A Writer Verification System Using the TMS320C6713 Digital Signal Processor

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Abstract

In this paper, a method for improving the reliability of an Automated Handwritten Signature Verification System (AHSVS) using a short handwritten sentence is realized using a dedicated hardware as a real time DSP system. The necessity of realising hardware based models emerges from the fact that modern DSP systems provide integration of the entire design process and flexibility due to hardware implementation and portability. In system level design, each word of the sentence is used to tackle an individual verification problem. The entire verification procedure is implemented by building both the image processing and classifier design modules using the TMSC6713 DSK and the SIMULINK model builder. The improvement in verification performance is due to both the fusion procedure applied and the full discretion of the writer to choose his own secret word.

1. Introduction.

Research studies concerning handwriting analysis show that handwritten patterns can be used in financial transactions or other security contacts, as for example in accessing large archive databases. A large number of person verification systems incorporates handwriting which is a behavioral biometric [1, 2]. Relevant to handwriting are two major fields that researchers all over the world are addressing; a first one that uses signatures and the second one that uses handwritten words in order to identify the claimed identity of an individual. One of the reasons that handwriting acts as a biometric characteristic is that written patterns constitute a non-invasive process with minimum effects on health or private rights [2,3]. Although signatures have been used widely to distinguish a person's identity, the use of handwritten samples has recently gained attention from researchers due to the reason that handwritten words can be used to extract information from their textual content. A writer verification system based on handwritten text is expected to provide discrimination results equivalent to those obtained from signatures, since text has been reported to comprise rich and stable information [4, 5].

In this paper, a method for improving the reliability of an Automated Handwritten Signature Verification System (AHSVS) using a short sentence is realized using a dedicated hardware like a real time digital signal processor. The necessity which has driven us to model a hardware based, writer verification system, is that modern DSP systems provide integration of the entire design process and flexibility due to hardware implementation and portability. A hardware based DSP system outclasses conventional software based writer verification system, since it provides dedicated and fast parts for image acquisition, image coding, feature extraction and classifier evaluation. For our application, we have selected the TMS320C6713 DSP floating-point processor for implementation and performance evaluation. The board is targeted under TI's software tools such as CCS and Mathworks SIMULINK. The entire verification procedure is implemented by building both the image processing and classifier design modules. In addition, the use of a sentence drawn up by the writer himself will further increase the reliability of the verification system. However, the number of words in the sentence must be kept small in order to avoid mistakes in memorizing its content. In our experiments a five-word sentence is used for writer verification. For this purpose, a large database was created employing 20 persons to record two different types of sentences, containing a total of 24000 words. In the verification procedure a computationally simple feature was selected, since we are not interested in the meaning of the word but only in the general characteristics of the curves involved. Accordingly, each word is represented in the feature space by means of a granulometric feature [9]. This feature is based on

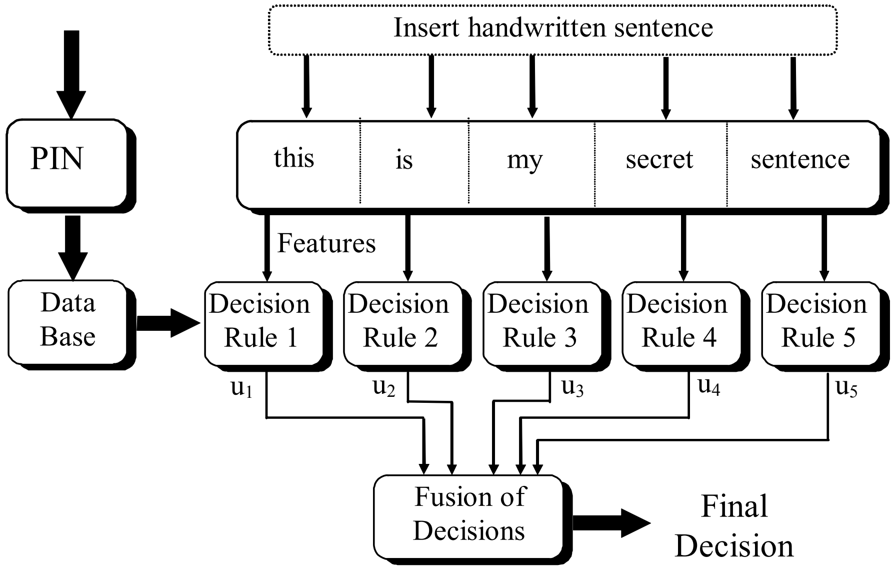

Figure 2. The proposed system architecture.

