Improving BPSO-based feature selection applied to offline WI handwritten signature verification through overfitting control

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ABSTRACT

This paper investigates the presence of overfitting when using Binary Particle Swarm Optimization (BPSO) to perform the feature selection in a context of Handwritten Signature Verification (HSV). *SigNet* is a state of the art Deep CNN model for feature representation in the HSV context and contains 2048 dimensions. Some of these dimensions may include redundant information in the dissimilarity representation space generated by the dichotomy transformation (DT) used by the writer-independent (WI) approach. The analysis is carried out on the GPDS-960 dataset. Experiments demonstrate that the proposed method is able to control overfitting during the search for the most discriminant representation.

CCS CONCEPTS

• **Computing methodologies** → **Feature selection**; Support vector machines; *Bio-inspired approaches*;

KEYWORDS

Feature selection, Binary PSO, Offline signature verification, Dichotomy transformation, Writer-independent systems

1 INTRODUCTION

In the Writer-Independent Handwritten Signature Verification (WI-HSV) approach, a single model is trained from a dissimilarity space and is responsible for verifying the signatures of any available writer in the dataset. Thus, the classification inputs are dissimilarity vectors, which represent the difference between the features of a queried signature and a reference signature of the writer.

The *SigNet*, proposed by Hafemann et al. [2], is a state of the art Deep Convolutional Neural Network (DCNN) model for feature representation in the HSV context and its feature vectors are composed of 2048 dimensions. Some of the features may be redundant when transposed to a WI dissimilarity space.

Thus, we propose to use a feature selection technique based on binary particle swarm optimization (BPSO) to obtain only the relevant dimensions on this transposed space [1]. The optimization is conducted based on the minimization of the Equal Error Rate (*EER*) of the SVM in a wrapper mode [4]. In this scenario, one possible problem that can be faced is overfitting. Thus, the objectives of this

study are: (i) to analyze the redundancy in the features obtained in the dissimilarity space generated by DT. (ii) The presence of overfitting when using Binary Particle Swarm Optimization (BPSO) to perform the feature selection in a wrapper mode. (iii) Whether overfitting control can improve optimization performance.

2 BASIC CONCEPTS

Writer-Independent Handwritten Signature Verification (WI-HSV). The Dichotomy Transformation (DT) allows to transform a multi-class pattern recognition problem into a 2-class problem. In this approach, a dissimilarity (distance) measure is used to distinguish whether a given reference and a questioned sample belong to the same class or not [5]. When applied to the HSV context it characterizes the writer-independent (WI) approach, the samples are signatures and to perform the verification means belonging to the same writer (*positive class*) or not (*negative class*) [5].

The dissimilarity vector resulting from DT, **u**, is obtained by applying the absolute value of the difference from x_{qi} and x_{ri}, where i is the respective feature of the questioned signature signature ($\mathbf{x}_q$) and reference signature ($\mathbf{x}_r$) [5].

Feature selection using BPSO. In a context of feature selection, particle swarm optimization algorithms are used in their binary version (BPSO) and have been obtaining good results [1]. We use a variation of PSO, in which the algorithm itself adjusts w, c_1 and c_2 dynamically over iterations, promoting global search in the beginning and local search in the final iterations [6].

The transformation of the continuous search space into a binary space is conducted by using a V-shaped transfer function [3].

We propose to use a BPSO-based feature selection for WI-HSV in a wrapper mode. The optimization is conducted based on the minimization of the Equal Error Rate (*EER*) of the SVM in a wrapper mode. The user threshold (considering just the genuine signatures and the skilled forgeries) was employed [5].

In the feature selection scenario, overfitting occurs when the optimized feature set memorizes the training set instead of producing a general model. To decrease the chance of overfitting, a validation procedure can be used during the optimization process in order to select solutions with good generalization power.

According to Radtke et al. [4], one possible validation strategy is the *last iteration strategy*, this approach validate final candidate solutions on another set of unknown observations âĂŞ the selection set. By using this approach, the optimization routine produces better results than selecting solutions based solely on the accuracy of the optimization set alone. However, this strategy has the disadvantage that the solution is validated only once, after the optimization process is completed.

Another approach is the *global validation strategy* [4], where the validation of the candidate solutions are executed in all iterations of the optimization process. This can be accomplished by storing the best validated solutions in an external (auxiliary) archive.

During both validation routines, the optimization set (Opt) is temporarily replaced by the selection set (Sel) to evaluate the fitness function. In the *global validation strategy*, at each iteration, all the best solutions previously found are grouped with the population of the new swarm and then ranked. Finally, the external archive maintains the N best candidate solutions.

