATION IN MCS

In feature selection, a part of the features is chosen as a new feature subset (like forward or backward features selection), while the rest of the features is ignored. The neglected features may however, still contain useful information for discriminating the data classes.

To make use of this information, the combined classifier approach can be used.

Moreover, we analyze conditions when combining classifiers on multiple feature subsets is more beneficial than exploiting a single selected feature set.

Before illustrating the three features familiers, we describe the preprocessing operation that are don in the word image.

3.1. Pre-processing

Pre-processing is applied to word images in order to eliminate noise and to simplify the procedure of feature extraction. It is worth noticing that these pre-processing methods are script independent.

Normalization: In an ideal model of handwriting, a word is supposed to be written horizontally and with ascenders and descenders aligned along the vertical direction. In real data, such conditions are rarely respected.

Contour smoothing: Smoothing eliminates small blobs on the contour.

Base line detection: Our approach uses the algorithm described in Vinciarelli [6] based on the horizontal projection curve that is computed with respect to the horizontal pixel density (Fig. 1). Baseline position is used to extract baseline dependent features that emphasize the presence of descenders and ascenders.

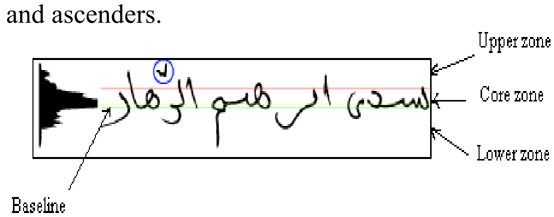

Figure 1. Upper and lower baselines detection

Among the different types of feature, we adopted three features classes:

3.2. The structural features

In our system, we kept the following global structural features (Fig. 2) which are detailed in [27]-[29]:

- The number of connected components (while using contour tracing);
- The number of descendants;
- The number of ascendants;
- The number of unique dot below the baseline;
- The number of unique dot above the baseline;
- The number of two dots below the baseline;
- The number of two dots bound above the baseline;
- The number of 3 bound dots;
- The number of Hamzas (zigzags) ;
- The number of stroke (Loop).
- The number of tasnine (by calculation of number of intersection in the middle of the median zone)

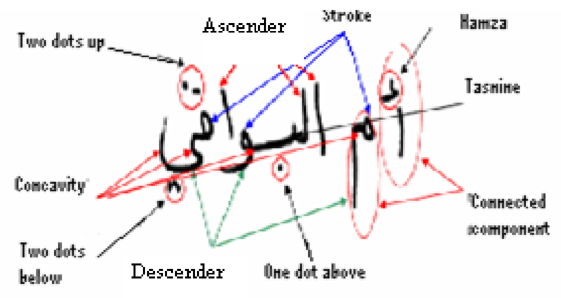

Figure 2. Structural features

3.3. The statistical features

The statistical features are based on density measures. A carving is applied of the image in a number of zones then the density of black pixels in each image is calculated. This carving technique is known as "zoning" and is inspired from human perception.
A survey of the use of this technique for OCR has been done by [30] in our paper; we chose the following subdivisions (Fig. 3). For every zone, we calculate two statistical measures that are the densities of black pixels and the variance (to localize the position of the majority of the black pixels in every zone selected). This will give: 55×2 = 110 statistical features.

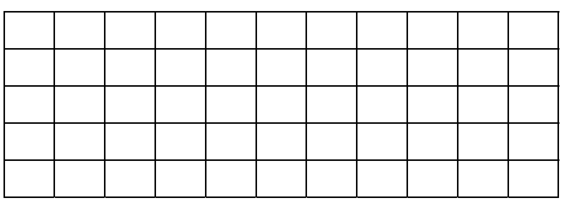

Figure 3. Example of zoning used

3.4. Selected features

This third class is added to permit to have a variety of most discriminative features assuring the performance of the system and the diversity between its elements (primitives); this is justified by the probability that a classifier will be weak to recognize
the different shapes by only one homogeneous whole of features. It is chosen by preliminary work studying the most discriminative features and the diversity between these primitives in all the set. The result of this work is summarized as follows:
- For the structural features, we kept the number of connected components, the ascendants, the descendants.
- For the zoning feature, we may retain the density and the variance of the median part of the word; because it contains the most discriminative pixels.

3.4. Approach steps

The stages of development of this approach can be summarized as follows:
- Every features family will be the entry of a neuronal classifier; what leads us has a multi classifiers system given by three classifiers;
- The same sets of characteristic are applied on a system constituted of three (03) HMMs (Hidden Markov Models), where the first one is a discrete HMM using the structural features as discrete observations and the 02 others are continuous HMM.

