Attention Based Multiple Siamese Network for Offline Signature Verification

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Abstract. Offline handwritten signatures play an important role in biometrics and document forensics, and it has been widely used in the fields of finance, judiciary and commerce. However, the skilled signature forgeries bring challenges and difficulties to personal privacy protection. Thus it is vital to discover micro but critical details between genuine signatures and corresponding skilled forgeries in signature verification tasks. In this paper, we propose an attention based Multiple Siamese Network (MSN) to extract discriminative information from offline handwritten signatures. MSN receives the reference and query signature images and their corresponding inverse images. The received images are fed to four parallel branches. We develop an effective attention module to transfer the information from original branches to inverse branches, which attempts to explore prominent features of handwriting. The weight-shared branches are concatenated in a particular way and formed into four contrastive pairs, which contribute to learn useful representations by comparisons of these branches. The preliminary decisions are generated from each contrastive pair independently. Then, the final verification result is voted from these preliminary decisions. In order to evaluate the effectiveness of proposed method, we conduct experiments on three publicly available signature datasets: CEDAR, BHSig-B and BHSig-H. The experimental results demonstrate the proposed method outperforms that of other previous approaches.

Keywords: Attention mechanism · Multiple siamese network · Offline signature verification

1 Introduction

The emergence of big data era has brought the rise in privacy concerns. Passwords are easy to guess, which creates a serious security threat for personal information. To tackle this problem, biometrics identification has been widely applied in various scenarios, since it is a promising replacement for conventional identification approaches. The biometric system takes into account inherent physiological or behavioral traits such as fingerprint, face, voice and

J. Lladós et al. (Eds.): ICDAR 2021, LNCS 12823, pp. 337–349, 2021.
https://doi.org/10.1007/978-3-030-86334-0_22

handwritten documents, and makes verification or identification decisions according to different tasks or objectives.

Handwriting carries rich information to reveal the identity of individuals, and it plays significant roles in human communication, perception, emotional behavior and so on. Signatures have been widely used in biometric systems to verify a person's identity. They are used in legal and financial fields such as contract agreement, bank checks, passports, receipts, identity certificates and many other applications. Besides the necessary characteristics of biometrics identification, signatures also have many good traits. For example, they are easy to access and readily accepted by people in daily life. Therefore, the researches about signature verification are very early. With the help of artificial intelligence technology, it is more convenient to build a automatic signature verification system.

Signature verification systems can be classified in two types according to the data acquisition means: online (dynamic) and offline (static). In online systems, signatures are collected as temporal sequences. The data such as positions, pressure, pen inclination and acceleration are recorded. In offline systems, the data are represented as static digital images. In both online and offline systems, the query signatures are judged as genuine samples or forgeries. The forgeries are commonly categorized into three types: random, simple and skilled forgeries. For random forgeries, the forger basically has no information about the forged object, and he/she has never seen the signature and does not even know the name of the forged person. In this case, the forged signature has a completely different shape and it contains very different semantic characteristics compared to genuine signature. For simple forgeries, the forger has basic information such as the name of the object being forged but not know about the writing pattern of signatures. The forgeries may be similar to the genuine signature under such circumstance. Skilled forgery means the forger not only knows the name of the object being forged, but also has the information of his/her signature, and even has practiced the writing pattern deliberately.

There exists highly similarities between genuine and forged signatures, and it is almost impossible to discriminate the difference for a person who has not been trained for handwriting verification, therefore it is a particularly challenging task. Many approaches have been proposed to solve the challenging problem. Various hand crafted features are used in the field. Ferrer et al. [1] used Local Binary Patterns (LBP) and statistical measures for automatic offline handwritten signature verification. Okawa [2] proposed a discriminative and robust feature extraction approach based on a Fisher Vector (FV) with fused "KAZE" features from both foreground and background offline signature images. Diaz et al. [3] proposed a complete framework to recover on-line Western signatures from image-based specimens. In Ref. [4], a parameter free, candidate graph mining method was introduced for offline signature coding and verification. In recent years, many deep learning based methods have been proposed. Convolutional Neural Network (CNN) has demonstrated its excellent capabilities in the fields of signature verification. Masoudnia et al. [5] combined the different but complementary advantages of different loss functions and proposed Multi-Loss Snapshot

