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Deep Multitask Metric Learning for Offline Signature Verification☆

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ABSTRACT

This paper presents a novel classification method, Deep Multitask Metric Learning (DMML), for offline signature verification. Unlike existing methods that to verify questioned signatures of an individual merely consider the training samples of that class, DMML uses the knowledge from the similarities and dissimilarities between the genuine and forged samples of other classes too. To this end, using the idea of multitask and transfer learning, DMML train a distance metric for each class together with other classes simultaneously. DMML has a structure with a shared layer acting as a writer-independent approach, that is followed by separated layers which learn writer-dependent factors. We compare the proposed method against SVM, writer-dependent and writer-independent Discriminative Deep Metric Learning method on four offline signature datasets (UTSig, MCYT-75, GPDSsynthetic, and GPDS960GraySignatures) using Histogram of Oriented Gradients (HOG) and Discrete Radon Transform (DRT) features. Results of our experiments show that DMML achieves better performance compared to other methods in verifying genuine signatures, skilled and random forgeries.

1. Introduction

Handwritten signature is one of the most socially acceptable and widespread personal attributes to authenticate individuals. Signature verification systems by comparing a questioned signature with reference samples, try to determine whether it is genuine or forgery. According to the acquisition approach, signatures are divided into offline and online. In offline, signatures are scanned and stored as grayscale or binary images, while in online, sequential information (e.g. x-y positions, velocity, acceleration, pressure, and pen inclination) describes signatures [21]. Generally, online signature verification systems have higher accuracy, whereas the performance drops considerably in offline modes.

Forgery in the signature verification literature is divided into two main categories: random forgery which is when forger signs regardless of genuine signature, and skilled (simulated, freehand, or simple) forgery which is when forger tries to simulate genuine one. However, some papers know simple forgery as a separate category defined as the time that forger has no attempt to mimic genuine signature [29] or when forger just knows genuine writer's name [30].

Hardships of offline signature verification systems lie in high intra-personal variability, limited number of training samples, inaccessibility of skilled forgeries in learning procedure, and forgers attempts to mimic genuine samples [32]. Previous works addressing such hardships can be categorized into employing better feature extraction, improving classification with limited number of samples, augmenting the datasets, and building model ensembles [16].

Writer-dependent (WD) and writer-independent (WI) are two approaches to design offline signature verification systems. In WD, a specialized classifier is trained separately for each individual based on his samples, but in WI, being trained by all authors samples, just one classifier determines the authenticity of questioned signatures [35]. WI by using samples from all authors can alleviate the problem of limited number of training samples [32], but it is probable that many writer-specific characteristics are missed in this approach.

Recently to solve the problem of face verification in the wild, some attempts have been done to use metric learning-based systems which learn good distance metric [17]. A good distance metric is a similarity measure that its output for similar samples is close to zero, and reversely for dissimilar ones, it is a large positive number. In the offline signature verification literature, various distance-based classifiers have been employed that their distance measures are mainly Euclidean and Mahalanobis [21], which are

