An On-Line Signature Verification System Based on Fusion of Local and Global Information

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Abstract. An on-line signature verification system exploiting both local and global information through decision-level fusion is presented. Global information is extracted with a feature-based representation and recognized by using Parzen Windows Classifiers. Local information is extracted as time functions of various dynamic properties and recognized by using Hidden Markov Models. Experimental results are given on the large MCYT signature database (330 signers, 16500 signatures) for random and skilled forgeries. Feature selection experiments based on feature ranking are carried out. It is shown experimentally that the machine expert based on local information outperforms the system based on global analysis when enough training data is available. Conversely, it is found that global analysis is more appropriate in the case of small training set size. The two proposed systems are also shown to give complementary recognition information which is successfully exploited using decision-level score fusion.

1 Introduction

Automatic extraction of identity cues from personal traits (e.g., signature, fingerprint, voice, and face image) has given raise to a particular branch of pattern recognition, biometrics, where the goal is to infer identity of people from biometric data [1]. The increasing interest on biometrics is related to the number of important applications where an automatic assessment of identity is a crucial point. Within biometrics, automatic 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 [2]. This work is focused on on-line signature verification, i.e., the time functions of the dynamic signing process (e.g., position trajectories, or pressure versus time) are available for recognition.

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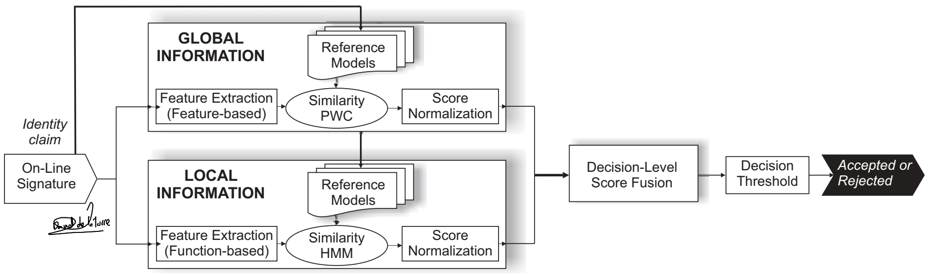


Fig. 1. System model of multilevel signature recognition

Different approaches are considered in the literature in order to extract relevant information from on-line signature data [2]; they can coarsely be divided into: *i*) feature-based approaches, in which a holistic vector representation consisting of global features is derived from the acquired signature trajectories [3–6], and *ii*) function-based approaches, in which time sequences describing local properties of the signature are used for recognition (e.g., position trajectory, velocity, acceleration, force, or pressure) [6–9].

Worth noting, one major research trend in biometric verification is the successful exploitation of the different information levels embodied in the biometric signal at hand. This is usually done by combining the different confidences provided by a number of different machine experts [10, 11] each one working at a different information level. Examples can be found regarding other biometrics like fingerprint verification, where the combined use of local (e.g., minutiae-based) and global (e.g, ridge-based) approaches has been shown to improve verification performance [12]. Regarding on-line signature verification, some works on multi-level approaches are [6, 13].

In the present contribution, we extend our previous work on local function-based recognition [8, 9, 14] by developing a new global feature-based approach. We then combine both systems at the decision level. Results using all the 16500 signatures from the 330 subjects of the publicly available MCYT Bimodal Biometric Database [15] are presented, yielding remarkable performance both with random and skilled forgeries.

The global machine expert is described in Sect. 2 with emphasis on the feature-based representation. The local expert is briefly sketched in Sect. 3. The decision-level combination strategies compared in this work (see Fig. 1 for the system model) are introduced in Sect. 4. Experimental procedure and results are given in Sect. 5. Conclusions are finally drawn in Sect. 6.

2 Machine Expert Based on Global Information

The subsystem exploiting global information is based on the precedent works [3–5]. Our contributions in this regard are as follows: *i*) the set of features described in these works (approximately 70 considering the three works) is extended, leading to a 100-dimensional feature vector representation, *ii*) feature selection experiments on the complete set are carried out, obtaining experimental evidence on the individual relative discriminative power of the proposed and the existing features, and *iii*) a non-parametric statistical recognition strategy based on Parzen windows is used, obtaining remarkable performance in the common case of small training set size.

