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Designing an Offline Method for Signature Recognition

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Abstract: In this work a new offline signature recognition system based on Radon Transform, Fractal Dimension (FD) and Support Vector Machine (SVM) is presented. In the first step, projections of original signatures along four specified directions have been performed using radon transform. Then, FDs of four obtained vectors are calculated to construct a feature vector for each signature. These vectors are then fed into SVM classifier for recognition of signatures. In order to evaluate the effectiveness of the system several experiments are carried out. Offline signature database from signature verification competition (SVC) 2004 is used during all of the tests. Experimental result indicates that the proposed method achieved high accuracy rate in signature recognition.

Key words: Offline Signature Recognition · Radon Transform · Fractal Dimension · Support Vector Machine

INTRODUCTION

Signature of a person is an important biometric attribute of a human being and is used for authorization purpose for decades [1-3]. While financial institutions and other commercial organizations primarily focus on the visual appearance of our signature for verification purposes, Signature Recognition examines behavioral aspects that manifest themselves when we sign our name. Many documents such as forms and bank checks necessitate the signing of a signature. Therefore it is essential to recognize the signatures, with high accuracy and no time consuming processes. A signature recognition system can be characterized by two factors: (1) representation, which refers to the internal description that the system extracts from each signature of the database and (2) match scheme, which includes the method that is used to select the best match from the set of identities of the signature database [4].

During the last few years, researchers have made great efforts on off-line signature recognition. In [5], the authors used hierarchical scheme of signature descriptors to identify a test signature. In [6] the authors considered a set of geometric and topologic features to map a signature image into two strings of finite symbols.

In [7], the application of active deformable models for approximating the external shape of a signature has been proposed. The authors in [8] compared different statistical methods, using a feature extraction preprocessing, to carry out the recognition of signatures. In another paper [9], the performance of a signature recognition system based on support vector machines (SVM) has been compared with a traditional classification technique, multi-layer perceptrons (MLP).

In this paper new offline signature recognition is presented. In the first step, radon transform is initially applied on the signature image with angles 0°, 45°, 90° and 135°. Then fractal dimension of the obtained vectors is calculates and the results are fed into SVM classifier. The simulated results indicate that the proposed method has a high accuracy in signature recognition.

This paper is organized as follows: Section 2 presents the theoretical foundation of radon transform, fractal dimension and SVM classifier. The proposed signature recognition algorithm is explained in Sections 3. The performance evaluation of the proposed method are provided in Section 4. Section 5 summarizes our conclusions.

Background Knowledge for the Proposed Method: Since this research is based on radon transform, fractal dimension and SVM, they are briefly reviewed here.

Radon Transform: The radon transform is projections of an image matrix along specified directions [10]. The Radon Transformation is a fundamental tool which is used in various applications such as radar imaging, geophysical imaging, nondestructive testing and medical imaging [11].

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A projection of a two-dimensional function *f(x,y)* is a set of line integrals [10]. The radon transform computes the line integrals from multiple sources along parallel paths, or beams, in a certain direction. The beams are spaced 1 pixel unit apart. To represent an image, the radon transform takes multiple, parallel-beam projections of the image from different angles by rotating the source around the center of the image. Projections can be computed along any angle. In general, the Radon transform of *f(x,y)* is the line integral of f parallel to the y′-axis.

$$R_{\alpha}(x') = \int_{-\infty}^{\infty} f(x'\cos\alpha - y'\sin\alpha, x'\sin\alpha + y'\cos\alpha)dy' \quad (1)$$

Where

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\alpha & \sin\alpha \\ -\sin\alpha & \cos\alpha \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \quad (2)$$

Fractal Dimension: Fractal dimension values indicate the complexity of a pattern, or the quantity of information embedded in a pattern [12]. Applications of fractal dimension have been found in different signal processing fields [13-17].

