Light Weight Online Signature Verification Framework by Compound Feature Selection and Few-shot Separable Convolution Based Deep Learning

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Abstract

Online Signature Verification (OSV) is an extensively used biometric trait aims to verify genuineness of a test signature by computing unique features of the signature. The advancements in mobile and communication technologies resulted in usage of computationally sparse mobile devices in critical applications like m-commerce etc., demands for OSV frameworks which are able to classify the dynamic test signature with fewer number of training signature samples and lesser number of features. The recent advancements in Deep Learning (DL) technologies, resulted in exponential improvements of accuracy in traditional tasks like Object Detection, Scene Text Detection etc. The main disrupt in usage of DL based frameworks for OSV is the requirement of extensive number of training samples and larger number of parameters to learn. To overcome the above pitfalls, we propose a novel dimensionality reduction technique which reduces the dimensionality of a feature set from 100 to 3 in case of MCYT-100 and 47 to 3 in case of SVC, SUSIG datasets respectively. In addition to it, we propose a depth wise separable (DWS) convolution based OSV framework which enables one/few shot learning for test signature verification. To inspect the robustness of our proposed dimensionality reduction technique and DWS OSV framework, exhaustive experiments are conducted with three widely used datasets i.e. MCYT-100, SUSIG and SVC. We have attained state of the art EER in majority of experimentation categories compared to many recent and state-of-the art OSV models.

1. Introduction

Biometrics is extensively used to verify user genuineness in a diverse of critical applications, e.g., banking, e-commerce, m-payments, etc. [1,24,51]. Among the wide range of biometric traits, owing to its ease of acquisition, challenging to morph, hand written signatures have been considered as the most authenticated source of personal verification [3, 4, 9, 29]. Online signature is defined as a multivariate time series signal sampled with specialized online acquisition device like Smart Phones, Stylus Pens, Graphic Tablets, PCs etc. which enables reading both the structural information (x, y coordinates) and the dynamic properties (such as velocity, pressure, acceleration, azimuth, total signature time etc.,) [1,5,6,11,30,32,35].

In literature, many techniques toward automatic online signature verification (OSV) have been put forward which can be commonly categorized into feature-based methods [1-8] that analyze signatures based on a collection of global or local features, function-based approaches which employ various techniques like Hidden Markov models [10], divergence based [14], stability based [16], feature fusion based [22], feature weighing based [25], feature fusion [26], DTW [18, 26, 27, 28, 29,47], matching based [30], neural network based [31], Gaussian Mixture Models [31, 35], random forest [35], sequence matching [14], stroke based [46], deep learning based [20, 26, 32,46,51,52,54], fuzzy-similarity [49] etc.

Inline with the advancements in mobile and networking technologies, to facilitate the usage of OSV frameworks in computationally sparse mobile devices demands for light weight verification models i.e. models which are able to classify the dynamic test signature with fewer number of training signature samples and with lesser number of features extracted from the signature samples. To overcome these drawbacks, various researchers have proposed efficient dimensionality reduction techniques, [44,49,50,53].

To address the above pitfalls, (i) in this work, we have proposed a novel feature dimensionality reduction technique, which performs feature selection and feature extraction simultaneously based on eigen values generated by Principal Component Analysis of feature set. In case of MCYT-100 dataset, the proposed technique drastically reduces the feature set size from 100 to 7 (maximum) and in a few cases 100 to 3 (minimum). In case of SVC and SUSIG datasets, the feature set size is reduced from 47 to 3.

The recent advances in machine learning and deep learning technologies using convolutional models have proven to be resulted improved accuracies in challenging problems like Object Detection, Scene Text Detection etc. [54]. However, the major pitfall of such DL based models is their high computational complexity, large parameter count and extremely expensive to train complex data models. To address the above problem, in literature, very few works have been proposed on the fewshot learning based OSV i.e. learning the user specific features with few signature samples. Kaiser et al [37] proposed Depthwise separable (DWS) convolutions, which condenses the parameter count and computation overload involved in convolutional operation, while increasing the representational efficiency. The second contribution is by Diaz et al [11], in which OSV model proposed is based on one signature sample and duplicating the single samplings based on kinematic analysis of rapid human movements and its sigma-lognormal parameters. The model attained an Equal Error rate (EER) of 13.56%.

To address above pitfalls, in this work, (ii). We design a CNN based online signature verification framework using depthwise separable convolutions, which enables a substantial reduction of the parameter count and the amount of computation required. (iii). Few shot learning, i.e. ability to learn the feature patterns specific to each user, even from the smaller number of signature samples, i.e. one, two, three etc. and achieves a higher level of classification accuracy.

The manuscript is systematized as follows. In section II, we discuss in brief about depthwise separable convolution operation. In section III, we discuss the different segments of our proposed OSV framework. In section IV, particulars of training and testing data, experimental investigation along with the results and comparison of the proposed framework with the recent models are discussed. Conclusions are drawn in section V.

2. Depthwise Separable Convolution

The standard convolution (SC) operation forms the heart of CNN. SC is performed between each input channel and with specific kernel. The standard deep Convolution Neural Networks (CNN) are slow to learn the approximation functions due to the fact that, the number of parameters at each layer of the network increases drastically. This results in overfitting of CNN and requires huge computation power and [42, 48].