Ensemble (MLSE). Li et al. [6] proposed the first black-box adversarial example attack against handwritten signature verification. Siamese network is a class of architecture that usually contains two weight-shared branches. It was first proposed by Bromley et al. [7] for verification of signatures written on a pen-input tablet. The siamese network tries to minimize the Euclidean distance between the feature representations and has been successfully used in face verification and signature verification. Dey et al. [8] designed a convolutional siamese network named Signet, and achieved good performance in writer independent feature learning. Wei et al. [9] proposed a novel inverse discriminative network (IDN) to resolve the sparse information issue in writer-independent handwritten signature verification. Mustafa et al. [10] proposed a two-channel CNN and fused user-independent CNN score with user-dependent SVM score to get verification results. Lin et al. [11] proposed to add dropout layers in the middle position of 2-Channel-2-Logit (2C2L) network to address the overfitting problems.

In this paper, we propose an attention based multiple siamese network for offline signature verification. The structure is regarded as an enhanced version of siamese network. It contains four weight-shared branches which two of them receive reference signatures and corresponding inverse images and the other two receive query signatures and corresponding inverse images. Both original reference and query signatures are gray scale images. Attention modules are used to connect the original and inverse signature branches, which can make the network focus on effective stroke details and suppress interference information. Then the model performance is improved with the help of attention modules. Furthermore, we propose contrastive pairs to learn useful representations by comparisons of branches. Specifically speaking, the features from four branches are grouped into four different pairs, then the contrastive pairs are fed into four classifiers and made final decisions by voting mechanism.

The remainder of this paper is organized as follows: Sect. 2 describes details of the proposed method; Sect. 3 provides experimental results and discussions, and Sect. 4 concludes this paper.

2 The Proposed Method

The network architecture of the proposed attention based multiple siamese network is illustrated in Fig. 1. The original reference and query signatures are images with white backgrounds and gray signature strokes. The images with black backgrounds are inverse signatures of original reference and query samples, respectively. The MSN contains four weight-shared branches. Two of them are original branches and the other two are inverse branches. These branches have the same structure. Each branch contains four convolutional modules, and the number of channels are 32, 64, 96 and 128, respectively. Every module contains two convolutional layers (the kernel size is 3×3 and the stride is 1) and a pooling layer (the kernel size is 2×2 and the stride is 2). Rectified Linear Units (ReLU) are utilized as the activation function in each module. There are eight attention modules in MSN. Between original and inverse branches, attention module plays a connecting role. In the forward propagation, it receives the output from convolutional module in the original branch and the output from the first convolutional layer in the inverse branch. Then the output of attention module are regarded as input of the second layer in the inverse branch convolutional module. The feature maps output from four branches are concatenated, forming four contrastive pairs. Then these pairs are fed into fully-connected layers through global average pooling layers and make classification decisions independently. The final verification results are obtained according to these decisions from voting.

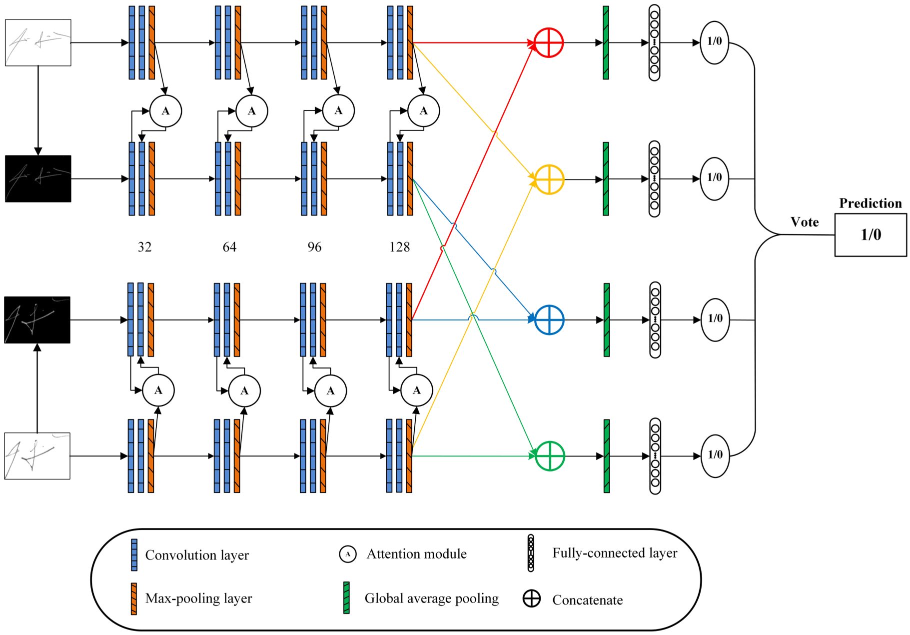

Fig. 1. Architecture of the proposed Multiple Siamese Network.