Several algorithms have been proposed to compute the fractal dimension of waveforms such as Higuchi [14], Petrosian [15] and Katz [16] methods. Selection of FD algorithm depends on the application [17]. Higuchi's method presents the most accurate estimation of the FD; but it is slower than Katz's method. Petrosian's method has less accuracy in calculating FD of a signal compared to Katz's approach. Katz's method is relatively insensitive to noise [16]. In this paper, we have used Katz's algorithm to calculate the FD of a time series. In the Katz's algorithm, the FD is obtained directly from the time series and can be defined as [16, 17]:

$$FD = \frac{\log(L/a)}{\log(d/a)} \quad (3)$$

Where L is the length of the time series, d is the distance (Euclidean) between the first point in the time series and the point that provides the furthest distance with respect to the first point and a is the average distance between the two successive data points.

Support Vector Machine: The SVM is a classifier derived from statistical learning theory initially presented in [18]. It is based on the structural risk minimization principle (SRM). The main advantages of SVM when used for image classification problems are: (1) ability to work with high-dimensional data and (2) high generalization performance without the need to add a-priori knowledge, even when the dimension of the input space is very high [19, 20]. The problem that SVMs try to solve is to find an optimal hyperplane that correctly classifies data points by separating the points of two classes as much as possible. Figure 1 is an example of the previous situation.

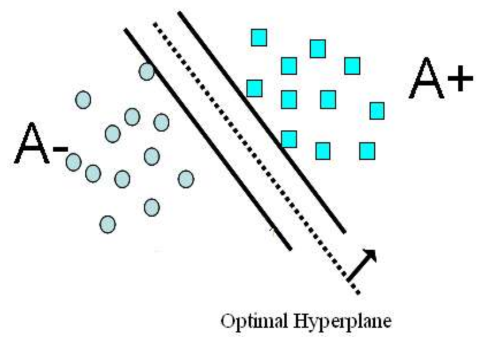

Fig. 1: An example of optimal hyperpalne.

The SVM's linearly learned decision function f(x) is described by weight vector w, a threshold b and input patterns x.

$$F(x) = sign(w.x + b) \quad (4)$$

Given a set of training vectors $\{S_l=((x_1,y_1),...,(x_l,y_l)),x_l \in R^l\}$, equation (4) belonging to two separate classes, A+ (y_i = +1) and A- (y_i =-1), the SVM finds the hyperplane with maximum Euclidian distance from the training set. According to the SRM principle, there will be just one optimal hyperplane with the maximal margin d, defined as the sum of distances from the hyperplane to the closest points of the classes. This linear classifier threshold is the optimal separating hyperplane.

Graphically the support vectors are the set of points that mark the border of the class. This approach is valid whenever the set of points of the two classes are linearly separable. Nevertheless in real data this is usually not the case. In order to work with non-linear decision boundaries the key idea is to transform x_i to a higher dimension space using a transformation function ϕ, so that in this new space the samples can be linearly divided. SVM solve these problems using kernels. The relationship between the kernels function K and ϕ is:

$$k(x_i, x_j) = \phi(x_i)\phi(x_j) \quad (5)$$

Intuitively, $k(x,y)$ represents the desired notion of similarity between data x and y. $k(x,y)$ needs to satisfy a technical condition (Mercer condition) in order for ϕ to exist. An example of a kernel function is the Gaussian kernel, which is defined as

$$k(x_i, x_j) = e^{-\|x_i - x_j\|^2 / \sigma^2} \quad (6)$$

When working with a Gaussian kernel, σ represents the standard deviation, and ideally should represent the minimum distance between any two elements of two different classes. As it can be seen when constructing a SVM based on a Gaussian kernel, the only value that needs to be defined is σ. When working with kernels, in general it would not be possible to obtain w. Nevertheless SVM can be still be used. N_S being the number of support vectors of the training set, the decision function can be expressed as

$$f(x) = \sum_{i=1}^{Ns_s} \alpha_i y_i \phi(x_i) \phi(x) + b = \sum_{i=1}^{Ns_s} \alpha_i y_i k(x_i, x) + b \quad (7)$$

two classes, SVM can be generalized to a set of C classes. In this case each one of the classes will be trained against the rest C–1 classes, reducing the problem to a 2-class classification problem.