To reduce the above downsides and to increase the learning efficiency, researchers [38,40] have proposed various techniques for faster computations and accurate metric learning. Depthwise separable (DWS) convolution is one among them which, the convolution operation is performed on each input image individually with a specific kernel. Later, 1×1 pointwise convolution is performed on the intermediate results.

Mathematically, the standard convolution (SC) and depthwise separable convolutions are defined as follows:

$$\mathrm{Conv}(\mathrm{I},\mathrm{F})_{(x,y)} = \sum_{p,q,r}^{P,Q,R} I(x+p, y+q, r).\, F_{(p,q,r)} \qquad (1)$$

is an element wise multiplication of an input image '$I_{(x,y,r)}$' with the weights '$F_{(p,q,r)}$' of a filter F, considering all the input channels 'r' simultaneously, where (p,q) and (x,y) represents the height and width of a filter 'F' and image 'F' respectively.

Depthwise separable convolution = Depthwise convolution + Pointwise convolution = (2) + (3)

$$\mathrm{DepthWiseConv}(\mathrm{I},\mathrm{F})_{(x,y)} = \sum_{p,q}^{P,Q} I(x+p, y+q) \odot F_{(p,q)} \qquad (2)$$

In depth wise convolution (DWC), for each input channel 'r', an input image $I_{(x,y)}$ is convolved with the filter locations $F_{(p,q)}$ to produce an intermediate result. For each input channel, a point wise convolution is performed on the intermediate result as shown below:

$$\mathrm{PointWiseConv}(\mathrm{I},\mathrm{F})_{(x,y)} = \sum_{r}^{R} W_{(r)}.\, f(x,y,r) \qquad (3)$$

If we substitute x = 1, p=1and r =1, the above equations (1), (2) and (3) represent one-dimensional feature vectors. As shown in Fig 1, each user's online signature is described as a feature vector of size 1× N (row vector). As shown in Fig. 2, considering the input signature of size $1 \times \mathrm{W} \times \mathrm{IC}$ (height × width × input_channel) and kernel size $1 \times K \times IC \times OC$ = (height × width × input_ channel × output_channel), the amount of weights and operations need to execute in both the cases are specified table I.

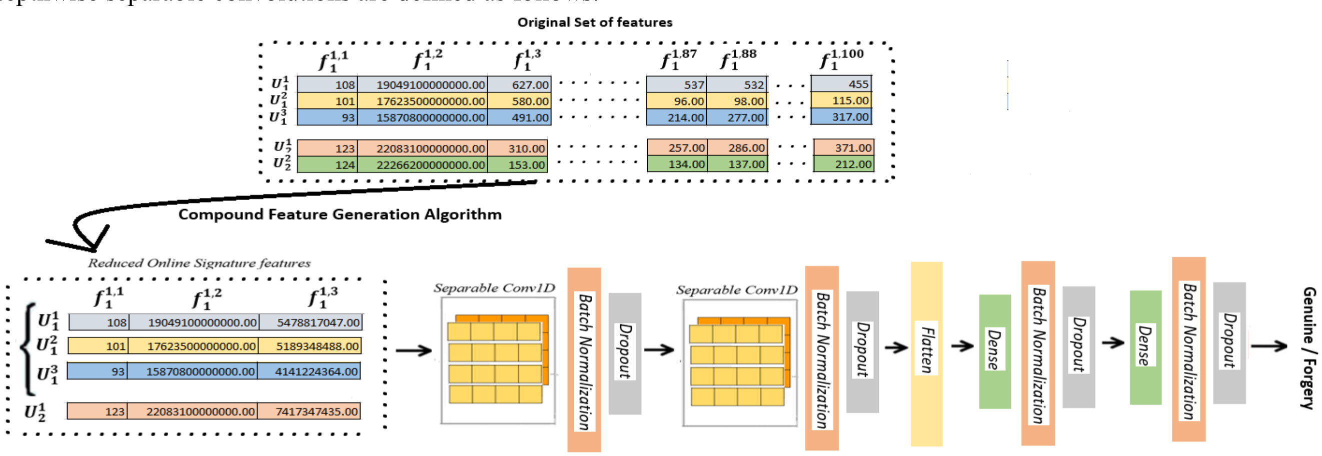

Figure 1. Overview of the proposed compound feature generation and separable Conv1D based OSV framework used in this work.

TABLE I. COMPARISION OF WEIGHTS AND OPERATIONS REQUIRED FOR CONV1D AND SEPARABLE CONV1D OPERATIONS

Convolution layer type	Number of weights	Number of operations
Convolution 1D	$K \times IC \times OC$	$W \times K \times IC \times OC$
Separable Convolution 1D	$K \times IC + IC \times OC$	$W \times K \times IC + W \times IC \times OC$
Reduction factor	$1/IC + 1/K$	$1/IC + 1/K$

Table 1 and Table II summarizes that standard convolutions are computationally intensive, whereas, depth wise separable convolutions are lightweight with reduced number of mathematical operations. The implementation of the proposed model with depth wise separable convolutions resulted in 12.31% decrease of parameter count compared to standard convolutions. The lesser number of operations and weights required for separable convolutions results in efficient learning of approximate functions by deep CNNs. The improved representational learning by the depth wise separable convolution gives a possibility for few shot learning, in which the framework must learn from very few training samples of signatures and achieve better signature classification accuracies.

