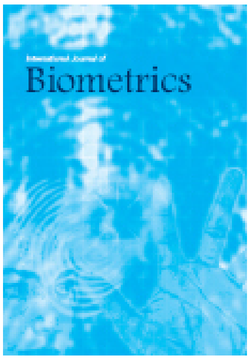

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Symbolic data analysis-based few-shot learning for offline handwritten signature verification

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Abstract: This paper presents a novel approach for offline handwritten signature verification using few-shot learning and symbolic data analysis. The method effectively handles high intra-class variability and limited data availability, common challenges in signature recognition. The model is trained on dissimilarities from the Signet feature extractor, capturing subtle differences within the same writer's signatures. A new weighted membership function measures similarity between query and reference signatures. The method outperforms traditional approaches, achieving competitive equal error rates on four public datasets (GPDS, CEDAR, MCYT, PUC-PR) using only five genuine reference signatures. The system surpasses state-of-the-art results on GPDS and PUC-PR datasets. This combination of few-shot learning and symbolic data analysis offers robust and efficient signature verification, ideal for real-world applications with scarce labelled data.

Keywords: few-shot learning; FSL; signature verification; intra-class variability; one-class symbolic data analysis classifier; dissimilarities.

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1 Introduction

Offline handwritten signature verification (OHSV) system deployed in a real environment (e.g., bank) should overcome three major issues. The first issue concerns the reduced number of reference signatures requested from users (writers) during the enrolment into the database (i.e. 3 to 5 reference signatures). Indeed, most signers possess large intra-personal variability due to physical or emotional factors, and thus, few reference samples are not enough for modelling the natural intra-personal variability and building an accurate signature style for each writer. A second issue concerns the use of only genuine signatures for designing the verification system, without employing any forged signatures. The third issue occurs when a skilled forgery is presented to the verification system. Unlike random forgery which occurs when a person tries to use his own signature to impersonate another person, a skilled forgery is an imitated signature drawn by a forged specialist, trying to claim a forged identity. By this fact, skilled forgeries are the most difficult to be detected by verification systems, due to their high similarities with genuine signatures.

Traditional approaches in signature verification heavily rely on large annotated datasets, which are often difficult and expensive to acquire. However, the emergence of few-shot learning (FSL) techniques has provided a promising solution to tackle this issue. FSL aims to recognise and generalise patterns from a small number of labelled examples, enabling robust classification even in scenarios with limited training data. By leveraging prior knowledge from reference samples, FSL algorithms can adapt and generalise to new, unseen instances efficiently.

Applying FSL to OHSV offers several advantages. First, it reduces the dependence on a large amount of data, which is often impractical to obtain in real-world applications. Secondly, it enables the model to handle intra-class variability by effectively capturing the underlying structure of signatures within the same writer (class), enhancing the discrimination between genuine and forged signatures. Finally, FSL techniques allow for the incorporation of symbolic data representation, which complements the concept of FSL by providing a symbolic representation of signatures that models essential features and dissimilarities.

Several noteworthy works in handwritten recognition using FSL have been proposed. For instance, Snell et al. (2017) introduced prototypical networks, which learn a metric space for few-shot recognition tasks. However, their fixed reliance on a Euclidean distance metric may lack robustness across diverse data distributions. Moreover, sensitivity to small support sets and limited exploration of hyperparameters, as well as class imbalance in few-shot tasks have not been appropriately addressed.

Finn et al. (2017) presented model-agnostic meta-learning (MAML), a meta-learning approach aiming to enable models to quickly adapt to new tasks with minimal data. Although versatile, a limitation is that MAML may require a relatively large number of iterations during meta-training, making it computationally expensive.

Sung et al. (2018) introduced relation networks for FSL, where the model learns to compare images in the support set and the query set to make predictions. A limitation could be the complexity of the learned relations, which may not generalise well to diverse datasets.

Unlike previous works, exemplified by Snell et al. (2017), where prototypical networks relied on a fixed Euclidean distance metric, the proposed work in this paper introduces a weighted membership function, enhancing robustness across diverse data distributions. Moreover, unlike cited works, which primarily focuses on specific benchmark datasets, our approach demonstrates superior performance across four public signature datasets (GPDS, CEDAR, MCYT, and PUC-PR). Moreover, the proposed system combines the strengths of FSL with symbolic data representation, providing a more versatile and effective solution. By utilising feature-dissimilarities extracted from the Signet model (Hafemann et al., 2017), instead of entire straightforward feature vectors, the proposed method ensures higher accuracy in discriminating skilled forgeries from genuine signatures (inter-class) and capturing intra-personal variations (intra-class). Indeed, each feature-dissimilarity component is modelled separately through a specific statistical model inspired from its real probability distribution, unlike the traditional approach, where the mean and standard deviation metrics are used for creating the statistical model associated to each feature component (Alaei et al., 2017). The proposed FSL verification system, built on intra-class feature-dissimilarities, outperforms traditional OHSV features-based methods, offering a robust framework for OHSV.

Hence, for a fair comparison against the state-of-the-art, feature components are extracted from *SigNet* model through the concept of transfer learning (Oquab et al., 2014; Shaha and Pawar, 2018). The training of *SigNet* respects the important restriction imposed in this work which is to use only genuine signatures during the design of the OHSV system. Hence, a decision threshold is defined for accepting or rejecting a signature, which consists of assigning for each writer his own tuned threshold computed automatically via a specific formulation based on the *leave-one-out* concept.

