Proceedings of the 2009 IEEE International Conference on Systems, Man, and Cybernetics
San Antonio, TX, USA - October 2009

Online Signature Verification Algorithm with a User-Specific Global-Parameter Fusion Model

Daigo Muramatsu
Department of Electrical and Machanical Engineering
Seikei University
Tokyo, Japan
muramatsu@st.seikei.ac.jp

Takashi Matsumoto
Department of Electrical Engineering and Bioscience
Waseda University
Tokyo, Japan
takashi@matsumoto.elec.waseda.ac.jp

***Abstract*—Fusion is a promising strategy to improve performance in biometrics, and many fusion methods have been proposed. Most of them are user-generic fusion strategies, because generating user-specific strategies for each user is difficult. In this paper, we propose an online signature verification method using a user-specific global-parameter fusion model. The basic fusion model is a user-generic (global-parameter) fusion model, but by introducing a user-dependent mean vector, we can generate a user-specific fusion model. To evaluate the proposed algorithm, several experiments were performed by using three public databases. The proposed algorithm yielded equal error rates (EERs) of 4.0%, 8.6%, and 6.1% for the MCYT, SVC2004 task2, and MyIDea databases, respectively.**

***Index Terms*—Biometrics, Online Signature Verification, Fusion**

I. Introduction

Recently, the renewed interest in biometric authentication has resulted in its application in many situations. Several methods of biometric authentication have been proposed and studied; however, no perfect method currently exists. The suitability of the method depends on the situation as well as the required security level. Among available authentication methods, online signature verification is a promising candidate for several reasons. First, handwritten signatures are widely accepted as the authentication method in many countries. Second, online signature verification can often achieve a higher performance than verification based on static signatures[1]. Third, it is difficult to obtain dynamic information from a static signature; hence, it is more difficult to forge. Fourth, people can modify their signature if it is stolen. This is a notable characteristic because physiological biometrics such as fingerprints or irises cannot be modified or renewed.

However, online signature verification is also not perfect. It is important to develop an online signature verification algorithm that achieves high performance. To improve the verification accuracy, fusion strategies[2] are promising.

With fusion strategies, several features extracted from online signature, or scores calculated using these features, are combined in an online signature verification algorithm. For example, Fierrez-Aguilar et al.[3] used fusion strategies based on the max or sum rules, and Van et al.[4] fused two scores by a simple arithmetic mean. Nalwa[5] and Munich et al.[6] used the harmonic mean to combine multiple scores. Muramatsu et al.[7] combined several distances using a Multi Layer Perceptron (MLP) trained using a Markov chain Monte Carlo (MCMC) method[8], [9]. In many of them, the same fusion strategies or the same models are used for all users, and user characteristics are not considered in combining scores. If user characteristics can be considered when these features or scores are combined, it should be possible to improve the performance. Thus, we attempted to generate a fusion model that can consider user characteristics. Generating a fusion model for each user is the best way to consider user characteristics; however, this approach is not easy because the amount of training data associate with each user is severely limited[7]. Thus, we propose a user-specific global-parameter fusion model.

One fusion model is generated using an available database. Then, a mean vector is calculated for each user to consider users' characteristics, and this mean vector is input to the fusion model together with calculated dissimilarity (dissimilarity vector) to combine dissimilarity. Even though the same fusion model is used for all users, user characteristics can be considered because a user-specific mean vector is input to the model. We call this fusion model a user-specific global-parameter fusion model.

Several experiments were performed using public databases. The BIOMET[10] database was used for training of the fusion model, and the MCYT[11], SVC2004[12], and MyIDea[13] databases were used for evaluation. The experimental results show that the proposed algorithm worked reasonably well.

II. The Algorithm

Fig. 1 depicts the algorithm. There are three phases in the proposed algorithm: a ”training phase,” an ”enrollment phase,” and a ”testing phase”.