The main contributions of our work can be precised as follows:

1. We have proposed a novel feature dimensionality reduction technique, which performs feature selection and feature extraction simultaneously based on Eigen values generated by Principal Component Analysis of feature set. In case of MCYT-100 dataset, the feature set is reduced from 100 to 7. In case of SVC and SUSIG datasets, the feature set size is reduced from 47 to 3.

2. A deep CNN framework for OSV based on depth wise separable convolution [37, 40] is proposed. This drastically reduces the number of parameters need to be trained by the framework.

3. Extensive experimentation and comprehensive set of assessment with the sate-of-the-art models based on three most widely used datasets.

3. Proposed online signature verification framework

3.1 Proposed novel dimensionality reduction algorithm:

Our proposed dimensionality reduction algorithm supports simultaneous feature selection and feature extraction is based on Principal Component Analysis (PCA) that provides best ordered linear approximation to a given high-dimensional data e.g. Feature set. PCA performs centering, rotating and scaling of input data and models the subspace with the maximum variance with descending order of eigenvalues, which outcomes the principal components in the order of significance. Top Eigen vectors (with larger eigen values) contain maximum variance and maximum discrimination information. PCA orders dimensionality by dropping insignificant (low-variance) dimensions. The dropping of low-variance dimensions can be considered as the amount of loss incurred while projecting the data to a reduced dimension space. If the loss incurred is not substantial, one can dispose of the Eigen vector with the smallest eigen value and preserve the top eigen vectors. This error, is termed as 'Dropping Loss'.

Let $F = \{f1, f2, f3, \ldots\ldots, fd\}$ be the set of features. Let PCA be the spectral feature extraction method i.e. $PCA(F)$ = λ = $\{\lambda 1, \lambda 2, , \lambda 3, \lambda 4, \ldots\ldots, \lambda d\}$ be the set of resulting Eigen values, where $\lambda 1 > \lambda 2 \cdots > \lambda d$, λd conveys the information along the nth component. It can be weigh up as the amount of loss incurred while reducing the data from k to $k-1$ dimension. Murthy et al [44] proposed a metric called 'Normalized Dropping Loss' (NDL) of the feature set $F = \{f1, f2, f3, \ldots\ldots, fd\}$ when dimension is condensed from 'd' to 'd – 1' i.e.,

$$NDL^{d,d-1} = \frac{\lambda d}{\sum_{i=1}^{d} \lambda i}$$

Similarly, the loss incurred while reducing the dimension from 'd' to 'p' = $NDL^{d,p} = \frac{\sum_{i=p+1}^{d} \lambda i}{\sum_{i=1}^{d} \lambda i}$

Based on NDL, we are defining three type of features.

Definition 1: (Weak-feature): A feature 'w' is called a weak-feature, if it's 'Normalized dropping loss' is zero i.e. $NDl^{d,w} = 0$;

Definition 2: (Moderate-feature): A feature 'm' is called a moderate-feature, if it's 'Normalized dropping loss' i.e. $NDl^{d,m} > 0$ and ≤ 0.1.

Definition 3: (Strong-feature): A feature 's' is called a strong-feature, if it's 'Normalized dropping loss' i.e. $NDl^{d,s} > 0.1$.

Algorithm 1: Computing writer specific Compound features based on NDL and three types of features discussed above.

Input: U: Set of Users, $\{u_1, u_2, u_3 \ldots, u_n\}$

F_i: Original Feature Set of u_i, $F_i = \{f1, f2, \ldots, fd\}$. $'f1'$ represents a column vector.

$T1$: Predefined threshold values. We set T1 to 0.1.

N: Number of signature samples for each user.

Output: C – Writer specific compound feature set.

for each User $u_i \in U$ do

Compute $\lambda = PCA(F_i)$ where $\lambda = \{\lambda 1, \lambda 2, \ldots\ldots, \lambda d\}$ be the set of resulting eigen values, where $\lambda 1 > \lambda 2 \cdots > \lambda d$. *// Computational complexity:* $O(N)$.

for each feature fp:

Compute: $NDL^{d,p} = \frac{\sum_{i=p+1}^{d} \lambda i}{\sum_{i=1}^{d} \lambda i}$ i.e. the normalized reduction loss when the feature set is reduced from size $'d'$ to $'p'$.

Based on $NDL^{d,p}$, classify each feature $'fp'$ as either weak (W), or moderate (M) or strong (S).

end *// Computational complexity:* $O(d)$.