- The classifiers will be trained with different samples of the training database, to assure more complementarities. This last point is very important in the conception of the multi classifiers systems to again ensure the independence.

- We used another system replacing HMM systems by NN (Neuronal Network) systems applying the cooperation of these sets of features to validate our propositions with obtained results.

4. Approach Based on a Progressive Algorithm for Set Classifier Selection

Different works have been done in the field of AOCR (Arabic Optical Character Recognition) [27]-[29], [31]-[33].
It is not an easy task to obtain a robust MCS, unifying the set of classifiers already achieved and tested. Indeed, the major goal of the combination is to try to maximise the benefits of the complementarily of different models and to compensate the weaknesses of each classifier.
To select the set of classifiers having the best individual performances doesn't imply a better rate of recognition in any case in the global system. It is justified by the nature of the classifiers [3], [33].
Diversity has been quantified in several ways for classification fusion. As a result, different measures have been proposed in the literature.
In this section, we present the adopted diversity measures followed by the proposed approach details.

4.1. Classifiers diversity measure

The diversity measure is calculated in term of the output value through all classifiers [34]. In this work, we used six well known diversity measures to construct the best classifier sub set:

. ***Correlation between the Errors:*** It is interesting to examine that the independence between the committed errors is beneficial for the MCS; the correlation between the classifiers errors is a natural choice to compare the classifiers subsets [18]:

$$\rho_{a,b} = \frac{Cov[v_e^a, v_e^b]}{\sqrt{Var[v_e^a]Var[v_e^b]}} \quad (1)$$

and v_e^b are binary vectors of the *a* and *b* classifiers errors. The best set is selected while choosing the one having the minimum average of these pairs of measures.

. ***Q Average*:** The Q average or Q statistic aims to calculate the similarity between two classifiers [18]. It is defined for two classifiers *a, b* as:

$$Q_{a,b} = \frac{N^{11}N^{00} - N^{01}N^{10}}{N^{11}N^{00} + N^{01}N^{10}} \quad (2)$$

Where N^{11} is the number of time where the two classifiers are correct, N^{00} the number of time where the two classifiers are incorrect, N^{01} and N^{10} represent the number of time where just the first or the second are either correct.

. ***Disagreement Measure*:** This measure represents the ratio between the numbers of observations where one classifier is correct and the other is incorrect with respect to the total number of observations [18], [34]:

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$$D_{a,b} = \frac{N^{10} + N^{01}}{N} \quad (3)$$

4.2. Progressive algorithm steps

Although our approach results published in [9], it suffers from some limits which we can summaries in the following points:

- Cost in time and memory capacity during the diversity measurements calculation for all the possible combinations of the *m* classifiers.
- As the majority of the subset selection approaches of classifiers based on diversity, neglect the individual criterion to classify accuracy. This last is a very important factor in the Multi classifiers systems design.
- Indeed, a subset selected by the diversity measurement application can not contain *el* the most powerful classifier (with dimensions rate of recognition) or even more serious than that, can contain that the M weak classifiers which represent the most diversified ones. What inevitably degrades the recognition rate of the total system.
- From this we used the idea which tries to combine two criteria ACCURACY and DIVERSITY for a subset of classifier, selection while avoiding the lasting test of all calculation of the possible combinations and of measurement diversity:

Our proposed approach chooses a fixed m out of all L base classifiers.

1) it starts with a set containing 1 classifier which is the best classifier (base on accuracy) during the test phase ;

2) At each iteration, it chooses among all possible classifiers the one that best improves the global system performance when added to the current ensemble. The performance is calculated using evaluation criterion (the three diversity meseaure as we will discuss next).Once the set of classifier is selected, it is impossible to use the methods of combination as the weighted average, or the sum of the results because outputs classifiers are heterogeneous. Methods based on output labels classes as, voting, weight voting, and BKS detailed in section III will be used in our study.

5. Experimental Results and Discussion

5.1. Used Data Base

We used two different databases in order to validate the two proposed approaches: the first one is a base containing all 48 Wilayas (regions) of Algeria, containing 10000 words, written by 100 different

writers. Among these word images, a set of 2400 were used to test the global systems.
The second database used is The IFN/ENIT - database for Arabic handwritten words. The database consists in 26459 Arabic words handwritten by 411 different writers, consisting of the 946 Tunisian town/village names [35]. Four distinct sets (a,b,c,d) are predefined in the database usable for training and testing systems. We use three of them for training and one set for testing our system fig.4.