Feature extraction. The complete set of global features is given in Table 1. Note that an on-line signature acquisition process capturing position trajectories and pressure signals both at pen-down and pen-up intervals is supposed. Otherwise, the feature set should be reduced discarding features based on trajectory signals during pen-ups (e.g., features 32 and 41). Even though the given set has demonstrated to be robust to the common distortions encountered in the handwritten scenario, note that not all the parameters are fully rotation/scale invariant, so either a controlled signature acquisition is assumed (as in MCYT database, where users where asked to sign within grid guidelines) or translation/rotation registration should be performed before computing them. Although pen inclination has shown discriminative power in some works [16], and pen inclination signals are available in MCYT [15], no features based on pen inclination are introduced in the proposed set (as pen inclination turned out to be highly unstable in previous experiments [9]). The features in Table 1 are sorted by individual inter-user discriminative power as described in Sect. 5.2.

Similarity computation. Given the feature vectors of the training set of signatures of a client $\mathcal{C}$, a non-parametric estimation $\lambda_{\mathcal{C}}^{\mathrm{PWC}}$ of their multivariate probability density function is obtained by using Parzen Gaussian Windows [17]. On the other hand, given the feature vector $\mathbf{o}_T$ of an input signature and a claimed identity $\mathcal{C}$ modelled as $\lambda_{\mathcal{C}}^{\mathrm{PWC}}$, the following similarity matching score is used

$$s_{\mathrm{PWC}} = p\left(\mathbf{o}_T | \lambda_{\mathcal{C}}^{\mathrm{PWC}}\right) \tag{1}$$

which is consistent with Bayes estimate in case of equal prior probabilities [17].

3 Machine Expert Based on Local Information

A brief description of the local function-based approach is given in this section, for more details we refer to [8, 9].

Feature extraction. Signature trajectories are first preprocessed by subtracting the center of mass followed by a rotation alignment based on the average path tangent angle. The signature is parameterized then as the following set of 7 discrete-time functions $\{x[n], y[n], p[n], \theta[n], v[n], \rho[n], a[n]\}$, $n = 1, \ldots, N_s$, sampling frequency = 100 Hz., and first order time derivatives of all of them, totaling 14 discrete functions; N_s, p, θ, v, ρ and a stand respectively for signature time duration in time samples, pressure, path tangent angle, path velocity magnitude, log curvature radius and total

Table 1. Set of global features considered in this work sorted by individual discriminative power as described in Sect. 5.2 (T denotes time interval, t denotes time instant, N denotes number of events, θ denotes angle, **bold** denotes novel feature, *italic* denotes adapted from [3–5], roman denotes extracted from [3–5]). Note that all notations are either defined or referenced somewhere in the table (e.g., j is defined and referenced in **4**, Δ is defined in *15*, histograms in 51, 61, 70, 93, ... are referenced in 34, etc.)