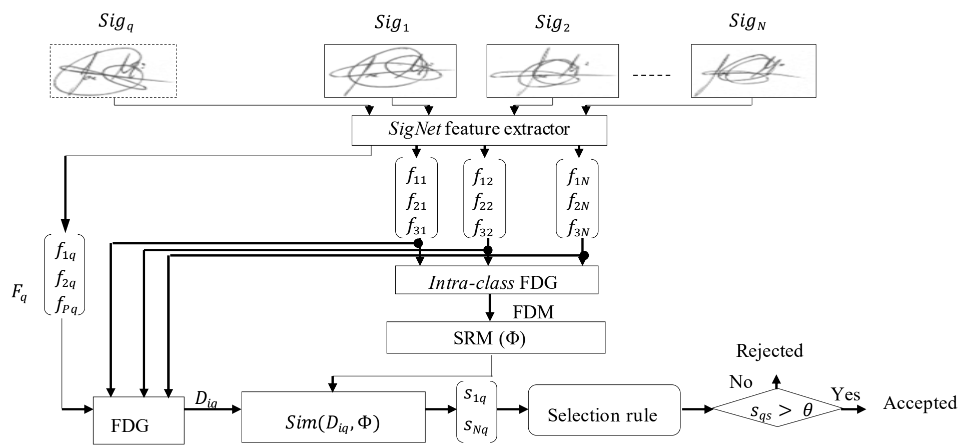
The remaining of this paper is organised as follows. Section 2 presents the detailed description of the proposed FSL system. To evaluate the performance of the proposed FSL system, extensive experiments in different conditions performed on four public offline signature datasets: GPDS-960, CEDAR, MCYT, and PUC-PR datasets, are presented in Section 3. Finally, a conclusions and perspective of the proposed work are provided in the last section.

2 Proposed FSL system

2.1 Overview of the proposed FSL system

The design of the proposed FSL system is composed of four main stages as depicted in Figure 1. In the beginning, a query signature (Sig_q) is presented to the FSL system's input. Then, a feature vector (F_q) is generated through the *SigNet* feature extractor. At the same time, an *intra-class* feature dissimilarity generation (FDG) is performed between each pair of the N reference feature vectors F_i $\{i = 1, \ldots, N\}$, which belongs to the claimed writer. This step allows generating a feature dissimilarity matrix (FDM), which is used for building thereafter the symbolic representation model (SRM). Next, a FDG is performed between F_q and all references (F_i), which allows generating N query feature-dissimilarity vectors (D_{iq}). In the sequel, a fuzzy similarity measure is performed between D_{iq} and the SRM (Φ), generating N output similarity scores (s_{iq}). Finally, a selection rule is performed for selecting only one representative score (s_{qs}), which is compared in the sequel to a decision threshold in order to accept or reject the query signature (Sig_q).

Figure 1 Overall scheme of the proposed FSL system



In the following sections, every single step is described more deeply for a better understanding of the proposed FSL system.

2.2 Feature-dissimilarity generation and verification

2.2.1 Feature-dissimilarity generation

Considering the recent success of using a deep learning approach for extracting features from images, a learned descriptor based on convolution neural network (CNN) is used in this work for characterising the signature images. For a fair comparison with the state-of-the-art, the features used in this work are extracted using the CNN model namely *SigNet*, through the transfer-learning concept (Oquab et al., 2014; Shaha and Pawar, 2018). *SigNet* architecture is genuinely inspired by the well-known *AlexNet* architecture proposed by Krizhevsky et al. (2012), used to resolve the *ImageNet* dataset classification. The input signature image passes through successive transformations starting by pre-processing (i.e., centring, removing background via the OTSU's algorithm, inverting greyscale, and resizing the image to the size 1 × 150 × 220), and then fed to convolutional layers, max-pooling layers, and fully-connected layers. Note that the size of the feature vector extracted from *SigNet* is 2,048, and only genuine signatures belonging to the first 531 writers of the GPDS-960 dataset (Vargas et al., 2007) are employed to train *SigNet*.

To effectively capture the intra-class variability, the proposed FSL model is trained using dissimilarities extracted from the *SigNet*_features. The dissimilarity concept was early introduced in the pattern recognition field by Pekalska and Duin (2002), and further used in handwritten recognition by Cha and Srihari (2002). For OHSV, dissimilarities are conventionally exploited in the writer-independent (WI) framework (Costa et al., 2020). The literature reports some interesting WI-based OHSV systems addressing the dissimilarity concept, using different engineered features such as contourlet transform (Hamadene and Chibani, 2016), graphometric (Bertolini et al., 2010) and dichotomy transformation features (Souza et al., 2020).

In this context, a new way of using *intra-class* feature-dissimilarities is investigated in a writer dependent (WD) framework. The proposed feature-dissimilarity based-scheme fits the problem of a reduced number of reference signatures framework, since it allows generating more data for creating an accurate signature style model. This concept has been used recently for signature identification (Djoudjai and Chibani, 2023), but has never been explored for signature verification. Precisely, it consists of generating an *intra-class* FDM by gathering the L *intra-class* feature-dissimilarity vectors. The generated *intra-class* FDM represents the base element for building the proposed FSL model based on the OC-SDA classifier, as described in the next section.

