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OFFLINE SIGNATURE VERIFICATION USING ARTIFICIAL IMMUNE RECOGINISATION SYSTEM

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ABSTRACT:

In various pattern recognition applications, artificial immune systems achieve comparable and commonly higher performance than other classification schemes such as SVM. In this paper, we investigate their applicability for handwritten signature verification. Specifically, Ridgelet transform and grid features are used to extract pertinent characteristics. Performance assessment is conducted on the CEDAR dataset comparatively to SVM classifiers. The results in terms of average error rate highlight the high performance of artificial immune recognition algorithm.

Keywords— Artificial immune system, Biometrics, Ridgelet transform, Signature verification, Support Vector Machines.

1. INTRODUCTION

Biometric theory provides several techniques to identify persons. In the past years, iris and fingerprint have shown a very high authentication performance. Despite this, in various real word applications such as bank checks, transactions and administrative contracts, handwritten signatures constitute the main identification tool [3]. Thereby, several research works were developed to improve automatic signature verification. Specifically, this task can be achieved according to on-line or off-line approaches. The on-line verification is performed simultaneously with the acquisition process. In this case, dynamic features such as the writing speed and the pen top-down, are used. On the other hand, the off-line signature verification is employed when signatures are already written over documents. Besides, off-line verification may be attempted in either writer-dependent or writer-independent context. In the writer-dependent case, the system is trained by using genuine signatures or both genuine and forgeries of a particular writer. This approach provides high precisions. However, the training process should be repeated each time a new writer is presented to the system. On the contrary, writer-independent approaches, which are less accurate provide generic systems that can be tested on any new writer.

Conventionally, the verification is based on similarity measures and template matching. Recently, robust classifiers like artificial neural networks, Hidden Markov Models and SVM are extensively used. Specifically, SVM are known as being the most proficient classifiers. However, satisfactory verification performance is not

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trivial [1]. To cope with classifier limitations, several hybrid systems as well as classifier ensembles were developed. In the present work, we investigate the usefulness of Artificial Immune Recognition System (AIRS) as signature verification process. AIRS is a bio-inspired classifier, which was introduced in 2001 by Watkins [2]. In the past recent years, it showed a promising performance in several pattern recognition applications such as disease diagnosis and fault detection . Also, it has been used in some handwriting recognition tasks [4]. Specifically, we note handwritten Russian uppercase letter recognition , Chinese letter recognition and handwritten character recognition. Presently, in the proposed signature verification system, Ridgelet and zoning are used to generate relevant features while AIRS performs the verification process.

The rest of this paper is organized as follows. The proposed signature verification system is presented in the next section [5]. Section 3 summarizes experimental results whereas the main conclusions are given in the last section.

2. SIGNATURE VERIFICATION SYSTEM

In this work, the signature verification is performed in a writer- dependent framework. The problem at hand is considered as a two- class pattern recognition problem where the training task is conducted to separate genuine signatures from skilled forgeries.

2.1. Feature Generation

Feature generation is based on two different descriptors. As shown in figure (1), zoning or grid features are generated using pixels densities [6]. These features are used with those obtained from Ridgelet transform to constitute the data feature vector. Note that, for each signature, Ridgelet features are computed as follows:

- Normalizing signature images to the same size.
- Apply Radon transform (The number of angular directions is experimentally tuned).

$$RA(\theta, r) = \iint f(x, y)\, ð(x \cos \theta + y \cos \theta - r) dxdy \qquad (1)$$

ð: Dirac distribution,

θ: Angular variable,

r: Radial variable.

- Ridgelet features are obtained by applying 1 Dimension Wavelet (1DW) transform on each Radon slice.

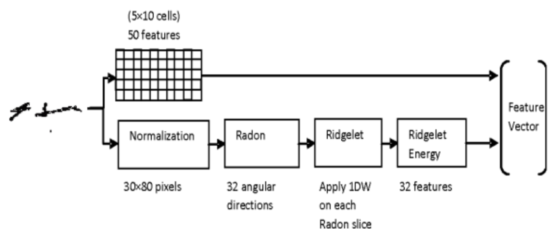

Figure 1. Feature generation for handwritten signatures

- Finally, each Ridgelet feature is substituted by its energy.
- Signature feature vector is obtained by concatenating grid features with the Ridgelet energy.