Proposed Signature Recognition Method: The proposed signature recognition method consists of three steps described below:

- In the first step, the 2D Radon transformation is applied on the signature image in order to projection of the image intensity along a radial line oriented at a specific angle. The projection of the 2D function $f(x,y)$ has been performed in α=0°, 45°, 90° and 135° directions according to equation (1). By using this transformation four vectors are obtained from the original image.
- Feature extraction is often one of the most important parts of any automated recognition system. If the qualities of extracted from this stage are poor, then the remaining stages of the system cannot perform to their full potential. In this stage, the fractal dimensions of the obtained vectors are calculated in a sliding window using equation (3). This technique has been used as a powerful tool for monitoring structure variations along the signal as the change in the signal characteristics are reflected on the fractal dimension of the signal. The calculated fractal dimensions are used as a feature for signature recognition.
- As it mentioned before, the SVM is a new classification technique in the field of statistical learning theory which has been applied with success in pattern recognition applications. In this step, a SVM classifier has been used for signature recognition system. The calculated fractal dimensions are fed into the SVM classifier.

Performance Evaluation: Algorithms of the proposed method were implemented using MATLAB from Math Works, Inc. The performance of these techniques was evaluated using the database can be found in [21]. Each database has 40 sets of signature data. For each set, there are 20 genuine signatures from one signature contributor. 12 signatures from each set, which make a total of 480 signatures, have been used for training the signature recognition system. Five original signatures per user, which make a total of 40 signatures, constitute the testing set. Besides, we test the SVM classification performances with different kernels.

The sample signatures of five people have been shown in Figure 2. In the proposed method, the 2D Radon transformation is initially applied on the signature image shown in Figure 2.a in α= 0°, 45°, 90° and 135° directions according to equation (1) and the results are shown in Figure 3. In feature extraction stage, the fractal dimensions of the obtained vectors are calculated in a sliding window with the length of 40 samples using Katz method. Figure 4 demonstrates the computed fractal dimension. Since the dimension of a plane is equal to 2 and the dimension of a line is equal to 1, we can expect that the calculated FD will always be between 1 and 2.

In order to evaluate the performance of the proposed method, the true positive ratio (TPR) and false positive ratio (FPR) are used as defined below [22]:

$$k(x_i, x_j) = e^{-\|x_i - x_j\|^2 / \sigma^2} \quad (8)$$

Where N_t, N_f and N represent the number of true, falsely detected and actual number of signatures respectively.