3 EXPERIMENTS

The experiments are carried out using GPDS-960 dataset, specifically in the GPDS-300 stratification. The Exploitation set, where the tested set is acquired, is composed of writers 1 to 300. The Development set is formed by the other 581 writers, from these: 146 writers are randomly selected to compose the train set, another 145 for the validation set, another 145 for the optimization set (Opt) and the remaining 145 for the selection set (Sel).

As in the work by Souza et al. [5], we use the highest value for the number of references, i.e., 12 references per writer, and the Max function as the partial decisions. In the training step, the model uses 10 genuine signatures and 10 random forgeries. During optimization (optimization and selection sets), the fitness function minimizes the EER with user threshold considering only genuine signatures and skilled forgeries. In this case, for each writer, 10 genuine signatures and 10 skilled forgeries are used. These operations are performed in the space with reduced samples, i.e., after prototype selection through Condensed Nearest Neighbors (CNN) [5]. The test set is acquired as in [2]. The SVM and IDPSO settings are the same as in [5] and [6], respectively. The maximum number of iterations was set to 40. Five replications were carried out.

3.1 Results and discussions

Table 1 presents the results obtained by the the models with and without feature selection. Table 2 contains the comparison of the presented models with the state of the art methods for the GPDS-300 dataset (references can be found in [5]).

Table 1: Comparison of EER considering the presented models, in the GPDS-300 dataset (errors in %)

Approach	#features	EER
No feature selection	2048	3.57 (0.10)
Feature selection and no validation	1124	3.76 (0.07)
Feature selection and last iteration validation	1120	3.64 (0.08)
Feature selection and global validation	1140	**3.46 (0.08)**

In terms of validation strategy, the improvement when using any of the validation stages was enough to obtain better results when compared to the model without feature selection. Results indicate that not using a validation stage is worse than using validation at the last iteration, which in turn is worse than using the global validation strategy. Thus, by using the global validation strategy it is possible to control the overfitting of the model and, thereby, improve the performance of the BPSO-based feature selection approach.

Another aspect that can be observed is the presence of redundant features in the dissimilarity space generated by DT. Since, the model with feature selection and global validation uses only almost 55% of the total number of features and still manages to obtain similar EER when compared to the model trained with all the 2048 features.

Table 2: Comparison of EER with the state of the art, in the GPDS-300 dataset (errors in %)

Type	HSV Approach	#Ref	#Models	EER
WD	Hafemann et al. (2016)	12	300	12.83
WD	Zois et al. (2016)	5	300	5.48
WD	Hafemann et al. (2017)	5	300	3.92 (0.18)
WD	Hafemann et al. (2017)	12	300	3.15 (0.18)
WD	Serdouk et al. (2017)	10	300	9.30
WD	Hafemann et al. (2018)	12	300	3.15 (0.14)
WD	Hafemann et al. (2018) (fine-tuned)	12	300	0.41 (0.05)
WD	Yilmaz and Ozturk (2018)	12	300	0.88 (0.36)
WD	Zois et al. (2019)	12	300	0.70
WI	Dutta et al. (2016)	N/A	1	11.21
WI	Hamadene and Chibani (2016)	5	1	18.42
WI	Souza et al. (2019)	12	1	3.47 (0.15)
WI	Zois et al. (2019)	5	1	3.06
WI	$SVM_{no-selection}$	12	1	3.57 (0.10)
WI	$SVM_{global-validation}$	12	1	3.46 (0.08)

In general, our $SVM_{global-validation}$ approach obtains low EER. In the WI scenario, it is only worse than the model proposed by Zois et al. (2019). In the comparison with WD models, our approach only got worse results than Hafemann et al. (2018) (fine-tuned), Yilmaz and Ozturk (2018) and Zois et al. (2019), being better or comparable than the other cases. It is important to point out that, as a WI model, our approach has greater scalability than these other models, since only one classifier is needed to perform signature verification.

4 CONCLUSIONS

In this work, we evaluated the use of BPSO-based feature selection for offline writer-independent handwritten signature verification. The optimization was conducted based on the minimization of the Equal Error Rate (EER) of the SVM in a wrapper mode. Experimental results showed that not using a validation stage is worse than using validation at the last iteration, which in turn is worse than using the global validation strategy. Thus, by using the global validation strategy it is possible to control the overfitting of the model and, thereby, improve the performance of the BPSO-based feature selection approach.

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