2.2. AIRS: ARTIFICIAL IMMUNE RECOGINATION SYSTEM

Artificial immune systems are inspired from the natural immune system, which uses antibodies (B-Cells) to recognize dangerous invaders that are known as antigens [7]. Based on this idea, interesting artificial immune algorithms were developed. Among them, we note the resource limited artificial immune system proposed by Timmis and Neal. This algorithm introduced the concept of Artificial Recognition Ball (ARB), which has the same meaning as a B-Cell. More recently, Watkins proposed the Artificial Immune Recognition System: AIRS. This algorithm is a resource limited algorithm that imitates immune metaphors such as antibody-antigen binding affinity maturation, clonal selection process, resource competition and memory cell acquisition. In AIRS, the ARB corresponds to the feature vector of a training sample in addition to its class and its resources number [8]. The AIRS algorithm can be summarized through the following steps.

a) Initialization:

In this step, data are normalized such that Euclidian distance is scaled in the range. Then, an Affinity Threshold (AT) is computed.

The initialization step is achieved by seeding of initial memory cells and initial ARB population. In other words, for each class of interest (two classes in our case), one training sample is randomly selected to be used as prototype of its class [9]. These selected samples are called antibodies or established Memory Cells (MC).

b) Training process:

The training of each datum (antigen: agi) is a one-shot process. It begins by finding the prototype 'MC', which has the highest stimulation to this antigen. The stimulation "ST" is defined as:

$$ST(agi, MC) = 1 - ED\ (agi, MC) \quad \ldots(3)$$

ED: Euclidian distance.

The selected MC is called MC-match. It is used to generate a set of randomly mutated clones. Then, a competition between generated clones is carried out and the one presenting the highest stimulation to the considered training sample is selected. This clone is called Memory Cell candidate. It will replace or just be added to the population of established memory cell on the basis of a comparison with MC-match [10]. Note that several user-defined parameters are required to ensure the AIRS functioning. Specifically, we note clonal, mutation and hypermutation rates, which control the generation of mutated clones, the resource number, which allows removing bad generated clones during the competition process and the stimulation threshold, which is the stopping criterion. Once the training stage is finished, test samples are classified according to a K-Nearest Neighbors decision computed with respect to the memory cells population. For further details on AIRS, reader can be referred to .

3. EXPERIMENTAL RESULTS

CEDAR dataset is used to assess the performance of AIRS-based signature verification. In this dataset, 55 individuals contributed 24 genuine signatures. Besides, some individuals were asked to forge three other writers' signatures, eight times per subject, which yields 24 skilled forgeries. In the present work, signature verification is a writer-dependent problem, which means that for each individual an AIRS is developed. Signatures were portioned into three sub-sets of 8 signatures to achieve training, validation and test stages. The feature vector is composed of 50 grid features (obtained by dividing signature images into 5×10 cells) and 32 Ridgelet features obtained as follows. Apply Radon

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transform according to 32 angular directions. Then, Wavelet transform with three decomposition levels is applied on each Radon slice to obtain a Ridgelet. Finally, the energy of Ridgelet feature is computed.

This yields 32 Ridgelet features. Note that the signature verification process can produce two type of errors the False Rejection Rate (FRR) which gives the percentage of genuine signatures that are rejected by the system and the False Acceptance Rate (FAR) which is the percentage of forged signatures that are accepted by the system. Also, the averaged sum of both FRR and FAR constitutes the Error Rate (ER).

Recall that AIRS training algorithm employs several user-defined parameters, which are namely, the clonal rate, resources number, mutation rate, hyper-mutation rate and the stimulation threshold. Since there is no theoretical rules to tune these parameters, several run-passes were executed to find the best value for each of them. Results indicated that some parameters have higher influence than the others. Specifically, the clonal rate, which controls the number of produced mutated clones has substantial effect on the AIRS performance. Figure (2) shows the behavior of AIRS in terms of runtime and error rate according to clonal rate variations. As expected, the more the clonal rate is large the more the runtime is. This outcome reflects the time required to produce mutated clones and search the memory cell candidate. Nevertheless, validation and test errors behave differently since the best scores are obtained for a clonal rate taken in the range . Besides, a value of 150 allows the best trade-off between the error rate and the runtime.

