*signature recognition,*
*DTW method, chi-square test*
*linear regression*

Tomasz PARA[*], Monika MITAS[**]

# DETERMINING SIGNATURES' CHARACTERISTIC FEATURES USING STATISTICAL METHODS

Many signatures verification systems have been developed so far. Most of them have some common algorithms and solutions. The problem is that authors of the solutions usually present the final results of a working system. They do not reveal effects of the particular components. This is why other researchers do not know which element improves the results and is worth using. This paper shows how to estimate, in an easy way, if the selected component/set of data/feature gives good results.

## 1. INTRODUCTION

The handwritten signature is a biometric attribute. It is the most common validation tool for documents or commercial transactions. But it also can be used in such systems that need to ascertain an attendance of a person (e.g. time clock and timekeeping systems). Signatures can be verified either on-line[12] or off-line [4]. Recently, many methods and models have been developed for automatic on-line signature verification, like linear regression, Regional Correlation, Tree Matching, Hidden Markov Models and many more.

Signature verification can be treated as a decision-making process, where the original signature is compared to another signature. This process consists of a few steps, but the final solution provides user with information only about the main algorithm (like e.g. Hidden Markov Model). The main algorithm is used to compare two sets of data (each set represents one signature). The complete solution contains also other algorithms which are used to prepare the data sets (during so called pre-processing phase). But researchers reveal information about efficiency of the whole system, not of the particular components. This is the reason other researchers are unable to decide which components (algorithms) are worth using in their solutions.

Quite similar situations occur during defining the data set. Selecting a good set of characteristic features of a signature is a very important step in designing a signature verification system. Also in this case, the researchers usually do not reveal why they picked up these features and not the others.

This paper presents the results of a research that shows the influence of different algorithms and data sets on the efficiency of the verification system. Our system is based on linear regression and Dynamic Time Warping (DTW) algorithm that is used to align sequences of different length (equal sequences are needed as input data for linear regression approach). This system was tested under different data sets and parameters of algorithms (e.g. types of distance for DTW algorithm, turning off and on rotation, etc). This way of testing shows the influence on efficiency of each algorithm and set of data separately.

## 2. CHI-SQUARE INDEPENDENCE TEST

The tested system allows to turn off/turn on particular algorithms to analysis and build different input data sets. Most of possible combinations have been checked. In consequence of that the system gave back 3705 results describing efficiency (EER, FAR, FRR [4]) under different settings. A Chi-square test of independence has been applied to estimate which components have an influence on the system. There has been also checked how each component (and its settings) affects the final result (it improves or deteriorate one).

One of the primary use of the chi-square independence test ( $\chi^2$ ) is to examine whether two variables are independent or not (comparing frequencies of one nominal variable to different values of a second nominal variable). Independence means that the two factors are not related.

The first step of the chi-square independence test is to establish hypotheses. To do that, the contingency table is needed (Table 1), which is a table of counts. A two-dimensional contingency table is formed by classifying subjects by two variables. One variable (*X*) determines the row categories; the other variable defines the column categories (*Y*).

[*] University of Silesia. Institute of Informatics, 41-200 Sosnowiec, Będzińska 39, Poland
[**] Silesian University of Technology, The Faculty of Mathematics and Physics, Institute of Mathematics, 44-100 Gliwice, Kaszubska 23, Poland

Table 1. Contingency table

| X \ Y | $y_1$ | $y_2$ | … | $y_m$ | |
|---|---|---|---|---|---|
| $x_1$ | $n_{1,1}$ | $n_{1,2}$ | … | $n_{1,m}$ | $\sum_{i=1}^{m} n_{1,i}$ |
| $x_2$ | $n_{2,1}$ | $n_{2,2}$ | … | $n_{2,m}$ | $\sum_{i=1}^{m} n_{2,i}$ |
| … | … | … | … | … | … |
| $x_k$ | $n_{k,1}$ | $n_{k,2}$ | … | $n_{k,m}$ | $\sum_{i=1}^{m} n_{k,i}$ |
| | $\sum_{i=1}^{k} n_{i,1}$ | $\sum_{i=1}^{k} n_{i,2}$ | … | $\sum_{i=1}^{k} n_{i,m}$ | $\sum\sum_{i=1}^{k} n_{i,m}$ |