(i) Training phase

Signatures in an available database are used for training. This available database is composed of genuine and forged signatures of several signers. To avoid confusion, persons who use the verification system are referred to as ”users”, and persons who provide their signatures for the training database are referred to ”signers” in this paper. After preprocessing and feature extraction, multiple dissimilarities (dissimilarity vectors) among the signatures are calculated, and a mean

978-1-4244-2794-9/09/$25.00 ©2009 IEEE

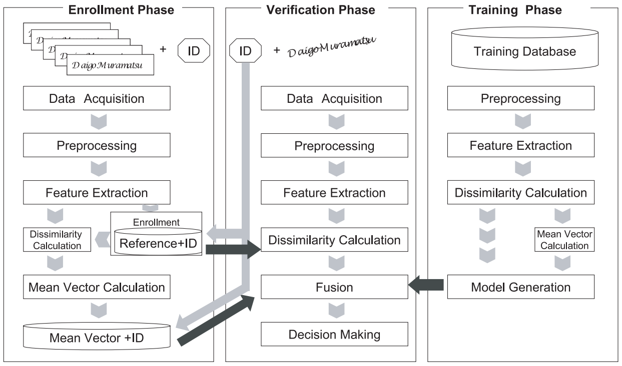

Fig. 1. Overall algorithm

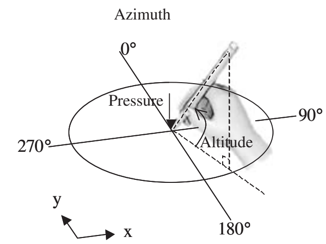

Fig. 2. Data from the tablet.

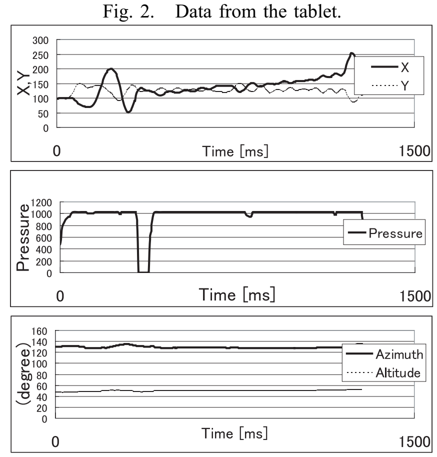

Fig. 3. Top: Trajectories of pen position x and y. Middle: Trajectory of pen pressure. Bottom: Trajectories of azimuth and altitude.

vector of each signer is calculated. A parameter set of the fusion model is estimated by using these dissimilarity vectors and mean vectors.

(ii) Enrollment phase

In the enrollment phase, a user provides candidate reference signatures together with his/her ID. After preprocessing and feature extraction, reference signatures of the user are selected. Dissimilarity vectors are calculated by using these reference signatures, and a mean vector of the calculated dissimilarity vectors is also calculated. Reference signatures and the mean vector are stored with IDs.

(iii) Verification phase

In the verification phase, a signature with a claimed ID is provided. After preprocessing and feature extraction, dissimilarity vectors between the input signature and reference signatures are calculated. Then, these dissimilarity vectors and a mean vector are combined by the fusion model generated in the training phase, and a decision is made by using a score output from the fusion model.

The training, enrollment, and verification phases involve some of the following stages: (a) data acquisition, (b) preprocessing, (c) feature extraction, (d) enrollment, (e) dissimilarity calculation, (f) mean vector calculation, (g) model generation, (h) fusion, and (i) decision making. These stages are explained in this section.

A. Data Acquisition

Raw data from the tablet consists of the five-dimensional time-series data:

$$RawSig = (x_j, y_j, p_j, \psi_j, \phi_j), j = 1, 2, ..., J \quad (1)$$

Here, (x_j, y_j) is the pen position; p_j, the pen pressure; ψ_j, the azimuth; and ϕ_j, the altitude of the pen at time j (depicted in Figs. 2 and 3).

