

Offline Signature Verification Using Local Radon Transform and Support Vector Machines

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Abstract

In this paper, we propose a new method for signature verification using local Radon Transform. The proposed method uses Radon Transform locally as feature extractor and Support Vector Machine (SVM) as classifier. The main idea of our method is using Radon Transform locally for line segments detection and feature extraction, against using it globally. The advantages of the proposed method are robustness to noise, size invariance and shift invariance. Having used a dataset of 600 signatures from 20 Persian writers, and another dataset of 924 signatures from 22 English writers, our system achieves good results. The experimental results of our method are compared with two other methods. This comparison shows that our method has good performance for signature identification and verification in different cultures.

Keywords: Offline Signature Verification, Radon Transform, Support Vector Machine.

1. INTRODUCTION

Signatures are most legal and common means for individual's identity verification. People are familiar with the use of signatures in their daily life. Automatic signature recognition has many applications including credit card validation, security systems, cheques, contracts, etc [1], [2].

There are two types of systems in this field, signature verification systems and signature identification systems. A signature verification system just decides whether a given signature belongs to a claimed writer or not. A signature identification system, on the other hand, has to decide a given signature belongs to which one of a certain number of writers [3].

Major methods of signature recognition can be divided into two classes, on-line methods and off-line methods. On-line methods measure the sequential data such as coordinates of writing points, pen pressure, angle and direction of the pen. While off-line methods use an optical scanner to obtain signature image [4], [5]. Offline systems are of interest in scenarios where only hard copies of signatures are available. Since online signatures also contain dynamic information, they are difficult to forge. Therefore, offline signature verification methods are less reliable than online methods [3].

In signature verification systems, two common classes of forgeries are considered: casual and skilled. A casual forgery is produced by only knowing the name of the writer, and without access to a sample of the genuine signature. When forger uses his own signature or genuine signature of another writer as a casual forgery, it is called a substitution forgery. So, stylistic differences are common in casual forgeries. In skilled forgeries, the forger has access to a sample of genuine signature and knows the signature very well. Since skilled forgeries are very similar to genuine signatures, some appropriate features for detection of casual forgeries are ineffective in detection of skilled forgeries [2], [4].

The precision of signature verification systems can be expressed by two types of error: the percentage of genuine signatures rejected as forgery which is called False Rejection Rate (FRR); and the percentage of forgery signatures accepted as genuine which is called False Acceptance Rate (FAR) [4].

The signature verification is performed in two steps, feature extraction and classification. During the feature extraction phase, personal features of each training signature are extracted and trained to the classifier. In the classification phase, personal features extracted from a given signature are fed into classifier in order to judge its validity.

Offline signature verification generally involves extraction of global or local features. Global features describe the characteristics of the whole signature and include the discrete Wavelet transform, the Hough transform, horizontal and vertical projections, edge points of signature, signature area, and smoothness features [2], [7]. Local features describe only a small part of signature and extract more detailed information from image. These features include unballistic motion and tremor information in stroke segments, stroke elements, local shape descriptors, and pressure and slant features [3], [7]. This paper presents a new offline signature verification method based on local Radon Transform.

The rest of paper is organized as follows. After this introduction, Section 2 presents some related works done in the field. Our proposed method is described in section 3. Experimental results of the proposed method on two signature sets are discussed in Section 4. Finally, Section 5 draws the conclusions and further work.

2. RELATED WORK

The problem of automatic signature verification has received big attention in past years because of its potential applications in banking transactions and security systems. Cavalcanti et al [8] investigates the feature selection for signature identification. He used structural features, pseudo-dynamic features and five moments in his study. Ozgunduz et al [9] has presented an off-line signature verification and recognition method using the global, directional and grid features. He has showed that SVM classifier has better performance than MLP for his proposed method. Mohamadi [10] has presented a Persian offline signature identification system using Principal Component Analysis (PCA) and Multilayer Perceptron (MLP) neural network.