2.2.2 Building the FSL model

The proposed FSL model is built using the OC-SDA classifier which is performed through two steps: Building the SRM, and computing similarity measures. Various SRMs based either on ISR and HSR models have been developed for different pattern recognition applications, such as character recognition (Vikram et al., 2008), document analysis (Alaei et al., 2014), classification of medical X-ray images (Rajaei et al., 2015), signature identification (Djoudjai and Chibani, 2023; Oquab et al., 2014; Shaha and Pawar, 2018; Krizhevsky et al., 2012; Vargas et al., 2007; Pekalska and Duin, 2002; Cha and Srihari, 2002; Costa et al., 2020; Hamadene and Chibani, 2016; Bertolini et al., 2010; Souza et al., 2020; Vikram et al., 2008; Alaei et al., 2014; Rajaei et al., 2015; Djoudjai et al., 2017), and verification (Prakash and Guru, 2010; Pal et al., 2015; Alaei et al., 2017). Usually in feature-based approach, the variation range of each k^{th} base feature interval is reduced via the mean, the *standard deviation*, as well as a control parameter α for rejecting intruder samples (Alaei et al., 2017). In this proposed work, a new base *intra-class* feature-dissimilarity interval (ID_k) is defined for each k^{th} *intra-class* feature-dissimilarity component: d_{kl}, where $k = 1, \ldots, P$ and $l = 1, \ldots, L$, by taking simply the *minimum* and the *maximum* value within the L samples.

The idea behind the proposed formulation consists of modelling each k^{th} *intra-class* feature-dissimilarity component (d_{kl}) through a novel weighted membership function, which takes into account the real probability distribution of *intra-class* feature-dissimilarity components (d_{kl}). For this purpose, a statistical analysis is performed on *intra-class* FDM components (i.e., d_{kl}), issued from some samples of training writers, aiming to observe the probability distribution shape that takes the training *intra-class* feature-dissimilarities (d_{kl}). The obtained curves demonstrates that the variation range of intra-personal variability of handwritten signatures, expressed with *intra-class* feature-dissimilarities, is approximately the same and take nearly the shape of half-Gaussian distribution.

In a similar context, Alaei et al. (2017) argued that Gaussian models are not suitable for OHSV in a feature-based approach, since it provides a probability very close to zero for samples that deviate much from the *mean*, especially when genuine signatures vary from other genuine signatures. However, in the proposed work, the Gaussian model seems being suitable for modelling *intra-class* feature-dissimilarities rather than straightforward features, since absolute differences issued from an *intra-class* matching of genuine signatures produce low values.

Thus, a control-parameter is introduced namely λ in the proposed model function, for adjusting the Gaussian width such that it matches the same shape of the *intra-class* feature-dissimilarity distribution, by analogy to α parameter commonly used for building SRMs in feature-based approach (Alaei et al., 2017) [equation (1)].

Hence, each k^{th} base feature-dissimilarity interval (ID_k) is then modelled through the novel weighted membership function, defined as follows:

$$\varphi_k = \begin{cases} 1 & \text{if } d_k^- < d_{kl} < \mu \\ e^{-\frac{1}{2}\left(\frac{d_{kl}-\mu_k}{\lambda\sigma_k}\right)^2} & \text{if } \mu \le d_{kl} < d_k^+ . \\ 0 & \text{else} \end{cases} \tag{1}$$

where μ_k and σ_k are the respective *mean* and the *standard deviation* values computed for each ID_k. In contrast, μ is a global *mean* value computed for all *intra-class* FDM components, such that:

$$\mu = \frac{1}{P \times L} \sum_{k=1}^{P} \sum_{l=1}^{L} d_{kl} \tag{2}$$

while λ is a unique control parameter of the Gaussian distribution which is tuned experimentally during the design step.

The proposed membership function, defined for each k^{th} *intra-class* feature-dissimilarity component (φ_k), contains three terms which refer to three different cases. Initially, the μ value is set as a maximum limit (confidence value) of possible *intra-class* similarity (i.e., internal variability). Indeed, the statistical analysis, shows that the highest probability frequencies are located in the interval $[d_k^-, \mu]$. For this reason, the proposed φ_k enhances the weight of feature dissimilarities when they are located within the interval $[d_k^-, \mu[$, by assigning the maximum probability value 1.

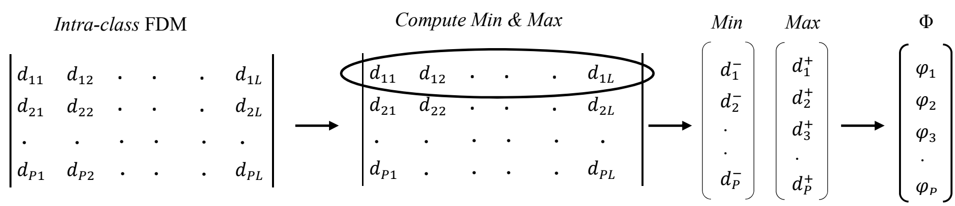
The second term (of φ_k) is similar to the Gaussian distribution when $\lambda = 1$. In contrast, when λ parameter takes other values (i.e., $\lambda \neq 1$), it allows modulating the Gaussian width. In other words, φ_k becomes restrictive due to the narrow width, resulted from low λ values. In contrast, φ_k is permissive when λ takes high values (i.e., large width of φ_k shape). For instance, when query feature-dissimilarity values are large (in case of random forgeries and skilled forgeries), low probability values are provided.

As a result, the SRM is then defined by considering the all P symbolic weighted membership functions (φ_k), such as:

$$\Phi = \{\varphi_1, \varphi_2, \ldots, \varphi_P\}. \tag{3}$$

Φ represents symbolically the signature style of a writer. Its building depends on both *means* (μ_k and μ), the *standard deviation* (σ_k) of *intra-class* feature-dissimilarities, and a unique parameter λ (tuned experimentally). Figure 2 depicts the overall scheme followed for building a SRM (Φ) of a given writer.