2.1 Pre-processing

For all signatures from training and testing datasets, we apply the same pre-processing strategy. In our research, signature images from different datasets have a variable size, for example, the size ranges from 153×258 to $819 \times 1{,}137$ in CEDAR. Our proposed model needs images with the same size as inputs. Therefore, all images are resized using linear interpolation. In signature images, there are large blanks around the foreground area which are useless. In order to reduce unnecessary calculations, we utilize a pixel search method to remove these margins. Besides, other pre-processing steps are also adopted. For example, we remove backgrounds while preserving the text. For convenience of network training, all original signature images are inverted using 255 minus the grayscale image matrix.

2.2 Attention Modules

In order to make the model focus on efficient and reliable stroke features in offline signature verification tasks, we introduce attention mechanism which may contribute to the feature learning in our network. Profiting from the special structure, MSN collects global information of the original image and combines them with features of the inverse image through attention modules, and discovers accurate stroke information effectively and quickly, thus guides the convolutional network focus on complement signature details.

The architecture of our redesigned attention module is inspired by [9,12–14]. The proposed attention modules are stacked to generate attention-aware features which can perform adaptively recalibration. Moreover, it can be used at any depth in the network. In the early layers, it enhances the quality of the shared lower-level feature representations. In later layers, it becomes specialised in a highly class-specific manner.

We adopt mixed attention mechanism in the module, which employs the residual learning method and is capable to capture crucial features. More specifically, spatial attention maps play an important role in deciding which area of signature images is informative. Channel attention maps are produced by exploiting the inter-channel relationship of features. Both global average-pooling and max-pooling method are utilized simultaneously. Average-pooling is to learn the extent of spatial information and aggregate them effectively. Max-pooling plays another significant role in gathering distinctive stroke features.

The architecture of designed attention modules is illustrated in Fig. 2. It contains both spatial and channel attention mechanisms. In the left side of the red dotted line, r is defined as the output from original branches. The feature map is resized to a fixed size using up-sampling operation which is based on nearest neighbor algorithm. Then a convolutional operation with sigmoid activation receives the resized feature maps. We defined g as the output after sigmoid activation, and o is the output of the first layer from convolutional modules in inverse branches. We multiply g and o, then make a element-wise addition which can be described as $g \cdot o + o$ to achieve desired spatial attention results. Subsequently, Global Average Pooling (GAP) and Global Max Pooling layers (GMP) are utilized to receive the spatial attention results. The architecture in the right side of the red dotted line in Fig. 2 can be regarded as channel attention mechanism which can be represented by:

$$W_c = \sigma(\mathrm{FC}(\mathrm{AvgPool}(g \cdot o + o)) + \mathrm{FC}(\mathrm{MaxPool}(g \cdot o + o))) \tag{1}$$

where σ denotes the sigmoid function, W_c is defined as channel attention weights of c-th channel. The features are fed into the shared network which is composed of Fully-Connected layers (FC), then we sum the output features to generate the weight vector f through sigmoid activation. Finally, we get an attention mask $(g \cdot o + o) \times f$ which is fed into the second layer of convolutional modules in inverse branches.

MSN contains eight attention modules between original and inverse branches. With the help of attention mechanism, the important and effective stroke features are focused and strengthened. Figure 3 shows an example of feature maps output from attention modules. Row 1 represents the signature images after preprocessing, and following rows denote different visualization results of the output from different level attention modules between original and reverse branches. We compare the visualization results of proposed attention module with that of IDN [9]. Column 1 and 2 are the visualization results of IDN and proposed MSN, respectively. It can be clearly seen that the proposed attention modules contain more reliable features and focus on stroke information.