Sigari and Pourshahabi [11], [12] proposed a method for signature identification based on Gabor Wavelet Transform (GWT) as feature extractor and Support Vector Machine (SVM) as classifier. In their study after size normalization and noise removal, a virtual grid is placed on signature

image and Gabor coefficients are computed on each point of grid. Next, all Gabor coefficients are fed into a layer of SVM classifiers as feature vector. The number of SVM classifiers is equal to the number of classes. Each SVM classifier determines whether the input image belongs to corresponding class or not (one against all method). In their study two experiments on two signature sets were done. They have achieved identification rate of 96% on Persian signature set and more than 93% on Turkish signature set. Their Persian signature set was the same as signature set that has been used in [10].

Coetzer [3], have used Discrete Radon Transform as global feature extractor and a Hidden Markov Model in a new signature verification algorithm. In their proposed method, The Discrete Radon Transform is calculated at angles that range from 0° to 360° and each observation sequence is then modeled by an HMM of which the states are organized in a ring. To model and verify signatures of each writer one HMM is considered. Their system is rotation invariant and robust with respect to moderate levels of noise. Using a dataset of 924 signatures from 22 writers, their system achieves an equal error rate (EER) of 18% when only high-quality forgeries (skilled forgeries) are considered and an EER of 4.5% in the case of only casual forgeries. These signatures were originally captured offline. Using another dataset of 4800 signatures from 51 writers, their system achieves an EER of 12.2% when only skilled forgeries are considered. These signatures were originally captured online and then digitally converted into static signature images.

3. THE PROPOSED METHOD

As shown in Figure 1, our proposed method consists of two major modules: (i) Learning genuine signatures, (ii) Verification or recognition of given signature. These modules share two common prior steps: preprocessing and feature extraction.

Preprocessing phase makes signature image ready for feature extraction. When system is in learning mode, extracted features resulting from feature extraction step are used by learning module and fed into SVM classifiers to learn signature. But, when system is in testing mode, extracted features resulting from feature extraction step are used by classification module and fed into SVM classifiers to classify given signature.

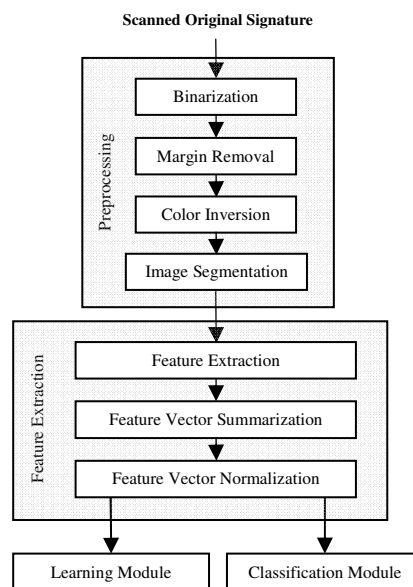


FIGURE 1: Block diagram of proposed system.

Removing margins of signature image in the preprocessing step leads to shift invariance property in our algorithm. Also, our method is scale invariant due to feature vector normalization in the

feature extraction phase. The proposed method can tolerate small rotations in signature image, however in the case of big rotations its performance will reduce.

The next sections describe these modules in more details. The data collection and preprocessing is described in Section 3.1. Feature extraction and idea of the system are presented in Section 3.2. In Section 3.3 some collected samples are used for training and finally the coming samples are tested to obtain the percentage of FRR and FAR.

3.1 Preprocessing

The purpose of preprocessing phase is to make signatures ready for feature extraction. The preprocessing stage includes three steps: Binarization and margin removal, Color inversion, Image segmentation.

Binarization and margin removal

In the first step, signature image is converted to binary image using Otsu binarization algorithm [13]. The next step is finding the outer rectangle of the signature and removing signature image margins. This gives us shift invariance property in our algorithm. We found the outer rectangle using horizontal and vertical projections of binary image. Figure 2 shows a sample original signature before preprocessing. Figure 3 shows horizontal and vertical projections of binary image.