Ranking	Feature Description	Ranking	Feature Description
1	signature total duration T_s	*2*	N(pen-ups)
3	N(sign changes of dx/dt and dy/dt)	**4**	average jerk $\bar{j}$ [3]
5	standard deviation of a_y	**6**	standard deviation of v_y
7	(standard deviation of y)/Δ_y	**8**	N(local maxima in x)
9	standard deviation of a_x	**10**	standard deviation of v_x
11	j_{rms}	**12**	N(local maxima in y)
13	t(2nd pen-down)/T_s	14	(average velocity $\bar{v}$)/$v_{x,\max}$
15	$\frac{A_{\min}=(y_{\max}-y_{\min})(x_{\max}-x_{\min})}{(\Delta_x=\sum_{i=1}^{\text{pen-downs}}(x_{\max}\|_i-x_{\min}\|_i))\Delta_y}$	*16*	$(x_{\text{last pen-up}}-x_{\max})/\Delta_x$
17	$(x_{\text{1st pen-down}}-x_{\min})/\Delta_x$	*18*	$(y_{\text{last pen-up}}-y_{\min})/\Delta_y$
19	$(y_{\text{1st pen-down}}-y_{\min})/\Delta_y$	**20**	$(T_w\bar{v})/(y_{\max}-y_{\min})$
21	$(T_w\bar{v})/(x_{\max}-x_{\min})$	*22*	(pen-down duration T_w)/T_s
23	$\bar{v}/v_{y,\max}$	*24*	$(y_{\text{last pen-up}}-y_{\max})/\Delta_y$
25	$\frac{T((dy/dt)/(dx/dt)>0)}{T((dy/dt)/(dx/dt)<0)}$	26	$\bar{v}/v_{\max}$
27	$(y_{\text{1st pen-down}}-y_{\max})/\Delta_y$	*28*	$(x_{\text{last pen-up}}-x_{\min})/\Delta_x$
29	(velocity rms v)/$v_{\max}$	*30*	$\frac{(x_{\max}-x_{\min})\Delta_y}{(y_{\max}-y_{\min})\Delta_x}$
31	(velocity correlation $v_{x,y}$)/$v^2_{\max}$ [4]	*32*	$T(v_y>0\|\text{pen-up})/T_w$
33	$N(v_x=0)$	34	direction histogram s_1 [4]
35	$(y_{\text{2nd local max}}-y_{\text{1st pen-down}})/\Delta_y$	36	$(x_{\max}-x_{\min})/x_{\text{acquisition range}}$
37	$(x_{\text{1st pen-down}}-x_{\max})/\Delta_x$	*38*	$T(\text{curvature}>\text{Threshold}_{\text{curv}})/T_w$
39	(integrated abs. centr. acc. a_{Ic})/$a_{\max}$ [4]	40	$T(v_x>0)/T_w$
41	$T(v_x<0\|\text{pen-up})/T_w$	*42*	$T(v_x>0\|\text{pen-up})/T_w$
43	$(x_{\text{3rd local max}}-x_{\text{1st pen-down}})/\Delta_x$	*44*	$N(v_y=0)$
45	(acceleration rms a)/$a_{\max}$	*46*	(standard deviation of x)/Δ_x
47	$\frac{T((dx/dt)(dy/dt)>0)}{T((dx/dt)(dy/dt)<0)}$	48	(tangential acceleration rms a_t)/$a_{\max}$
49	$(x_{\text{2nd local max}}-x_{\text{1st pen-down}})/\Delta_x$	*50*	$T(v_y<0\|\text{pen-up})/T_w$
51	direction histogram s_2	**52**	t(3rd pen-down)/T_s
53	(max distance between points)/$A_{\min}$	**54**	$(y_{\text{3rd local max}}-y_{\text{1st pen-down}})/\Delta_y$
55	$(\bar{x}-x_{\min})/\bar{x}$	56	direction histogram s_5
57	direction histogram s_3	58	$T(v_x<0)/T_w$
59	$T(v_y>0)/T_w$	60	$T(v_y<0)/T_w$
61	direction histogram s_8	62	(1st $t(v_{x,\min})$)/T_w
63	direction histogram s_6	**64**	T(1st pen-up)/T_w
65	spatial histogram t_4	66	direction histogram s_4
67	$(y_{\max}-y_{\min})/y_{\text{acquisition range}}$	68	(1st $t(v_{x,\max})$)/T_w
69	(centripetal acceleration rms a_c)/$a_{\max}$	**70**	spatial histogram t_1
71	θ(1st to 2nd pen-down)	*72*	θ(1st pen-down to 2nd pen-up)
73	direction histogram s_7	**74**	$t(j_{x,\max})/T_w$
75	spatial histogram t_2	**76**	$j_{x,\max}$
77	θ(1st pen-down to last pen-up)	**78**	θ(1st pen-down to 1st pen-up)
79	(1st $t(x_{\max})$)/T_w	**80**	$\bar{j}_x$
81	T(2nd pen-up)/T_w	82	(1st $t(v_{\max})$)/T_w
83	$j_{y,\max}$	**84**	θ(2nd pen-down to 2nd pen-up)
85	$j_{\max}$	**86**	spatial histogram t_3
87	(1st $t(v_{y,\min})$)/T_w	**88**	(2nd $t(x_{\max})$)/T_w
89	(3rd $t(x_{\max})$)/T_w	90	(1st $t(v_{y,\max})$)/T_w
91	$t(j_{\max})/T_w$	**92**	$t(j_{y,\max})/T_w$
93	direction change histogram c_2	**94**	(3rd $t(y_{\max})$)/T_w
95	direction change histogram c_4	**96**	$\bar{j}_y$
97	direction change histogram c_3	*98*	θ(initial direction)
99	θ(before last pen-up)	**100**	(2nd $t(y_{\max})$)/T_w

acceleration magnitude. A claim-dependent linear transformation is finally applied to each discrete-time function so as to obtain zero mean and unit standard deviation function values.