// Feature Extraction.

for all the weak features $w \in W$, ***compute:*** $\sum_w \lambda w \,.\, fw$ resulting a single column feature vector.

end *// Computational complexity:* $O(1)$.

for all the moderate features $m \in M$, ***compute***:

$\sum_m \lambda m \,.\, fm$, results into a single column feature vector.

end *// Computational complexity:* $O(1)$.

compute: Writer specific Compound feature vector C = {S} ∪ $\sum_m \lambda m \,.\, fm$ ∪ $\sum_w \lambda w \,.\, fw$ = {S}∪ {M}∪{W}. The set of strong features, moderate features and weak features are combined to form the final writer specific compound feature set C. *// Computational complexity:* $O(1)$.

Return C.

end

In our proposed dimensionality reduction algorithm, we are applying PCA on feature set of size 'd' corresponding to each user. PCA on the feature set results in an ordered set of Eigen values $\{\lambda 1 > \lambda 2 \cdots > \lambda d\}$. To select and extract best features, which results in higher classification accuracies, the features are categorized into three sets 1. Weak 2. Moderate 3. Strong features. The features which are having zero impact (loss) on the classification result when dropped from the feature set are classified as weak features and the features having negligible impact (loss) when dropped are classified as moderate features. The features having strong impact on the classification result are classified as strong features. The loss is computed based on the 'Normalized Dropping Loss' (NDL) discussed above.

The strong features are considered with out performing any operations on them (feature selection) and in case of weak features, a scalar product is performed between the weak features and the corresponding Eigen values. The summation of the resulted columns outcomes a single column vector, which is considered as an extracted feature vector. Similar is the case with the set of moderate features. Finally, the aggregation of strong features and extracted column vectors from weak and moderate features are considered as writer specific feature set.

Computational Complexity: For each user u_i, with $'N'$ number of signature samples, complete feature set F_i is given as input to PCA, is of complexity $O(N)$. On computing PCA, $'$Normalized Dropping Loss$'$ for each feature $fj \in F_i$, $1 \leq j \leq d$ is computed, is of complexity $O(d)$. The feature extraction step for weak, moderate features and computation of compound feature set requires $O(1) + O(1) + O(1) = 3 \star O(1) = O(1)$. A constant computational complexity can be neglected. Therefore, the computational complexity for each user is $(O(N) + O(d)) \simeq 2 \star O(N) = O(N)$. The total complexity of the proposed dimension reduction algorithm $= n \star O(N)$.

3.2 Proposed separable Convolution Operation based OSV framework:

Encouraged by the recent contributions [37,42,48], in this present work, we examine and put forward an OSV framework based on depth wise separable convolution operation. We propose a CNN framework in which a depth wise separable one-dimensional convolution operation is executed as an alternative to a standard convolution operation on each input signature. As shown in Fig 1, the input signature is characterized as a feature vector of size $1\times N$ (row vector). As shown in Table II and III, the depth wise separable 1D convolution requires 12.55% reduced parameters to train the framework compared to standard convolution operation. The set of separable convolution layers and framework optimization procedures outcomes an improved representational learning of input signature and rapid learning by the framework which leads to condensed overfitting and increased input signature classification accuracy.

TABLE II. COMPARISION OF PARAMETERS REQUIRED FOR CONV1D AND DWS CONV1D OF PROPOSED FRAMEWORK.

Convolution layer type	Trainable params:	Non-trainable params:	Total
Conv1D	20,342	400	20,742
SeparableConv1D	17,789	400	18,189
% of reduction	**12.55%**	**-**	**12.31%**

3.2.1 Separable convolution layer

As depicted in Fig 3, our proposed framework consists of five layers. The first two layers consists of two sequential groupings of DWS convolutional layer and batch normalization layers which constitute the convolutional part of the DWS CNN. The input to the first DWS convolution layer is an online signature of size (1× N), where 'N' represents the size of writer specific feature set. In our proposed framework, minimum value of N = 3 and maximum is 7. A set of 36 filters, each of size 1×3 accomplishes a depth wise separable convolution operation as represented in equation (2) to yield N feature maps, each of size 1 × 36. As presented in equation (3), a 1 × 1 pointwise convolution operation is performed on intermediate feature maps, which outcomes N feature maps, each of size 1 × 36. To regularize the inputs of each layer, and to make the model less sensitive to the initial set of weights, we performed batch normalization [13,32] operation on the output of the first DWS convolution layer, which results in the normalization of the output data from the activation layer. Similar to the first set of DWS convolutional and batch normalization layers, the second DWS convolution layer uses 36 filters, each of size 1×3 to produce N feature maps, each of size 1 × 36. A 1 × 1 pointwise convolution operation is performed on these intermediate feature maps to result an output of a feature vector of size 1 × 36. A batch normalization is performed on these feature maps.

A part from batch normalization technique, to achieve better generalization and to resist overfitting, we have applied a dropout of 50% to both the DWS convolutional layers. In dropout, random set of nodes are dropped from the hidden layers of the framework [45]. The output from the DWS convolutional layers represents the deep features learnt by the framework and forms an input to the fully connected layers. We have set Padding = same, which results in the input signature feature vector from the convolution operation doesn't differ in size as input vector.