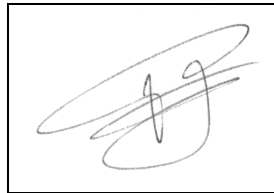


FIGURE 2: An original sample signature.

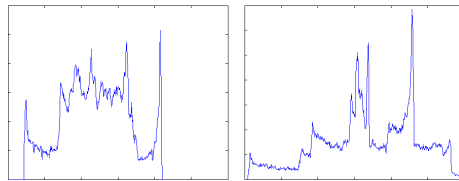


FIGURE 3: Horizontal (left) and vertical (right) projections of binary image.

Color inversion

The Radon Transform counts pixels with nonzero value in desired direction to produce image projection. In our binary images foreground is black with zero value and background is white with nonzero value. Hence, in this step we invert image before giving it to Radon Transform. Thereafter, when we give inverted image to Radon Transform, the biggest peak in the result of Radon Transform will be corresponding to line segment direction. Figure 4 shows inverted signature image.



FIGURE 4: Inverted signature image

Image Segmentation

Our proposed method works locally, so signature image must be segmented to some local windows and then orientation and width of line segment must be detected in each local window. The size of local window (n) has a direct effect on precision of line detection process. A small/big window will result in narrow/wide line segments detection. By choosing an appropriate window size, all line segments can be detected.

Another parameter that has great effect on our algorithm precision is overlay rate of neighboring windows. Non-overlaid windows will reduce algorithm precision substantially. Therefore, we define a new parameter "step" that its combination with window size will determine overlay rate of neighboring windows. Figure 5 shows overlaying windows.

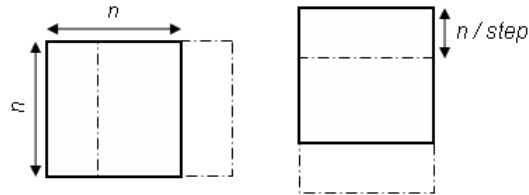


FIGURE 5: Overlaying windows

3.2. Feature extraction

The feature extraction stage includes four steps: line segment detection, line segment existence validation, feature vector extraction and summarization, and feature vector normalization.

Radon Transform and line segment detection

“The Radon Transform computes projection sum of the image intensity along a radial line oriented at a specific angle” [14]. For each specific angle θ , the radon transform produce a vector R containing the projection sum of image intensity at angle θ . A mathematical definition of Radon Transform is given in [14], [15], [16], [17]. The radon transform of a function $g(x,y)$ in 2-D Euclidean space is defined by

$$R(p, \theta) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) \delta(p - x \cos \theta - y \sin \theta) dx dy \quad (1)$$

Where the $\delta(r)$ is Dirac function. Computation of Radon Transform of a two dimensional image intensity function $g(x,y)$, results in its projections across the image at arbitrary orientations θ and offsets p [17].

The local image is squared shape; therefore occurrence of peak value in diagonal directions is more probable than other orientations. We solve this problem, by applying a circular mask to the local image before giving it to Radon Transform. Figure 6 shows this circular mask and its application.

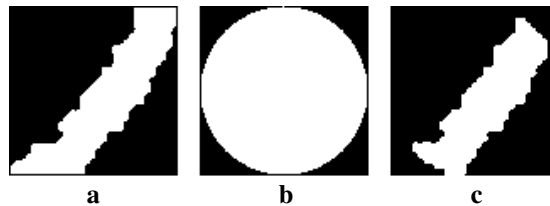


FIGURE 6: Filtering local window using a circular mask
a) local window b) mask c) masked window

The biggest peak value in the result of Radon Transform is the projection of probable line segment in its orientation angle. We call this orientation angle α and the projection peak value along it P_α . In the next step, P_α is processed to specify existence of the line segment in the local window.