Figure 4. IFN/INIT database words example

5.2. Used Classifiers

The single classifier members used for the selection are:
- 02 SVM (Support Vector Machine), with the strategy "one against all ", elaborated under the library lisb SVM, version 2.7. The inputs on this SVM system are the structural features. We have used polynomial and Gaussian kernel function.
- 03 KPPV (k - Nearest Neighbor with K=2 ,3,5).
- 03 NN (Neuronal Network with different number of the hidden layer neurons and different inputs corresponding in features families detailed in section 3.
- 02 HMM (Discret and Continuous with modified viterbi algorithm).

5.3. Simulation Results

5.3.1. For the first approach based on features cooperation

Two MCS systems were implemented composed of three classifiers each; (HMM and neuronal network). They are trained using the two databases cited earlier

For combination method, we have applied 03 methods: voting, Weighted voting, and BKS. Table1 (Table. 1) summarizes the mean results of these tests.. Based on these results, we can clearly see that the HMM MCS is more effective than the neuronal network one.

Table 1: Mean recognition result of the two systems with the 03 fusion methods

MCS	Fusion methods	Top1	Top2	Top3	*Top5*
Multi classifieur based on HMMs	Voting	87.92	88.24	89.66	*92.45*
		88.55	90.06	93.45	*95.65*
	Weighted voting	88.15	89.04	94.12	*96.12*
		89.26	90.12	94.12	*96.78*
	BKS	89.12	90.56	92.56	*95.65*
		89.23	**91.52**	**94.58**	***97.12***
Multi classifieur based on Neurenal network	Voting	87.14	87.45	88.45	*91.25*
		87.45	89.89	92.45	*93.56*
	Weighted voting	88.22	89.69	93.45	*94.02*
		89.78	90.09	93.01	*94.35*
	BKS	89.01	89.99	92.14	*94.06*
		88.98	***90.69***	***93.15***	***95.65***

For each of the two systems, we found that the recognition rate combining several sets of features is superior to the one using only one set; especially, the one using the selection features

5.3.2. For the second approach based on diversity influence in set classifier selection

Classifiers are indexed from 01 to 10 and their individual performance using the two databases are resumed in (Table. 2).

Classifier index	*Member classifier*	*Accuracy (database 01)*	*Accuracy (database 02)*
01	SVM(1)	86.88	*87.03*
02	SVM(2)	87.12	*87.69*
03	KNN(1)	82.45	*82.78*
04	KNN(2)	83.41	*83.42*
05	KNN(3)	85.02	*84.96*
06	NN(1)	86.69	*87.12*
07	NN(2)	87.08	*87.46*
08	NN(3)	86.23	*87.05*
09	HMM(1)	88.23	*88.78*
10	*HMM(2)*	*89.15*	*89.23*

Table2. Individual classifier accuracy

In this study, we have tested several set classifier size equal to see the effect of size set classifier on global Accuracy MCS.
Three diversity measures are applied for training. We have also used the three fusion methods detailed in section III and Experimental results after execution of our progressive algorithm are resumed in table 3, 4, 5.
The obtained results have shown that diversity is of paramount importance in selecting member classifiers. It means that individual performances of members are one factor that contributes to the overall performances, but they are not sufficient to lead to a final conclusion. Indeed, diversity is requested to get the highest performances. We noted that "Disagreement " and "correlation" measures generate the most powerful set, better than combining best Individual classifiers. a weighted vote as a combination method. This encourages taking this research path for average size databases. The results using BKS are better than the one using
In any case, it is now clear that MCS performance strongly depends on careful selection of classifiers to be combined. The effectiveness of various classifier fusion methods depends again on the selections made within classifiers.
We can also see size set classifier in rate recognition.
Finally, it can be concluded that diversity is a very important factor in the subset selection of classifiers by not neglecting the individual criterion to classify accuracy.
Realizing an optimal MCS imposes the study of the following factors: the used diversity measures, the fusion methods and the size set classifier.

		DATA BASE 01			*DATABASE 02*		
Diversity measures	Subset classifier	Voting	Weight voting	BKS	Voting	Weight voting	*BKS*
Correlation /	10,1	89.15	89.36	90.85	88.41	90.36	*90.54*
Q Average	10,2	83.65	84.36	85.25	83.26	84.23	*84.61*
Disagreement	10,1	83.02	83.74	89.96	83.95	86.05	*85.36*
Best Classif	*1,2*	*87.45*	*87.98*	*88.12*	*87.56*	*88.79*	*89.36*

Table3. Best sub set classifiers with the obtained performances Size set equal to 2