Similarity computation. Given the parameterized enrollment set of signatures of a client $\mathcal{C}$, a left-to-right Hidden Markov Model $\lambda_{\mathcal{C}}^{\mathrm{HMM}}$ is estimated [17]. No transition skips between states are allowed and multivariate Gaussian Mixture density observations are used. On the other hand, given the function-based representation $\mathbf{O}_T$ of a test signature (with a duration of N_s time samples) and a claimed identity $\mathcal{C}$ modelled as $\lambda_{\mathcal{C}}^{\mathrm{HMM}}$, the following similarity matching score is used

$$s_{\mathrm{HMM}} = \frac{1}{N_s} \log p \left(\mathbf{O}_T | \lambda_{\mathcal{C}}^{\mathrm{HMM}} \right) \tag{2}$$

4 Fusion of Global and Local Information

Two sound theoretical frameworks for combining classifiers with application to biometric verification are described in [10] and [11]. More recent works are reviewed in [1]. These works conclude that the weighted average is a good way of combining the similarity scores provided by the different experts (under some mild assumptions that may not hold in practice).

In this work, fusion strategies based on the max and sum rules [11] are compared. Similarity scores given by the global and local experts are normalized to zero mean and unit standard deviation before fusion.

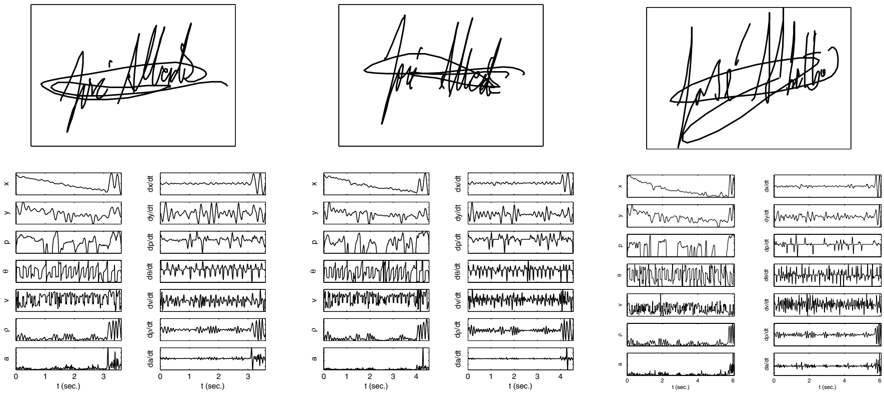
5 Experiments

5.1 Database and Experimental Protocol

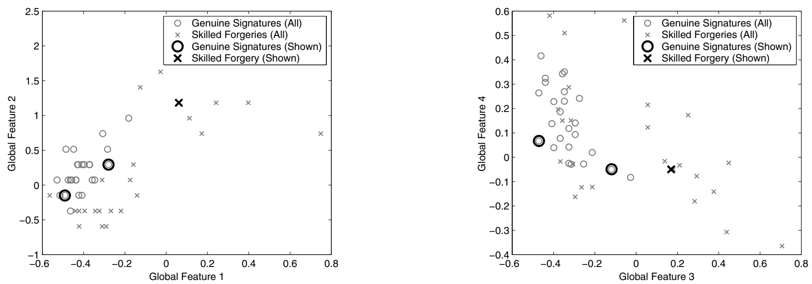
All the signatures of the MCYT database [15] are used for the experiments (330 signers with 25 genuine signatures and 25 skilled forgeries per signer –forgers are provided the signature images of the clients to be forged and, after training with them several times, they are asked to imitate the shape with natural dynamics, i.e., without breaks or slowdowns). Two examples of genuine signatures (left and central columns) and one forgery (right column) are given in Fig. 2.

Signature corpus is divided into training and test sets. In case of considering skilled forgeries, training set comprises either 5 or 20 genuine signatures and test set consist of the remaining samples (i.e., 330×20 or 330×5 client, respectively, and 330×25 impostor similarity test scores). In case of considering random forgeries (i.e., impostors are claiming others' identities using their own signatures), client similarity scores are as above and we use one signature of every other user as impostor data so the number of impostor similarity scores is 330×329.