3.2.2 Fully connected layers

In the proposed framework we have used a Multilayer Perceptron (MLP) with two hidden layers as classifier. The number of neurons in each dense layer are 64. The deep features resulted from the second DWS convolution layer of size (5 × 36) = 180 forms an input to the classifier. To reduce overfitting, we have adopted optimization techniques, as a part of it, we initialize the weights and bias of the proposed framework as$'random_uniform'$. The final layer of the classifier is an output layer with sigmoid function. It uses the sigmoid activation function outputs a binary response, in order to produce a probability output in the range of 0 to 1 that can easily map to crisp values corresponding to all the output classes. We have selected '*binary_crossentropy*' as the loss function that enumerates the discrepancy between the ground truth and the model output.

In current OSV framework, the size of the output layer is two i.e. Genuine and Forgery. To achieve faster learning, sparsity and reduced likelihood of vanishing gradient, we have used '*ReLU*' as an activation function in all DWS convolution and hidden layers of the framework. A dropout of 40% is applied to both the hidden layers. We have used '*adam*' as an optimizer, 0.004 as learning rate, with batch size of 8 and 100 epochs for each user with hyper parameters set to beta_1=0.9, beta_2=0.999, epsilon=1e-08, decay=0.00.

4. Experimentation and results

We have extensively conducted verification experiments and validated the proposed OSV framework by conducting the experiments on three widely accepted datasets i.e. MCYT_100 signature sub corpus dataset (DB1) [9,11], SVC - Task 2 [14, 19], SUSIG [31, 32]. The results are illustrated in tables below.

TABLE III. DETAILS OF THE TRAINING AND TESTING SIGNATURES OF THE PROPOSED FRAMEWORK WITH DB1 (ONE TIME ACTIVITY)

	S_05: Skilled 05	**S_20 : Skilled 20**	**R_05: Random05**	**R_20: Random20**
No of Training Signatures	U1's Randomly selected 5 genuine signatures.	U1's Randomly selected 20 genuine signatures.	U1's Randomly selected 5 genuine signatures.	U1's Randomly selected 20 genuine signatures.
No of Testing Signatures (Testing Phase)	U1's remaining 20 genuine + U1's all the 25 skilled forgery signatures.	U1's remaining 5genuine + U1's all the 25 skilled forgery signatures.	U1's remaining 20 genuine + randomly selected 1 genuine from each writer i.e. U2-U99 (other than the signature used in training) = 1 * 99.	U1's remaining 5 genuine + randomly selected 1 genuine from each writer i.e. U2-U99 (other than the signature used in training) = 1 * 99.

for briefness, in the above table the user is named as U1. In common U_i, where i = {1,2,3,…100}. S_05: Skilled 05, S_10: Skilled 10, S_15: Skilled 15, S_20: Skilled 20, R_05: Random 05, R_10: Random 10, R_15 : Random 15, R_20: Random20.

TABLE IV. RELATIVE EXAMINATION OF THE PROPOSED FRAMEWORK AGAINST THE RECENT MODELS ON MCYT (DB1) DATABASE

Method	**S_01**	**S_05**	**S_20**	**R_01**	**R_05**	**R_20**	**Number of Features for each signature**
Proposed: Compound Feature Selection + Separable Convolution	**22.94**	**8.58**	**2.65**	**4.21**	**3.7**	**0.27**	**(Minimum: 3 features, Maximum: 7 features)**
Few shot learning[6]	**13.42***	7.03	2.2	**2.0***	0.05	**0.00***	80
LSTM+CNN[7]	15.57	1.88	**0.00***	**16.70**	**0.16**	**0.00***	80
writer dependent features and classifiers[8]	-	19.4	1.1	-	7.8	0 .8	100
Writer dependent parameters (Interval Valued representation) [9]	-	2.51	**0.03****	-	0.70	**0.00***	100
Common feature dimension and threshold (Interval Valued representation) [9]	-	10.36	5.82	-	10.32	0.74	100
Writer dependent parameters (conventional) [9]	-	6.79	**0.00***	-	1.73	**0.00***	100
Common feature dimension and threshold (conventional) [9]	-	13.12	11.23	-	5.61	1.66	100
Cancelable templates - HMM Protected [10]	-	10.29	-	-	-	-	100
Cancelable templates - HMM[10]	-	13.30	-	-	-	-	100
Stroke-Wise [11]	**13.72****	-	-	5.04	-	-	100
Target-Wise [11]	13.56	-	-	**4.04****	-	-	100
Writer dependent parameters (Symbolic) [12]	-	2.2	0.6	-	1.0	**0.1****	100
Information Divergence-Based Matching [13]	-	3.16	-	-	-	-	100
WP+BL DTW[14]	-	2.76	-	-	-	-	100
Histogram + Manhattan [15]	-	4.02	-	-	1.15	-	100
discriminative feature vector + several histograms [15]	-	4.02	2.72	-	1.15	0.35	100
VQ+DTW[16]	-	**1.55***	-	-	-	-	100
GMM+DTW with Fusion [17]	-	3.05	-	-	-	-	100
Combinational Features and Secure KNN-Global features [18]	-	5.15	-	-	1.70	-	100
Combinational Features and Secure KNN-Regional features [18]	-	4.65	-	-	1.33	-	100
Stability Modulated Dynamic Time Warping (F13) [18]	-	13.56	-	-	4.31	-	100
Dynamic Time Warping-Normalization(F13) [18]	-	8.36	-	-	6.25	-	100
Probabilistic-DTW(case 1) [19]	-	-		-	**0.0118***	-	100
Probabilistic-DTW(case 2) [19]	-	-	-	-	**0.0187****	-	100
Curvature feature [20]	-	10.22	-	-	4.12	-	100
Torsion Feature [20]	-	9.22	-	-	3.42	-	100
Curvature feature + Torsion Feature [20]	-	6.05	-	-	2.95	-	100
Representation learning + DTW (Skilled forgery) [20]		**1.62****			0.23		100
Representation learning + DTW (Random forgery) [20]		1.81			0.24		100