morphologically processing the projective profiles of the words. For improved discrimination performance other features can also be used for word-level decision making [4-10].

The extracted features are used to tackle an individual verification problem for each word. Thus, five decisions are obtained from each sentence concerning the identity of a specific person (word-level decision). These five individual decisions are combined by means of a decision fusion algorithm (DFA) so as to obtain the final and more reliable decision [11-12]. The Neyman-Pearson formulation is applied to the DFA since it is regarded as the optimal scheme [13, 14] compared to the Bayesian approach. This work is organized in the following way: Section 2 presents an overview of the proposed verification system structure and the employed database. Section 3 gives a brief description of the feature used and addresses the word level decision procedure. Section 4 provides the hardware implementation procedure using the TMSC6713 DSK. In section 5 a description of the Neyman-Pearson decision fusion rule is provided along with experimental results. Finally, the conclusions are drawn in section 6.

2. The Database.

The proposed system architecture for increased reliability in writer verification is shown in Figure 2. Each person uses a specific PIN number as an index in order to enter the archive database in which his/her personal handwriting information has been recorded. Then, the writer is requested to write down a short five-word secret sentence along with his signature. Each word is preprocessed and features are extracted in order to produce the local binary decision u_i. The set of local decisions u_i is then combined using the fusion rule and the final decision is made. Twenty persons were employed for this purpose within a time period of three months. Each sentence was written by each writer 120 times. Consequently, 4800 sentences were recorded in our database containing a total of

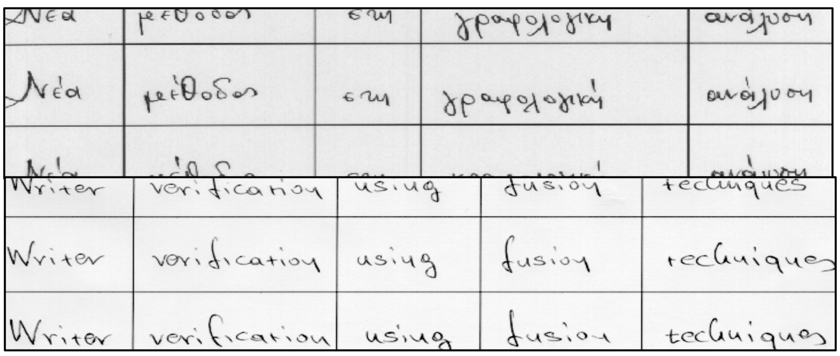

Figure 3. Samples of the database constructed to apply decision fusion for improving reliability in writer verification using a Greek and an English sentence.

24000 words. The sentence given in Figure 3, is the Greek equivalent of "New method in graphologist analysis". The Greek language, being our native language, was used in order to maintain constant handwriting characteristics. The sentence is made up of two words with relatively small length (three letters), two medium length words (seven letters) and a lengthy word (eleven letters). The English sentence shown in Figure 3, was selected in order to further test the proposed writer verification procedure. Each word was recorded inside a specific field so that preprocessing and feature extraction procedures could easily be carried out. To the knowledge of the authors no other database was found suitable for testing the proposed method. The publicly available databases do not contain any kind of text written by specific persons repeatedly, as the database described previously. The preprocessing stage incorporates thresholding to binarize the images and thinning of each word in order to obtain a one-pixel-width trace. This is because we need to remove the redundancies that originate from sources like ink absorption, background scanning noise, and type of pen used. The training samples were enrolled in the database as follows: For each writer we used 60 samples representing the genuine class, denoted hereafter as H_1, and 1140 samples from the rest nineteen writers representing the forged class, denoted as H_0. The remaining samples were used to test the efficiency of the system by means of measuring miss and false alarm errors.

