signature analysis and recognition
Walsh transform, Walsh coefficients,
support vector machine

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SIGNATURE PRE – PROCESING BASED ON WALSH COEFFICIENTS

Recognition and verification of persons are difficult and important tasks today. In many fields of human activities (driver's licenses, passports, electronic cards, etc.), signature recognition of person is needed. Hence, it inspires the development of a wide range of automatic identification systems. Signatures have been used for many centuries as a method of people's identification. Signatures recognition was performed manually by experts in the past. Nowadays, these procedures are very often automatically applied. In this paper the system that automatically authenticates documents based on the owner's handwritten signature is presented.

1. INTRODUCTION

Many biometric systems recognized fingerprint, face, iris pattern, DNA, retina, ear, thermogram, gait, hand geometry, palm-vein pattern, keystroke dynamics, smell, signature, and voice. Signature verification is found already as a traditional biometric method, having wide public acceptance, particularly in authentication and authorization within financial and transactions legalisation process. Many works, conducted in the past, indicate that signature analysis remains a complex pattern recognition problem. Automatic signature analysis can be categorised into two types: the on-line [4,5,6] and the off-line signature verification [7]. In the on-line signature analysis special pens are used, where pressure and dynamic movements can be recorded. The reason is that the off-line signature analysis is more complex due to the absence of stable dynamic characteristics. Signature analysis and verification can be treated as a decision-making process, where the original signature is compared to other signature. Analysis and verification consist of some stages – it is depicted on Fig. 1.

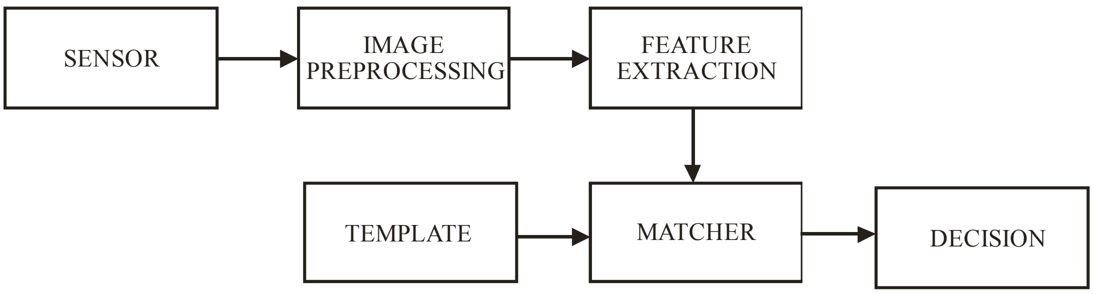

Fig.1 The main modules of a biometric system

Many signature analysis schemes have been investigated in the past years. Among others the Hidden Markov models, the Hough transform or vector quantisation method were proposed [1,5,7]. Fortunately, there are modern devices, which are able to register dynamic features of signature, such as pen pressure, acceleration, velocity or pen location on the surface. For this reason, the off-line methods of signature analysis can be joined with the on-line methods, where unique dynamic signature features can be also analysed.

The signature images should be preliminary processed very often, due to different image resolution and colours, signature rotations, artefacts, etc. Some pre-processes can also be used in task of the matchers. It will be presented in the paper.

2. WALSH TRANSFORM

Traditional Fourier transform is applied to represent large classes of functions by appropriate using of the sine and cosine functions. Proposed in this paper approach is based on the implementation of the Walsh transform in the image pre-processing phase. A very useful property of Walsh functions is that they take only two values +1 and -1 and in that respect are compatible with switching functions, which are also two-valued. Moreover, fast algorithms of the Walsh transform are very convenient to real-time applications. The time and memory complexity of the fast Walsh transform is exactly the same as classic Fast Fourier Transform [2].