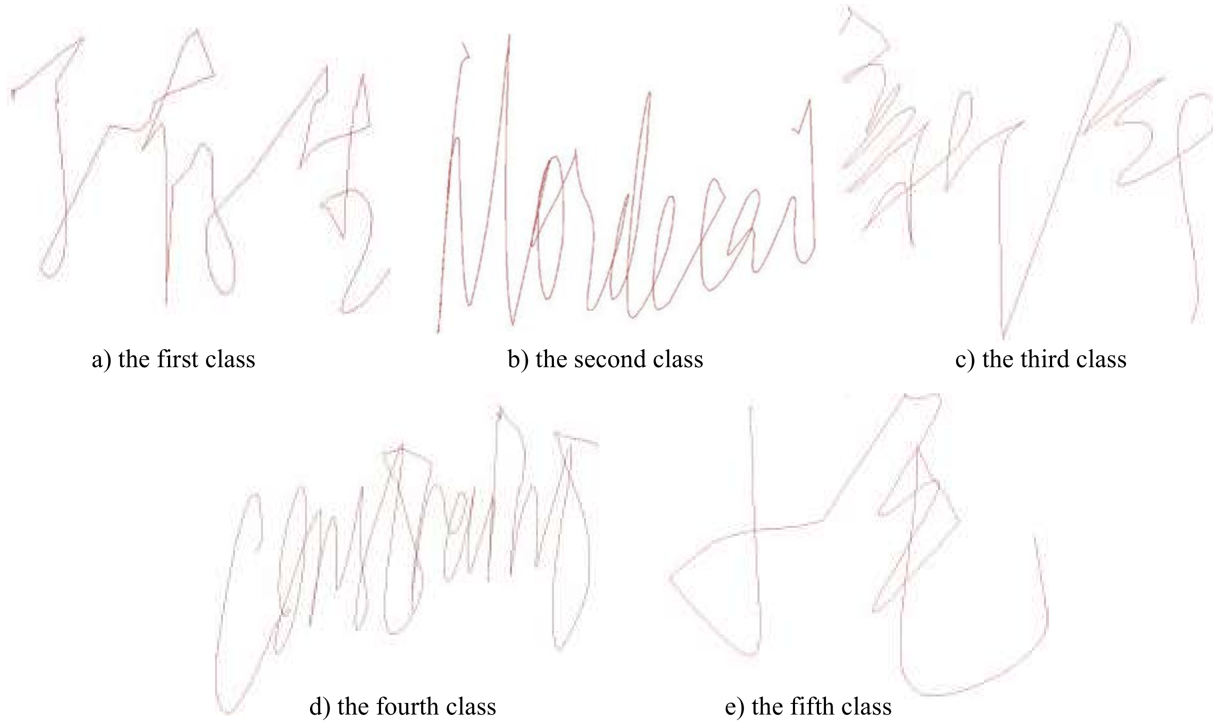

Fig. 2: The sample signatures of five people

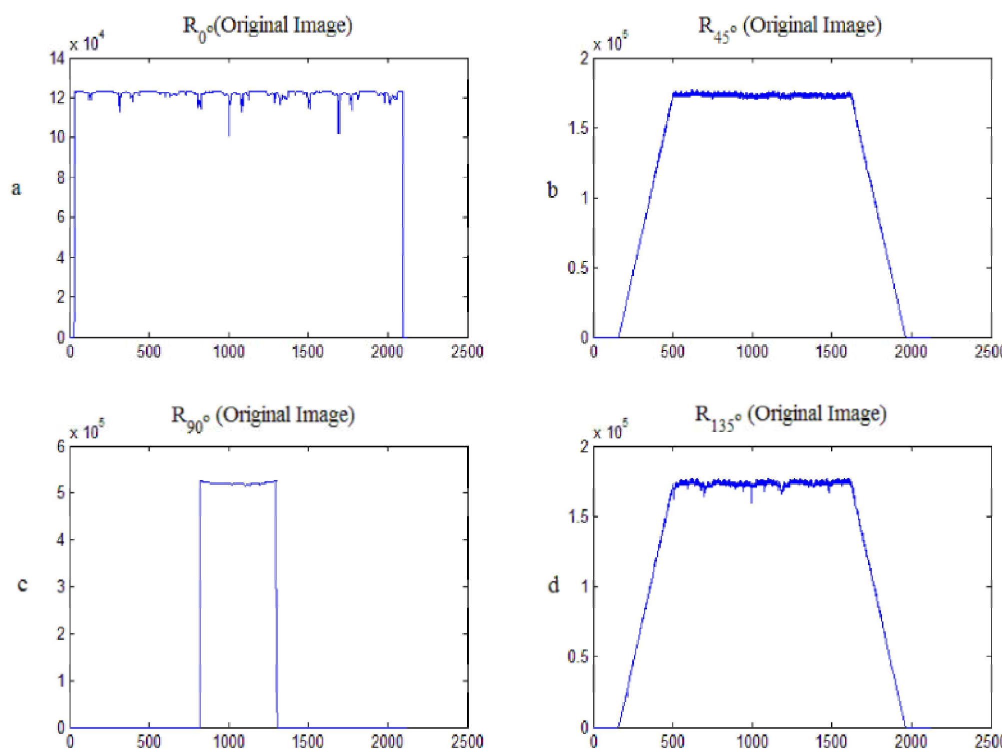

Fig. 3: The Result of applying Radon Transform on the signature image shown in Figure 2.a in $\alpha = 0°, 45°, 90°$ and $135°$ directions