3. Word level decision.

Among the various shape descriptors that have been used for handwritten pattern representation and signature analysis are granulometries [6]. A granulometric feature vector is employed in this work for word representation [9]. It contains spatial information about the orientation of the line segments in a handwritten pattern. Accordingly, the original image of each
word is partitioned into sub-blocks. The partition *W(n,m)* of the word is defined as the division of the original image into a grid of $n \times m$ equal rectangular blocks. Each sub-block is designated by the indexes i,j as follows:

$W_{i,j}(n,m)$ or $W_{i,j}$: *The (i,j) sub-block of partition W(n,m).*

Next the projection functions $f_{i,j}(n,m)$ of the partition *W(n,m)* are defined. The vertical projection function $f_{\mathrm{i,j}}^{\mathrm{V}}$ (VPF) is defined as the sum of the black pixels with the same abscissa *k* inside the $W_{i,j}$ sub-block. Similarly, the horizontal projection function $f_{\mathrm{i,j}}^{\mathrm{H}}$ (HPF) is defined as the sum of the black pixels inside the $W_{i,j}$ sub-block with the same ordinate *l*.

Obviously for the *W(n,m)* partition a total of $2 \times n \times m$ projection functions are evaluated. The final feature vector is obtained when two successive morphological openings $f_{\mathrm{i,j}} \circ g_k$ are performed on the projection functions $f_{\mathrm{i,j}}$ with a line Structuring Element (SE) g_k having two different lengths. As a result, the corresponding parameters *c* (coarse details) and *e* (fine details) are derived, which measure the gradual reduction in the area of each waveform according to equations (1):

$$\mathrm{e}_{i,j}^{V,H} = \left[\frac{\mathrm{mes}(f_{i,j}^{V,H}) - \mathrm{mes}(f_{i,j}^{V,H} \circ g_1)}{\mathrm{mes}(f_{1,1}^{\mathrm{V,H}})} \right] \tag{1.a}$$

$$\mathrm{c}_{i,j}^{V,H} = \left[\frac{\mathrm{mes}(f_{i,j}^{V,H} \circ g_1) - \mathrm{mes}(f_{i,j}^{V,H} \circ g_2)}{\mathrm{mes}(f_{1,1}^{\mathrm{V,H}})} \right] \tag{1.b}$$

where mes(.) is the area under the function in the argument and $f_{1,1}^{V} = f_{1,1}^{H} = f_{1,1}$ are the projection functions corresponding to the primary (1,1) partition. The set of all parameters $\left\{ \mathrm{e}_{\mathrm{n,m}}^{\mathrm{V}}, \mathrm{c}_{\mathrm{n,m}}^{\mathrm{H}} \right\}$ constitutes the feature vector corresponding to each word. It is obvious that the feature space dimensionality is determined by the partition level. In the general case of a $n \times m$ partition, the procedure results in a $4 \times n \times m$ dimensional feature vector.

The verification efficiency using only one word depends on both the partition level and the size of the SE used. The length of the SEs used must be chosen so that the correlation between the components of the feature vector be kept as low as possible. Experimentally, the best verification performance was achieved when the partition level (2,2) was applied to the short words, while the partition (3,2) to the long words. This resulted in a feature dimensionality of 16 and 24 respectively. However, using eigenvalue analysis, the intrinsic dimensionality of the obtained feature space is found to be much smaller. The optimal length for the SEs was found to be the same for all the configurations and was set to three and nine.