The data vector $Y=[y_1,\ldots,y_n]$ can be transformed into spectral domain by a linear transformation $S=H\cdot Y$, where H is a $2^n \times 2^n$ transform matrix, and S is a vector of spectral coefficients. Proposed transform usually is called Walsh-Hadamard transform and the decomposition of the Walsh matrix H can be written as:

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$$H_N = \prod_{i=1}^{n} (I_{2^{n-i}} \otimes P_{2^i}) \quad (1)$$

where $\otimes$ denotes the Kronecker product, $N = 2^n$, I_N is the identity of size *N* and:

$$H_2 = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix},\ P_2 = H_2,\ P_N = \begin{bmatrix} I_{N/2} & I_{N/2} \\ I_{N/2} & -I_{N/2} \end{bmatrix} \quad (2)$$

For instance, if *n*=2, then from (1-2) the Walsh matrix has form:

$$H_4 = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & -1 & 1 & -1 \\ 1 & 1 & -1 & -1 \\ 1 & -1 & -1 & 1 \end{bmatrix}$$

Taking into account above considerations the fast Walsh transform can be defined as follows:

$$S = H_N Y = P_N (I_2 \otimes P_{N/2})(I_4 \otimes P_{N/4}) \cdots (I_{2^{n-1}} \otimes P_2) Y \quad (3)$$

3. SIGNATURE PREPARATION

In many cases, signatures even those that belong to the same person, have different direction and position, hence it should be normalized. Signature direction can be observed as a line trend. In the approach this trend is eliminated. In this paper to trend elimination, the linear regression was used [4].

In the next stage signature is displacement according to the formula:

$$x_i^{new} = x_i - x_{min}$$
$$y_i^{new} = y_i - y_{min} \quad (4)$$

where:

$x_{min} = min\{x_1,...,x_n\}$, $y_{min} = min\{y_1,...,y_n\}$,

(x_i^{new}, y_i^{new}) – signature coordinates after displacement.

After these procedures, the signature centre point $(\overline{x}, \overline{y})$ is determined. It is so-called signature centre of gravity, where:

$$\overline{x} = \frac{1}{N}\sum_{i=1}^{N} x_i, \qquad \overline{y} = \frac{1}{N}\sum_{i=1}^{N} y_i \quad (5)$$

The signature consists of points (x_i, y_i). For some from these points, the distance d_i between (x_i, y_i) and centre point of the signature $(\overline{x}, \overline{y})$ is determined:

$$d_i = \sqrt{(x_i - \overline{x})^2 + (y_i - \overline{y})^2},\ i = 1,...,N \quad (6)$$

Then, a global distance vector $G_a = [d_1, d_2, ..., d_N]$ is calculated. In the next step the vector G_a is also normalised:

$$l_i = \frac{d_i}{d_{\max}},\ i = 1,...,N \qquad d_{\max} = \max\{d_1, d_2, ..., d_N\} \quad (7)$$

Hence, the all coordinates of the vector G_a are re-scaled. Finally, this vector has form:

$$G_b = [l_1, l_2, ..., l_N] \quad (8)$$

Around the signature centre of gravity straight-lines are drawn. These lines cross signature line in points. This idea is depicted on Fig.2. The signature from Fig. 2 was taken from SVC database [8]. In proposed method, for any signature, its 128 points was determined (hence *N*=128) and according to equation (6), appropriate distances and Walsh coefficients were computed.

For this reason instead of two-element signature points, only one-element distance are used.

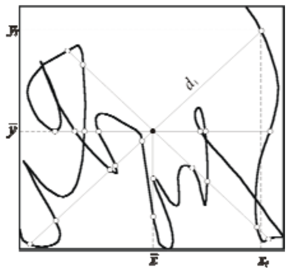

Fig.2 The signature points determination

From observations follow that Walsh coefficients give better values concentration in comparison with concentration of values of the distances when two signatures will be analysed. It was depicted by means of Figs. 3 (a-f) where concentration appropriate points were presented. This investigation was carried out by means of artificial signatures generated in MATLAB program. The artificial signature samples were generated by means of the functions:

- the signature $s1$: $x = \cos(t); y = \sin(t) + \sin(2t)$
- the signature $s2$: $x = 0.5 + \cos(12t) + \cos(82t); y = 1 + \sin(87t)$

discrete points where signatures will be determined (MATLAB description):
$t = 0 : pi / 64 : 2pi - pi / 64$

