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DeepHSV: User-independent Offline Signature Verification Using Two-Channel CNN

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***Abstract*—Off-line handwritten signature verification has practical significance in financial, administrative and judicial field. Traditional methods rely on handcrafted local and global feature descriptors. Recently, researchers start to apply convolutional neural network (CNN) to learn representative features towards this task. However, most of these methods suffer from overfitting. In this paper we propose a novel two-channel CNN network, namely 2-Channel-2-Logit (2C2L), to address this issue. The input to the network is the concatenation of reference and query signatures. The output of convolutional layers are two logits that measure the similarity between reference and query signatures. We explicitly add dropout layers and a 2-Logit layer to make the network less prone to overfitting issues. The proposed method uses only one reference signature for testing and the training system is independent from the queried user. Experiments on the latest GPDS-Synthetic database demonstrate that the proposed method can significantly improve verification accuracy. We improve the performance by a large margin, from 22.24% in state-of-the-art to 9.95% in terms of equal error rate (EER).**

***Index Terms*—Offline signature verification, two-channel CNN, feature learning**

I. Introduction

Handwritten signatures are one of the most commonly used methods for identity authentication. Signed documents such as contracts, checks, documents are legally binding. A handwritten signature verification system aims to determine whether a handwritten signature is a genuine signature from the claimed user. It has been a long-standing problem to develop an accurate verification system for practical applications [1]–[3].

There are two categories of handwritten signature verification systems based on the acquisition method: online [4], [5] or offline [6], [7]. In an online system, dynamic data is collected using electronic devices as a function of time. It contains position, pressure, and inclination of the pen at each point. In an offline system, the signature is scanned as a static image in gray scale. Normally, an online system performs better than the offline counterpart in consequence of dynamic information available in online signature. However, offline systems are more popular due to the fact that most signatures were collected as static images.

Broadly speaking, offline signature verification methods could be classified into two categories, i.e. user-dependent and user-independent. A user-dependent system is trained in a one-versus-all manner to capture dissimilarities among different users in the training set. Nevertheless, an ad-hoc user-specific threshold has to be decided to make binary decision between the input and the claimed writer [8]. Furthermore, a user-dependent system is cumbersome to deploy because the system has to be retrained whenever a new user is introduced. A user-independent system is more appealing as the system does not need to be trained with signatures from the queried user. It takes a query signature along with a reference signature and checks whether the query is genuine or forged.

(a) (b) (c)

Fig. 1: Demonstration of challenges in offline signature verification with skilled forgeries. Signatures are from the Bengal and GPDS Synthesis datasets. (a) and (c) are genuine signatures and (b) is skilled forgeries, respectively.

The goal of signature verification is to determine whether a signature is genuine or forged. Depending on the efforts to mimic a genuine signature, forgeries are commonly classified as: 1) random, the forger has no information about the genuine signature; 2) simple, the forger knows the user's name but has never seen the user's signature; and 3) skilled, the forger has access for both the user's name and signature [9]. Skilled forgeries are hard to detect as the forgeries have higher resemblance to the genuine signature. Figure 1 shows representative signatures commonly used in the community. We could observe that genuine signatures from the same user exhibit reasonable variance and skilled forgeries are similar with genuine signatures.

It is challenging to develop an offline user-independent signature verification system. Traditional approaches for offline signature verification rely on handcrafted feature engineering, such as local geometric features [10]–[12], histogram of oriented gradients (HoG) [13], local binary patterns (LBP) [8], [14]–[16] and scale invariant feature transform (SIFT) [17]. Recently, deep Convolutional Neural Network (CNN) achieved better performance on signature task over traditional methods via representative feature learning [18]–[22]. However, these

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methods suffer from overfitting issue due to limited number of genuine signatures per user in training data. Consequently, a multitask strategy [18], [20] or a hybrid framework [21], [22] are proposed in a user-dependent fashion to alleviate signature differences across different users. Nevertheless, a user specific decision threshold has to be decided empirically and it is still a challenging task to learn the threshold automatically.

