

COMBINING MULTIPLE APPROACHES FOR ON-LINE SIGNATURE VERIFICATION

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Abstract: An on-line signature verification system exploiting temporal, local and global information through score-level fusion is presented. Global information is extracted with a feature-based representation and recognized by using Mahalanobis distance Classifier. Temporal information is extracted as time functions of various dynamic properties and recognized by using Dynamic Time Warping Model. Local information is extracted by using Discrete Radon Transform and recognized by using Dynamic Time Warping Model. Experimental results are given on the SVC2004 database (40 signers, 1600 signatures) for random and skilled forgeries. It is shown that the performance of all systems is improved when using more signatures in the enrollment. The three proposed systems are shown to give complementary recognition information which is successfully exploited using score-level fusion. The combining strategy leads to 0,18 EER for skilled forgeries and 0,07 for random forgeries in comparison to the individual algorithms.

1. Introduction

The goal of biometrics is to infer the identity of people based on anatomical or behavioral data (e.g., fingerprint, face, signature, or voice) [2]. The current interest in biometrics is due to the increasing number of important applications where an automatic assessment of identity is crucial. Within biometrics, on-line signature verification has been an intense research area because of the social and legal acceptance and widespread use of the written signature as a personal authentication method [4], and still is a challenging problem. This is mainly due to the large intra-class variations and, when considering forgeries, small inter-class variations.

In order to increase the security of biometric systems some approaches attempt to reach a better performance by combination of various biometric modalities. Such multibiometric systems consist of several biometric subsystems for different modalities (e.g. fingerprint and iris). In general a multibiometric system is based on one of three fusion levels, feature extraction level, matching score level or decision level [3]. In the feature extraction level the information extracted from the different sensors are stored in separate feature vectors. These feature vectors are combined to a joint feature vector, which is the basis for the matching process. In some cases this results in a very high dimensional joint feature vector. The fusion on matching score level is based on the combination of matching scores after the comparison of reference data and test data. Additionally, matching scores of the different modalities may be weighted. The fusion results in a new matching score, which is the basis for decision. With the fusion on the decision level, each biometric subsystem involved is completely processed. Afterwards, the individual decisions are combined to a final decision, e.g. by Boolean operations [3].

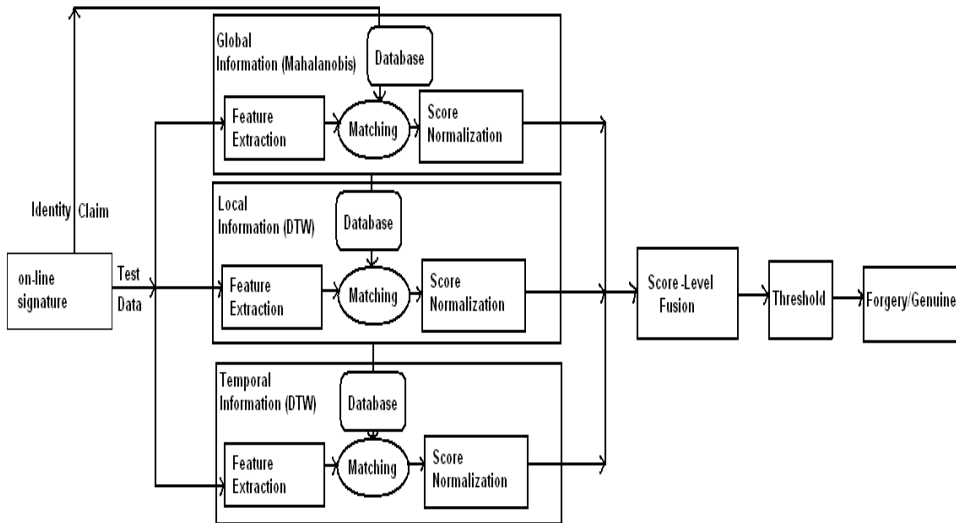


Fig. 1. Multi-Level Signature Verification System

Our system is based on biometric characteristics of only one modality (the on-line signature) whereby different independent settlement proceedings are consulted for the verification. For this purpose the strategies of the multibiometric fusion can be used likewise. Our approach combines three distance measures within a biometric system and is based on the matching score level strategy. A fusion on score level is represented in fig. 1. In contrast to the multibiometric fusion, our procedures involved use reference data from the same sensor. The input data for all three algorithms are identical. They consist of physical characteristics of the specimen of on-line signature over time. Each approach uses its own feature extraction algorithm.