B. Preprocessing

The raw data are not invariant with size and position. In the proposed algorithm, therefore, the pen position trajectories (x_j, y_j) are normalized as follows:

$$\bar{x}_j = \frac{x_j - x_g}{x_{max} - x_{min}} \quad (2)$$

$$\bar{y}_j = \frac{y_j - y_g}{y_{max} - y_{min}} \quad (3)$$

$$x_g = \frac{1}{J}\sum_{j=1}^{J} x_j, y_g = \frac{1}{J}\sum_{j=1}^{J} y_j$$

where (x_g, y_g) is the centroid of a signature, and x_{min} and y_{min} and x_{max} and y_{max} are the minimum and maximum values of x_j and y_j, respectively.

C. Feature Extraction

After preprocessing, two additional features, pen movement direction θ and pen velocity $|V|$, are calculated from the pen position data $(\bar{x}_j, \bar{y}_j)$:

$$\theta_j = \begin{cases} 0 & (j = 1) \\ \tan^{-1} \frac{\bar{y}_j - \bar{y}_{j-1}}{\bar{x}_j - \bar{x}_{j-1}} & (j > 1) \end{cases} \quad (4)$$

$$|V|_j = \begin{cases} 0 & (j = 1) \\ \sqrt{(\bar{x}_j - \bar{x}_{j-1})^2 + (\bar{y}_j - \bar{y}_{j-1})^2} & (j > 1) \end{cases} \quad (5)$$

Then, the following time-series seven-dimensional feature data are considered:

$$sig = (\bar{x}_j, \bar{y}_j, \theta_j, |V|_j, p_j, \psi_j, \phi_j), j = 1, 2, ...J \quad (6)$$

D. Enrollment

M raw signatures are provided by a user in the enrollment phase. We use all the genuine signatures given by the user, and time-series feature data are extracted from the signatures. The extracted time-series feature data are enrolled as reference signatures for the user ID $Rsig_m^{(ID)}, m = 1, 2, ..., M$.

E. Dissimilarity calculation

Two signatures are compared, and an N-dimensional dissimilarity vector is calculated. For example, two sets of time-series feature data "sig_A" and "sig_B" are compared, and the calculated dissimilarity vector $D(sig_A, sig_B)$ is described as

$$\begin{aligned} &D(sig_A, sig_B) = (D_1, D_2, ..., D_N) \\ &= (\frac{d_1(sig_A, sig_B)}{J_A}, \frac{d_2(sig_A, sig_B)}{J_A}, ..., \frac{d_N(sig_A, sig_B)}{J_A}). \end{aligned} \tag{7}$$

Where J_A is a duration time of sig_A. Each factor of the dissimilarity vector $d_n(\cdot,\cdot)$ is associated with the n-th feature in (6) and is calculated independently using dynamic time warping[14]. Thus, the dimension of the dissimilarity vectors is $N = 7$.

F. Mean vector calculation

A mean vector of each signer is calculated using genuine signatures of the signer in the training phase, and a mean vector of each user is calculated using reference signatures of the user with ID in the enrollment phase. The mean vector of the user with ID calculated in the enrollment phase is described as:

$$Mean^{(ID)} = (mean_1^{(ID)}, mean_2^{(ID)}, ..., mean_N^{(ID)}) \tag{8}$$

$$mean_n^{(ID)} = \frac{1}{M(M-1)} \sum_{m=1}^{M} \sum_{\substack{k=1 \\ k \neq m}}^{M} \frac{d_n(Rsig_m^{(ID)}, Rsig_k^{(ID)})}{J_m^{(ID)}} \tag{9}$$

These mean vectors have a very important role in this algorithm, because users' characteristics are considered only with these mean vectors.

Mean vectors of signers are used for fusion model generation, and mean vectors of users are used as inputs to the fusion model.

G. Fusion

A user-specific global-parameter fusion model is used for combining factors of dissimilarity vectors. Fig.4 is a schematic diagram of the user-specific global-parameter fusion model. One fusion model $F(\cdot;\Theta)$ is generated in the model generation phase explained in the next subsection, and this model is used for all users. Here, Θ is a parameter set of the model. This fusion model is designed to combine a $2N$-dimensional input vector and output a score.