		DATA BASE 01			*DATABASE 02*		
Diversity measures	Subset classifier	Voting	Weight voting	BKS	Voting	Weight voting	*BKS*
Correlation /	10,1,8,9	91.18	92.56	92.91	91.74	93.26	*94.89*
Q Average	10,2,7,8	90.15	90.78	91.25	90.74	90.14	*91.08*
Disagreement	10,1,7,9	91.56	93.16	93.96	91.66	93.45	*93.81*
Best Classifier	*1,2,9,10*	*89.12*	*90.68*	*91.16*	*90.45*	*91.68*	*91.56*

Table 4. Best sub set classifiers with the obtained performances Size set equal to 3

		DATA BASE 01			DATABASE 02		
Diversity measures	Subset classifier	Voting	W.vote	BKS	Voting	W/vote	BKS
Correlation / errors	1, 6, 10	90.11	91.85	91.37	89.12	91.74	91.76
Q Average	2,7, 8	84.06	84.65	85.92	83.78	84.33	85.36
Disagreement measure	5,6,8	89.15	90.23	90.76	90.65	90.46	91.02
Best individual classifiers	2,9,10	87.63	88.45	89.26	88.16	89.82	90.76

Table 5. Best sub set classifiers with the obtained performances Size set equal to 4

6. CONCLUSION

Two newly applied methods based on MCS for AOCR have been investigated in this paper.
The Diversity notion may be obtained either by diversifying the used features representing the word image, on finding the most diversified subset of classifiers among the existing combinations.
In order to reach a decent objective, two independent systems were designed. The first one is a MCS composed of 03 HMM classifiers, with different inputs representing the three characteristics families (structural, statistic and selection of characteristics).

The latter is to show that one single system using a single set containing a selection of characteristics, neglecting the rest of the elements that may enhance the chances of recognizing the candidate word, does not give the desired performances. In order to best validate the proposition, the classifier was replaced by an Artificial Neural Network, and showed that both MCS with characteristics cooperation including the selected characteristic selection, outperform a single one using a selection of characteristics.

With the optimizing aim, and with th objective to take into account individual classifier accuracy during the selection, the progressive algorithm was proposed; its goal is creating a subset containing at the beginning the best individual classifier (based on accuracy) and adds after each iteration the best classifier which returns the subset more diversified.
The obtained results are encouraging when compared to prior work. Future research will be to implement newer algorithms for (features extraction / selection and set classifier selection) Genetic Algorithms in order to maximize the robustness and increase performances.

REFERENCES:

[1] Cheriet M. Horst Bunke, Jianying Hu,, Fumitaka Kimura,Ching Y. Suen, NewFrontiers in Handwriting Recognition, Pattern Recognition,2009, Editorial

[2] Koerich, G.A.L., Sabourin, R., Suen, V.C.Y., 2005. Recognition and verification of unconstrained handwritten words. IEEE Trans. Pattern Anal. Machine Intell. 27,(10), 1509–1522.

[3] Plamondon, R., Srihari, S.N., 2000. On-line and off-line handwriting recognition: A comprehensive survey. IEEE Trans. Pattern Anal. Machine Intell. 22 (1), 63–84.

[4] Vinciarelli, A., Bengio, S., Bunke, H., 2004. Off-line recognition of unconstrained handwritten texts using HMMs and statistical language models. IEEE Trans. Pattern Anal. Machine Intell. 26 (6), 709–720.

[5] El-Yacoubi, M.A., Gilloux, M., Bertille, J.M., 2002. A statistical approach for phrase location and recognition within a text line: An application to street namerecognition. IEEE Trans. Pattern Anal. Machine Intell. 24 (2), 172–188.

[6] Vinciarelli, A., Bengio, S., 2002. Off-line cursive word recognition using continuous density HMMs trained with PCA or ICA features. In: Proc.ICPR'02, pp. 493–498.

[7] Amin, A.,Off-line Arabic character recognition: The state of the art. Pattern Recognition, 31(5):517–530, 1998

[8] Ben Amara, E.N., Bouslama, F., 2003. Classification of Arabic script using multiple
sources of information: State of the art and perspectives. Internat. J. Doc. Anal.Recog. (IJDAR) 5 (1), 195–212.

[9] Lorigo, L.M., Govindaraju, V., 2006. Offline Arabic handwriting recognition: A survey. IEEE Trans. Pattern Anal. Machine Intell. 28 (5), 712–724.

[10] Xu, l., Krzyzak, A., Suen, C.Y., Methodes of combining multiple classifiers and their applications to handwritten recognition, IEEE trans. Syst., Man, Cybern, vol SMC-22, N°.3,

[11] pp.418-435, May/ june 1992

[12] Kuncheva, L.I.and Whitaker, C.J., Measures of diversity in classifier ensembles and their relationship with the ensemble accuracy, Mach. Learn, vol 51(2), pp.181–207, 2003.