The null hypothesis is that the two variables are independent:

$$H_0: P(X = x_k, Y = y_m) = P(X = x_k) \cdot P(Y = y_m). \tag{1}$$

The alternative hypothesis to be tested is that the two variables are dependent:

$$H_1: P(X = x_k, Y = y_m) \neq P(X = x_k) \cdot P(Y = y_m); \tag{2}$$

by an established level of significance $\alpha$ .
To verify the above hypothesis the chi-square statistic is calculated by the following formula:

$$\chi^2 = \sum_{j=1}^{m} \sum_{i=1}^{k} \frac{(n_{ij} - \overline{n}_{ij})^2}{\overline{n}_{ij}} \tag{3}$$

where:

$n_{ij}$ – number of observations that meet condition $x_i$ and $y_j$,
$m$ – number of columns of contingency table,
$k$ – number of rows of contingency table,
$\overline{n}_{ij}$ – number of expected observations that meet condition $x_i$ and $y_j$.

The expected value for each cell of the table can be calculated using the following formula:

$$\overline{n}_{t,p} = \frac{\sum_{j=1}^{m} n_{t,j} \sum_{i=1}^{k} n_{i,p}}{n} \tag{4}$$

where:
$m$ – number of columns of contingency table,
$k$ – number of rows of contingency table,
$n$ – total number of observations.
Next, the critical region of test is obtained from chi-square distribution table[8]:

$$\left[\chi^2_{1-\alpha,f}, +\infty\right) \tag{5}$$

where:

$\alpha$ – established level of significance,
$\chi^2$ – chi-square statistic,
$f$ – degrees of freedom

$$f = (k-1)(m-1) \tag{6}$$

When the computed $\chi^2$ statistic belongs to the critical region of test, then the null hypothesis is rejected. Otherwise the null hypothesis is accepted. $\alpha$ indicates the probability of making an error when the null hypothesis is rejected. By adjusting the value of $\alpha$ the required critical region can be obtained. During the tests it has been tried to achieved as low value of $\alpha$ as possible to rejected the null hypothesis.

The influence on EER factor following features/variables has been tested by chi-square independence test:

- types of variables used by linear regression,
- types of DTW distances,
- number of variables used by DTW,
- types of variables used by DTW,
- signature rotation.

The EER output results have been divided into 7 ranges:

Table 2. The EER Ranges

| Name of range | Range |
|---|---|
| Excellent | <0,5) |
| Very good | <5,7) |
| Good | <7,9) |
| Average | <9,13) |
| Poor | <13,16) |
| Bad | <16,20) |
| Very bad | <20,100> |

Table 2 is common for all following tests in this paper.

## 3. SIGNATURE SIMILARITY MEASURE

*Sim* is a quality of fit measure between two multidimensional sequences *X* and *Y*, which contain data describing two compared signatures.

As a *Sim* the $ER^2$ factor is used [2]:

$$ER^2 = \frac{\left[\sum_{j=1}^{m}\left(\sum_{i=1}^{n}(x_{ji}-\bar{x}_j)(y_{ji}-\bar{y}_j)\right)\right]^2}{\sum_{j=1}^{m}\sum_{i=1}^{n}(x_{ji}-\bar{x}_j)^2\sum_{j=1}^{m}\sum_{i=1}^{n}(y_{ji}-\bar{y}_j)^2} \tag{7}$$

$\bar{x}_j(\bar{y}_j)$ – average of the *j-th* dimension of the sequence $x_j(y_j)$, respectively.

As it was mentioned above, the compared sequences (*X*,*Y*) can be multidimensional – so they can have many variables at each point. In our tests it was investigated if the EER factor depends on the number of variables used to calculate $ER^2$ and which variables give the best results. The contingency table (table 3) for $ER^2$ calculated with different combination of coordinates *x*, *y* and *p* (pressure):

Table 3. Contingency table for $ER^2$

| | $ER^2_{xyp}$ | $ER^2_{xy}$ | $ER^2_{xp}$ | $ER^2_{yp}$ | $ER^2_{x}$ | $ER^2_{y}$ | $ER^2_{p}$ | |
|---|---|---|---|---|---|---|---|---|
| **Excellent** | 79 | 74 | 1 | 49 | 0 | 33 | 0 | 236 |
| **Very good** | 27 | 25 | 19 | 71 | 19 | 88 | 0 | 249 |
| **Good** | 43 | 46 | 56 | 47 | 54 | 42 | 3 | 291 |
| **Average** | 167 | 163 | 74 | 83 | 79 | 65 | 35 | 666 |
| **Poor** | 82 | 83 | 120 | 111 | 128 | 119 | 71 | 714 |
| **Bad** | 75 | 77 | 102 | 76 | 106 | 82 | 132 | 650 |
| **Very bad** | 63 | 61 | 156 | 91 | 142 | 99 | 287 | 899 |
| | 536 | 529 | 528 | 528 | 528 | 528 | 528 | 3705 |