We focus on *user-independent offline signature verification with skilled forgeries* in this work. It is considered to be the most challenging scenario. We propose a novel two-channel CNN network, namely 2-Channel-2-Logit (2C2L), to address the aforementioned issues. The input to the network is the concatenation of reference and query signatures. The output of convolutional layers are two logits that correspond to the input signature pair to measure the similarity between reference and query signatures. The novel design helps to maintain higher similarity between genuine and genuine signature pair and smaller similarity between genuine and forgery signature pair. It is worthwhile to point out that the proposed method uses only one reference signature for testing and the training system is independent from the queried user. Experimental results show that the proposed method achieves significant improvements over existing methods under a similar protocol. We achieve an equal error rate (EER) of 9.95% compared with 22.24% reported in state-of-the-art [19].

The rest of the paper is organized as follows. The proposed 2C2L network is detailed in Section II. Experimental results are presented in Section III. Conclusion remarks are drawn in Section IV.

II. Proposed method

Image similarity measurement is a fundamental task in computer vision. There are two commonly used networks depending on the stage where dissimilarity is fused together, *i.e*. Siamese Network and 2-Channel Network. We briefly review the two basic models and then introduce the proposed architecture.

A. Basic models

Siamese Network Metric learning networks in this class usually contain two branches serve as feature descriptor. The two branches share exactly the same architecture and weights. During the training stage, parameter updating is mirrored across both branches. The output of the two branches are concatenated to measure the similarity of inputs. A similarity metric with the Euclidean distance, *i.e*. contrastive loss, is commonly used as the loss function.

2-Channel Network The input pairs are concatenated as a two channel image. The system does not explicitly extract features of inputs but measures their distance at the first step. Such a design greatly reduces parameter space to search and makes 2-Channel network particularly suitable for signature verification.

Traditionally, the 2-Channel Network output only one value at the final global average pooling layer, representing the similarity between reference and query signatures. The similarity is commonly measured by the following formula

$$1 - \max(0, 1 - y_i o_i^{net}), \tag{1}$$

where o_i^{net} represents the output of the network, $y_i \in -1, 1$ indicates label of the the input signature. $y_i = 1$ denotes a genuine pair and $y_i = -1$ for a forged pair, respectively.

Usually a hinge-based loss term and squared l_2-norm regularization is adopted in 2-Channel network. The learning objective function is given in Eq. 2. The first term is l_2 regularization and the second term measures the loss of the network

$$\min_w \frac{\lambda}{2} \|w\|^2 + \sum_{i=1}^{N} \max(0, 1 - y_i o_i^{net}), \tag{2}$$

where w denotes the weights of the network.

B. Proposed CNN architecture

2-Channel-2-Logit Network we propose a novel 2-Channel-2-Logit (2C2L) network based on the 2-Channel-CNN structure. The difference is that the last global average pooling layer of 2C2L output two values corresponding to the input signature pair. The distance of the two values represents the similarity between reference signature and query signature, which is given by

$$D(x1, x2) = logit(o_{x1}^{net}) - logit(o_{x2}^{net}), \tag{3}$$

where $x1$ and $x2$ denote the input signature pairs. o_{x1}^{net} and o_{x2}^{net} represent the output of global average pooling layer, respectively. We adopt the commonly used softmax as loss function

$$L_i = \frac{e^{D_i}}{\sum_j e^{D_j}}, \tag{4}$$

where D_i denotes the distance between genuine signature pairs and D_j represents that of both genuine and forged pairs, respectively.

The architecture of the proposed 2C2L network is given in Fig. 2 and structure details are given in Tab. I. The input to the network is the concatenation of a pair of signatures. A two-logit layer is inserted after the global average pooling layer. A two-way softmax layer is used after the convolution network to determine whether the input is a genuine-genuine or genuine-forgery pair. The input to softmax layer is the subtraction of the two values and the output is used to measure similarity of input signature pair. A genuine-forgery pair will lead to a larger value and a genuine-genuine pair will result in a smaller value.

The proposed convolutional network bears resemblance to Inception-V3 [23]. Thus, we choose not to give the complete network structure diagram in this paper but to point out the difference between them. We insert 4 dropout layers after middle conv and inception layers. The reason is that previous CNN based methods suffer from over-fitting due to insufficient samples in current signature datasets. We empirically find that adding dropout layer in the middle layer of the network greatly alleviates the over-fitting problem.