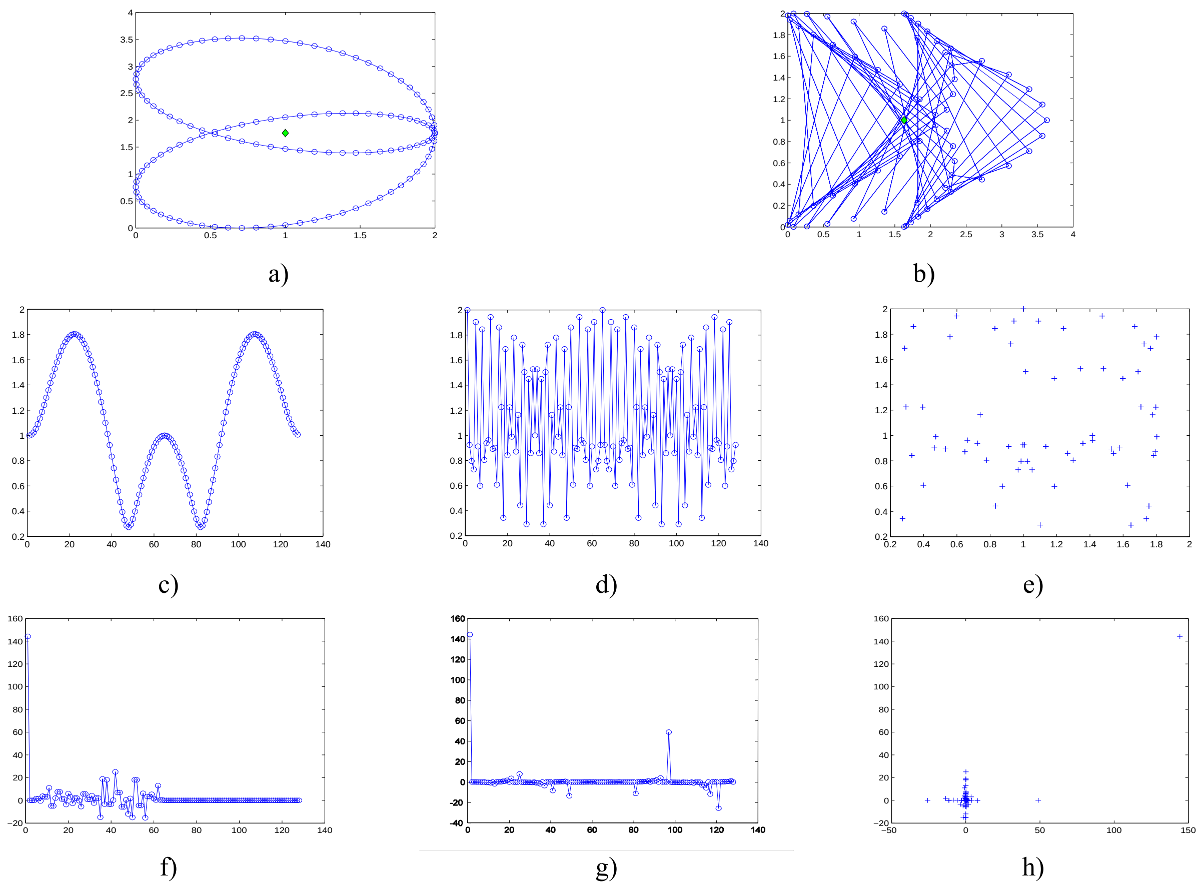

Fig.3 Artificial signatures: a) signature one ($s1$), b) signature two ($s2$), c) distance $d1$ between centre point and points of envelope of the signature $s1$, d) distance $d2$ between centre point and point of and envelope of the signature $s2$, e) dependence $d1=f(d2)$, f) the Walsh spectrum $w1$ of the function from fig.3c, g) the Walsh spectrum $w2$ of the function from fig. 3d, h) dependence $w1=f(w2)$ SVM. Basic Theory

A Support Vector Machine (SVM) performs classification by constructing an *n*- dimensional hyperplane that optimally separates the data into two categories [3].