In the next step, the expected values have been calculated:

Table 4. Expected values of $ER^2$

| | $ER^2_{xyp}$ | $ER^2_{xy}$ | $ER^2_{xp}$ | $ER^2_{yp}$ | $ER^2_{x}$ | $ER^2_{y}$ | $ER^2_{p}$ | |
|---|---|---|---|---|---|---|---|---|
| **Excellent** | 34,14 | 33,69 | 33,63 | 33,63 | 33,63 | 33,63 | 33,63 | 236 |
| **Very good** | 36,02 | 35,55 | 35,48 | 35,48 | 35,48 | 35,48 | 35,48 | 249 |
| **Good** | 42,09 | 41,54 | 41,47 | 41,47 | 41,47 | 41,47 | 41,47 | 291 |
| **Average** | 96,34 | 95,09 | 94,91 | 94,91 | 94,91 | 94,91 | 94,91 | 666 |
| **Poor** | 103,29 | 101,94 | 101,75 | 101,75 | 101,75 | 101,75 | 101,75 | 714 |
| **Bad** | 94,03 | 92,80 | 92,63 | 92,63 | 92,63 | 92,63 | 92,63 | 650 |
| **Very bad** | 130,05 | 128,35 | 128,11 | 128,11 | 128,11 | 128,11 | 128,11 | 899 |
| | 536 | 529 | 528 | 528 | 528 | 528 | 528 | 3705 |

From the formula (3) $\chi^2$ has been calculated:

$$\chi^2 = 646.05 \,;$$

and the critical region from the formula (5) has been determined:

$$[89.32, +\infty)\,;$$

where:

$\alpha$ – established level of significance = 0.000002,

$f$ – degrees of freedom =36 (from the formula (6))

The $\chi^2$ statistic belongs to the critical region of the test so the hypothesis about independence $ER^2$ and EER is rejected. Moreover, from table 5 (differences between observed and expected values respectively) there can be observed which combinations of variables have the strongest influence on EER.

It can be noticed that the best results are observed for the set of three variables ($x$,$y$,$p$). Quite good results can be achieved also for two variables ($x$,$y$). The interesting thing is that using variable $p$ (pressure) with combination of $x$ or $y$ gives not satisfactory results.

Table 5. Differences between observed and expected values respectively

| | $ER^2_{xyp}$ | $ER^2_{xy}$ | $ER^2_{xp}$ | $ER^2_{yp}$ | $ER^2_{x}$ | $ER^2_{y}$ | $ER^2_{p}$ |
|---|---|---|---|---|---|---|---|
| **Excellent** | 44,86 | 40,3 | -33 | 15,4 | -34 | -0,6 | -34 |
| **Very good** | -9,02 | -11 | -16 | 35,5 | -16 | 52,5 | -35 |
| **Good** | 0,901 | 4,45 | 15 | 5,53 | 13 | 0,53 | -38 |
| **Average** | 70,65 | 67,9 | -21 | -12 | -16 | -30 | -60 |
| **Poor** | -21,3 | -19 | 18 | 9,25 | 26 | 17,2 | -31 |
| **Bad** | -19 | -16 | 9,4 | -17 | 13 | -11 | 39 |
| **Very bad** | -67,1 | -67 | 28 | -37 | 14 | -29 | 159 |

## 4. THE DTW METHOD ANALYSIS

The factor $ER^2$ as input data needs data sets of the same length. In addition, signatures even of the same person can be different. The dynamic time warping (DTW) technique [1] overcomes this limitation and gives intuitive distance measurement. By means of DTW algorithm optimal alignment between two time series can be achieved. This method is often used to match the signatures. The DTW is a simple technique well known in the research community. For this reason, the details of this method were omitted.