A specific word sample is classified either as genuine (H_1: the specific writer is present) or forger (H_0: the specific writer is not present). For each word, the training samples form the required feature space. The cluster which corresponds to hypothesis H_1 is a multidimensional pdf $p(x|H_1)$, which is usually well known, since it comprises information about the genuine writer. The rest of the clusters (forgers) form the pdf $p(x|H_0)$, which is generally unknown. The clusters corresponding to both classes have almost the same mean vectors since the samples are generated from the same words. However, they have different covariance matrices making the shape of the cluster a hyperellipsoid. Thus a single hypothesis scheme can be employed. Typically, we measure the distance y of a sample **x** from the mean (M_1) of H_1 class (normalised by class covariance matrix C_1) according to equation:

$$y = \left\{(\mathbf{x} - \overline{M}_1)C_1(\mathbf{x} - \overline{M}_1)^T\right\}^{\frac{1}{2}} \tag{2}$$

The single hypothesis scheme transforms the hyperellipsoid in the feature space into a donut in the distance space. Classification of the unknown feature vector **x** involves the selection of two suitable thresholds y_1 and y_2 ($y_1 < y_2$) to decide upon the validity of either H_1 or H_0 :

$$\begin{aligned} &H_1: \ y_1 < y < y_2 \\ &H_0: \ \text{elsewhere} \end{aligned} \tag{3}$$

The total classification error equals to the weighted summation of the P_{fa} and P_m:

$$\textit{Total error} = \frac{1}{2}\ (P_{fa} + P_m) = \frac{1}{2}\ (1+P_{fa}-P_d) \tag{4}$$

P_{fa} is the probability to accept hypothesis H_1 while hypothesis H_0 is true,

$$P_{fa} = \textit{Sum (samples classified } H_1\textit{, belong to } H_0\textit{)/1140} \tag{5}$$

and P_m is the probability to accept hypothesis H_0 while hypothesis H_1 is true,

$$P_m = \textit{Sum(samples classified as } H_0 \textit{ but belong to } H_1\textit{)/60} = 1 - P_d \tag{6}$$

where P_d is the corresponding probability of detection.

For an unknown feature vector **x** the described classifier will decide whether hypothesis H_1 is valid ($u_i = 1$) or not ($u_i = 0$). These hard decisions u_i, $i=1,\dots,5$, are extracted for all five words of each sentence and for the entire set of writers. Each u_i corresponds to a different word and it is associated with the individual P_{fa_i} and P_{m_i} (local operating points). The above quantities were evaluated for every single writer so that the minimum classification error is achieved when the thresholds y_1 and y_2 are located at some portion of the maximum distant point of the genuine cluster. This portion was experimentally found between 60 and 70% for the y_2 threshold, while it was kept at 10% of maximum distance for y_1, for almost all clusters formed in the experimental procedure.

4. System Realization.

The procedure followed at the previous section is realized using the combined capabilities of the SIMULINK environment and the power provided by the TI's C6000 floating point digital signal processor family. The tool used is the TMS320C6713 starter kit which operates at 225MHz and provides access to a 16 MB SDRAM for data and code storage. Figure 4 provides the entire image processing stage as it is imprinted to the SIMULINK model builder. The model below describes the feature extraction method for the Greek small size words ('Nea' and 'sti'). As it is easily seen, the process of transforming the original grey-level image to a 16-dimensional feature vector is based on various sub-procedures. First, the processor acquires from two predetermined memory locations 4096 elements. They represent the primary images, in a grey-level format and correspond to a size of 64 $\times$ 64 pixels. The original signature images are not of the same size due to variations to each person signature type and writing style. Therefore, a normalization algorithm must be applied to the family of images prior to DSP acquisition. The algorithm is based on the bounding rectangle and the bilinear image resize method. Therefore, a scale vector is used for resizing this rectangle in both horizontal and vertical axes, resulting in a final image of 64×64 pixels. A similar procedure will follow in case of using the large words; this will provide a scaled version of them to an equivalent size of 128×192 pixels. The total writing procedure of a 64×64 image, in a byte – precision format (1 byte per pixel) takes about 1 second and it depends exclusively on software limitations.