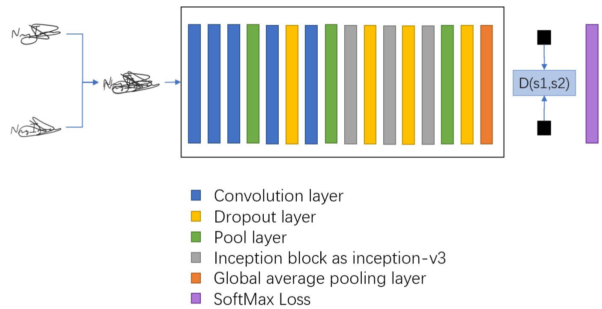


Fig. 2: The proposed 2-Channel-2-Logit (2C2L) network that extends a 2-Channel based architecture to process concatenated channels.

C. Preprocessing

Considering that most of the signatures are horizontally written and CNN needs fixed input size, we use bilinear interpolation to resize the signature image to fixed height and width of 155×220. We do not use any other special preprocessing methods, such as cropping, alignment, pixel flipping (255 to 0), background removal, binarization, etc. The proposed method is robust to the background of signature image and misalignment between input signature pair.

D. Model training

2-Channel CNN takes concatenated signature pair as input. The two signatures can be genuine-genuine pair or genuine-forgery pair. Current signature databases have imbalance data issue, the number of genuine-forgery pair per user is larger than that of genuine-genuine pair. For example, the number of genuine and forgery samples in CEDAR and GPDS-synthetic datasets are 276/576 and 276/720, respectively.

We randomly remove forgery samples and keep the same number of genuine and forgery samples during training stage. The full database will be used during the testing stage. Suppose there are M genuine signatures and N forgery samples, respectively. Signature pairs are constructed by taking the combination of genuine samples and cross-product between genuine and forgery samples, respectively. There are ${}^{M}C_2$ genuine-genuine pairs in the positive set

$$U_{pos} = \bigcup_{i,j} (g_i, g_j) \quad \forall 1 \leq i \neq j \leq M, \tag{5}$$

and $M \times N$ genuine-forgery pairs in the negative set

$$U_{neg} = \bigcup_{i,j} (g_i, f_j) \quad \forall 1 \leq i \leq M, 1 \leq i \leq N, \tag{6}$$

where g and f denote the signature is from genuine and forgery signature sets, respectively.

E. Implementation Details

The experiment was performed using Tensorflow 1.7, and the AdamOptimizer without batch normalization is used for training. The batch size is set to 192. The weights of the model are initialized according to Xavier and Yoshua's method [24] with the initialization bias value is equal to 0. The initial learning rate is set to be 1e-4 and momentum [25] with a decay of 0.9.

Type	**Patch size/stride or remarks or keep rate**	**Input size**
conv	$3\times3/2$	$220\times155\times3$
conv	$3\times3/1$	$109\times77\times32$
conv padded	$3\times3/1$	$107\times75\times32$
pool	$3\times3/2$	$107\times75\times64$
conv	$3\times3/1$	$53\times37\times64$
dropout	0.9	$53\times37\times80$
conv	$3\times3/1$	$53\times37\times80$
pool	$3\times3/2$	$51\times35\times192$
3×Inception	As in inception-v3	$25\times17\times192$
dropout	0.8	$25\times17\times288$
5×Inception	As in inception-v3	$25\times17\times288$
dropout	0.7	$12\times8\times768$
2×Inception	As in inception-v3	$12\times8\times768$
pool	5×3	$5\times3\times2048$
linear	logits	$1\times1\times2048$
Softmax	classifier	$1\times1\times2$

TABLE I: Architecture of the proposed 2-channel. We insert dropout layers and a two-logit layer to the Inception-V3 architecture.

III. Experimental results

A. Datasets

We evaluate the proposed method on CEDAR dataset [2], BHSig260 dataset [26], and GPDS-Synthetic dataset [27]. It is worth noting that the GPDS-Synthetic dataset has different releases, like GPDS-100, GPDS-160, GPDS-300 and GPDS-960. The suffix digits indicate the number of writers participated. Since previous releases were no longer available for the public to download, we report the results on the latest release, i.e. GPDS-Synthetic dataset.