To determine line width, we go left and right from peak offset in projection along angle α until reach a value smaller than $level \cdot P_{\alpha}$. These two places are line segment start and end positions. Level is another parameter of our algorithm and must be in (0, 1].

Line segment existence validation

In the next step, we detect existence of the line segment in the local window by comparing projection peak value P_{α} with a predetermined threshold value. To use the same threshold value for windows with different size, the Projection peak value P_{α} must be normalized before comparing with the line validation threshold. To do this we compute line validity value by dividing P_{α} to window size (n) as below:

$$line\ validity = \frac{P_{\alpha}}{n} \tag{2}$$

If the line validity value is greater than the line validation threshold then a line segment is detected in the current local window.

Feature vector extraction and summarization

Based on detected line segments with different orientations and widths, for each line width a feature vector containing histogram of detected line segments in orientations of 0° to 179° is produced. This feature vector is computed for line widths of 1, 2, 3, 4, 5 and 6 pixels. All line segments with line width greater than 6 counted in sixths histogram. This approach for feature extraction gives us a long feature vector with 1080 elements that is inappropriate for classification purpose. To solve this problem, we summarize this feature vector by combining some line widths together and also considering a degree resolution. To do this, we first combine some line widths together by summing corresponding feature vector elements of these line widths. Then based on selected degree resolution dr , we extend number of angle values spanned by each bin from 1 to dr angles. To do this, we combine each dr neighboring elements in the resulted feature vector from prior step by summing them into a new corresponding bin in final feature vector. This approach gives us a good flexibility in feature vector summarization. The optimum number of bins in the histogram is a function of the desired accuracy and the amount of data to be examined. Figure 7 shows this summarization process for {1,2,3} {4,5} {6} width combination and degree resolution of 3. This sample combination results in a feature vector with 180 elements.

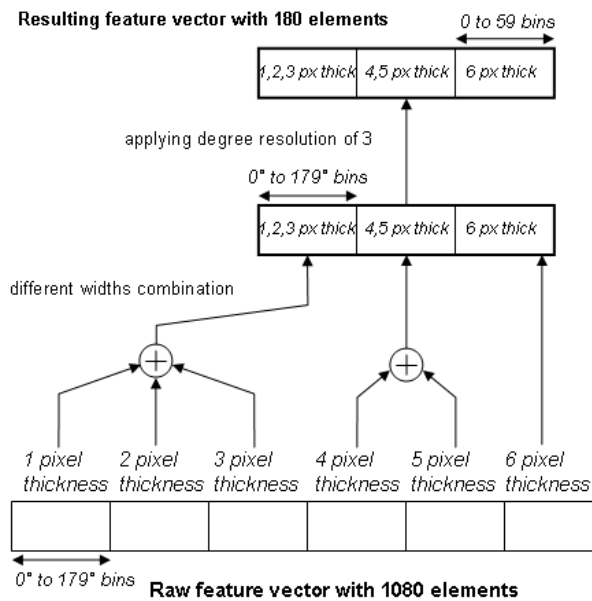


FIGURE 6: Feature vector summarization process

Feature vector normalization

In the last step of feature vector generation, we normalize feature vector by dividing its elements to its maximum element value. This leads to scale invariance property in our algorithm.

3.3. Classification

In the classification step, signature images are classified using a layer of Support vector machine (SVM) classifiers. The number of SVM classifiers in classification layer is equal to number of signature classes.

The main characteristic of a learning machine is its generalization property [18]. This is the ability of the classifier to correctly classify unseen data which were not present in the training set. Recent advances in the field of statistical learning have led to SVM classifier which has been applied with success in many applications like face and speaker recognition [19], [21]. The concept of SVM classifier was introduced by Vapnik in late of 1970's. The main idea of SVM is to construct a hyperplane as the decision surface with maximal margin of separation between positive and negative examples [20]. This leads to high generalization ability in SVM classifier with respect to other statistical classifiers. When samples are nonlinearly separable in input space, SVM must used in feature space using appropriate kernel function. In our experiment, we have used SVM classifier with Radial Basis Functions (RBF) kernel to achieve the best results.