The entire system is synchronized by using a master clock which provides proper triggering every 0.1 second. Thus, the master clock (Fig. 4, clock module) enables a multi-port switch in order to ensure that proper image data pass every time, using two different paths, to the image processing module. Thus, the first image accesses the processing module for the four first cycles while the other image accesses the processing module for the other four. The 4096 integer elements that have been stored in the memory are subtracted from 255 in order to provide the negative image. The signal is discriminated from the background by considering the background pixels belonging to the lower portion of the histogram image. In the next step, the 4096 integer elements are reshaped in order to represent a matrix of 64×64 double precision pixels which have a dynamic range between [0,1]. The above storage technique demands a low amount of data to be stored to the SDRAM portion of the DSK. A benefit of the above discussion is that we can implement all the word models of a sentence into a single SIMULINK file.

Then, the image is transferred to the image processing block in order to provide segmentation and feature extraction. Figures 5 and 6 provide the segmentation procedure and the feature extraction method for the case of the small length words. In figure 6, each small word is divided to a 2×2 set of sub-image blocks using an embedded MATLAB function. Each sub-image passes to the feature extraction block using a secondary clock. Then, for each sub-image block the projection functions $f_{i,j}^{V}, f_{i,j}^{H}$ are evaluated and two morphological filters of length 3 and 7 are applied in order to provide the final feature set according to Eqs. (1a, 1b). These sixteen values are stored in a memory location while a MATLAB based program has been employed in order to acquire them. An analogous model is created in the case of the large words. The above feature extraction procedure is iterative for every writer and for every sentence of the training set. Namely, for each writer two classes are created. The genuine class (H_1) contains 60 genuine sentences while the forgery class (H_2) contains 60 sentences from the rest of the writers, resulting in a total number of 1140 (19×60) sentences. For each sentence, five associated words are extracted as they are representing the corresponding inputs to the model described in figure 7.

Next, using the algorithms described in the previous sections we are calculating for each i-writer ($i\in\{1,2,...,20\}$) and for each j-word ($j\in\{1,2,...,5\}$) the mean value and the corresponding covariance matrix of the genuine features. The training phase continues by using the procedure described in section 3 in order to derive the binary decisions u_i. According to figure 5, for obtaining each u_i the threshold y_2 was set at the position of the minimum total error for all local verification problems. The threshold y_1 was kept constant at 20% of the maximum distant point of the corresponding cluster. The operating parameters P_{fa_i} and P_{m_i} were evaluated as well, and accompany the corresponding

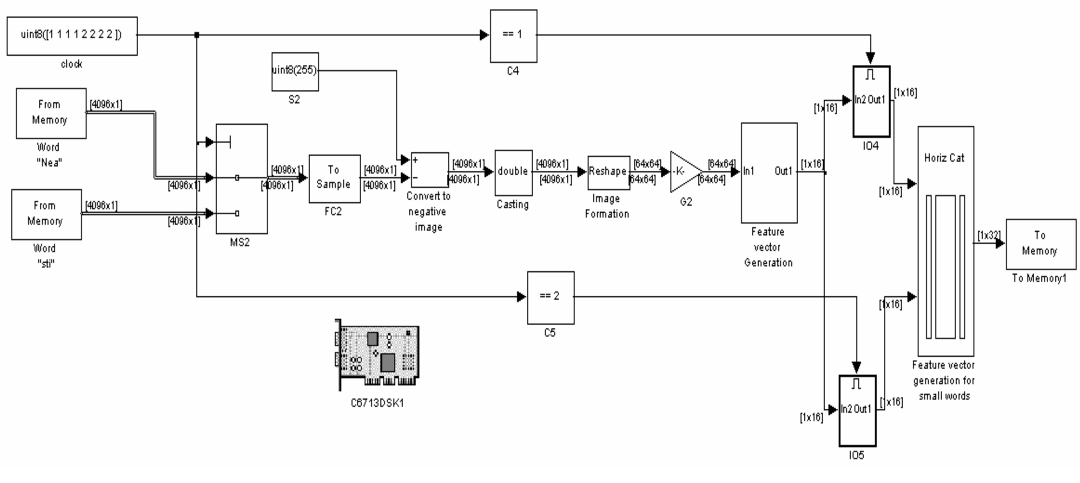

Figure 4. The image processing stage as imprinted in SIMULINK.