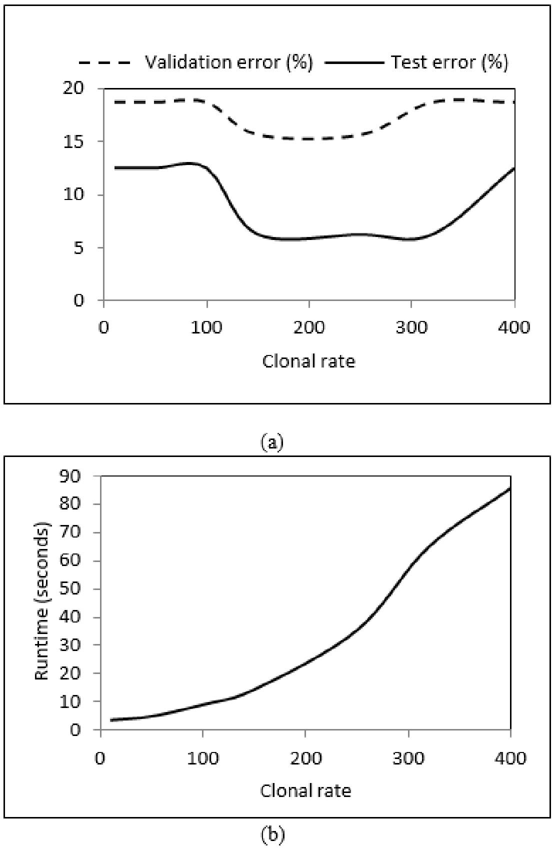

Figure 2. AIRS behavior according to the clonal rate variations

(a)Error rate, (b) Runtime

Furthermore, the AIRS performance was assessed comparatively to SVM for which, RBF kernel parameter and the regularization factor were selected using cross-validation. Therefore, table 1 reports the average FRR, FAR obtained for the 55 individuals. This table reports, the results obtained using grid and Ridgelet features separately. Also, it reports the results obtained by the proposed system in which, grid and Ridgelet features are grouped in the same feature vector. It is easy to see that the AIRS requires a large runtime compared to SVMs. Furthermore, both AIRS and SVMs perform better when using grid features where the gain in FAR and FRR reaches 3% compared to Ridgelet features. In addition, using grid features, AIRS outperforms SVMs. Also, we remark

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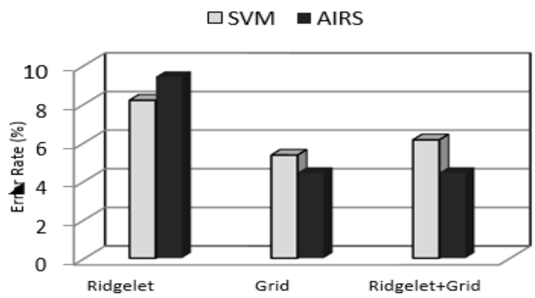
that when grid and Ridgelet energy are used simultaneously, the FAR and FRR are not necessarily improved. This outcome is obtained specifically, with SVMs where Ridgelet energy alters the scores already obtained with grid features. On the contrary, the AIRS keeps approximately the same scores. This means that Ridgelet transform cannot bring relevant knowledge compared to grid features. Consequently, as indicated in figure (3), the AIRS gives the best error rate which is about 4.43% with a gain of 1% over SVMs. Also, as reported in table 2, the results obtained using the proposed system outperforms several stat of the art systems. Finally, as reported in table 2, which lists some state-of-the-art results, the proposed system gives quite satisfactory performance.

Figure 3. Error rate obtained using various data features

	Ridgelet Energy (32 features)			Grid features (50 features)			Grid + Ridgelet Energy (82 features)		
	FRR	FAR	Runtime (s)	FRR	FAR	Runtime (s)	FRR	FAR	Runtime (s)
SVM	7.72	8.63	0.08	4.82	5.90	0.12	5.45	6.81	0.27
AIRS	8.40	10.45	5.70	3.63	4.71	5.20	3.63	4.64	12.30

4. CONCLUSION

The present work investigates the use of the Artificial Immune Recognition Algorithm (AIRS) for off-line handwritten signature verification. In the proposed system, signatures are described using grid features and Ridgelet transform. Performance assessment was conducted on CEDAR dataset. Experiments showed that user-defined parameters of AIRS should be



This parameter should be close to 1 in order to improve the quality of produced memory cells but this leads to a large runtime. Finally, this work shows promising results but further tests using some other databases and various signature verification scenarios are important to confirm again the validity of AIRS for signature verification.

Table 1. Verification results obtained for AIRS and SVM

System	**Error Rate (%)**
Word shape	21.5
Zernike moments	16.4
Graph matching	7.9
Signature morphology	11.59
Surroundedness feature (writer independent)	8.33
Proposed system	4.18

Table 2. Comparison of the proposed system with the state of the art on CEDAR dataset

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