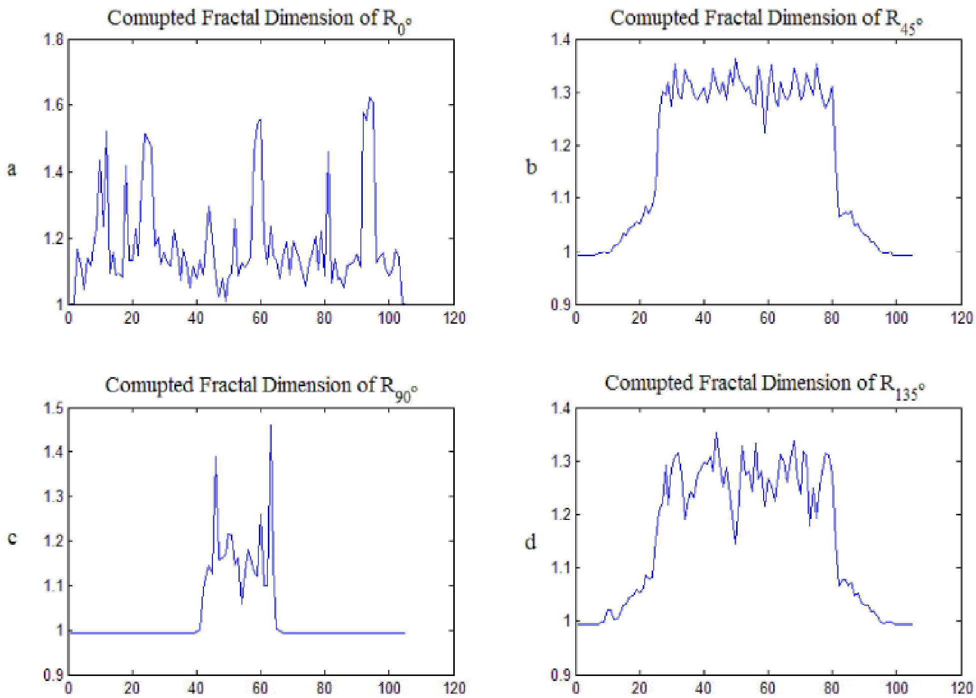

Fig. 4: The Computed Fractal Dimension of the signal shown in Figure 3

Table 1: Classification Result Using Linear Kernel

	Class 1	Class 2	Class 3	Class 4	Class 5
TPR (%)	90.0	82.5	67.5	92.5	87.5
FPR (%)	12.5	12.5	20.0	7.5	15.0

Table 2: Classification Result Using Polynomial Kernel

	Class 1	Class 2	Class 3	Class 4	Class 5
TPR (%)	97.5	95.0	95	78.5	92.5
FPR (%)	50	7.5	5	17.5	10.0

Table 3: Classification Result Using Radial Basis Function Kernel

	Class 1	Class 2	Class 3	Class 4	Class 5
TPR (%)	52.5	65	62.5	75.0	57.5
FPR (%)	35.0	25	32.5	22.5	35.0

Tables 1-3 reports the TPR and FPR obtained by applying the proposed method using different kernels. As can be seen from the results, the best classification results are obtained by using polynomial kernel. The polynomial order value changes between 2-5.

Table 2 reveals that the proposed method has a better accuracy when the order 4 polynomial kernel has been used.

Conclusions and Future Work: Signature recognition is a difficult pattern recognition problem. In this paper a new signature recognition system based on Radon Transform, Fractal Dimension (FD) and Support Vector Machine (SVM) has been introduced. The performance of the proposed method was evaluated using SVC database. Simulation results indicated proposed method is promising in signature recognition. In addition, the SVM classification performances have been evaluated with different kernels. By the fact that the approach shown in this paper seems to be effective, it could be validated on a large signature database where several types of signatures can be taken into account.