CEDAR. The CEDAR dataset [2] consists of 24 genuine signatures per writer from 55 writers. There are 24 forgeries per writer collected from about 20 skillful forgers. Hence, The number of genuine signatures is equal to that of forged signatures. Signatures were scanned in gray scale and stored as PNG images.

BHSig260. The BHSig260 dataset [26] contains 260 sets of handwritten off-line signatures. It consists of two parts based on the script, i.e. 100 sets for Bangla and 160 sets for Hindi. The dataset was collected from 260 individuals with various educational backgrounds and ages. There are 24 genuine and 30 skilled forgeries per writer. The data was scanned in gray scale and stored in TIFF format.

GPDS-Synthetic. The GPDS-Synthetic dataset [27] is a recently constructed dataset. It contains 4000 writers and is the largest scale signature dataset so far. There are 24 genuine and 30 forged signatures per writer. The dataset was constructed following the same procedure and replaced previous GPDS signature datasets. All signatures were scanned in gray scale and released in JPEG format.

Datasets	State-of-the-art Methods	Signers	Accuracy	EER	AUC
GPDS Synthetic Signature Corpus	SigNet (Hafemann *et al.* [20])	4000	77.76	22.24	-
	2-Channel	4000	84.15	15.85	0.916
	2-Channel-2-Logit	4000	**90.05**	**9.95**	**0.964**
CEDAR Signature Database	Graph Matching (Chen and Srihar *et al.* [28])	55	92.10	8.33	–
	Surroundedness features (Kumar [29])	55	91.67	8.33	-
	SigNet (Hafemann *et al.* [20])	55	**100.00**	**0.00**	**1.00**
	2-Channel-2-Logit	55	**100.00**	**0.00**	**1.00**
Bengali	LBP+NN(Pal *et al.* [26])	100	66.18	33.82	
	SigNet (Hafemann *et al.* [20])	100	86.11	13.89	-
	2-Channel-2-Logit	55	**88.08**	**11.92**	**0.955**
Hindi	LBP+NN(Pal *et al.* [26])	100	75.53	24.47	
	SigNet (Hafemann *et al.* [20])	100	84.64	15.36	-
	2-Channel-2-Logit	55	**86.66**	**13.34**	**0.94**

TABLE II: Comparison of the proposed method with the state-of-the-art methods on various signature databases.

Dataset	Train	Total	Positive	Negative
CEDAR	50	55	276	276/540
Bengali	80	100	276	276/720
Hindi	100	160	276	276/720
GPDS-Synthetic	3500	4000	276	276/720

TABLE III: Details of experimental protocol on different datasets. Column 2 and 3 give the number of writers used for training and the total number of writers, respectively. Column 4 and 5 give the number of positive and negative pairs per writer used for training, respectively. The nominator/denominator entries indicate a down-sampling of negative pairs.

	GPDS-Synthetic	Hindi	Bengali	CEDAR
GPDS-Synthetic	0.96 (0.92)	0.71 (0.62)	0.73 (0.65)	0.67 (0.64)
Hindi	0.58 (0.50)	0.94 (0.91)	0.87 (0.82)	0.53 (0.37)
Bengali	0.57 (0.55)	0.82 (0.78)	0.95 (0.92)	0.49 (0.38)
CEDAR	0.62 (0.60)	0.74 (0.69)	0.76 (0.71)	1.0 (1.0)

TABLE IV: Cross Datasets validation results. Each entry denotes the AUC of 2-Channel-2-Logit network and 2-Channel network in parenthesis, respectively.

B. Experimental Protocol

We randomly select some writers to train the proposed method. Table III gives the number of writers used for training and the total number of writers are given in column 2 and 3, respectively. The remaining writers are used as validation set. We consider a (genuine, genuine) pair from the same writer a positive sample. Thus, there are $\binom{24}{2} = 276$ samples since all datasets contains 24 genuine signatures per writer. By combining all of the (genuine, forgery) signatures per writer, there are $24 \times 30 = 720$ negative samples for BHSig260 and GPDS-Synthetic datasets. The CEDAR dataset is an exception which has $24 \times 24 = 576$ negative samples. We randomly sample 276 negative samples during the training stage to avoid imbalanced data issue. It is worth noting that there is no need to conduct down-sampling on negative samples. The results are reported on all positive and negative samples on the validation set.