TABLE V. RELATIVE EXAMINATION OF THE PROPOSED FRAMEWORK AGAINST THE RECENT MODELS ON SVC DATASET

Method	S_01	S_05	S_10	S_15	R_01	R_05	R_10	R_15	Number of Features for each signature
Proposed: Compound Feature Selection + Separable Convolution	1.67*	0.00*	0.00*	0.0*	9.77	0.82	0.59	0.44	Maximum : 3
Few shot learning[6]	5.83**	0.87**	0.35**	0.2	9.08	1.4	0.15*	0.02*	40
LSTM+CNN[7]	6.71	1.05	0.00*	0.10*	9.53	0.16	0.18**	0.16**	40
Target-Wise [11]	18.63	-	-	-	0.50*	-	-	-	47
Stroke-Wise [11]	18.25	-	-	-	1.90**	-	-	-	47
DTW based (Common Threshold) [14]	-	7.80	-	-	-	-	-	-	47
Probabilistic-DTW(case 1) [19]	-		-	-	-	0.0025*	-	-	47
Probabilistic-DTW(case 2) [19]	-	-	-	-	-	0.0175**	-	-	47
Curvature feature + Torsion Feature [20]	-	9.83	6.61	3.10	-	3.54	1.24	1.81	47
LCSS (User Threshold) [22]	-	-	5.33	-	-	-	-	-	47
Stroke Point Warping [24]	-	1.00	-	-		-	-	-	47
SPW+mRMR+SVM(10-Samples) [24]	-	1.00	-	-	-	-	-	-	47
Variance selection [25]	-	-	13.75	-	-	-	-	-	47
PCA [25]	-	-	7.05	-	-	-	-	-	47
Relief-1 (using the combined features set) [25]	-	-	8.1	-	-	-	-	-	47
Relief-2 [25]	-	-	5.31	-	-	-	-	-	47
RNN+LNPS [26]	-	-	-	-	-	2.37	-	-	47

TABLE VI. RELATIVE EXAMINATION OF THE PROPOSED FRAMEWORK AGAINST THE RECENT MODELS ON SUSIG DATASET

Method	S_01	S_05	S_10	S_15	R_01	R_05	R_10	R_15	Number of Features for training
Proposed: Compound Feature Selection + Separable Convolution	0.98*	0.1*	0.0*	0.0*	14.86	10.82	7.03	3.74*	Maximum : 3
Few shot learning [6]	10.41	0.8**	0.63	-	8.7	2.5**	1.26*	-	40
LSTM+CNN [7]	13.09	1.95	0.47**	-	12.40	2.86	1.28**	-	40
Target-Wise [11]	6.67**	-	-	-	1.55**	-		-	47
Stroke-Wise [11]	7.74	-	-	-	2.23	-	-	-	47
Information Divergence-Based Matching [13]	-	1.6	2.13	-	-	-	-	-	47
Association of curvature feature with Hausdorff distance [25]	-	7.05	-	-	-	1.02*	-	-	47
cosα, speed + enhanced DTW [27]	-	-	3.06	-	-	-	-	-	47
pole-zero models [28]	-	2.09	-	-	-	-	-	-	47
Kinematic Theory of rapid human movements [29]	7.87	-	-	-	3.61	-	-	-	47
with all domain [31]	-	-	3.88	-	-	-	-	-	47
with stable domain [31]	-	-	2.13	-	-	-	-	-	47
DCT and sparse representation [32]	-	-	0.51	-	-	-	-	-	47
Length Normalization + Fractional Distance [33]	-	-	3.52	-	-	-	-	-	47
writer dependent features and classifiers [33]	-	-	1.92	-	-	-	-	-	47
Association of curvature feature with Hausdorff distance [25]	-	7.05	-	-	-	1.02*	-	-	47