2.3 Contrastive Pairs

Our proposed MSN aims to learn useful representations by comparisons of reference and query signature samples. To achieve such a goal, we consider the ordered combination of original and inverse branches. More specifically speaking, four feature maps are generated from these branches. They are concatenated to four pairs which are inverse reference and original query signature, original reference and original query signature, original reference and inverse query signature, inverse reference and inverse query signature, respectively. Each pair is fed into FC layers through a GAP layer. The c-th channel value z after GAP layer is calculated from feature map p_c by:

$$z_c = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} p_c(i, j) \tag{2}$$

Each pair makes a two-class classification independently. The MSN is expected to make the same decisions for all pairs in spite of the background colors. In order to achieve this ambitious objective, we utilize a binary cross entropy based loss function to measure the performance of contrastive pairs.

$$Loss\,(X_i, Y_i) = -\sum_{i=1}^{4} w_i \left[y_i \log x_i + (1 - y_i) \log (1 - x_i) \right] \tag{3}$$

y_i denotes ground truth label, and it is binary variables. 0 indicates that reference and query samples are written by different person which means the query signature sample is forged. 1 indicates the query sample is genuine. x_i represents predicted probability results, and it ranges from 0 to 1. w_i is a hyper-parameter, and we set it in different values for different datasets.

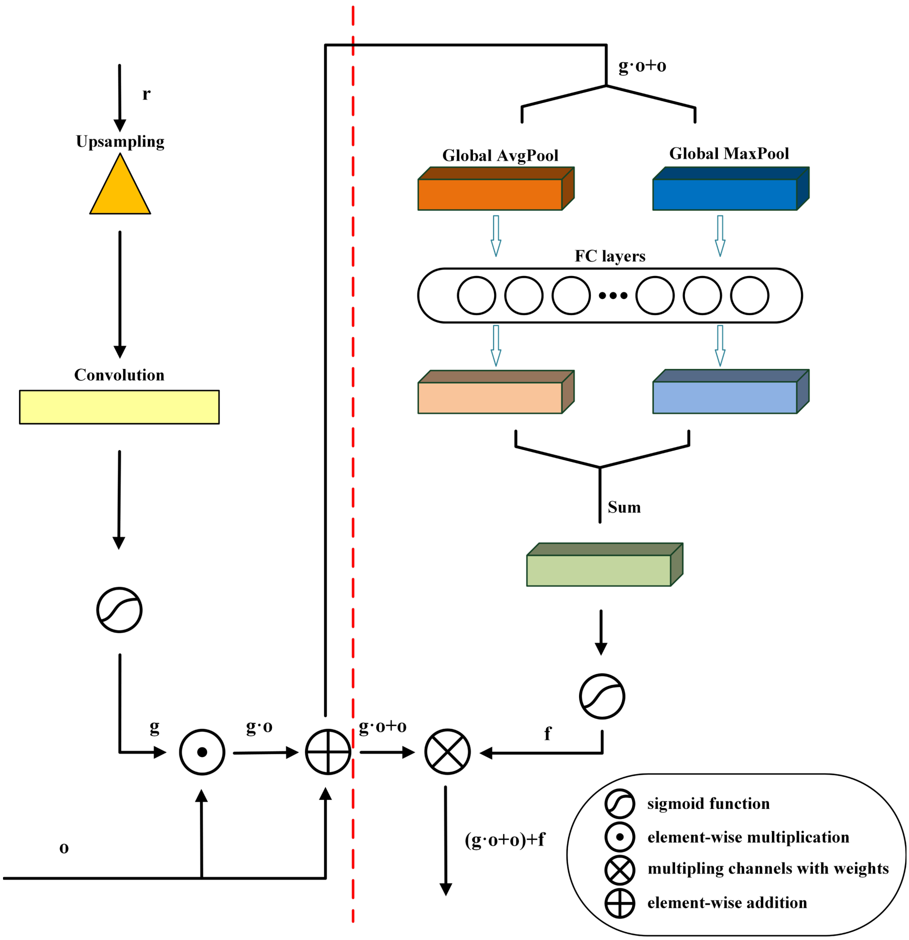

Fig. 2. Architecture of the proposed attention module.

$$Pre = \begin{cases} 1, \ N_p \geq 3 \\ 0, \ \ N_p < 3 \end{cases} \tag{4}$$

We also design a voting mechanism for the final prediction results. N_p indicates the number of contrastive pairs being regarded as the same writer's sample. Pre has two values where 0 denotes the query signature is forged and 1 denotes both reference and query signatures belong to the same writer's handwriting.