Figure 2 Overall scheme for constructing the SRM (Φ) of a given writer



2.2.3 Verification process

To verify the authenticity of a query signature (Sig_q), represented by the query feature vector of size P: $F_q = \{f_{1q}, f_{2q}, f_{3q}, ,\dots, f_{Pq}\}$, the first step is to perform a straightforward absolute difference between F_q and the N reference feature vectors: $F_i = \{f_{1i}, f_{2i}, f_{3i}, \dots, f_{Pi}\}$, $i = 1, 2, \dots, N$, belonging to the claimed writer. Thus, N feature-dissimilarity vectors are produced: $D_{iq} = \{d_{1iq}, d_{2iq}, d_{3iq}, \dots, d_{Piq}\}$. The second step is to perform a fuzzy similarity measure between each feature-dissimilarity vector (D_{iq}) and the generated SRM (Φ) of the claimed writer, producing N scores (s_{qi}), such as:

$$s_{iq} = Sim\left(D_{iq}, \Phi\right) = \frac{1}{P}\left(\sum\nolimits_{k=1}^{P} \varphi_k\right). \tag{4}$$

Consequently, N output scores ranged between 0 and 1 are then generated. In the sequel, a selection rule is performed for selecting only one representative score (s_{qs}), via the *maximum* metric.

As a last step, the selected score (s_{qs}) is submitted to a decision threshold (θ), in order to accept or reject the query signature (Sig_q), according to the following rule:

$$Sig_q \in \begin{cases} \text{accepted} & \text{if } s_{qs} > \theta \\ \text{rejected} & \text{Otherwise} \end{cases}. \tag{5}$$

The optimal decision threshold (θ) value is tuned in the range [0, 1] during the design step.

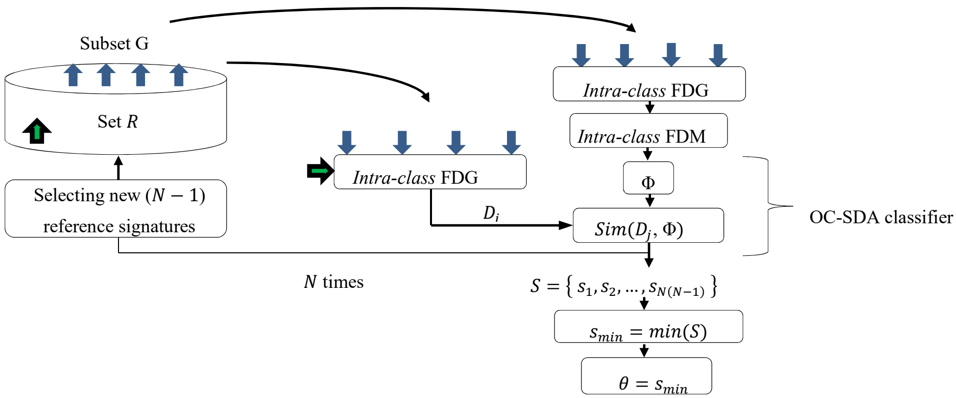
Usually in feature-based SDA approaches applied for OHSV, a user threshold is required for accepting or rejecting query signatures. Hence, the common formulation for defining an acceptance user threshold (θ) is given as follows (Alaei et al., 2017):

$$\theta = \mu_t + \beta \times \sigma_t \tag{6}$$

where μ_t and σ_t are the mean and the *standard deviation* of $Sim(F_i, \Phi)$, $i = 1, \dots, N$, respectively. While β is a control-parameter tuned during the training step. However, this formulation is not appropriate in feature-dissimilarity based approach. Alternatively, this work proposes a new technique for adjusting the decision threshold (θ), based on the *leave-one-out* concept. Genuinely, this technique is proposed for handling the small number of reference signatures imposed in this work. Indeed, it allows obtaining a set of

$N(N-1)$ *intra-class* similarity scores from an initial set of N reference signatures. The idea behind this proposed formulation illustrated in Figure 3, is to extend the confidence margin of *intra-class* variation, in order to handle the case of genuine samples little resembling reference signatures. Thus, it justifies why the *minimum* metric is used for selecting the local threshold (θ) (i.e., a minimum requirement of similarity).

Figure 3 Proposed scheme for generating the local threshold (θ_{LT}) using N reference signatures provided by a writer (see online version for colours)



3 Experiments and results discussion

3.1 Dataset description and evaluation criteria

Four public signature datasets are used to evaluate the proposed FSL system: GPDS-960, MCYT, CEDAR, and Brazilian PUC-PR datasets. All images belonging to the fourth used datasets are acquired initially in a greyscale mode, without any further preprocessing step. Since the access to PUC-PR dataset is not possible, the PUC-PR features made publically available by Hafemann et al. (2017) are straightforward used for evaluating the proposed work.

3.2 Experimental protocol

A small development set ($\mathfrak{D}$) containing W writers ($W = 30$), is randomly selected from the development set considered by Hafemann et al. (2017), for finding the unique FSL system parameter, which is the OC-SDA classifier parameter via minimising the AER.

For the evaluation step (testing phase), a standard 10 cross-validation protocol is first performed on GPDS-300 dataset by computing the *mean* and *standard deviation* values AER/EER. In the second step, a ten blind cross-validation protocol is performed on CEDAR, MCYT, and PUC-PR datasets, without any training of their respective signatures. In this case, features are generated using the GPDS model for extracting features of three datasets. Table 1 reports briefly the experimental protocol used during the design and evaluation step.

Besides, it has been decided in all experiments to use only five reference signatures (N = 5) as a maximum, in order to respect practical conditions of real environment. In addition to AER criteria, the equal error rate (EER) is also used during the evaluation step, for a fair comparison against the state-of the-art.