An n-dimensional pattern (object) $\boldsymbol{z}$ has n coordinates, $\boldsymbol{z}=(z_1,\ldots,z_n)$, where each z_i is a real number. In our case the pattern is a vector of the Walsh coefficients. Each multi-valued pattern $\boldsymbol{z}_j$ belongs to the class $y_j \in \{+1,-1\}$. Consider a training set T of m patterns together with their classes, $T=\{(\boldsymbol{z}_1, y_1),\ldots,(\boldsymbol{z}_m, y_m)\}$. Consider a dot product of two vectors: $\boldsymbol{a}=[a_1,...,a_k]$, $\boldsymbol{b}=[b_1,...,b_k]$ as operation $<a,b>=\sum_{i=1}^{k} a_i b_i$. In the dot product space $\boldsymbol{P}$ are included the patterns $\boldsymbol{z}_1,\ldots,\boldsymbol{z}_m$. In such a case any hyperplane in the space $\boldsymbol{S}$ can be written as:

$$\{\boldsymbol{z}_i \in \boldsymbol{P} :< \boldsymbol{w},\boldsymbol{z}_i > +b = 0\}, \qquad \boldsymbol{w} \in \boldsymbol{P},\ \ b \in \boldsymbol{R} \tag{9}$$

A training set of patterns is linearly separable if at least one linear classifier defined by the pair ($\boldsymbol{w}$, b) correctly classifies all training patterns. This linear classifier is represented by the hyperplane ($<\boldsymbol{w},\boldsymbol{z}_i>+b=0$) and defines a region for the class $(<\boldsymbol{w},\boldsymbol{z}_i>+b>0) \rightarrow y_j=+1$ and another region for the class $(<\boldsymbol{w},\boldsymbol{z}_i>+b<0) \rightarrow y_j=-1$. Hence, the classification of the new patterns depends only on the sign of the expression $\boldsymbol{w}\cdot\boldsymbol{x}$+b.

After training, the classifier is ready to predict the class membership for new patterns, different from those used in training. In order to classify the data by means of the SVM method, the optimal separating hiperplane is estimated. This plane maximizes the margin between the two kinds of samples and minimizes the classifying error at the same time. Instead of linear also nonlinear classification can be carried out, where kernel function $\Phi(x_i,x_j)=\varphi(x_i)\circ\varphi(x_j)$ is introduced. Taking into account above considerations the optimal nonlinear classifying function can be defined as follows:

$$f(x) = sign\left(\sum_{i\in V} \alpha_i y_i \Phi(x,x_i) + b\right), \quad 0 \le \alpha_i \le C \tag{10}$$

where V is the is the number of samples in the training set, α_i, i=1,…,m is the Lagrange multiplier, x_i is a support vector with $\alpha_i > 0$ and Φ is a kernel function. Parameter C is chosen be the user. A large value of C corresponds with assignment of a higher penalty to errors and x is an unknown sample feature vector and b is a threshold. As kernel, the Gaussian Radial Basis Function (RBF) was selected $k(x,x_i)=\exp(-\|x-x_i\|^2/\delta^2)$ because this kernel gave the best recognition quality. In proposed approach $\delta=1$ and C=25.

4. RECOGNITION OF SIGNATURE BASED ON SVM

In experiment ten classes of signatures were tested. In any class five signatures of the same person is performed. Hence, database includes 10×5=50 signatures. All signatures were taken from the well-known signatures database SVC. Some of these signatures were presented by Figs. 3–4.