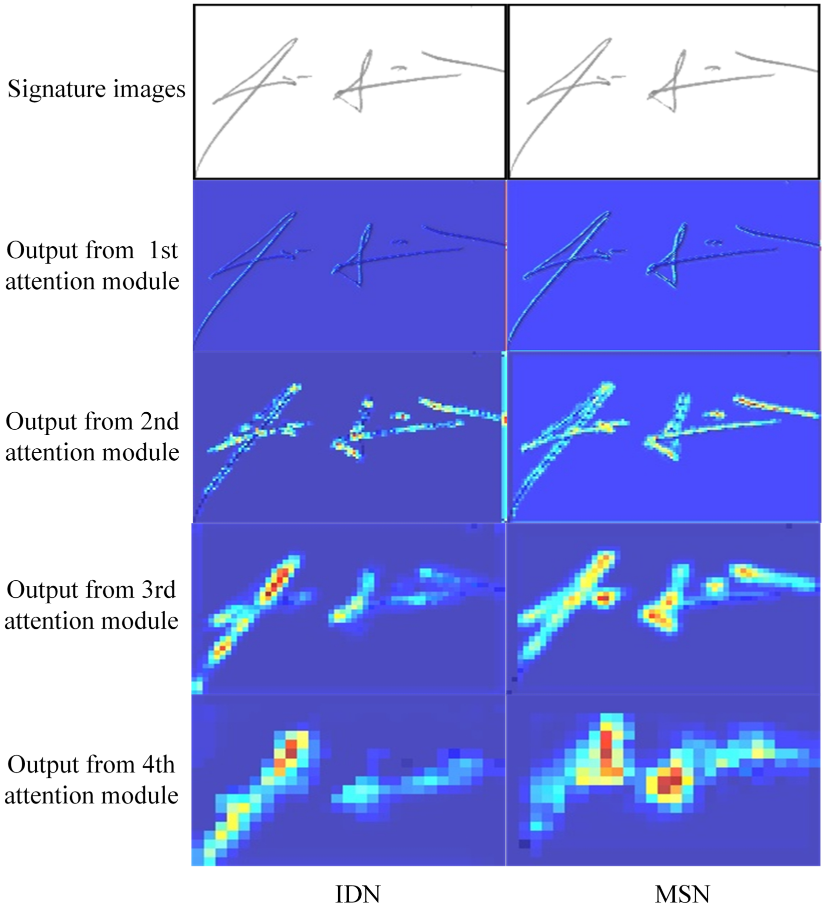

Fig. 3. Feature maps visualization results output from attention modules of IDN and proposed MSN.

3 Experimental Results

3.1 Datasets

In order to evaluate the effectiveness of our method, we conduct experiments on several widely used public datasets: (1) CEDAR [15], (2) BHSig-B and (3) BHSig-H [16]. The brief introduction of three datasets is as follows.

CEDAR is an English signature dataset which contains 55 individuals' samples. Every writer are asked to sign 24 genuine signatures and 24 skilled forgeries in a predefined space of 22 in. Therefore, there are $55 \times 24 = 1{,}320$ genuine and 1,320 forged signature images. These signatures are scanned at 300 dpi in 8-bit gray scale and stored as PNG images.

BHSig-B is a Bengali dataset which contains 100 individuals' samples. 24 genuine signatures and 30 skilled forgeries are available for each writer, which results in $100 \times 24 = 2{,}400$ genuine and $100 \times 30 = 3{,}000$ forged signatures.

BHSig-H contains 160 individuals' samples which are written in Hindi. It consists of $24 \times 160 = 2{,}840$ genuine signatures and $30 \times 160 = 4{,}800$ skilled forgeries from 160 individuals altogether. Both BHSig-B and BHSig-H dataset are collected from individuals with different educational backgrounds and ages. The signatures are scanned in gray scale with 300 dpi resolution and stored in TIFF format.