Since SVM is a binary classifier (can categorize two classes) for classification of N classes, N SVM classifiers are needed. So in our application, number of SVM classifiers is equal with the number of writers. Each SVM classifier is used for identification of one writer signatures against all other writers (one against all strategy).

We have used two rules in our method for signature identification and verification. If all classifiers except only one generate negative result, the corresponding class of the classifier that generates positive result is considered as the class of input signature. For identification purpose this class is notified as the signer identity. For verification purpose, input signature is genuine if this class is equal to claimed signer class. In the case of skilled or casual forgeries, output of all classifiers can be negative or two or more classifier outputs can be positive. In this case the input signature will not belong to known classes, and is detected as a forgery signature.

4. EXPERIMENTAL RESULTS

Two experiments were done to evaluate our method and compare it with other methods. The first experiment was on a Persian signature set and the second experiment was on an English signature set.

4.1. Persian signature dataset

This signature set is same as the signature set that is used in [10-12]. It contains 20 classes and 30 signatures per class. For each class, 10 signatures for training and 10 genuine signatures and 10 skilled forgery signatures for test were used.

The results of our algorithm are compared to the results of algorithm developed by M.H. Sigari on this dataset [12]. Sigari developed SVM-based algorithm only for identification of offline signatures. He used Grid Gabor Wavelet coefficients to identify signature images, and achieved 96% identification rate.

Table 1 shows the performance of our method on this dataset for different width combinations and degree of resolutions. Comparing our results with the Sigari results on this dataset, our algorithm in the best case achieved the same 96% identification rate (FRR of 4%) and FAR of 17%. The main advantage of our algorithm is that it can also give us good results for verification purposes. We achieved these results using local window size of $n=31$, line validation threshold of $L=0.7$, level=0.95 and step=3.

Width combination	Degree resolution	FRR	FAR
{1,2,3,4,5,6}	3	0.09	0.23
{1,2,3,4,5,6}	5	0.09	0.25
{1,2,3,4,5,6}	10	0.09	0.29
{1,2,3} {4,5,6}	3	0.12	0.16
{1,2,3} {4,5,6}	5	0.06	0.21
{1,2,3} {4,5,6}	10	0.08	0.27
{1,2,3,4} {5,6}	3	0.07	0.17
{1,2,3,4} {5,6}	5	0.04	0.22
{1,2,3,4} {5,6}	10	0.08	0.26
{1,2} {3,4} {5,6}	3	0.11	0.14
{1,2} {3,4} {5,6}	5	0.09	0.19
{1,2} {3,4} {5,6}	10	0.06	0.22
{1,2} {3,4,5} {6}	3	0.07	0.20
{1,2} {3,4,5} {6}	5	0.08	0.23
{1,2} {3,4,5} {6}	10	0.07	0.26
{1,2,3} {4,5} {6}	3	0.09	0.13
{1,2,3} {4,5} {6}	5	0.04	0.17
{1,2,3} {4,5} {6}	10	0.08	0.22
{1} {2} {3} {4} {5} {6}	3	0.24	0.08
{1} {2} {3} {4} {5} {6}	5	0.13	0.11
{1} {2} {3} {4} {5} {6}	10	0.06	0.19

TABLE 1: Performance on the Persian signature dataset.

4.2. The Stellenbosch dataset

This signature set is same as the signature set that is used in [3]. It contains 22 classes and 30 genuine signatures, 6 skilled forgeries, and 6 casual forgeries in each class. For each writer, 10 genuine signatures are used for training and 20 genuine signatures for testing.

