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A low-cost system for signature recognition

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Keywords: Signature Recognition, time-frequency representation, accelerometers, artificial neural networks.

Abstract- **Automatic signature recognition or verification have many practical applications. In this paper we propose a recognition method based on handwritting acceleration, line-crossing points segmentation, macrostructures (isolated traces), chain coding and time-frequency analysis. The acceleration information is integrated twice to get a visual representation of the signature. Further processing generates coefficients and images whose characteristics can be used as a representation. This coefficients, along with dynamic information, are applied as inputs to a 3-layered neural network, to train it. The output patterns are selected to be a binary number that represents an identification index for the signer.**

I. Introduction

Signature recognition has become a point of high interest for the scientific comunity. In the next paragaphs we depict the actual methodologies and the hypotesis that supports our approach.

A. *Prior work.*

The various strategies reported in the literature rely tipically either on comparing specific features of signatures or on comparing specific temporal functions captured during signature production (for on-line signatures), or, perhaps, on both [1]. Typical signature functions that are compared include pressure of the pen on the paper versus time, and the horizontal and vertical components of position, velocity, acceleration, and force, each versus time [2]-[6].

In the case of static signatures (i.e., scanned), some steps are found to be common in literature, such as normalization, skeletonizing or thinning, and others, all of them located in the phase of preprocessing or pixel level processing. They are intended to provide a noiseless version of the image. After this stage, segmentation is often used. The next step consists in the characterization of the signature to obtain certain coefficients, nearly constants, associated to the signature. Some tools applied include 2D-FFT, 1D-FFT, topological features, geometric moments, among others. These parameters are used to feed a recognition system, which could be a neural network, a genetic learning machine, a dynamic programming system, or others.

B. Space-frequency representation of signatures.

Our hypotesis relies on the idea that the application of time-frequency methods can contribute to the solution of the characterization problem for handwritten signatures, since the variations of frequency through-out signature's space can be representend and correspond directly to the nature of the shape of the signature. The representation in frequency space is selected since it is well known that this concept used in conjunction with chain codes for contour description provides invariance to rotation and displacement. In order to take advantage of such invariances, we present a segmentation algorithm based on the queue concept to collect and dispose critical and crossing points of a signature's image.

Although the 2D-FFT was used in handwritten and character recognition, it was applied on the full image and it differs from our approach in the fact that we accomodate this operation in the context of the time-frequency converted to space-frequency [7], realizing a signature-oriented segmentation process first and then applying this tool.

II. Development

A. *Capturing signature's dynamics.*

A dual axis accelerometer is used to get the signature's dynamics. The accelerometer has a working range of operation of +/- 2g, where g is gravity's acceleration. Graphs in Fig. 1 show the X,Y coordinates obtained double integrating the signals coming from the accelerometer.

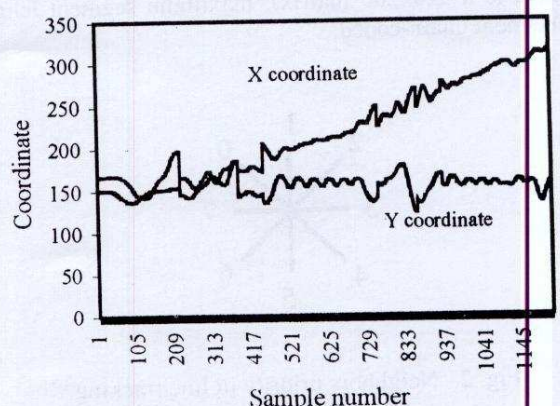


Fig. 1. X and Y coordinates, from the double integral of the PWM signals from the accelerometer

The information provided by the accelerometer is a signal of variable duty cycle; after proper scaling, the double-integral of this information combined in a X,Y coordinate frame allows us to have the visual representation, which is equivalent to scan the signature, but has the advantage of being noise free, so no further pre-processing is required.

The vertical speed variations is the most significant parameter to characterize a signature's dynamics [8].

B. Segmentation.

A good segmentation algorithm must provide more or less the same output for different versions of the same input, despite of the size variation and certain little natural variations in signers performance. Besides, the algorithm must be signature-oriented. Our method consists in detecting the 8 nearest-neighbors to an actual or starting point and follow the trace continuity by doing the next actual point equal to the first neighbor in the order of appearing shown in Fig. 2.