3.2 Evaluation Metrics

In order to evaluate our proposed method, we applied several standard metrics: False Rejection Rate (FRR), False Acceptance Rate (FAR), Equal Error Rate (EER), Average Error Rate (AER) and Accuracy (Acc).

3.3 Experimental Settings

The experiments are performed under the framework of Pytorch (1.4.0), with NVIDIA-2080 for GPU acceleration, Inter (R) Core (TM) i7-9700k CPU and 16G memory. The operating system is Ubuntu 18.04 and the programming language for all methods is Python.

The method is designed for writer independent signature verification, and the datasets need to be divided into training and testing samples. In column 2 and 3 of Table 1, the number of writers used for training and testing are given. For CEDAR dataset, it contains 24 genuine signatures for each writer, thus there are $C_{24}^2 = 276$ sample pairs (genuine-genuine). By combining all the (genuine-forgery) signatures of each writer, we can get $24 \times 24 = 576$ pairs. 276 genuine-forgery pairs are randomly selected to avoid imbalanced data issue between different classes. Likewise, for BHSig-B dataset, we use 50 individuals' samples for training, and there are $2 \times C_{24}^2 = 552$ pairs for each individual. For BHSig-H dataset, we use 100 individuals' samples for training and 60 individuals' samples for testing. Thus, the dataset was split with $100 \times 2 \times C_{24}^2 = 55{,}200$ pairs of samples assigned to the training dataset and $60 \times 2 \times C_{24}^2 = 33{,}120$ pairs to the testing dataset. The column 4 and 5 in Table 1 give the number of positive and negative pairs of each writer used for training and testing in different datasets.

3.4 Results and Discussions

The structure of proposed MSN is similar to Inverse Discriminative Network (IDN) [9], thus we compare our proposed method with it. We conduct our experiments using two proposed approaches, respectively. The first approach aims to focus on efficient stroke features using our proposed attention module. The second approach considers using four contrastive pairs to concatenate the output of original and inverse branches, thus enhance the feature learning ability.

Table 1. Details of experimental protocol on different datasets.

Dataset	Train	Test	Positive pairs	Negative pairs
CEDAR	50	5	276	276 out of 576
BHSig-B	50	50	276	276 out of 720
BHSig-H	100	60	276	276 out of 720

Table 2 shows the comparison results with IDN on CEDAR dataset. $\mathscr{A}ttention^1$ denotes the attention module used in IDN. $\mathscr{A}ttention^2$ represents our proposed attention module. From row 1 and 2, it can be seen that our proposed attention module is able to focus on more efficient and reliable stroke features. In row 3 and 4, MSN employs four contrastive pairs in our experiments. MSN + $\mathscr{A}ttention^1$ and MSN + $\mathscr{A}ttention^2$ means that we utilize $\mathscr{A}ttention^1$ and $\mathscr{A}ttention^2$ in MSN, respectively. By comparing the results of MSN + $\mathscr{A}ttention^1$ and IDN + $\mathscr{A}ttention^1$, we can notice that our proposed MSN achieves the higher accuracy compared to IDN, which demonstrates that MSN is more capable of learning effective feature representations by comparisons of reference and query signature samples. We also conduct experiments to discover if our proposed $\mathscr{A}ttention^2$ can achieve better performance in MSN than $\mathscr{A}ttention^1$. As can be seen in Table 2, the accuracy of MSN + $\mathscr{A}ttention^2$ is higher than MSN + $\mathscr{A}ttention^1$, which demonstrate that our proposed $\mathscr{A}ttention^2$ is workable in MSN. To sum up, our proposed approaches are more effective than IDN on CEDAR dataset.

Table 2. Comparison with IDN on CEDAR Dataset.

Model	Acc	FAR	FRR	EER
IDN [9] + $\mathscr{A}ttention^1$	96.77	2.75	3.69	3.22
IDN [9] + $\mathscr{A}ttention^2$	97.28	3.98	1.45	2.71
MSN + $\mathscr{A}ttention^1$	97.93	**2.02**	2.10	2.06
MSN + $\mathscr{A}ttention^2$	**98.40**	3.18	**0**	**1.63**

∗ Note: $\mathscr{A}ttention^1$ denotes the attention module used in IDN, and $\mathscr{A}ttention^2$ represents our proposed attention module.