To align two sequences using DTW a $n \times k$ costs matrix is constructed, where elements ($i$,$j$) of the matrix contain the so-called cost values. The cost values determine the warp path. It matches sequences $X(Y)$. The cost value is typically computed as the distance between two points $x_i \in X$ and $y_i \in Y$, respectively. It should be stressed that between vectors of features, various similarity measures can be proposed:

- the Euclidean distance:

$$d(X,Y) = \sqrt{\sum_i (x_i - y_i)^2} \ ; \tag{8}$$

- the Canberra distance:

$$d(X,Y) = \sum_i \left| \frac{x_i - y_i}{x_i + y_i} \right| \ ; \tag{9}$$

- the Chebyshev distance:

$$d(X,Y) = max(|x_i - y_i|) \ ; \tag{10}$$

- the Manhattan (city-block) distance:

$$d(X,Y) = \sum_i |(x_i - y_i)| \ . \tag{11}$$

Our researches allowed to estimate which type of distance gives the best results (EER). The contingency table for different type of distances used by DTW:

Table 6. Contingency table for different type of distances used by DTW

| | Canberra | Manhattan | Euclidian | Chebyshev | no DTW | |
|---|---|---|---|---|---|---|
| **Excellent** | 68 | 56 | 59 | 53 | 0 | 236 |
| **Very good** | 95 | 47 | 42 | 49 | 16 | 249 |
| **Good** | 68 | 76 | 74 | 73 | 0 | 291 |
| **Average** | 147 | 165 | 153 | 153 | 48 | 666 |
| **Poor** | 168 | 184 | 187 | 175 | 0 | 714 |
| **Bad** | 132 | 155 | 165 | 174 | 24 | 650 |
| **Very bad** | 220 | 216 | 218 | 221 | 24 | 899 |
| | 898 | 899 | 898 | 898 | 112 | 3705 |

From the formula (3) $\chi^2$ has been calculated:

$$\chi^2 = 131.28 ;$$

and critical region from the formula (5):

$$[70.25, +\infty) ;$$

where:

$\alpha$ – established level of significance = 0.000002,

$f$ – degrees of freedom =24 (from the formula (6)).

The $\chi^2$ statistic belongs to the critical region of the test so the hypothesis about the independence of the type of distances and EER is rejected.

From table 7 (differences between observed and expected values respectively) can be observed, that the Canberra distance gives the best results:

Table 7. Differences between observed and expected values of DTW distances respectively

| | Canberra | Manhattan | Euclidian | Chebyshev | No DTW |
|---|---|---|---|---|---|
| **Excellent** | 10,79 | -1,26 | 1,79 | -4,20 | -7,13 |
| **Very good** | 34,64 | -13,41 | -18,35 | -11,35 | 8,47 |
| **Good** | -2,53 | 5,39 | 3,46 | 2,46 | -8,79 |
| **Average** | -14,42 | 3,39 | -8,42 | -8,42 | 27,86 |
| **Poor** | -5,05 | 10,75 | 13,94 | 1,94 | -21,58 |
| **Bad** | -25,54 | -2,71 | 7,45 | 16,45 | 4,35 |
| **Very bad** | 2,10 | -2,13 | 0,10 | 3,10 | -3,17 |

A test for variables was another chi-square independence test which has been carried out for detecting the best settings of DTW. The contingency table for different variables used by DTW:

Table 8 Contingency table for different variables used by DTW

| | $DTW_{xyp}$ | $DTW_{xy}$ | $DTW_{xp}$ | $DTW_{yp}$ | $DTW_x$ | $DTW_y$ | $DTW_p$ | No DTW | |
|---|---|---|---|---|---|---|---|---|---|
| **Excellent** | 117 | 106 | 0 | 13 | 0 | 0 | 0 | 0 | 236 |
| **Very good** | 69 | 61 | 27 | 50 | 2 | 28 | 2 | 10 | 249 |
| **Good** | 63 | 68 | 17 | 85 | 0 | 58 | 0 | 0 | 291 |
| **Average** | 112 | 87 | 118 | 146 | 39 | 115 | 19 | 30 | 666 |
| **Poor** | 69 | 73 | 125 | 90 | 156 | 109 | 80 | 12 | 714 |
| **Bad** | 28 | 52 | 133 | 52 | 153 | 74 | 99 | 59 | 650 |
| **Very bad** | 12 | 15 | 42 | 26 | 112 | 78 | 262 | 352 | 899 |
| | 470 | 462 | 462 | 462 | 462 | 462 | 462 | 463 | 3705 |

From the formula (3) $\chi^2$ has been calculated:

$$\chi^2 = 2514{,}70\ ;$$

and critical region from the formula (5):

$$[98.41, +\infty)\ ;$$

where:

$\alpha$ – established level of significance = 0.000002,

$f$ – degrees of freedom =42 (from the formula (6)).