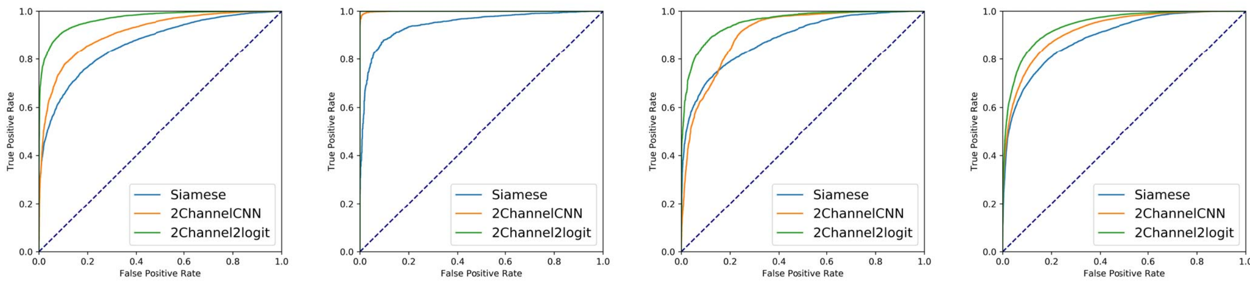
C. Evaluation Metrics

A global threshold T is applied on the network output to decide whether the input signature pair (s_i, s_j) is a genuine-genuine pair or a genuine-forgery pair. The proposed method works in a user-independent manner thus the same global threshold T is used for all users. There are multiple metrics available in the literature: 1) Equal Error Rate (EER) along side with False Positive Rate (FPR) and False Negative Rate (FNR). EER is the error rate when the FPR and FNR are equal. 2) Accuracy (ACC), which is half of the sum of True Positive Rate (TPR) and True Negative Rate (TNR) by varying threshold T from the minimum distance to the maximum distance. 3) Area Under Curve (AUC), which is the area under the ROC curve. We choose to use the more commonly used metric EER (with FPR and FNR) and AUC as evaluation metrics for more robust and informative comparisons.

D. Comparisons to the state-of-the-art

We compare the proposed 2-Channel-2-Logit network with traditional feature engineering based methods [26], [28]–[30] and the Convolutional Siamese Network proposed in [19]. The results are given in Table II. The model trained through the 2-Channel-2-Logit network obtains the best results on all public databases. Specifically, we improve the performance by a large margin from an EER of 22.24%, reported in [19], to 9.95% on the GPDS-Synthetic database. We also get performance improvements, an EER of 2% on BHSig260-Bengali and BHSign260-Hindi datasets than SigNet [19].

The ROC curves of SigNet, 2-Channel CNN and 2-Channel-2-Logit during the training stage on four databases were given in Fig. 3. It is clear that the proposed 2-Channel-2-Logit network converges faster and achieves lower EER than other methods.



(a) (b) (c) (c)

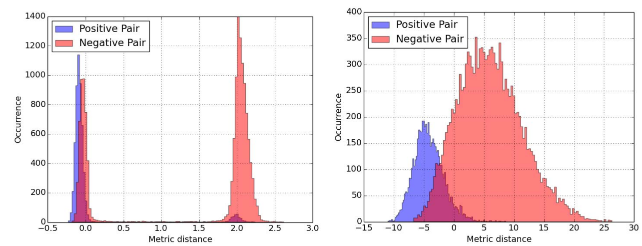
Fig. 3: ROC curves of Siamese, 2-Channel, 2-Channel-2-Logit netwroks on the GPDS-Synthetic, CEDAR, Bengali, and Hindi datasets, respectively. Note that the CEDAR dataset is relatively easy to train. Thus the curves of 2-Channel and 2-Channel-2-Logit methods almost overlap with each other.