In the verification phase, this model is used for combining dissimilarity vectors calculated from a test signature sig and reference signatures $Rsig_m, m = 1, 2..., M$. Here, we set the input vector X_m to the fusion model as:

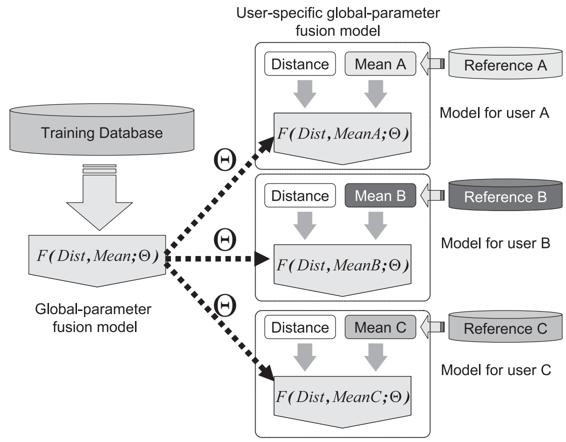

Fig. 4. User-specific global-parameter fusion model

$$X_m = (\overline{D(sig, Rsig_m^{(ID)})}, Mean^{(ID)}) \tag{10}$$

where $\overline{D(sig, Rsig_m^{(ID)})}$ is a normalized dissimilarity vectors described as:

$$\overline{D(sig, Rsig_m^{(ID)})} = (\frac{D_1}{Z_1}, \frac{D_2}{Z_2}, ..., \frac{D_N}{Z_N}). \tag{11}$$

Z_n is a normalization constant to equalize the range of each factor of dissimilarity vector, and is calculated using training database. Here, X_m is a $2N$-dimensional vector because the dimensions of both the dissimilarity and mean vectors are N. By setting the input vector like this, a mean vector is input to the fusion model together with a dissimilarity vector. Note that the parameter Θ of the fusion model is the same for all users. Thus, this is a global-parameter fusion model. On the other hand, the model is also a user-specific fusion model because the mean vector input to the model is different for each user. Thus, even though the parameter set of the fusion model is global, a mean vector makes it possible to consider user characteristics. By using this user-specific global-parameter model, a final score is calculated:

$$score = \frac{1}{M} \sum_{m=1}^{M} F(X_m; \Theta). \tag{12}$$

H. Model generation

Fusion models $F(\cdot;\Theta)$ are generated by following three steps:

Step 1

$H \times L$ pieces of $2N$-dimensional simple perceptrons $g(\cdot; \mathbf{w}_{hl})$ are generated as weak models. Weight parameter sets $\mathbf{w}_{hl}$ are samples drawn from the uniform distribution $U(-1, 1)$.

Step 2

The real AdaBoost algorithm[15] is applied to these weak models, and H boosted models $f_h(\cdot; \mathrm{A}_h, \mathbf{W}_h)$ are generated by using a training database:

$$\begin{aligned} f(\cdot; \mathrm{A}_h, \mathbf{W_h}) &= \sum_{l}^{L} \alpha_{hl} g(\cdot; \mathbf{w}_{hl}) \qquad (13) \\ & \alpha_h = (\alpha_{h1}, \alpha_{h2}, ..., \alpha_{hL}) \\ & \mathbf{W}_h = (\mathbf{w}_{h1}, \mathbf{w}_{h2}, ..., \mathbf{w}_{hL}) \end{aligned}$$

Here, α_{hl} is the confidence level of each weak model.

Step 3

One fusion model $F(\cdot; \Theta)$ is generated from the H boosted models:

$$\begin{aligned} F(\cdot; \Theta) &= \frac{1}{H} \sum_{h=1}^{H} f(\cdot; \mathrm{A}_h, \mathbf{W}_h) \qquad (14) \\ & \Theta = (\mathrm{A}_1, \mathrm{A}_2, ..., \mathrm{A}_H, \mathbf{W}_1, \mathbf{W}_2, ..., \mathbf{W}_H) \end{aligned}$$

With these steps, a global parameter set Θ is estimated. If there is enough training data for each user, a good user-dependent parameter set can be estimated for each user. However, the number and types of training data for each user are severely limited. Under this situation, estimating a good parameter set for each user is very difficult. On the contrary, a larger database can be used for estimating the global parameter set because online signature databases can be used for the estimation. Thus, better parameters can be obtained in the global model. This is the reason why we use the global-parameter fusion model in this paper.