The $\chi^2$ statistic belongs to the critical region of the test so the hypothesis about the independence of the number of variables used by DTW and EER is rejected.

It can be observed from table 9 that the best results are achieved when three variables (*x*, *y*, *p*) are enclosed to calculation. But it is worth mentioning that two variables (*x*,*y*) also give quite good results.

Table 9. Differences between observed and expected values of DTW variables respectively

| | $DTW_{xyp}$ | $DTW_{xy}$ | $DTW_{xp}$ | $DTW_{yp}$ | $DTW_x$ | $DTW_y$ | $DTW_p$ | No DTW |
|---|---|---|---|---|---|---|---|---|
| **Excellent** | 87,06 | 76,57 | -29,42 | -16,42 | -29,42 | -29,42 | -29,42 | -29,49 |
| **Very good** | 37,41 | 29,95 | -4,049 | 18,95 | -29,04 | -3,049 | -29,04 | -21,11 |
| **Good** | 26,08 | 31,71 | -19,28 | 48,71 | -36,28 | 21,71 | -36,28 | -36,36 |
| **Average** | 27,51 | 3,95 | 34,95 | 62,95 | -44,04 | 31,95 | -64,04 | -53,22 |
| **Poor** | -21,57 | -16,03 | 35,96 | 0,96 | 66,96 | 19,96 | -9,03 | -77,22 |
| **Bad** | -54,45 | -29,05 | 51,94 | -29,05 | 71,94 | -7,05 | 17,94 | -22,22 |
| **Very bad** | -102,04 | -97,10 | -70,10 | -86,10 | -0,10 | -34,10 | 149,89 | 239,65 |

## 5. SIGNATURE ROTATION

In many cases, signatures, even those that belong to the same person, have different direction and position, hence they should be normalized. Some techniques normalize the signature position by aligning the centres of the two signatures. Another approach is the transformation of the signatures, so that they have the same starting point. Signatures can be also shifted towards Cartesians axes – this method was used in this paper.

Signature direction can be observed as a line trend. In the pre-processing procedures this trend should be eliminated. In our researches to eliminate the trend, the linear regression method was used. From statistics follows that linear regression is a classic statistical issue, where relationship between two random variables x and y should be determined. Linear regression attempts to explain this relationship with a straight line that is the best fit for the data. More information about signature rotation can be found here [14].

The influence of rotation on EER has been examined. The contingency table for rotation:

Table 10. Contingency table for rotation

| | Rotation | No rotation | |
|---|---|---|---|
| **Excellent** | 128 | 104 | 232 |
| **Very good** | 94 | 155 | 249 |
| **Good** | 154 | 135 | 289 |
| **Average** | 326 | 338 | 664 |
| **Poor** | 347 | 367 | 714 |
| **Bad** | 355 | 295 | 650 |
| **Very bad** | 469 | 430 | 899 |
| | 1849 | 1848 | 3697 |

From the formula (3) $\chi^2$ has been calculated:

$$\chi^2 = 26.68;$$

and critical region from the formula (5):

$$\left[26.62, +\infty\right);$$

where:

$\alpha$ – established level of significance = 0.00017,

$f$ – degrees of freedom =6.

The $\chi^2$ statistic belongs to the critical region of the test so the hypothesis about the independence of rotation and EER is rejected. It is interesting that higher level of significance is needed to reject hypothesis (comparing to previous tests). Also table 11 gives ambiguous results. It is hard to deduce if rotation improves or deteriorates final results. It can come out from the fact that tested signatures had quite similar position in spite of everything. It means that other algorithms had more influence on final results than rotation itself.

Table 11. Difference table for rotation

| | Rotation | No rotation |
|---|---|---|
| **Excellent** | 12,03 | -12,03 |
| **Very good** | -30,53 | 30,53 |
| **Good** | 9,46 | -9,46 |
| **Average** | -6,08 | 6,08 |
| **Poor** | -10,09 | 10,09 |
| **Bad** | 29,91 | -29,91 |
| **Very bad** | 19,37 | -19,37 |

## 6. RESEARCHES AND CONCLUSION

The proposed software of signatures verification [4,5,14] was evaluated by using the online signature database Signature Verification Competition (SVC) 2004 [15]. In the performed experiments the FRR, FAR and EER factors were determined. The FRR factor measures the rate of genuine signatures classified as forgeries, while FAR represents the rate of forgeries recognized as genuine ones. As a measure of system-quality the EER factor was established. The recognition system works better, when the ERR coefficient has low value.