Table 1 Proposed experimental protocol

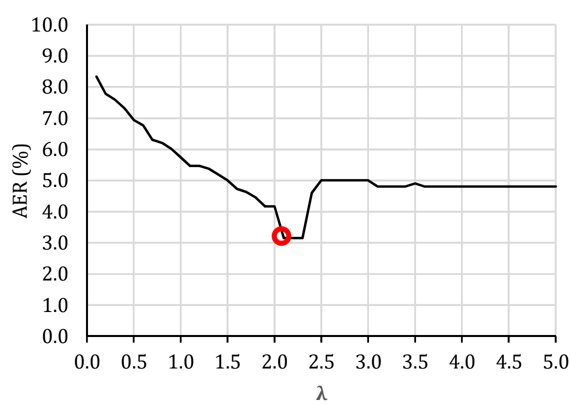
Dataset	*Design step*		*Evaluation step*			
	Writers	*References*	*Writers*	*References*	*Genuine*	*Skilled forgeries*
GPDS-300	30	5	300/160	3 to 5	19	30
CEDAR	-	-	55	3 to 5	19	24
MCYT	-	-	75	3 to 5	10	15
PUC-PR	-	-	100	3 to 5	35	20

3.3 Experimental design

The proposed FSL system requires adjusting only one parameter during the design step, which is the OC-SDA classifier parameter (λ). For finding the optimal parameter, the AER is computed according to the decision threshold based-scenario for each λ value within the interval [0.1, 5] with a step 0.1, as shown in Figure 4. The defined range of λ values is set considering experimental observations which reveal that beyond λ = 5, no significant changes are reported.

As can be seen, the AER curve reveals clearly the effect of the OC-SDA classifier parameter. As already mentioned in Section 2.2.2, the proposed weighted membership functions (φ_k) becomes restrictive when λ takes low values, which explains the reject of random forgeries. Nevertheless, φ_k seem rejecting also some genuine samples (i.e., among the M signatures) which could be a little dissimilar with reference signatures. The optimal parameter is obtained when the AER reaches the first minimum value of around 3.15%, corresponding to three different values of $\lambda = \{2.1, 2.2, 2.3\}$. Hence, the optimal λ value is selected once the AER has reached its first minimum value, i.e., λ_{opt} = 2.1.

Figure 4 AER (%) versus λ parameter performed for 30 writers during the design step (see online version for colours)



3.4 Experimental evaluation

Various experiments are conducted for evaluating the proposed FSL system, in front of different signature types, and in different experimental conditions. As a first step, verification results achieved on GPDS are presented. Then, a ten blind cross-validation protocol is performed on CEDAR, MCYT, and PUC-PR datasets, without any training of their respective signatures. Additionally, to prove the superiority of feature-dissimilarity based model (FDBM) against traditional feature-based model (FBM), the same experimental protocol followed for designing FDMB is reproduced for FBM. Furthermore, for more advantageous conditions, the number of reference signatures is increased for FBM (i.e., $N = \{10, 12\}$), while a *maximum* of five reference signatures are allowed to use for FDBM. Table 2 summarises the obtained verification results for various numbers of reference signatures (N) performed on GPDS-300, CEDAR, MCYT, and PUC-PR datasets.

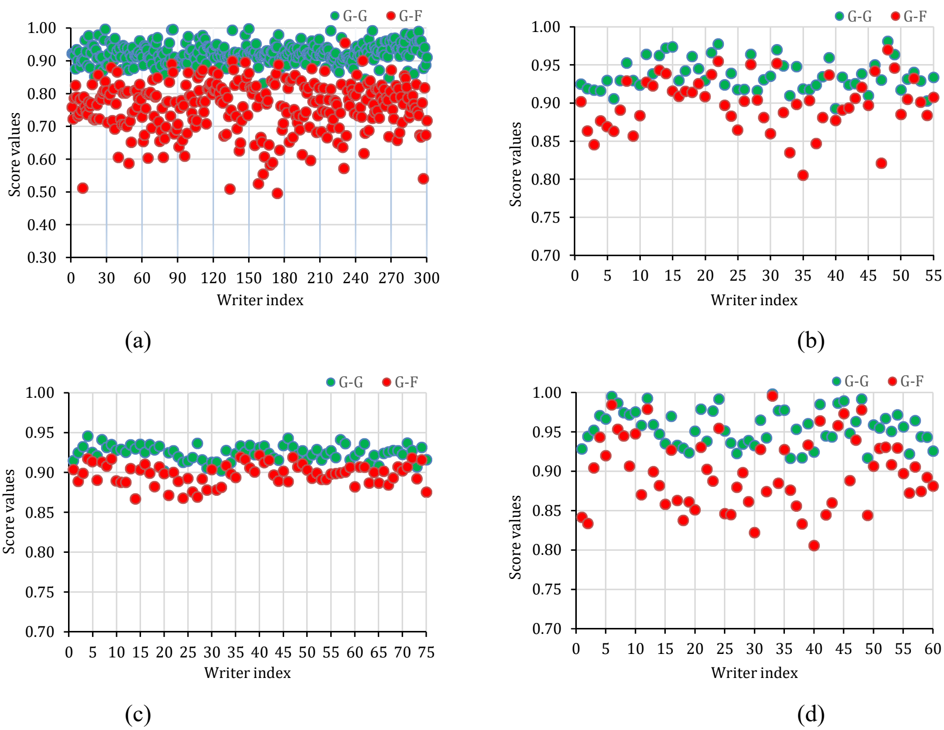
Table 2 EER results achieved by FDBM and FBM on GPDS-300, CEDAR, MCYT, and PUC-PR datasets for various numbers of reference signatures (N)