I. Decision Making

A decision is made using a $score$ output from the fusion model:

$$\text{A user is} \begin{cases} \text{accepted} & if \quad score \geq Threshold \\ \text{rejected} & if \quad score < Threshold \end{cases} \qquad (15)$$

III. Experiments

A. Experimental setting

A subset of BIOMET[10] was used as training data, and subsets of MyIDea[13], SVC2004[12] task2, and MCYT[11] were used for performance evaluation (verification). Table I summarizes details of the database subsets used in this experiment.

First five genuine signatures were used as candidate reference signatures in the enrollment phase ($M = 5$), and the remaining genuine signatures and forged signatures were used for evaluation. The number of weak models (L) was 5000, and the number of boosted models H combined in (14) was 10.

TABLE II
Experimental Results: EER [%]

DB	MCYT	SVC2004 task2	MyIDea
Proposed	4.0	8.6	6.1
Without mean vector	5.4	11.7	8.5
SUM rule	5.4	11.8	9.5
Harmonic mean	8.9	17.4	16.0
Harmonic mean (MAD)	16.7	24.5	12.0

B. Evaluation Criteria

The equal error rate (EER) and error tradeoff curve are often used for performance comparison. The experimental results were thus expressed as the EER value together with an error tradeoff curve.

Using these criteria, following fusion strategies are also evaluated for comparison purpose:

- **Fusion model without mean vector**
  Factors of normalized dissimilarity vectors are combined by using fusion model in this strategy. Different from the propose fusion model, user-dependent mean vector is not used for this fusion model. This strategy is referred to as ”Without mean vector” in figures and tables.
- **SUM rule**
  Factors of normalized dissimilarity vector are added with equal weights. This strategy is referred to as ”SUM rule” in figures and tables.
- **Harmonic mean**
  Unweighted harmonic mean[5] and weighted harmonic mean using MAD (Median Absolute Deviation) [6]were evaluated. These strategies are referred to as ”Harmonic Mean (a=1)”and ”Harmonic Mean (MAD)” respectively.

C. Experimental Results

The experimental results are summarized in Table II and illustrated in Fig. 5–7.

In these experiments, the proposed fusion model outperformed other strategies, and EERs were improved from 5.4% to 4.0% for MCYT100, 11.7% to 8.6% for SVC2004 task2, and 8.5% to 6.1%.

IV. Conclusion

An online signature verification algorithm using a user-specific global-parameter fusion model was developed. Our goal was to generate a user-specific fusion model that can consider user characteristics, where parameters are estimated using available databases that are not related to users. In order to demonstrate the effectiveness of this approach, we performed experiments to evaluate the algorithm with three different public databases: MCYT, SVC2004 task2, and MyIDea, and compared the results with other fusion strategies. Our proposed user-specific global-parameter fusion model outperformed compared strategies, and the results revealed EERs of 4.0% for MCYT, 8.6% for SVC2004 task2, and 6.1% for MyIDea.

In this study, we tried to consider users' characteristics merely by introducing a mean vector for each user. Our

TABLE I
DATABASE SUBSETS

DB	persons	Training genuine signatures	Training forged signatures	Enrollment genuine signatures	Enrollment forged signatures	Verification genuine signatures	Verification forged signatures
BIOMET	61	15	12	0	0	0	0
MCYT	100	0	0	5	0	20	25
SVC2004	40	0	0	5	0	15	20
MyIDea	47	0	0	5	0	13	36