The prepared database consists of the 172 signatures. This database contains 86 genuine signatures and 86 skilled imitations that were written by three forgers. In our database there are four signatures of the same person. All signatures are stored as textual files containing coordinates of the points ($x$,$y$) as well as the values of time and pen-pressure. Each signature is compared to the remaining signatures (DTW and linear regression were used). Our application allows to set different parameters of the test:

- DTW distant type,
- number and types of input variables,

- rotation.

Using software to automatic test [16] all combinations of all the settings above have been checked. Each combination has tested a set of 172 signatures. Running the test for all combinations gave 3705 results (EER values).

As it can be noticed, the results that we have obtained clearly indicated which variables and settings are valuable for further research. It is very important that each part of the verification system has been tested separately. This way of testing shows the influence of each system's element on the final result. Also the chi-square independence test proved that it is a reliable way of estimating the influence of the algorithm on the system's efficiency.

BIBLIOGRAPHY


[1] SALWADOR S., CHAN P., FastDTW: Toward Accurate Dynamic Warping in Linear Time and Space. Proc. of the Int. Conf. on knowledge discovery and data mining – KDD'04, Seattle, USA, pp. 70–80, 2004.

[2] LEI H, et all., ER2: an Intuitive Similarity Measure for On-line Signature Verification. 9th Int. Workshop on Frontiers in Handwriting Recognition – IWFHR'04, Tokyo, Japan, pp. 191–195, 2004.

[3] FANG B, et all., Off-line signature verification by the tracking of feature and stroke positions. Pattern Recognition. Vol. 36, pp. 91–101., 2003

[4] PORWIK P., PARA T., Some Handwritten Signature Parameters in Biometric Recognition Process. Proc. of the 29th Int. Conf. on Information Technology Interfaces – ITI'07, pp. 185–190. Cavtat, Croatia, 2007.

[5] PORWIK P., The compact three stages method of the signature recognition. Proc of the 6th Int. IEEE Conf. Computer Systems and Industrial Management Applications, CISIM 2007. Ełk, pp. 282–287, 2007.

[6] RIOJA F. et all. Dynamics features Extraction for on-Line Signature verification. Proc of the 14th IEE Int. Conf. on Electronics, Communications and Computers, Veracruz, Mexico, pp.156–162., 2004

[7] COETZER J., et all. Offline Signature Verification Using the Discrete Radon Transform and a Hidden Markov Model. EURASIP J. on Applied Signal Processing 2004, pp. 559–57, 2004.

[8] KRYSICKI W., BARTOS J., Rachunek prawdopodobieństwa i statystyka matematyczna. Wydawnictwo Naukowe PWN, Warszawa, 1986.

[9] SAEED K., ADAMSKI M., Extraction of Global Features for Offline Signature Recognition. Image Analysis, Computer Graphics, Security Systems and Artificial Intelligence Applications, WSFiZ Press, pp. 429–436, 2005.

[10] ADAMSKI M., SAEED K., Signature image recognition by shape context image matching [appear in proceedings of XII Int. Conf. Medical Informatics and Technologies, Osieczany near Cracow, Poland, 2007].

[11] ADAMSKI M., SAEED K., Signature identification by view-based feature extraction and Dynamic Time Warping classifier. Proc. of the 13th Int. MultiConf. on Advanced Computer Systems–ACS–AIBITS/CISIM'06, Miedzyzdroje, Poland, pp. 67–74, 2006.

[12] LEE L., BERGER T., AVICZER E., Reliable On-Line Human Signature Verification Systems. IEEE Trans. on Pattern Analysis and Machine Intelligence , pp. 643–647, 1996.

[13] RHEE T., CHO S., KIM J., On-Line Signature Verification Using Model-Guided Segmentation and Discriminative Feature Selection for Skilled Forgeries. The 6th International Conference on Document Analysis and Recognition (ICDAR), 2001.

[14] DOROZ R., PORWIK P., PARA T., WRÓBEL K. Dynamic Signature recognition based on velocity changes of some features. International Journal of Biometrics, Vol.1 no.1 , pp. 47 – 62, 2008.

[15] Signatures database: http://www.cse.ust.hk/svc2004/index.html

[16] Software for automatic testing http://www.autoitscript.com/autoit3/