	GPDS-300		*CEDAR*		*MCYT*		*PUC-PR*	
N	*FBM*	*FDBM*	*FBM*	*FDBM*	*FBM*	*FDBM*	*FBM*	*FDBM*
3	6.76 ± 0.46	*1.32 ± 0.27*	7.43 ± 0.73	*7.40 ± 0.79*	8.97 ± 0.46	*4.85 ± 0.32*	5.78 ± 0.37	*1.45 ± 0.56*
4	5.95 ±0.37	*0.75 ± 0.18*	6.91 ± 0.65	*5.40 ± 0.76*	7.81 ± 0.42	*4.78 ± 0.45*	4.51 ± 0.34	*1.34 ± 0.51*
5	5.78 ± 0.25	*0.65 ± 0.16*	6.16 ± 0.48	*5.23 ± 0.75*	7.13 ± 0.32	*4.12 ± 0.52*	3.75 ± 0.21	*1.23 ± 0.59*
10	4.72 ± 0.44	-	5.33 ± 0.47	-	5.41 ± 0.46	-	3.56 ± 0.22	-
12	4.58 ± 0.39	-	5.05 ± 0.23	-	4.21 ± 0.74	-	3.17 ± 0.17	-

High competitive result are obtained when $N = 5$ on GPDS dataset. Performances remain stables even when reducing the number of reference signatures. Moreover, the achieved low *standard deviation* values show the stability of the proposed FSL system even when reducing the number of reference signatures. Competitive performances are also obtained on the three blind signature datasets. For instance, 4.52%, 4.23% and 1.23% of EERs are achieved when $N = 5$, for CEDAR, MCYT, and PUC-PR datasets, respectively.

On the other hand, experiments reveals clearly the superiority of the proposed verification model based on feature-dissimilarity (FDBM), over the FBM. For instance, EERs achieved via FDBM on GPDS dataset outperform the FBM performances by 4.25%, 8.67%, and 12.22%, for $N = 3, 4, 5$, respectively. Hence, this study demonstrates that using straightforward features do not provide an accurate discrimination between patterns (signature samples) for one-class classifiers, even increasing the number of reference signatures. In contrast, the use of a reduced number of reference signatures in a feature-dissimilarity space has not affected the accuracy of the signature style model, thanks to the proposed solutions for handling hard conditions and the scheme for generating local thresholds. Consequently, this leads to conclude that the one-class classification based on SDA approach can fit OHSV if each target class (writer) is well-represented by *intra-class* feature-dissimilarities, and each component is well-modelled by a suitable weighted membership function (φ_k).

Figure 5 Distribution of output similarity scores generated by the FSL system when query signatures are genuine or forged for: (a) GPDS, (b) CEDAR, (c) MCYT, and (d) PUC-PR datasets, using five reference signatures ($N = 5$) (see online version for colours)



For completing the result analysis, scatter graphs are displayed in Figure 5 to observe the distribution of similarity scores issued from the four signature datasets: GPDS, CEDAR, MCYT, and PUC-PR datasets. The similarity scores computed between genuine references against both genuine and forgeries are designated as G-G and G-F, respectively. Hence, the scatter graphs demonstrate the effective adjustment of the decision threshold for each writer to get high performances.

3.5 *Comparative analysis against the state-of-the-art*

For evaluating the proposed FSL system against similar works in the literature, a comparative analysis is performed against existing WD-based OHSV systems. Meanwhile, a specific performance comparison is achieved versus the similar work proposed in Hafemann et al. (2017), where the same feature extraction method is used (i.e., *SigNet*). Hence, Tables 3 and 4 summarise EERs obtained by the last state-of-the-art works on GPDS, CEDAR, MCYT, and PUC-PR datasets, for different number of reference signatures (N). Note that GS and FS mean genuine signature and forged signature, respectively, involved during the training step while *SigNet-D* means the *SigNet* features associated with the dissimilarity concept.

Table 3 Comparative analysis of the proposed FSL system against the state-of-the-art results performed on GPDS dataset, according only to the WD-based approach, for different number of reference signatures (*N*)

Dataset	*Reference*	*Features*	*Classifier*	*Training signatures*	*N*	*AER/EER (%)*
GPDS-150	Hu and Chen (2013)	LBP, GLCM, HOG	SVM+GRA	GS	10	7.66
	Alaei et al. (2017)	LBP	OC-ISR	GS	4	21.22
	-	-	-	-	12	11.74
	Yilmaz and Yanikoglu (2016)	LBP, HOG, SIFT	Combined SVMs	GS	12	6.97
	Yilmaz and Öztürk (2018)	CNN	Combined SVMs	GS	12	4.13
GPDS-160	Hafemann et al. (2017)	*SigNet*	SVMs	GS	5	3.28 ± 0.36
	-	-	-	-	12	2.63 ± 0.36
	Proposed work	*SigNet-D*	OC-SDA	GS	3	1.06 ± 0.17
	-	-	-	-	4	0.70 ± 0.19
	-	-	-	-	5	0.60 ± 0.17
	Guerbai et al. (2015)	Curvelet transform	OC-SVM	GS	4	16.92
	-	-	-	-	12	15.07
	Serdouk et al. (2017)	HOT	AIRSV	GS	10	9.30
	Bhunia et al. (2019)	LPQ	OC-SVM	GS + FS	12	8.03
	Hafemann et al. (2017)	*SigNet*	SVMs	GS	5	3.92 ± 0.18
	-	-	-	-	12	3.15 ± 0.18
	-	*SigNet-F*	SVMs	GS + FS	5	2.41 ± 0.12
GPDS-300	-	-	-	-	12	1.69 ± 0.18
	Hafemann et al. (2018)	*SigNet-SPP-F*	SVMs	GS + FS	12	0.41 ± 0.05
	Maergner et al. (2019)	*MAML*	OC	GS + FS	5	4.39 ± 0.18
	-	-	-	-	12	2.68 ± 0.17
	Zois et al. (2019)	K-SVD/OMP	SVMs	GS	5	1.50
	-	-	-	-	12	0.70
	Maruyama et al. (2020)	*SigNet-F*	SVMs	GS + FS	22	1.04
	Proposed work	*SigNet-D*	OC-SDA	GS	3	1.23 ± 0.27
	-	-	-	-	4	0.75 ± 0.18
	-	-	-	-	5	0.65 ± 0.16