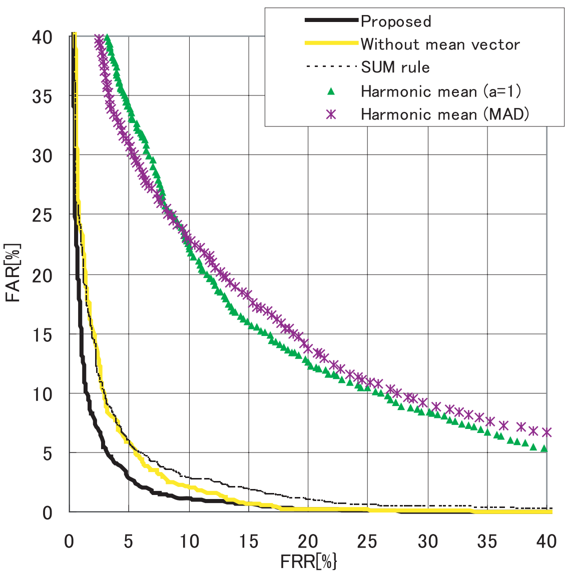

Fig. 5. Error Tradeoff Curves (MCYT)

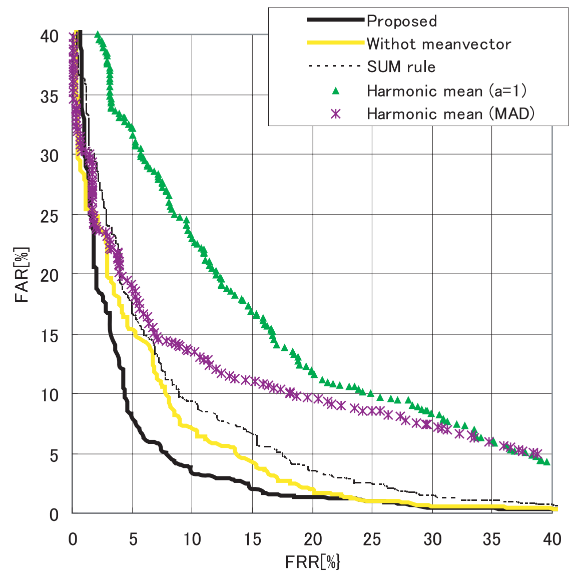

Fig. 7. Error Tradeoff Curve (MyIDea)

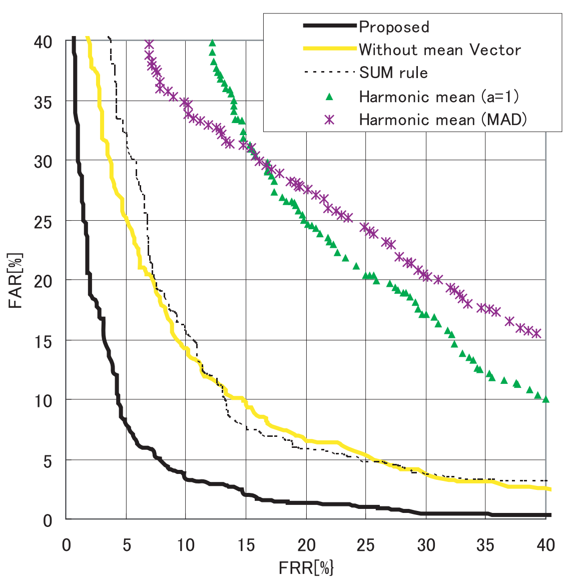

Fig. 6. Error Tradeoff Curve (SVC2004)

future work will include generating many fusion models using available databases by clustering them, and combining these models with user-specific weights or selecting the best model for each user. By doing this, more user characteristics can be considered and performance will be improved. Only seven features were used in this work. Many features have been proposed for online signature verification[3], [16]. In future work, therefore, we will also consider these additional features. Furthermore, we would also like to apply this strategy to online signature data captured by a web camera[17].

ACKNOWLEDGEMENTS

This work was supported by the New-Generation Information Security Technologies R&D project (Ministry of Economy, Trade and Industry of Japan).