If two or more neighbors are detected the track continues on neighbor found on direction 0 and the remaining neighbors are sent to a queue. The track continues on the same line until no more neighbors are detected (an end point). As soon as a new point is detected to belong to the line under tracking it is chain-coded and sended to a text file for further processing. Despite the order of tracking, the chain-code is a normal one, where zero corresponds to the right side horizontal direction. Then the queue emptying begins. This forces to process the signature in a left-rigth/up-down manner. When a datum comes out of the queue or a starting point is detected, a new segment for frequency analysis is generated.

Let's take the signature in Fig. 3 as an example. It is shown segmented. The following statistics were obtained for this signature: 5 macrostructures, 34 segments, 1193 pixels-on, original size: 197x128, normalized size: 128x83, normalizing factor: 64.97%, first starting point: 98,200 (relative to a 320x200 matrix); maximum segment length: 140 element chain-coded.

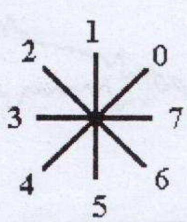


Fig. 2. Neighbors priority in line tracking.

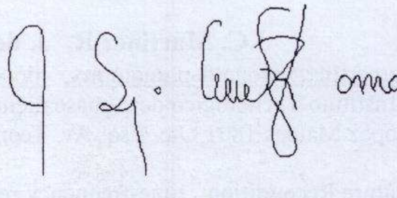


Fig. 3. Five macrostructures detected, now separated.

With all the segments prepared in a file in a matrix form, the frequency analysis is carried out. To get a constant length of all the rows, 0's are right padded to adjust the length of every row equal to the largest segment length in the whole matrix.

In the next section will be talking about the FFT effect on every segment that we have already got and the full space-frequency representation.

C. The space-frequency representation.

Putting together the chain codes of two signature samples, we can see the 2-D color coded graphics in Fig. 4, where the darkest color correspond to zero in the chain code and the brightest correspond to 7. The horizontal axis correspond to the data of every segment. The vertical axis correspond to the segments. The first segment is displayed at the top, and the last segment is displayed at the bottom. These images clearly shows that the segmentation algorithm is capable of creating regular and very close segmentations for various samples of the same signature.

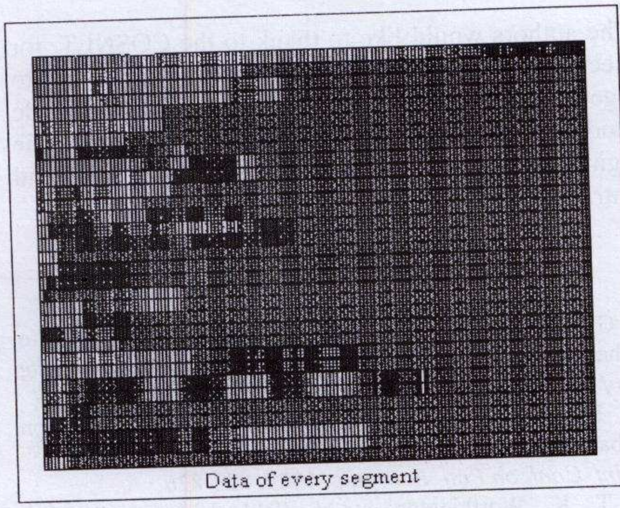
The basic objective of time-frequency analysis is to devise a function that will describe energy density of a signal simultaneously in time and frequency, and that can be used and manipulated in the same manner as any density [7]. In our case we are dealing with an off-line signature and timing information is not avalaible. However, spatial information is avalaible, so we can use the segments in similar manner as if they were time information. The algorithm described in the last section closely resembles this information. Now, according to Cohen [7], being s(t) a function of time of limited bandwidth, we can write the energy densitiy spectrum as

$$\left| \int_{-\infty}^{\infty} s(t)\, e^{-j\omega t} \right|^2 , \qquad (1)$$

and the joint density is expressed as

$$P(t, \omega) \, . \qquad (2)$$

which is interpreted as a two-dimensional digital image. The low frequency information is selected. This image is further analized to obtain features that have demonstrated to be nearly constants, with a low statistical deviation.