Table 4 Comparative analysis against the state-of-the-art results on CEDAR, MCYT and PUC-PR datasets

Reference	*Training/testing*	*Features*	*Classifier*	*Training signatures*	*N*	*EER (%)*
Guerbai et al. (2015)	GPDS/CEDAR	Curvelet transform	OC-SVM	GS	12	5.60
Hafemann et al. (2017)	GPDS/CEDAR	*SigNet*	SVMs	GS	5	5.58 ± 0.73
-	-	-	-	-	12	4.76 ± 0.36
-	-	*SigNet-F*	SVMs	GS + FS	5	3.70 ± 0.79
-	-	-	-	-	10	3.00 ± 0.56
Hafemann et al. (2018)	CEDAR/CEDAR	*SigNet-SPP*	SVMs	GS	10	3.64 ± 1.04
Hafemann et al. (2019)	CEDAR/CEDAR	*MAML*	OC-classifier	GS + FS	4	8.27 ± 1.45
-	-	-	-	-	8	7.07± 1.08
Maergner et al. (2019)	CEDAR/CEDAR	Triplet CNN	Set of classifiers	GS + FS	10	5.91
Zois et al. (2018)	CEDAR/CEDAR	K-SVD/OMP	SVMs	GS	10	0.79
Liu et al. (2021)	CEDAR/CEDAR	MSDN	Similarity scores	GS + FS	4	2.17
Maruyama et al. (2020)	CEDAR/CEDAR	*SigNet-F*	SVMs	GS + FS	22	2.47
Avola et al. (2021)	CEDAR/CEDAR	*R-SigNet*	SVMs	GS + FS	12	0
Banerjee et al. (2021)	CEDAR/CEDAR	Mixed features	Naïve Bayes	GS + FS	-	0.02
Proposed work	GPDS/CEDAR	*SigNet-D*	OC-SDA	GS	3	7.40 ± 0.79
-	-	-	-	-	4	5.40 ± 0.76
-	-	-	-	-	5	5.23 ± 0.75
Vargas et al. (2007)	MCYT/MCYT	LBP	SVMs	GS	10	10.07
Serdouk et al. (2017)	MCYT/MCYT	HOT	AIRSV	GS	12	10.60
Bhunia et al. (2019)	MCYT/MCYT	LPQ	OC-SVM	GS + FS	12	8.50
Hafemann et al. (2017)	GPDS/MCYT	*SigNet*	SVMs	GS	4	8.27 ± 1.45
-	-	-	-	-	5	3.58 ± 0.54
-	-	*SigNet-F*	SVMs	GS + FS	4	8.27 ± 1.45
-	-	-	-	-	12	2.87 ± 0.42

Table 4 Comparative analysis against the state-of-the-art results on CEDAR, MCYT and PUC-PR datasets (continued)

Reference	*Training/testing*	*Features*	*Classifier*	*Training signatures*	*N*	*EER (%)*
Hafemann et al. (2018)	MCYT/MCYT	*SigNet-SPP*	SVMs	GS	10	3.64 ± 1.04
Hafemann et al. (2019)	MCYT/MCYT	*MAML*	OC-classifier	GS + FS	5	12.77 ± 0.46
-	-	-	-	-	10	12.44 ± 0.97
Okawa (2018)	MCYT/MCYT	Fused KAZE features	SVMs	GS + FS	4	5.47 ± 1.18
Maergner et al. (2019)	MCYT/MCYT	Triplet CNN	Set of classifiers	GS + FS	10	3.91
Zois et al. (2019)	MCYT/MCYT	K-SVD/OMP	SVMs	GS	5	3.67
Zois et al. (2018)	MCYT/MCYT	K-SVD/OMP	SVMs	GS	10	1.37
Maruyama et al. (2020)	MCYT/MCYT	*SigNet-F*	SVMs	GS + FS	22	0.72
Avola et al. (2021)	MCYT/MCYT	*R-SigNet*	SVMs	GS + FS	8	2.25
Proposed work	GPDS/MCYT	*SigNet-D*	OC-SDA	GS	3	4.85 ± 0.32
-	-	-	-	-	4	4.78 ± 0.45
-	-	-	-	-	5	4.12 ± 0.52
Bertolini et al. (2010)	PUC-PR/PUC-PR	Graphometric	Set of classifiers	GS	15	8.23
Batista et al. (2010)	PUC-PR/PUC-PR	Pixel density	HMMs	GS	30	10.5
Hafemann et al. (2017)	GPDS/PUC-PR	*SigNet*	SVMs	GS	5	4.85 ± 0.32
-	-	-	-	-	12	4.78 ± 0.45
-	-	*SigNet-F*	SVMS	GS + FS	5	6.7 ± 0.87
-	-	-	-	-	15	5.74 ± 0.84
Hafemann et al. (2018)	PUC-PR/PUC-PR	*SigNet-SPP*	SVMs	GS	15	1.33 ± 0.65
Hafemann et al. (2019)	PUC-PR/PUC-PR	*MAML*	OC-classifier	GS + FS	5	6.70 ± 0.87
-	-	-	-	-	15	5.74 ± 0.84
Proposed work	GPDS/PUC-PR	*SigNet-D*	OC-SDA	GS	3	1.45 ± 0.56
-	-	-	-	-	4	1.34 ± 0.51
-	-	-	-	-	5	

As reported in the Table 3, the proposed FSL system achieves an outstanding EER of 1.06% on the GPDS-160 dataset, for only three reference signatures, while the second best EER is 2.63% achieved by Hafemann et al. (2017) using 12 reference signatures. Moreover, the proposed SRM outperforms that proposed by Alaei et al. (2017).