2. Three Approaches for modeling on-line signature

The temporal information subsystem is described in Section 2.1. The local information subsystem is briefly explained in Section 2.2. The global information subsystem is declared in section 2.3.

2.1. System based on temporal information (DTW). The algorithm is based on the string matching technique called Dynamic Time Warping (DTW). In order to distinguish between skilled forgeries and genuine signatures, a higher weight must be assigned to the temporal information (pressure, speed) because they are invisible, which makes them much harder to imitate [1].

Preprocessing: A very simple although useful, preprocessing procedure is to perform position normalization. This is performed by subtracting the mean x and y coordinates of the signature from each individual point, which is defined as follows:

$$x' = x - \frac{\sum_{i=0}^n x_i}{n}; \quad (1)$$

$$y' = y - \frac{\sum_{i=0}^n y_i}{n}, \quad (2)$$

x, y – the original x and y coordinates; x', y' – the transformed coordinates. (See the effect of position normalization in fig. 2 below.)

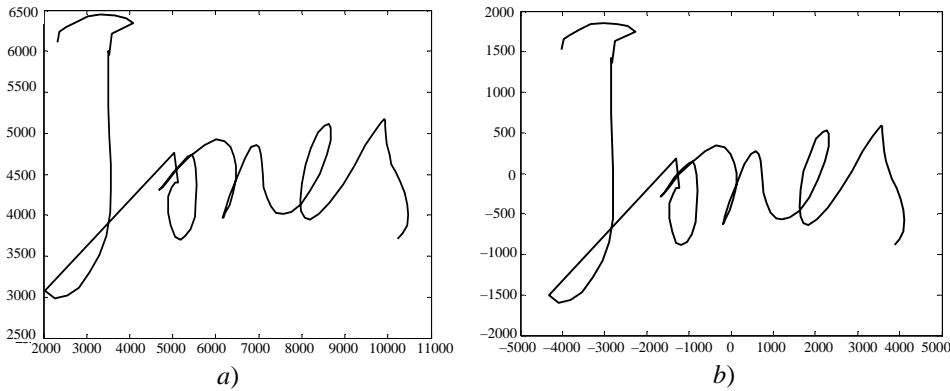


Fig. 2. Position normalization:
a – raw signature; *b* – signature after position normalization

Feature Extraction: the δx , δy , are used as features values, which contain the horizontal and vertical velocity information, respectively. Without resampling the distance between two points in the signature is equivalent to the speed. This is because the signature is sampled at a constant rate. The raw pressure signal is also used as a feature value without any transformation. During feature extraction the feature values are normalized using min-max normalization before matching these vectors. This is because these features values have different distributions.

Matching: After the temporal features are extracted from two signatures, these signatures need to be compared to find a difference or similarity measure between them. To compute this difference the standard DTW algorithm is used [10]. For example to find the matching distance between a template T and an input I is defined as follows:

$$D'(i, j) = (x_T(i) - x_I(j))^2; \quad (3)$$

$$D(i, j) = \min \left\{ \begin{array}{l} D(i-1, j-1) + D'(i, j) \\ D(i-1, j) + D'(i, j) \\ D(i, j-1) + D'(i, j) \end{array} \right\}; \quad (4)$$

$$\text{Dist}(T, I) = D(N_T, N_I), \quad (5)$$

$D'(i, j)$ – euclidean distance between node i in the template signature and node j in the input signature; $D(i, j)$ – the distance until nodes i and j between the two signatures; $\text{Dist}(T, I)$ – the distance between the two signatures; N_T and N_I – the number of points in the template and input signatures, respectively.

This is a normalized distance by the number of points in each signature.

2.2. System based on local information (DTW). This subsystem uses the Discrete Radon Transform (DRT) to extract local information from signatures. The DRT is obtained when projections of the signature are calculated at equally distributed angles between 0 and 180° [7].

Preprocessing: Firstly we remove all the zero-valued components from each projection in order to insure shift invariance. Although almost all the information in the original signature is contained in the projections at angles that range from 0 to 180°, the projections at angles that range from 180 to 360° are also included. These additional projections are added, in order to ensure rotation invariance [7].

Feature extraction: the DRT can be expressed as follows:

$$R_j = \sum_{i=1}^{\Psi} w_{ij} I_i; \quad j = 1, 2, \dots, N_{\varphi} N_{\theta}, \quad (6)$$

where R_j – the cumulative intensity of the pixels that lie within the j^{th} beam; Ψ – total pixels in an image; w_{ij} – the contribution of the i^{th} pixel to the j^{th} beam-sum; I_i – the intensity of the i^{th} pixel; N_{φ} – nonoverlapping beams per angle; N_{θ} – number of total angles.