In order to evaluate the proposed approaches on BHSig-B and BHSig-H, we use MSN with our proposed attention module to conduct contrast experiments. These experiments are also to verify whether the query samples are genuine signatures or skilled forgeries. In Table 3, it shows that the proposed method achieves good performance on the two datasets. The system achieves the best performance on BHSig-B. Compared with IDN [9], the accuracy increases most on BHSig-B which is 2.16%, FRR and EER decrease most on BHSig-B which is 2.60% and 2.16%, respectively. It can be concluded from Table 3 that the performance of proposed method excels IDN [9] effectively.

Table 3. Comparison with IDN on BHSig-B and BHSig-H Dataset.

Dataset	Method	FAR	FRR	EER	Acc
BHSig-B	IDN [9]	12.16	9.04	10.59	89.40
	MSN + $\mathscr{Attention}^2$	**10.42**	**6.44**	**8.43**	**91.56**
BHSig-H	IDN [9]	18.55	6.02	11.51	87.71
	MSN + $\mathscr{Attention}^2$	**17.06**	**5.16**	**11.31**	**88.88**

∗ Note: We reproduced the network architecture of IDN and got the results.

We also compare the method with other approaches on the three datasets. Table 4 shows the comparative analysis on the BHSig-B dataset. It is clear from the table that the proposed MSN performs better than previous approaches which consider handcrafted or deep learning based features as feature extractors.

Table 4. Comparison with other approaches on the BHSig-B dataset.

Model	FRR	FAR	EER	Acc
Dey et al. [8]	13.89	13.89	-	86.11
Lin et al. [11]	-	-	11.92	88.08
Pal et al. [16]	33.82	33.82	33.82	66.18
Jadhav and Chavan [19]	-	-	-	90.36
Jain et al. [20]	-	-	-	76.03
MSN + $\mathscr{Attention}^2$	**6.44**	**10.42**	**8.43**	**91.56**

Table 5 gives the evidence that the proposed method outperforms other approaches on CEDAR dataset. A possible reason for the higher performance on this dataset is the plenty number of signature samples for training. It is observed that the proposed method achieves performance improvement on all metrics than other approaches, which proves the superiority of our MSN.

Table 5. Comparison with other approaches on the CEDAR dataset.

Model	FRR	FAR	EER	AER
Hafemann et al. [17]	-	-	4.63	-
Kumar et al. [21]	8.33	8.33	-	8.33
Bhunia et al. [22]	-	-	-	1.64
Sharif et al. [23]	4.67	4.67	-	4.67
MSN + $\mathscr{Attention}^2$	**0**	**3.18**	**1.63**	**1.59**

Table 6 depicts the comparison results on BHSig-H dataset. We receive 88.88% accuracy compared with previous approaches. It is easy to see that the proposed method achieves good performance and is capable of distinguishing reference and query samples effectively.

Table 6. Comparison with other approaches on the BHSig-H dataset(%).

Model	FRR	FAR	EER	Acc
Dey et al. [8]	15.36	15.36	-	84.64
Lin et al. [11]	-	-	13.34	86.66
Pal et al. [16]	24.47	24.47	24.47	75.53
Dutta et al. [18]	15.09	**13.10**	-	85.90
Jain et al. [20]	-	-	-	83.50
MSN + $\mathscr{A}ttention^2$	**5.16**	17.06	**11.31**	**88.88**

4 Conclusions

In the field of pattern recognition, offline signature verification task has been considered as a challenging problem since it is difficult to capture the small differences between genuine and forged samples. In this paper, we introduce attention based multiple siamese network to extract discriminative information from offline signature images. Attention modules are utilized to discover stroke details between original and inverse pairs. The discriminative information can be learned through contrastive pairs by comparing reference and query signature samples. Experiments on CEDAR, BHSig-B and BHSig-H dataset demonstrate our proposed method is effective in offline signature verification tasks.

In our future work, we would like to apply the proposed method into online signature verification and investigate more reliable feature learning approaches in cross-language verification tasks.

Acknowledgements. This work is jointly sponsored by the National Natural Science Foundation of China (Grant No.62006150), Shanghai Young Science and Technology Talents Sailing Program (Grant No. 19YF1418400), Shanghai Key Laboratory of Multidimensional Information Processing (Grant No. 2020MIP001), and Fundamental Research Funds for the Central Universities.

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