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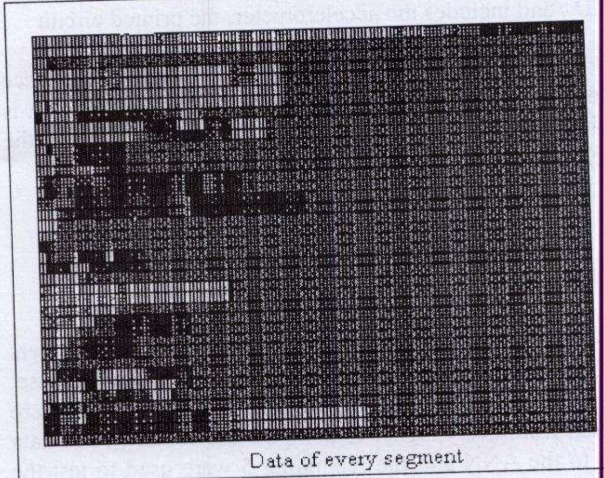


C

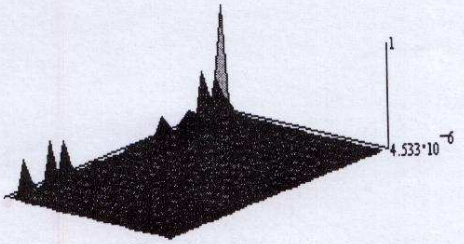
Fig. 4. Each row in this images is a segment of the signature. Here are shown all the segments of two different signatures. This is the color representation of the chain codes.

Fig. 5 shows the power spectrum obtained using the methodology narrated in the precedent sections. The representation selected is the spectrogram [7]. It is notorius that the bigest contribution is given by the low frequencies. This representation can be considered as a measurement of the smoothness of the signature. As long as this characteristics are measurable, a set of coefficients can define a signature. It is expected that two different signatures have different representations. Even if two signatures could have more or less the same space-frequency distribution, other discriminating parameters should be observed, such as the amount of macrostructures and segments.

D. Vector of features for recognition.

It is time now to join all the concepts stated in previous sections. We will begin with the static information.

From de segmentation process we take the following information: the mean value of normalizing factor (N), ratio of the width to the height (X/Y), number of macrostructures (M), number of pen lifts (PL).



E

Fig. 5. Power spectrum of the space representation of signature shown in Fig. 3, low frequencies. Normalized with the bigest value equal to one.

From the spectrogram we take the following information: the mean value of the centroid in X (Cx) and the centroid in Y (Cy).

The dynamic contribution is represented, as we said before, by the root mean square (RMS) value of the vertical velocity (Vy).

All the factors mentioned above are used to build a column vector with the folowing composition

$$\mathbf{V} = [\ N \ \ X/Y \ \ M \ \ PL \ \ Cx \ Cy \ Vy\ ]^T. \qquad (3)$$

In the next section, a set of vectors like this one is used to feed the a neural network.

E. The classifier.

The classifier used was a 3 layer artificial neural network (ANN) trained using supervised learning with the standard back propagation algorithm described by Rumelhart *et al* [9]. The ANN had a single hidden layer with eight neurons. The output layer had five neurons, in order to classify up to 32 signers. Training was halted when the maximum error produced by any exemplar in the training set fell below 20%, which generally gave an RMS error of 2% for the set.

The output pattern presented to the ANN during the training phase was, for each vector **V**, a 5 bits binary number. With this quantity of bits it is possible to classify up to 32 signers for recognition.

F. The cost.

It was claimed in the title of this paper that it is a low cost system. Indeed it is. The components cost is under $40.00 U.S.D., and includes the accelerometer, the printed circuit board, the pen, and a special base, as well as the interface cable and connector for a printer port. No engineering cost is included. A personal computer is necessary to run the system, but is not considered as a part of it.

III. RESULTS AND CONCLUSIONS.

A. Results.

The data base used consisted of 640 signatures: 32 signers and 20 signatures per signer. Although it is a little data base, it was enough to test the proposed system. 15 samples were selected from every signer to compute the vector (V) of data input to the ANN and the reamining 5 were used to test the system.

The recognition rate was high. Only five errors out of the 100 test input patterns were present, giving a performance of correct classification of about 95%. Of course, the need of continue testing the system remains. In further testing we realize that more complex patterns should be included.

B. CONCLUSIONS.

The space-frequency representation of a signature can provide concise and repeatable information if the segmentation algorithm is signature oriented. The advantage over other descriptors for signature recognition consists in it's inherent simplicity and short time implementation, as well as it's short computing time. Still remains the need to extensively test this approach with large sets of signatures; besides, it is desirable to apply other time-frequency representations.

The cost for the overall system components is low. It is expected that at production volumes the cost become lower.

An ANN was used as classifier, but there exist a number of other approaches for the classifier. Of course, there exist a large amount of other feature sets and methodologies intended to solve this problem. However, some of those applications are computationally heavy and non-economic.

ABREVIATIONS

FFT	Fast Fourier Transform.
1D-FFT	1-Dimensional FFT
2D-FFT	2-Dimensional FFT
PWM	Pulse Width Modulation
ANN	Artificial Neural Network

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