Each column of the DRT represents a projection of the signature at a certain angle. After these projections are processed and normalized, they represent an initial set of feature vectors for the signature in question.

Matching: During enrollment, a number of reference signatures are used for each registered user and cross aligned to find the distance between each pair. In order to find the distance between two signatures, we use the DTW algorithm, which discussed in the previous section 2.1. From these alignment scores we store the minimum score of all the dissimilarity values as a reference distance.

A test signature is compared with each reference signature for the claimed user using the DTW algorithm.

Then, the resulting distance is fused with other resultant distances from two subsystems and used in classifying the signature as genuine or forgery.

2.3. System based on global information (Mahalanobis). Global information can quickly increase performance by calculating simple features about the overall signature. For example, the duration of signatures is very discriminating between subjects [5].

Feature extraction: This subsystem calculates sixteen features representing the overall signature; these features are displayed in table 1. The features in Table 1 are sorted by individual inter-user discriminative power [5].

Matching: Each client of the system or target T is represented by a statistical model $\lambda_T = \{\mu_T, \sigma_T\}$ where μ_T and σ_T denote mean and variance vectors respectively. These are estimated by using an enrollment set of K training signatures $\{o_T^{(1)}, \dots, o_T^{(k)}\}$ as follows

$$\mu_T = \frac{1}{K} \sum_{k=1}^K o_T^{(k)}; \quad (7)$$

$$\sigma_T = \frac{1}{K} \sum_{k=1}^K (o_T^{(k)} - \mu_T)^2. \quad (8)$$

Similarity score between a parameterized test signature «o» and a claimed model $\lambda_T = \{\mu_T, \sigma_T\}$ is computed as Mahalanobis distance [5]

$$S(o, \lambda_T) = \sqrt{\frac{(o - \mu_T)^2}{\sigma_T}}. \quad (9)$$

3. Combining of three approaches information

Two theoretical frameworks for combining matchers with application to biometric verification are described in [11] and [12]. More recent approaches are reviewed in [1]. It is now generally agreed that the weighted average is a good way of combining the similarity scores provided by the different systems.

Table 1

**Set of global features considered in this work ordered
by their individual discriminative power**

Feature Description	Comments
Signature total duration T_s	T – time interval
N (pen-ups)	N – number of pen ups
N (sign changes of dx/dt and dy/dt)	N – number of sign changes
standard deviation of a_y	a_y – acceleration in the y direction
standard deviation of v_y	v_y – velocity in the y direction
N (local maxima in x)	N – number of local maxima
standard deviation of a_x	a_x – acceleration in the x direction
standard deviation of v_x	v_x – velocity in the y direction
N (local maxima in y)	N – number of local maxima
t (second pen down) / T_s	t – time instance
$v / v_{x,max}$	v – average velocity
$(T_w v) / (y_{max} - y_{min})$	T_w – total time duration of all pen downs
$(T_w v) / (x_{max} - x_{min})$	
T_w / T_s	
$v / v_{y,max}$	
v / v_{max}	v – total velocity

In this work, a fixed fusion strategy based on the sum rule is used. Similarity scores of the three approaches are normalized to zero mean and unit standard deviation before fusion.

4. Experiments

4.1. Database and Experimental Protocol. Not many signature databases are publicly available for research purposes [8]. As a result, the common practice in on-line signature verification research is to evaluate the proposed verification strategies on small data sets acquired at individual research laboratories. The First International Signature Verification Competition (SVC) was organized in 2004 to provide a common reference for system comparison on the same signature data [9]. Development corpus (Task 2) in SVC2004 is used in the experiments. The on-line signature data in this case include not only position coordinates but also pressure and pen angles at a sampling frequency equal to 100 Hz. The corpus consists of 40 sets of signatures. Each set contains 20 genuine signatures from one subject and 20 skilled forgeries from five other subjects. Five or ten training signatures randomly selected are used to construct a signature model for each subject. For each user, 15 or 10 genuine signatures; it depends on number of training signatures used; and 15 skilled forgeries are used for testing. In case of random forgeries, one random genuine signature from each of 15 different subjects randomly selected is used as impostor data. Whenever randomness was involved, the same random sets are used for the three systems under study.

4.2. Results. Verification performance results in four common conditions (skilled/random forgeries for ten training signatures and skilled/random forgeries for five training signatures) are given for the global, the local, the temporal, and their combination through sum rule (table 2 and Fig. 3). Verification performances of individual and combined systems are carried out for user-independent thresholds. It is shown that the performance of all systems is improved when using more signatures in the enrollment.