REFERENCES

[1] R. Plamondon and G. Lorette, "Automatic signature verification and writer identification - the state of the art," *Pattern Recognition*, vol. 22, no. 2, pp. 107–131, 1989.
[2] A. A. Ross, K. Nandakumar, and A. K. Jain, *Handbook of Multibiometrics*. Springer Science+Business Media, LLC., 2006.
[3] J. Fierrez-Aguilar, L. Nanni, J. Lopez-Penalba, J. Ortega-Garcia, and D. Maltoni, "An on-line signature verification system based on fusion of local and global information," *Proc. Audio- and Video-Based Biometric Person Authentication, LNCS*, vol. 3546, pp. 523–532, 2005.

[4] B. L. Van, S. Garcia-Salicetti, and B. Dorizzi, "Fusion of HMM's likelihood and viterbi path for on-line signature verification," in *Proc. ECCV 2004 International Workshop, BioAW2004, LNCS*, vol. 3087, 2004, pp. 318–331.

[5] V. S. Nalwa, "Automatic on-line signature verification," *Proceedings of the IEEE*, vol. 85, no. 2, pp. 215–239, 1997.

[6] M. E. Munich and P. Perona, "Visual identification by signature tracking," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 25, no. 2, pp. 200–217, 2003.

[7] D. Muramatsu, M. Kondo, M. Sasaki, S. Tachibana, and T. Matsumoto, "A Markov chain Monte Carlo algorithm for Bayesian dynamic signature verification," *IEEE Trans. Information Forensics and Security*, vol. 1, no. 1, pp. 22–34, 2006.

[8] R. M. Neal, *Bayesian Learning for Neural Networks*. Springer-Verlag, 1996.

[9] W. Gilks, S. Richardson, and D. Spiegelhhalter, *Markov chain Monte Carlo in Practice*. Chapman and Hall, 1996.

[10] S. Garcia-Salicetti, C. Beumier, G. Chollet, B. Dorizzi, J. L. les Jardins, J. Lunter, Y. Ni, and D. Petrovska-Delacrétaz, "BIOMET: A multimodal person authentication database including face, voice, fingerprint, hand and signature modalities," in *Proc. Audio- and Video-Based Biometric Person Authentication, LNCS*, vol. 2688, 2003, pp. 845–853.

[11] J. Ortega-Garcia, J. Fierrez-Aguilar, D. Simon, M. F. J. Gonzalez, V. Espinosa, A. Satue, I. Hernaez, J. J. Igarza, C. Vivaracho, D. Escudero, and Q. I. Moro, "MCYT baseline corpus: A bimodal biometric database," *IEE Proceedings Vision, Image and Signal Processing, Special Issue on Biometrics on the Internet*, vol. 150, no. 6, pp. 395–401, 2003.

[12] D.-Y. Yeung, H. Chang, Y. Xiong, S. George, R. Kashi, T. Matsumoto, and G. Rigoll, "SVC2004: First international signature verification competition," in *Proc. International Conference on Biometric Authentication, LNCS*, vol. 3702, 2004, pp. 16–22.

[13] B. Dumas, C. Pugin, J. Hennebert, D. Petrovska-Delacrétaz, A. Humm, F. Evéquoz, R. Ingold, and D. V. Rotz, "MyIDea - multimodal biometrics database, description of acquisition protocols," *Proc. Third COST 275 Workshop, University of Hertfordshire*, pp. 59–62, 2005.

[14] L. Rabiner and B.-H. Juang, *Fundamentals of speech recognition*. Prentice Hall, 1993.

[15] R. E. Schapire and Y. Singer, "Improved boosting algorithms using confidence-rated predictions," *Machine Learning*, vol. 37, no. 3, pp. 297–336, 1999.

[16] L. L. Lee, T. Berger, and E. Aviczer, "Reliable on-line human signature verification systems," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 18, no. 6, pp. 643–647, 1996.

[17] K. Yasuda, D. Muramatsu, and T. Matsumoto, "Visual-based online signature verification by pen tip tracking," 2008, pp. 175–180.