The results of our algorithm are compared to the results of a HMM-based algorithm developed by J. Coetzer on this dataset [3]. Coetzer algorithm is flexible and can achieve different FRR and FAR pairs. He achieved equal error rate (ERR) of 4.5% when only casual forgeries are considered and ERR of 18% when only skilled forgeries are considered.

Width combination	Deg. Res.	FRR	FAR casual	FAR skilled
{1,2,3,4,5,6}	3	0.49	0	0.07
{1,2,3,4,5,6}	5	0.33	0	0.14
{1,2,3,4,5,6}	10	0.24	0.01	0.19
{1,2,3,4,5,6}	15	0.24	0.01	0.20
{1,2,3,4,5,6}	20	0.19	0.02	0.22
{1,2,3} {4,5,6}	3	0.61	0	0.05
{1,2,3} {4,5,6}	5	0.43	0	0.11
{1,2,3} {4,5,6}	10	0.28	0	0.18
{1,2,3} {4,5,6}	15	0.27	0.01	0.19
{1,2,3} {4,5,6}	20	0.23	0.04	0.18

{1,2,3,4} {5,6}	3	0.70	0	0.03
{1,2,3,4} {5,6}	5	0.54	0	0.05
{1,2,3,4} {5,6}	10	0.34	0	0.14
{1,2,3,4} {5,6}	15	0.29	0	0.17
{1,2,3,4} {5,6}	20	0.28	0.01	0.18
{1,2} {3,4} {5,6}	3	0.7	0	0.03
{1,2} {3,4} {5,6}	5	0.54	0	0.05
{1,2} {3,4} {5,6}	10	0.34	0	0.14
{1,2} {3,4} {5,6}	15	0.29	0	0.17
{1,2} {3,4} {5,6}	20	0.28	0.01	0.18
{1,2} {3,4,5} {6}	3	0.66	0	0.05
{1,2} {3,4,5} {6}	5	0.49	0	0.10
{1,2} {3,4,5} {6}	10	0.33	0.01	0.18
{1,2} {3,4,5} {6}	15	0.28	0.01	0.19
{1,2} {3,4,5} {6}	20	0.24	0.02	0.22
{1,2,3} {4,5} {6}	3	0.75	0	0.01
{1,2,3} {4,5} {6}	5	0.65	0	0.04
{1,2,3} {4,5} {6}	10	0.42	0.01	0.10
{1,2,3} {4,5} {6}	15	0.33	0	0.18
{1,2,3} {4,5} {6}	20	0.29	0.01	0.19
{1} {2} {3} {4} {5} {6}	3	0.77	0	0.02
{1} {2} {3} {4} {5} {6}	5	0.74	0	0.01
{1} {2} {3} {4} {5} {6}	10	0.57	0	0.06
{1} {2} {3} {4} {5} {6}	15	0.46	0	0.09
{1} {2} {3} {4} {5} {6}	20	0.36	0	0.13

TABLE 2: Performance on the English signature dataset.

Table 2 shows the performance of our method on this dataset. Comparing our results to Coetzer results on this dataset, our algorithm in the best case achieved the FRR of 19% and FAR of 2% when only casual forgeries are considered and FAR of 22% in the case of only skilled forgeries. The best case for our algorithm is when no line width information is used on this dataset. Due to using a HMM classifier with ring topology, when only casual forgeries are considered Coetzer result in identification are better than our results on this dataset. However, the results of our algorithm are satisfying on this dataset. We achieved these results using local window size of $n=31$, line validation threshold of $L=0.7$, level=0.95 and step=3.

5. CONCLUSION

In this work we presented an approach to offline signature identification and verification problems based on local Radon Transform and SVM classifier. Using Radon Transform as a local feature extraction method gives us fine information and more detailed features. The main advantage of our algorithm with respect to identification method in [12] is its ability to produce good results for verification purposes beside identification purposes. Also, it exhibits a good performance for signature identification and verification purposes in different cultures.

6. ACKNOWLEDGMENT

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