Table 2

Verification performance on skilled and random forgeries for user independent decision threshold

Information	EER			
	Five signature		Ten signatures	
	skilled	random	skilled	random
	forgeries			
Temporal information	0,28	0,17	0,25	0,11
Local information	0,3	0,12	0,28	0,09
Global information	0,26	0,19	0,18	0,12
Combined	0,22	0,09	0,18	0,07

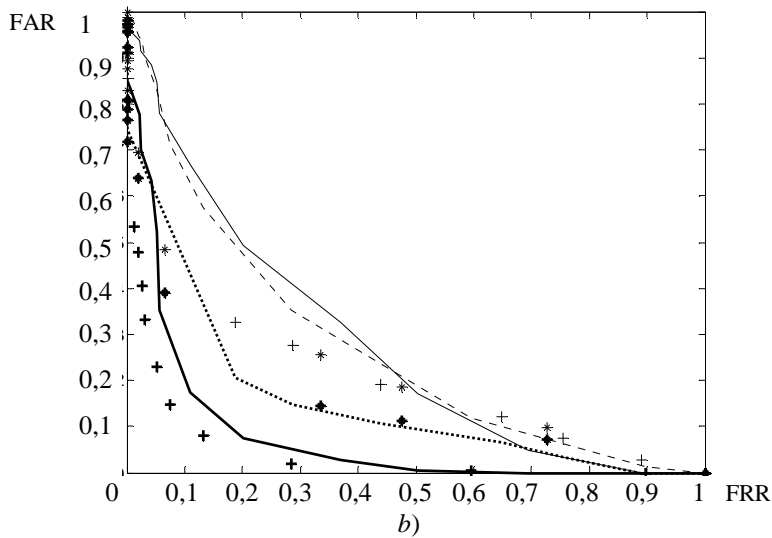
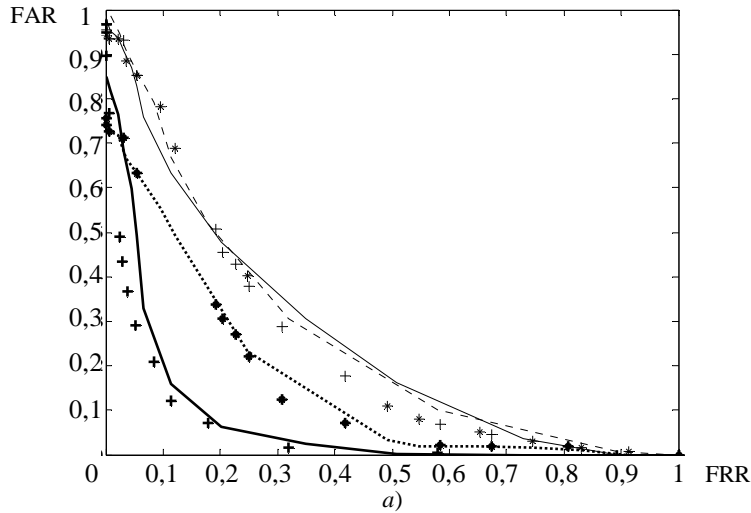


Fig. 3. Verification performance on skilled and random forgeries for user independent decision threshold:

a – for five signatures: ——— local SF (0,30); - - - - - temporal SF (0,28); * – global SF (0,26); +- sum SF (0,22); ——— local RF (0,12); temporal RF (0,17); * – global RF (0,19); +- sum RF (0,09); *b* – for ten signatures: *b*) ——— local SF (0,28); - - - - - temporal SF (0,25); * – global SF (0,18); +- sum SF (0,16); ——— local RF (0,09); temporal RF (0,11); * – global RF (0,12); +- sum RF (0,07)

For example, when considering professional forgeries and 5 training signatures the combined system leads to 0,22 EER while the combined system leads to 0,18 EER when 10 training signatures is used, so an improved is obtained when the number of training signatures is increased. The three systems are shown to provide complementary information for the verification task, which is well exploited using the sum rule. For example, when considering professional forgeries and 5 training signatures the combined system leads to 0,22 EER which is better than other results.

5. Conclusion

An on-line signature verification system based on fusion of temporal, local and global information of input signatures has been described. Global information is based on feature-based description of signatures and based on calculation of Mahalanobis distance. Local and temporal information relies on modeling through Dynamic Time Warping Model. Performance experiments are conducted on the SVC2004 database comprising 1600 different signatures from 40 contributors.