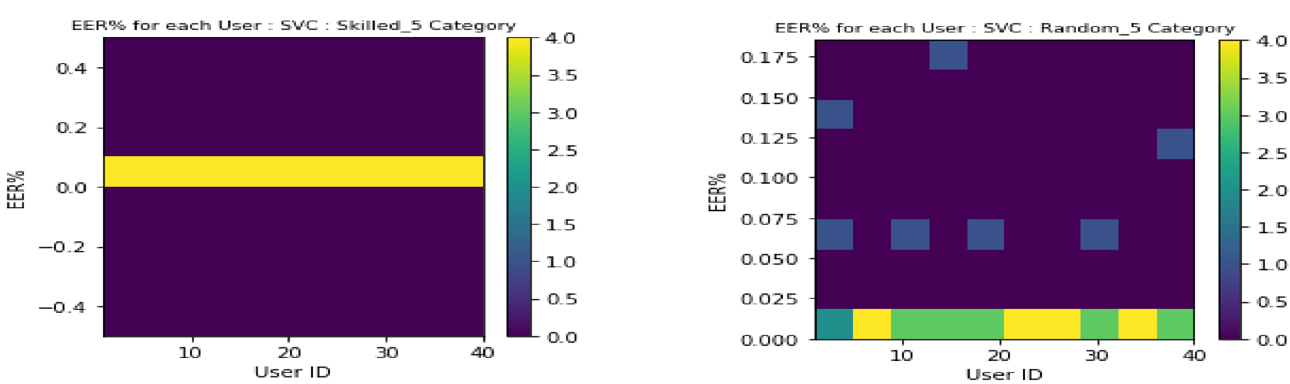

Figure 2: a) The EERs of 94 users of SUSIG dataset obtained for Skilled_15 b) The EERs of 40 users of SVC dataset obtained for Random_1 category.

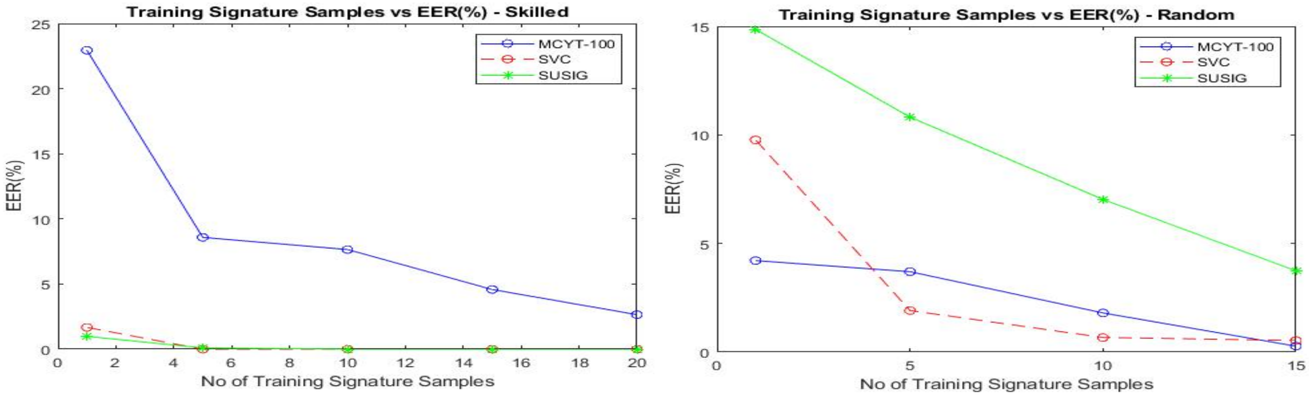

Figure. 3. The average EER with three different datasets for Skilled Forgeries (a) and for Random Forgeries (b).

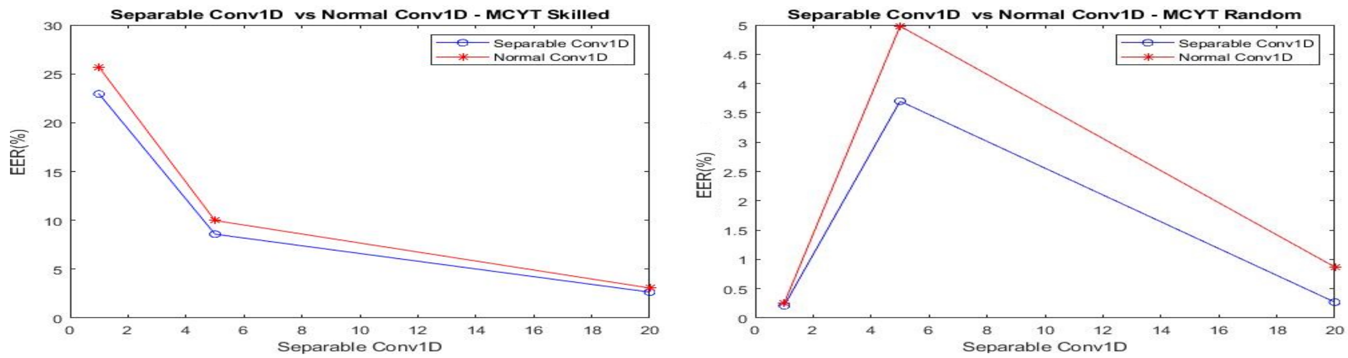

Figure. 4. The EER resulted by the OSV framework for MCYT-Dataset with varying training signature samples (a) Separable Conv1D b) Normal Conv1D