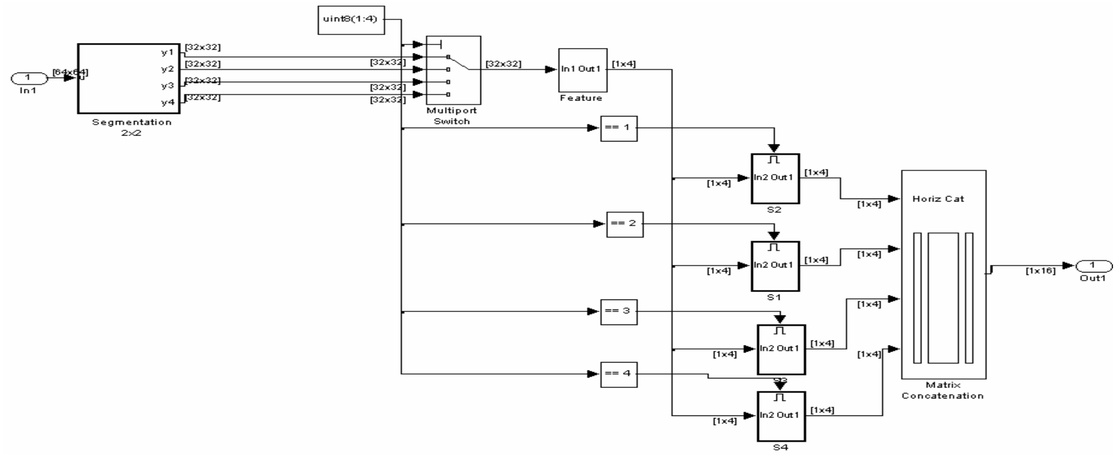

Figure 5. The segmentation procedure as it is imprinted in SIMULINK

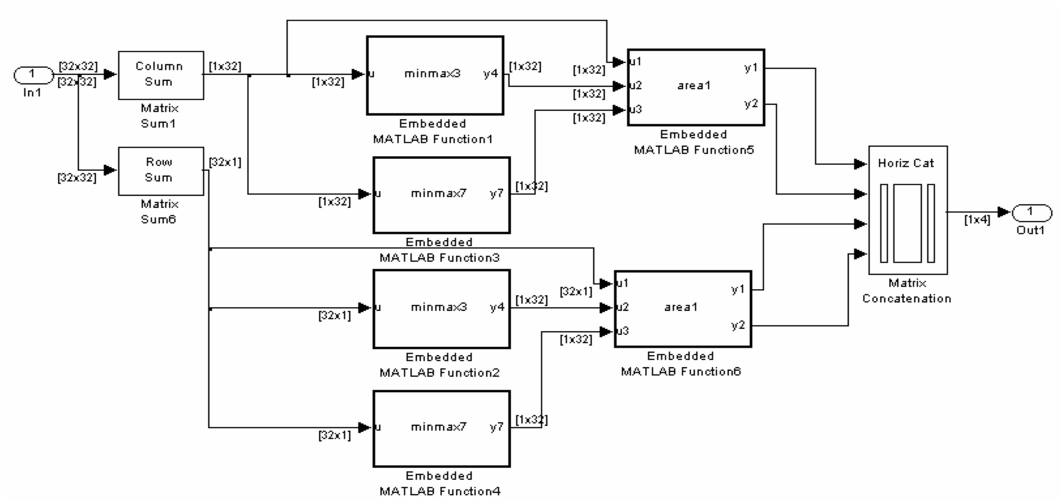

Figure 6. Layout of the feature extraction method

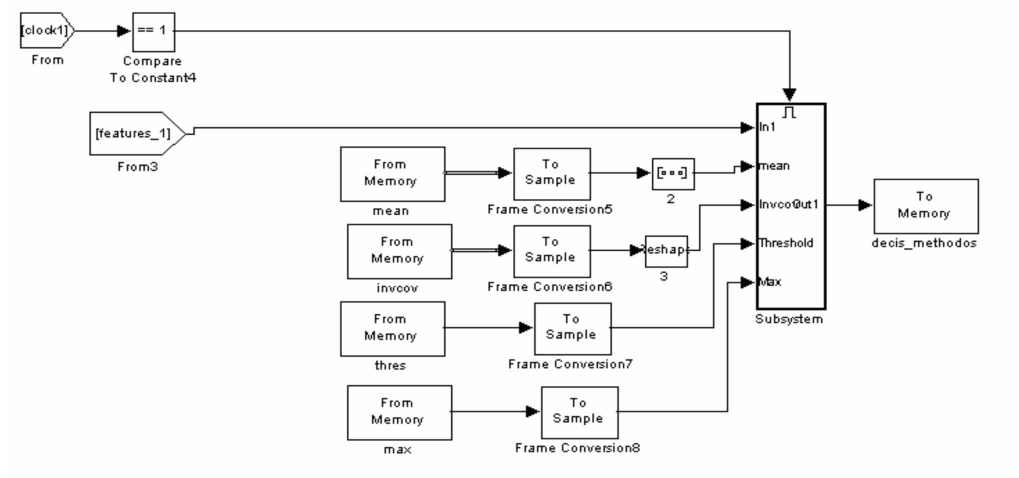

Figure 7. Implementation of classification rule

decisions u_i. Table 1 shows the individual P_{fa_i} and P_{d_i} for 3 of the writers and every word for the Greek sentence, while figure 7 provides a schematic diagram of the local decision rule using SIMULINK. In conclusion, the inputs to the decision rule as it is represented by eq. (2) are: the unknown feature vector **x,** the class mean and inverse covariance matrix, as well as the y_1, y_2 thresholds.

Table 1. P_{d_i} and P_{d_i} for each word and three of the writers for the Greek sentence.

Writer No.	Op. points	word 1	word 2	word 3	word 4	word 5
1	P_{fa_i}	0.04	0.05	0.16	0.05	0.07
	P_{d_i}	0.96	0.85	0.90	0.98	0.96
2	P_{fa_i}	0.20	0.27	0.11	0.14	0.19
	P_{d_i}	0.83	0.83	0.90	0.81	0.93
3	P_{fa_i}	0.15	0.14	0.27	0.17	0.01
	P_{d_i}	0.90	0.83	0.98	0.96	0.96

5. Fusion of decisions.

The vector $U=[u_1,u_2,u_3,u_4,u_5]$ of the decisions u_i, is used in the decision fusion algorithm (DFA) by means of the proper fusion rule in order to obtain a more reliable decision about the presence of a writer. The optimum combining scheme for the DFA, when the local decisions are provided, is the Neyman-Pearson (N-P) approach [17]. Since the input space, as represented by the local decisions is discrete, a randomized N-P decision rule is to be used. This is defined as follows:

$$\theta(U)=\begin{cases}1 & \text{if } \mathrm{T(U)}>t\\ \eta & \text{if } \mathrm{T(U)}=t\\ 0 & \text{if } \mathrm{T(U)}<t\end{cases} \tag{7}$$

where $\theta(U)$ corresponds to the final decision and expresses the probability of accepting the presence of a writer (H_1), given that the DFA observes U. The quantity T(U) is the likelihood ratio:

$$T(U)=\frac{P_1(U)}{P_0(U)} \tag{8}$$

where $P_j(U)$ is the probability of U under hypothesis H_j, j=0,1. The randomization constant η and the threshold t must be chosen so that the overall system probability of detection

$$P_D(\theta)=E_1[\theta(U)]=P_1(T(U)>t)+\eta P_1(T(U)=t) \tag{9}$$

and the overall system probability of false alarm

$$P_F(\theta)=E_0[\theta(U)]=P_0(T(U)>t)+\eta P_0(T(U)=t) \tag{10}$$

satisfy the N-P criterion

$$P_F\leq\beta \quad \text{and} \qquad P_D\geq \max(P_{Di}) \tag{11}$$

where β is a pre-specified upper bound for the false alarm probability and P_D the achieved probability of detection at the DFA. P_{d_i} is the probability of detection corresponding to the individual verification procedures determined in the previous section. The decision rule T(U) at the DFA, which is expressed by (8), is formed in the following way:

$$T(U)=\frac{\prod_{i=1}^{5} p_{d_i}^{u_i}\left(1-p_{d_i}^{1-u_i}\right)}{\prod_{i=1}^{5} p_{fa_i}^{u_i}\left(1-p_{fa_i}^{1-u_i}\right)} \tag{12}$$