E. Ablation Study

Cross Datasets Validation In order to evaluate the generalization ability of the proposed network, we perform cross datasets validation on the proposed 2-Channel-2-Logit network and compare its performance with 2-Channel Network. Each time we select one of the databases for training. Then the trained model is used to test on all the remaining databases. The results are shown in Table IV.

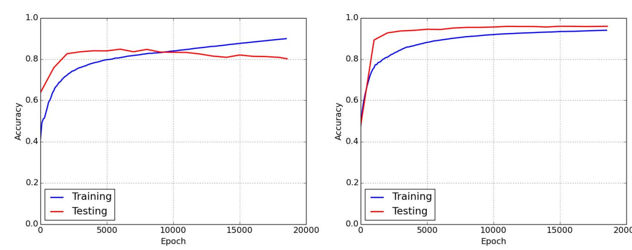
The row and column of the table indicate the database used for training and testing, respectively. Each entry denotes the accuracy of the proposed 2-Channel-2-Logit network and traditional 2-Channel network (in parenthesis). As expected, the performance drops in a cross datasets scenario. We also notice that 2-Channel-2-Logit network always outperforms traditional 2-Channel network on all databases. Probably this is because the two networks use different loss functions. The loss function of 2-Channel network is Eq. 2. Fig. 4 (a) shows the distribution of the distance of 2-Channel network. It can be seen that the results are divided into two parts that are far apart. The metric is not suitable for the task that leads to low accuracy. In contrast, as shown in Fig. 4 (b), the distance of 2-Channel-2-Logit are normally distributed. The data that cannot be easily distinguished is distributed in the overlapping region.

Over-fitting problem of Siamese. We also found a noteworthy phenomenon during our experiments. When we try to use more complex networks with Siamese structure, such as Inception-v3, the network experiences serious over-fitting issue. However the 2-Channel network and 2-Channel-2-Logit structure are less prone to this issue. This can be demonstrated in Fig. 5 that shows the training and testing accuracies. The blue and red curves indicate training and testing accuracies, respectively. It can be seen that over-fitting occurs very quickly when training with Siamese network. As the accuracy of the training set increases, the accuracy of the test set begins to decline. But this is not the case with the proposed 2-Channel-2-Logit network. We think the reason is the amount of data in the off-line signature verification databases is too small and the same signature image will be used multiple times in a Siamese network. However, signature pairs were concatenated and used as input to the 2C2L network.



(a) (b)

Fig. 4: Distribution of the metric distance of 2-Channel network and the proposed 2-Channel-2-Logit network. The output of the proposed network are normally distributed with overlapping region in-between.



(a) (b)

Fig. 5: Training and testing accuracies of each epoch. (a) Siamese network. (b) 2-Channel-2-Logit network.

	AUC	EER
GPDS-Synthetic-Binarized	0.9616	10.01
GPDS-Synthetic-Gray	0.9646	9.95

TABLE V: Model Trained After Binarization and Original Model.

Performance on binarized data In addition, we also binarized the signature data and perform same procedure on the GPDS-Synthetic database. The results are given in Table V. We could find that the accuracy is as high as that of gray scale signature data. This indicates that the proposed method is robust to signature image background. The proposed model is easy to apply as real signature can be easily binarized. This feature is essential as signature images have poor quality.

IV. Conclusion and future work

In this paper, we proposed a 2-Channel-2-Logit network structure that greatly improves the accuracy of writer-independent off-line handwritten signature verification. The input to the network is the concatenation of reference and query signatures. The output of convolutional layers are two logits that measure the similarity between reference and query signatures. We explicitly add dropout layers and a 2-Logit layer to make the network less prone to overfitting issues. We perform experiments on the widely used databases to show that 2-Channel-2-Logit outperforms SOTA by a large margin. Especially, the accuracy improves from 77.76% to 90.05% on the latest GPDS-Synthetic database. The proposed network is also robust to signature image format and achieves same accuracy on binarized signature images. We also study the generalization ability by conducting cross datasets validation. Furthermore, we investigate that Siamese network is prone to over-fitting on small datasets and find that 2-Channel network is superior to measure image similarity in this case. In the future, we will study multiple samples learning and apply 2-Channel-2-Logit network structure to further improve its performance.

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