Further perspectives and attractive challenges for future research lie in two aspects: how to extract more effective features and how to combine SVM-based classifier with other signature recognition methods.

REFERENCES

1. Faundez-Zanuy, M., 2005. Biometric recognition: why not massively adopted yet?, *s*. Syst. Mag., 20(8): 25-28.
2. Bolle, R.M., J.H. Connell, S. Pankanti, N.K. Ratha and A.W. Senior, 2004. Guide to Biometrics. Springer, New York.
3. Yeung, D.Y., *et al*., 2004. SVC2004: first international signature verification competition, In: International Conference on Biometric Authentication 2004, Fort Lauderdale, USA, pp: 15-17, 16-22.

4. Frias-Martinez, E., A. Sanchez and J. Velez, 2006. Support vector machines versus multi-layer perceptrons for efficient off-line signature recognition, Engineering Applications of Artificial Intelligence, 19: 693-704.
5. Ammar, M., Y. Yoshida and T. Fukumura, 1990. Structural description and classification of signature images. Pattern Recognition, 23: 697-710.
6. Han, K. and K. Sethi, 1996. Handwritten signature identification. Pattern Recognition Letters, 17: 83-90.
7. Pavlidis, I., N.P. Papanikolopoulos and R. Mavuduru, 1998. Signature Identification through the use of deformable structures. Signal Processing, 71: 187-201.
8. Riba, J.R., *et al*., 2000. Method for invariant signature classification. Proceedings of 15^{th} International Conference on Pattern Recognition, 2: 953-956.
9. Frias-Martinez, E., A. Sanchez and J. Velez, 2006. Support vector machines versus multi-layer perceptrons for efficient off-line signature recognition, Engineering Applications of Artificial Intelligence, 19: 693-704.
10. Asano, A., 2002. Radon transformation and projection theorem, Topic 5, Lecture notes of subject Pattern information processing, 2002 Autumn Semester.
11. Kupce, E. and R. Freeman, 2004. The Radon Transform: A New Scheme for Fast Multidimensional NMR, Concepts in Magnetic Resonance, Wiley Periodicals, 22: 4-11.
12. Falconer, J., 2003. Fractal Geometry-Mathematical Foundations and Applications, John Wiley and Sons.
13. Tykierko, M., 2008. Using invariants to change detection in dynamical system with chaos, Physica D: Nonlinear Phenomena, 237: 6-13.
14. Higuchi, T., 1988. Aproach to an irregular time series on the basis of the fractal theory, Physica D., 31: 277-283.
15. Petrosian, A., 1995. Kolmogorov Complexity of Finite Sequences and Recognition of Different Preictal EEG Patterns, Proc. IEEE Symposium on Computer-Based Medical Systems, 5: 212-217.
16. Katz, M.J., 1988. Fractals and the Analysis of Waveforms, Comput. Biol. Med., 18(3): 145-156.
17. Esteller, R., G. Vachtsevanos, J. Echauz and B. Litt, 2001. A comparison of fractal dimension algorithms using synthetic and experimental data, IEEE Trans. Circuits Syst., 48: 177-183.
18. Boser, B.E., I.M. Guyon and V.N. Vapnik, 1992. A training algorithm for optimal margin classifiers. Proceedings of Fifth Annual Workshop on Computational Learning Theory, pp: 144-152.
19. Cristianini, N. and J. Shawe-Taylor, 2000. An Introduction to Support Vector Machines. Cambridge University Press, Cambridge.
20. Frias-Martinez, E., A. Sanchez and J. Velez, 2006. Support vector machines versus multi layer perceptrons for efficient off-line signature recognition, Engineering Applications of Artificial Intelligence, 19: 693-704.
21. http://www.cse.ust.hk/svc2004/download.html.
22. Lv, H., W. Wang, C. Wang and Q. Zhuo, 2005. Off-line Chinese signature verification based on support vector machines, Pattern Recognition Letters, 26: 2390-2399.