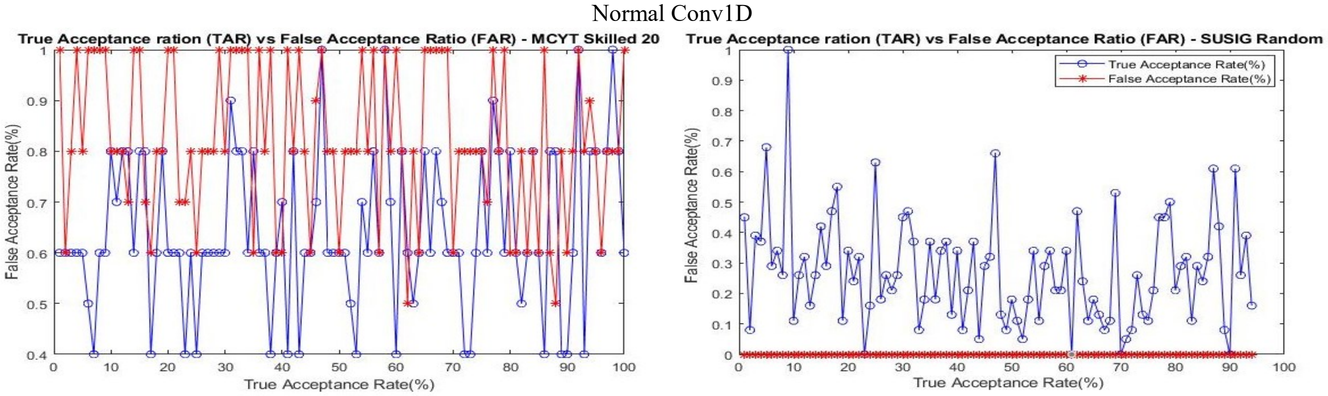

Figure 5. The ROC curves in the test on MCYT-100 (DB1) database. (a) The TAR and FAR for 100 users with 20 training samples for each user under Skilled 20 category. (b) The TAR and FAR for 94 users for each user with 1 training samples under Random 1 category.

The complete details about the number of signatures available in each dataset and the number of signatures used for training and testing are available in [6, 22]. Table III, illustrates the training and testing procedures followed in various experimentation categories. Tables IV-VII depicts the comparison of Equal Error Rate (EER) with the latest and the state-of-the art proposed OSV frameworks. In case of MCYT-100, all the existing models considered higher number of features, 100 in many cases, where as we have used only 3 to 7 features per user and are still able to attain the best state of the art results. The first best EER values are marked with (*) and the second best are marked with (**). In case of MCYT-100 (DB1) our framework achieved very good results in S_01, S_20, R_01, R_05 and R_20 categories. In case of SVC, the framework achieved the state-of-the-art results in all skilled categories and very descent results in R_05, R_10 and R_15 categories with just three features per signature. In case of SUSIG, the framework achieved the best EER in all skilled categories and R_15 category with three features per signature. As illustrated in table IV-VII, even though the frameworks proposed in [11,19,20] are resulting in better EER values compared to the proposed framework, the models [11,19,20] are not extensively evaluated with all categories of training, like skilled_1, random_1 etc., whereas we have evaluated the model with all the possible training samples and the performance is assessed. As depicted in 2D-Histogram of Figure 4.a), the proposed framework results in zero EER for all the users with five training signature samples and as illustrated in Fig 4.b) with slight deviation, the EER increases in seven cases as represented in blue square boxes. As depicted in Fig 5.a) in case of all datasets and for both skilled and random categories, the framework achieves decreasing EER, with the increase of training signature samples. The SVC and SUSIG datasets demonstrate a steep decrease in the EER values, where as MCYT-100 displays a stable drop. As illustrated in table VI, the Depth wise separable convolution resulting in lesser EER values compared to normal convolution operation for both skilled and random categories. In case of random categories, the sudden raise in the EER with the increased training samples is possibly due to the initial set of weights set for the model. Fig 7 depicts the True Acceptance Rate (TAR) and False Acceptance Rate (FAR) for each user for MCYT-Skilled 20 and SUSIG Random 1 categories. Fig 7. b) reveals that with one genuine signature sample, the framework achieves zero FAR and a decent TAR.

To conclude this section, we see that our proposed OSV framework based on a novel dimensionality reduction technique and depth wise separable convolution operation achieves state of the art EER values with as minimum as one trained signature samples and maximum seven features per signature sample. This confirms the accurate learning of the inter and intrapersonal variability of the samples. Although the proposed framework achieved efficient results, the tables summarizes that there is a room for enhancement in the case of random categories. Hence, we confirm that the framework reflects the realistic scenario.

5. Conclusion and future work

In this manuscript, our contribution is two-fold. We presented a novel light weight dimensionality reduction technique, which categorizes the feature set into weak, moderate and strong features. We selected maximum seven features per user in case of MCYT-100 and three features in case of SVC and SUSIG datasets. In addition to this, we have proposed an OSV frame work based on depth wise separable convolutions which enables a substantial reduction of the parameter count and amount of computation required and still achieves higher level of classification accuracies by learning the inter and intrapersonal variability specific to each user, even from one signature sample and achieves higher level of classification accuracy. The proposed model achieves better accuracies compared to state of the art models. The proposed framework is having an opportunity for progress of the in the case of random categories.

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