For the GPDS-300 dataset, the proposed system achieves 0.65%, 0.75%, and 1.23% of EERs, for 5, 4 and 3 reference signatures, respectively. In contrast, Hafemann et al. (2017) and Zois et al. (2019) achieve almost the same performance corresponding to 0.41% and 0.70% of EERs, but using numerous reference signatures ($N = 12$). For getting these outstanding results, Hafemann et al. (2017) employed a CNN model which is trained with forgeries namely *SigNet-SPP-F*. In contrast, they obtained an EER of 3.15% with *SigNet*, which is trained with only genuine signatures. Authors in Zois et al. (2018) and Liu et al. (2021), achieve the outstanding 0.70% and 1.50% of EER when $N = 5$ and $N = 12$, respectively. However, their proposed OHSV system requires several preprocessing steps, as well as a lot of parameter adjustments related to their method for extracting features, making their proposed verification system more complex and heavier. In contrast, the proposed FSL system requires the adjustment of only one parameter during the design step, related to the OC-SDA classifier (λ) for achieving a better EER (0.65%), using a smaller number of reference signatures ($N = 5$).

For CEDAR and MCYT, the proposed FSL system achieves 4.12% and 5.23% of EERs for five reference signatures ($N = 5$), respectively. Following the same experimental protocol, and using the same feature extractor (*SigNet*), Hafemann et al. (2017) achieve a slightly better performance on CEDAR (3.92%) but slightly worse on MCYT (5.58%). In the other hand, Liu et al. (2021) achieve on CEDAR an EER of 2.17% using four reference signatures, but they introduced forged signatures for training their *MSDN* model. While Zois et al. (2018) achieve 2.78% and 3.67% of EERs on CEDAR and MCYT datasets, respectively, for five reference signatures. In contrast, a perfect verification result is achieved on CEDAR by Avola et al. (2021) for 12 reference signatures. However, they trained their verification system with forged signatures which are not available in real applications as for instance in a bank. Also, Roy et al. (2023) achieved an EER of 0.02% on CEDAR but using forged signatures during the training process of their system.

The same observation is reported for Maruyama et al. (2020), they obtained an outstanding EER of 0.72% on MCYT dataset. However, they retrained their verification model on MCYT dataset (i.e., not as blind test) using numerous reference signatures ($N = 22$), and also, they have introduced forged signatures for training their verification system.

For PUC-PR dataset, the proposed FSL system improves the-state-of-the-art performances using only few reference signatures, as highlighted in Table 4. Indeed, 1.23% of EER is obtained for only five reference signatures, while 1.33% is obtained by Hafemann et al. (2018) for a great number of reference signatures ($N = 15$). It is worthy to recall that the number of reference signatures is fixed in this work to five at maximum ($N = 5$), in order to respect real environment constraints.

4 Conclusions

This paper aimed to propose an efficient OHSV model based on the one-class symbolic data analysis (OC-SDA) classifier, using only few genuine reference signatures. In feature generation step, Intra-class dissimilarities generated from learned features are introduced in writer-dependent framework, for better representing the intra-personnel variability of handwritten signatures. The proposed verification scheme proposes to model each feature-dissimilarity component by a suitable SRM, which is inspired from the real probability of intra-class feature dissimilarities. Hence, the proposed OC-SDA model can be assumed as a combination of the well-known interval and histogram of symbolic representation (ISR and HSR) models, adapted for a reduced number of reference signatures.

Experimental results demonstrated that using straightforward features do not provide an accurate discrimination between patterns (signature samples) for OCCs, even when increasing the number of reference signatures. In contrast, the use of a reduced number of reference signatures in a feature-dissimilarity space has not affected the accuracy of the writing style through the proposed OC-SDA model. Besides, scatter graphs depicted during the evaluation step reveals the importance of introducing intra-class feature-dissimilarities for generating approximately a uniform distribution of similarity scores even on blind signature datasets. In addition to the high performances obtained in blind datasets, the use of the OC-SDA classifier offers the advantage of adding a new writer without the need to retrain a second time the whole verification system. Indeed, it consists of assigning only one parameter to design the OC-SDA classifier for the new writer. Hence, the proposed OHSV system is assumed as a WI parameter' system.

An interesting perspective of work is to address conjointly signature identification/verification in the framework of an efficient hybrid behavioural biometric system.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests.

Availability data statement

Four public signature datasets are used to evaluate the proposed system:

- GPDS-960 dataset (Vargas et al., 2007) available only with License agreement: https://figshare.com/articles/dataset/GPDS960signature_database/1287360/1.
- MCYT dataset (Ortega-Garcia et al., 2003) available only with License agreement: http://atvs.ii.uam.es/atvs/licenses/MCYT-75-SignatureOff_License.pdf.
- CEDAR dataset (Kalera et al., 2004) available in https://www.kaggle.com/datasets/shreelakshmigp/cedardataset.
- Brazilian PUC-PR (Freitas et al., 2000) dataset, the non-access to PUC-PR datasets, led us to use straightforward the PUC-PR features, made publically available in https://www.etsmtl.ca/unites-de-recherche/livia/recherche-et-innovation/projets/signature-verification.

Due to the nature of this research, participants of this study will agree to share publicly all the source code after the acceptation of the manuscript.

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