The DFA results in significant improvement regarding the overall probabilities of miss and false alarm. For the Greek sentences the total verification error was found to be 0.97%, whereas for the English ones this error amounts to 0.53% due to the longer words contained.

6. Conclusions.

Using the proposed decision fusion method, security systems based on handwritten signatures can gain further reliability in writer verification. This is achieved by means of a short handwritten sentence. The words of the sentence are used separately to reach decisions about the authenticity of the writer, and then they are fused for achieving higher verification performance.

Three different factors can affect the verification performance of the proposed fusion procedure. The first important design parameter is the selection of a discriminative feature vector for modeling the shape of the words. After that, the correlation of the decisions must be studied and appropriately incorporated into the fusion algorithm. Finally, the verification performance of the fusion algorithm is improved when the number of the words in the sentence increases. Experimental results were obtained using 4800 handwritten sentences and a total of 24000 words. The proposed decision fusion method improves the efficiency of writer verification systems by means of the following two aspects. Firstly, the sentence employed is secret and can be changed by the writer. Secondly the fusion algorithm provides an adequate number of operating points to work with.

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7. References.

[1] B. Carter, Biometric technologies, what they are and how they work, Proc. CTST' 97, Orlando, FL, 1997.

[2] J. Woodward, Biometrics: Privacy's foe or Privacy's friend?, IEEE Proceedings, Vol. 85, 9, 1480-1492, 1997.

[3] M.C. Fairhurst, Signature verification revisited: Promoting practical exploitation of biometrics technology, Electronics and Communications Journal, 273-280, 1997.

[4] Ameur Benfensia, Thierry Paquet and Laurent Heutte, 'A writer identification and verification system', Pattern Recognition Letters, 26, pp. 2080-2092, 2005.

[5] R. Plamondon and G. Lorette, Automatic signature verification and writer identification-The state of the art, Pattern Recognition, Vol. 22, 2, 107-131, 1989.

[6] R. Sabourin, G. Genest, and F. Preteux, Off-line signature verification by local granulometric size distributions, IEEE Trans. PAMI, Vol. 19, 9, 976-988, 1997.

[7] M. Ammar, Y. Yoshida, and T. Fukumura, Off-line preprocessing and verification of signatures, Int. J. Pat. Rec. Artif. Intell., Vol. 2, 4, 589-602, 1993.

[8] J.P. Drouhard, R. Sabourin and M. Godbout, A neural approach to off-line signature verification using directional PDF, Pattern Recognition, Vol. 29, 3, 415-424, 1996.

[9] E.N. Zois and V. Anastassopoulos, Contour Features Using Morphological Transforms, Electronics Letters, Vol. 34, 1, 56-57, 1998.

[10] Y. Qi, and B.R. Hunt, Signature verification using global and grid features, Pattern Recognition, Vol. 27, 12, 1621-1629, 1994.

[11] R. Viswanathan and P.K. Varsney, Distributed Detection with multiple sensors: Part I-Funtamentals, IEEE Proceeding, Vol. 85, 1, 54-63, 1997.

[12] P.K. Varsney, Multisensor data fusion, Electronics and Communications Journal, 245-253, 1997.

[13] S.C.A. Thomopoulos, R. Viswanathan and D.C. Bougoulias, Optimal Decision Fusion in Multiple Sensor Systems, IEEE Trans. On Aerospace and Electronic Systems, Vol. 23, 5, 644-653, 1987.

[14] Z. Chair and P.K. Varshney, Optimal data fusion in multiple sensor detection system, IEEE Trans. On Aerospace and Electronic Systems, Vol. 22, 1, 98-101, 1986.