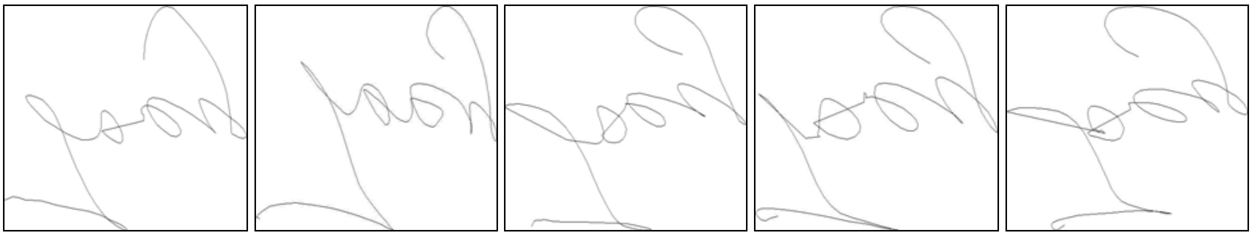

Fig.3 Signature attempts of the same person. The class no. "10".

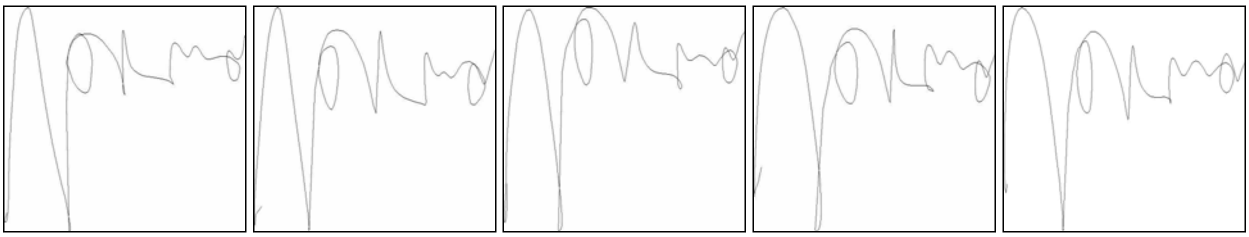

Fig.4 Signature attempts of the same person. The class no. "8".

For each signature, vector of the 64 Walsh coefficients was generated and signature class was marked. These data in the consecutive columns of the Microsoft Excel spreadsheet file `signature.xls` were stored. The main program statements, where classification rate was computed with short comments, are presented below. In this program the class "1" is analysed.

```
%Load data
kol = xlsread('signature.xls');
X=[kol(:,1),kol(:,2),…,kol(:128)]
%Extract the '1' class
groups = ismember(kol(:,129),1);
%Randomly select training and test sets
[train, test] = crossvalind('holdOut',groups);
%Use a support vector machine classifier
svmStruct = svmtrain(X(train,:),groups(train),'Kernel_function','rbf');
classes = svmclassify(svmStruct,X(test,:));
cp = classperf(groups)
classperf(cp,classes,test);
% queries for the correct classification rate
cp.CorrectRate;
result=(result+cp.CorrectRate);
```

For training samples of ten classes, "one to rest" SVM recognition algorithm was applied. In other words, during training the first signature "1" was taken as a category and the rest of classes as another category. In the second step, similarly as previously, the signature "2" is separated from other nine classes, and so on for signatures "3","4",…,"10". Finally, ten kinds of two-classes SVM classifiers have been obtained. In the recognition process, another samples where used as input of mentioned classifiers. In Table 1 recognition level of different classes is presented.

Table 1 Efficiency of different signature classes recognition

Signature classes									
"1"	"2"	"3"	"4"	"5"	"6"	"7"	"8"	"9"	"10"
0.9787	0.9342	0.9387	0.9467	0.9678	0.9567	0.9667	0.9404	0.9142	0.9167

Comparing data from Table 1 we can observe that the signatures recognition level of the proposed method is satisfactory, especially when number of signatures in any class is small. It can suppose that recognition ratio will be better if number of signatures in individual classes will be increased.

5. CONCLUSION AND FUTURE WORKS

Further research should be carried out to evaluate the effect of using other kernels on the performance of handwriting recognition. In performed investigations only few samples were used, hence utilization only Walsh spectra has the disadvantage of poor generalization, which leads to wrong conclusions when samples participate in recognition process. It will be improved and larger number of samples will be used in recognition process.

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