[13] Zhou, D., Zhang, J., 2002. Face recognition by combining several algorithms. Pattern Recognition 3 (3), 497–500;

[14] Giacinto, G. and Roli, F., An approach to the automatic design of multiple classifier systems, PatternRecognition Letters, vol 22(1), pp.25- 33, 2001

[15] Farah, N., Khadir, M.T., Sellami, M., Artificial neural network fusion: Application to Arabic words recognition, 13th European Symposium on Artificial Neural Networks ESANN , pp. 151-155, 2005

[16] Azizi, N., Farah, N., Khadir, M., Sellami, M.; Arabic Handwritten Word Recognition Using Classifiers Selection and features Extraction / Selection , 17 th IEEE Conference in Intelligent Information System,IIS09, Poland, pp735-742, 2009

[17] Aydın, U., Semerci M., Olcay Y., Alpaydın E., Incremental construction of classifier and

[18] discriminant ensembles, Information Sciences 179 (2009) 1298–1318

[19] Aksela M., Comparison of Classifier Selection Methods for Improving Committee Performance. Multiple Classifier Systems 2003: 84-93.

[20] Kuncheva, L. I, Combining Pattern Classifiers : Methods and Algorithms. Wyley-Interscience, 2004

[21] Aksela, M., Adaptive combinations of classifiers with applicatio to on-line handwritten.character recognition, dissertations in computer and information science espoo 2007 report d19.

[22] Kittler, J., Hatef, M., Duin, R.P.W. and Matas, J., On combining classifiers, IEEE transactions on pattern analysis and machine intelligence, vol 20, no 3, 1998.

[23] Ruta, D. and Gabrys, B., Application of the Evolutionary Algorithms for Classifier Selection in Multiple Classifier Systems with Majority Voting. Multiple Classifier Systems 2001: 399-408, 2001

[24] L. Lam and C. Y. Suen. Increasing experts for majority vote in ocr: Theoretical considerations and strategies. In *Proceedings of the 4th International Workshop on Frontiersin Handwriting Recognition*, pages 245–254, 1994.

[25] L. Lam and C. Y. Suen. A theoretical analysis of the application of majority voting to pattern recognition. In *Proceedings of the 4th International Conference on Pattern Recognition*, volume 2, pages 418–420. IEEE ComputerSociety Press, 1994.

[26] Dara, R. A., Cooperative Training in Multiple Classifier Systems; thesis :Doctor of Philosophy; Waterloo, Ontario, Canada, 2007;

[27] Ko, A.H.R., Sabourina, R., Britto, A. , Oliveira, L. , Pairwise fusion matrix for combining classifiers, Pattern Recognition 40 (2007) ,pp2198 – 2210

[28] Raudys, S., and Roli, F, The Behavior Knowledge Space Fusion Method: Analysis of Generalization Error and Strategies for Performance Improvement, 2006.

[29] Azizi, N. Sari, T., Souici, L. and Sellami, M., Une architecture de combinaison floue de classifieurs neuronaux pour la reconnaissance de mots arabes manuscrits, CIFED'2002, pp: 89-96, Hammamet, Tunisie, 2002.

[30] Azizi, N..Khadir, M.T and Sellami, M., Un système HMM pour le tri postal algérien, th Maghrebian Conference on Information Technologies MCSEAI, pp. 256-262,2006.

[31] Farah N., Souici L. and Sellami M., Classifiers combination and syntax analysis for arabic literal amount recognition, Engineering Applications of Artificial Intelligence, Volume 19, Issue 1,2006.

[32] Suen, C.Y., Guo, J., and Li, Z.C, Analysis and recognition of alphanumeric handprints by parts, IEEE Trans. on Systems, Man, and Cybernetics, 24(4) :614–631, 1994.

[33] Benouareth. A., Ennaji, A. and Sellami, M., Semi-continuous HMMs with explicit state duration for unconstrained Arabic word modeling and recognition, Pattern Recognition Letters 29(12): pp.1742-1752, 2008.

[34] Souici, L. and Sellami, M., A hybrid neuro-symbolic approach for arabic handwritten word recognition, , Journal of Advanced Computational Intelligence and Intelligent Informatics, Vol. 10, N°1, 2006.

[35] Sari, T.,Un système de reconnaissance de mots arabe manuscripts basé segmentation, Mémoire de magister, Laboratoire LRI, 890-894

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