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0167-8655/

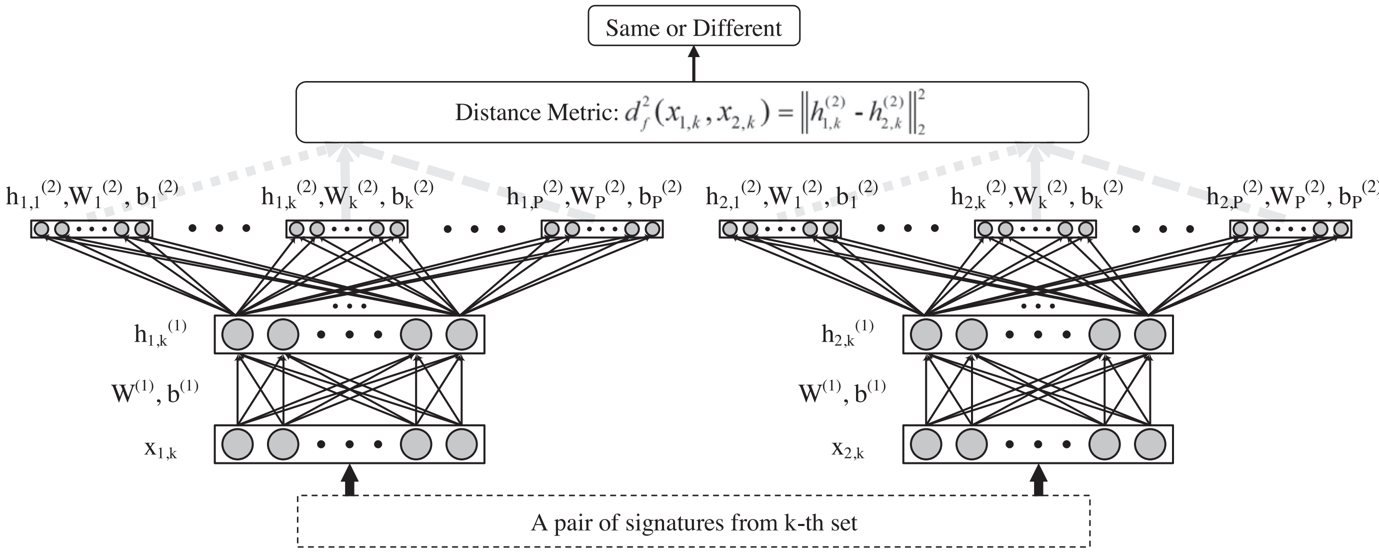

Fig. 1. Basic ideal of proposed DMML method. There is a shared layer for each pairs of signatures that is followed by separated layers which belong to distinct authentic individuals. To determine the authenticity of a signature $x_{2,k}$, which is claimed as a genuine sample of k-th person, questioned signature along with reference sample $x_{1,k}$ pass through the first layer (shared layer) and k-th unit in the second layer. Then distance metric determines whether they are the same or different. h, W, and b are respectively, output, weight and bias of a layer.

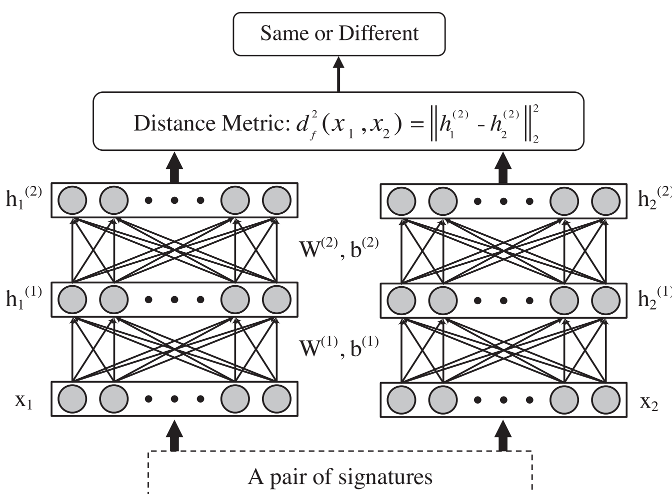

Fig. 2. The basic idea of DDML. A pair of objects (such as face, signature and ...) pass through hierarchical nonlinear transformations. Finally a distance metric determines whether they are the same or different.

not strong enough to discover the similarities and dissimilarities among genuine and forged samples. To our knowledge, this paper is the first to use metric learning based methods in the signature verification literature.

In this paper, we mix the idea of WD and WI approaches, multitask and transfer Learning with Discriminative Deep Metric learning (DDML) method [17]. Fig. 1 and Fig. 2 show the basic idea of DMML (proposed method) and DDML, respectively. DDML consists of a deep neural network that learns a set of hierarchical nonlinear transformations to make a good distance metric. We contribute to DDML by sharing a layer for all authors to involve WI approach and considering separated layers for each distinct authentic signer to handle WD approach. Our structure is benefited from the idea of multitask and transfer learning that helps to transfer the knowledge from the similarities and dissimilarities among other signers genuine and forged samples to each specific signer. Experiments on four offline signature datasets, UTSig [34], MCYT-75 [13], GPDSsynthetic [11], and GPDS960GraySignatures [12] indicate promising results for the proposed method.

The rest of this paper is organized as follows: Section 2 presents related works in metric learning specially DDML, and overviews the definition of transfer learning and multitask learning. Section 3 describes proposed DMML. Section 4 presents datasets details, experimental setups, and discusses results. Section 5 concludes the paper with some suggested works for the future.

2. Related works

2.1. Metric learning

Supervised metric learning methods aims to learn a metric or similarity measure from labeled data that outputs positive values close to zero for same-class data and large value for objects from different classes. Recently, some applications have benefited from these methods such as visual search [25], photo clustering [38], face verification [17], and person re-identification [23]. Among metric learning methods, DDML [17] by training a deep neural network to learns a set of hierarchical nonlinear transformations, shows promising results in face verification in the wild. Fig. 2 shows the basic idea of DDML. In that a pair of objects (in our application signatures), x_1 and x_2, are separately transformed from multiple layers with similar weights and biases for each object, then the similarity of the pair is calculated at the final layer ($h_1^{(2)}$ and $h_2^{(2)}$) by squared Euclidean distance.

Unlike DDML, which uses only common layers for all pairs, we use the idea of multitask learning to consider separated layers after a shared layer for different pairs from different sets (each set belongs to one authentic signer). The basic idea of our method is shown in Fig. 1. In that, squared Euclidean distance is calculated for pairs $x_{1,k}$ and $x_{2,k}$ from k-th set (k = 1,2,…,P) which pass through the k-th separate layer.

2.2. Multitask and Transfer Learning

When source domain and target domain, or source task and target task are not equal, transfer learning approaches can be used to transfer the knowledge from the source domain or the source task