Verification performance on random and skilled forgeries has been given for global decision thresholds. It is showed that when using more number of training signatures it leads to improve the efficiency of each system. The three proposed systems are shown to give complementary verification information which has been exploited with simple sum rule.

Future work includes exploiting the user-specific decision thresholds and using other weighting rules like max and product.

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Комбинирование методов в верификации интерактивных подписей

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Ключевые слова и фразы: верификация подписи; динамическая трансформация времени; классификатор Махаланобиса; порог; слияние.

Аннотация: Представлена система верификации интерактивных подписей с помощью временных, локальных и глобальных данных благодаря слиянию на уровне сопоставления значений. Глобальные данные выделены путем представления образа, основанного на признаках, и распознаны с помощью классификатора расстояния Махаланобиса. Временные данные выделяются как функции времени различных динамических свойств и распознаются с помощью модели динамической трансформации времени. Локальные данные выделены с помощью дискретного преобразования Радона и распознаны с помощью модели динамической трансформации времени. Результаты экспериментов даны в базе данных SVC2004 (40 индивидуумов, давших подписи, 1600 подписей) для случайных и квалифицированных подделок. Показано, что производительность всех систем улучшается при использовании большего количества подписей при записи их в систему. Три предложенных системы показаны для представления дополнительной информации о распознавании, которая успешно используется со слиянием на уровне сопоставления значений. Стратегия комбинирования приводит к эквивалентной ошибке, равной 0,18 для квалифицированных подделок и 0,07 для случайных подделок в сравнении с частными алгоритмами.

Kombination von Methoden in der Verifikation der interaktiven Signaturen

Zusammenfassung: Es ist das System der Verifikation der interaktiven Signaturen mit Hilfe der zeitlichen, lokalen und globalen Angaben dank der Fusion auf dem Niveau des Kennwertvergleichs dargelegt. Es sind die Globalangaben mit Hilfe des Entfernungsklassierers von Mahalanobis ausgewählt und erkannt. Die zeitlichen Angaben werden als Zeitfunktionen der verschiedenen dynamischen Eigenschaften ausgewählt und mit Hilfe des Modells der dynamischen Zeittransformation erkannt. Die Lokalangaben sind mit Hilfe der diskreten Radon-Transformation ausgewählt und mit Hilfe des Modells der dynamischen Zeittransformation erkannt. Die Ergebnisse der Untersuchungen sind in der SVC2004-Datenbank (40 Individuen, 1600 Signaturen) für die zufälligen und qualifizierten Fälschungen angegeben. Es ist gezeigt, daß die Produktivität aller Systeme bei der Benutzung mehrerer Signaturenzahl bei dem Eintragen ins System verbessert wird. Drei vorgeschlagene Systeme sind für die Darlegung der Zuschlagsinformation über Erkennung, die mit der Fusion auf dem Niveau der Kennwertvergleichung erfolgreich benutzt wird, dargelegt. Die Strategie der Kombination führt zum äquivalenten Fehler, der für die qualifizierten Fälschungen 0,18 gleich ist und für die zufälligen Fälschungen im Vergleich mit den einzelnen Algorithmen 0,07 gleich ist.

Approches multiples combinées envers la vérification des signatures On-Line

Résumé: Est présenté le système de vérification des signatures interactives à l'aide des données temporelles, locales et globales grâce à la fusion au niveau de la comparaison des valeurs. Les données globales sont extraites présentant une image fondée sur les indices et reconnues à l'aide des classificateurs de la distance de Mahalanobis. Les données temporelles sont extraites comme fonctions de temps de différentes propriétés dynamiques et reconnues à l'aide du modèle de la transformation dynamique du temps. Les données locales sont extraites à l'aide de la transformation discrète Radon et reconnues à l'aide du modèle de la transformation dynamique du temps. Les résultats des expériences sont cités dans la base de données SVC2004 (40 individus qui ont donné leurs signatures, 1600 signatures) pour les erreurs occasionnelles et qualifiées. Est montré que le rendement de tous les systèmes s'améliore avec l'emploi d'un grand nombre de signatures lors de la composition du système. Trois systèmes proposés sont montrés pour la présentation de l'information supplémentaire sur la reconnaissance qui est employé avec succès avec la fusion au niveau de la comparaison des valeurs. La stratégie de la combinaison aboutit à une erreur équivalente égale à 0,18 pour les erreurs qualifiées et 0,07 pour les erreurs occasionnelles en comparaison avec les algorithmes particuliers.

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