Overall system performances using *a posteriori* user-independent decision thresholds are reported by means of DET plots [19]. Average EER tables for *a posteriori* user-dependent thresholds are also given following the operational



Two genuine signatures (left and central columns) and one skilled forgery (right column) for a client using name and complex flourish [18]. The function-based description used for local recognition is depicted below each signature.



Best individually performing global features, i.e., 1st versus 2nd (left), and 3rd versus 4th (right), are depicted for all the signatures of the user above. Features from the genuine signatures and forgery above are highlighted.

Fig. 2. Signature examples from MCYT corpus together with their extracted features

procedure proposed in [20] for computing the individual EER of each user. For more details on *a priori* and *a posteriori* decision thresholding techniques and their application to signature verification, we refer the reader to [14].

5.2 Feature Selection

Due to the high number of proposed features (100), and the large number of signatures considered (16500), features have been ranked according to scalar inter-user class separability. Feature selection is then based on selecting an increasing number of ranked features.

For each feature F_k, $k = 1, \ldots, 100$, we compute the scalar Mahalanobis distance [17] d^{M}_{i,F_k} between the mean of the F_k-parameterized training signatures of client i, $i = 1, \ldots, 330$, and the F_k-parameterized set of all training signatures

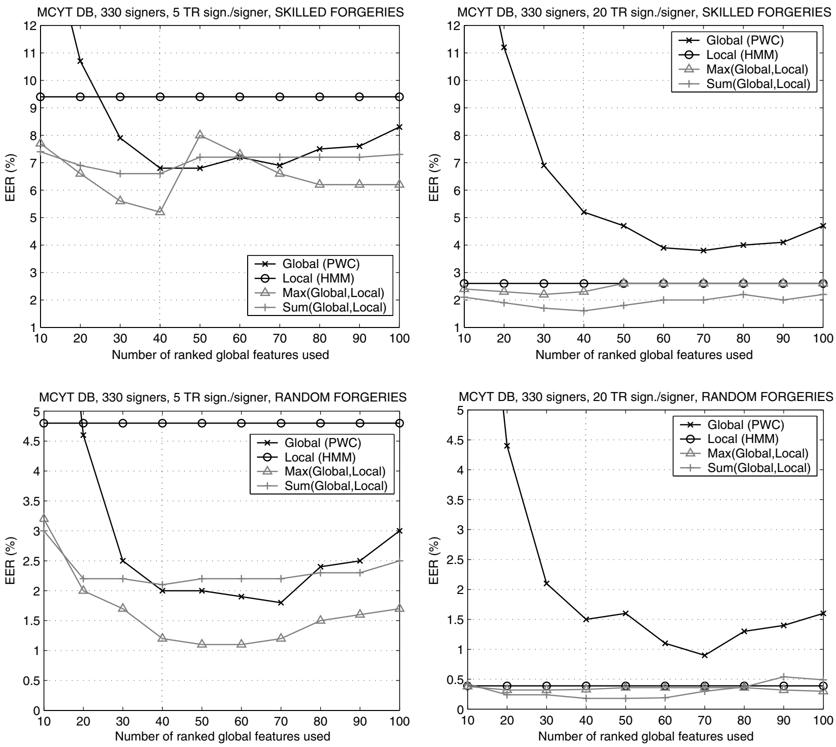


Fig. 3. Verification performance using *a posteriori* user-independent decision thresholding for an increasing number of ranked global features

from all users. Features are then ranked according to the following inter-user class separability measure $S(F_k)$

$$S(F_k) = \sum_{i=1}^{330} \sum_{j=1}^{330} |d^{\mathrm{M}}_{i,F_k} - d^{\mathrm{M}}_{j,F_k}| \tag{3}$$

5.3 Results

In Fig. 3, verification performance results in four common conditions (few/many training signatures and skilled/random forgeries) are given for *i*) the global expert with an increasing number of ranked global features, *ii*) the local expert, and *iii*) their combination through max and sum rules.

Worth noting, the system based on global analysis outperforms the local approach when training with 5 signatures, and the opposite occurs when training with 20 signatures. The two systems are also shown to provide complementary information for the verification task, which is well exploited in the cases of small and large training set sizes using the max and sum rules respectively. Also interestingly, we have found a good working point of the combined system in the

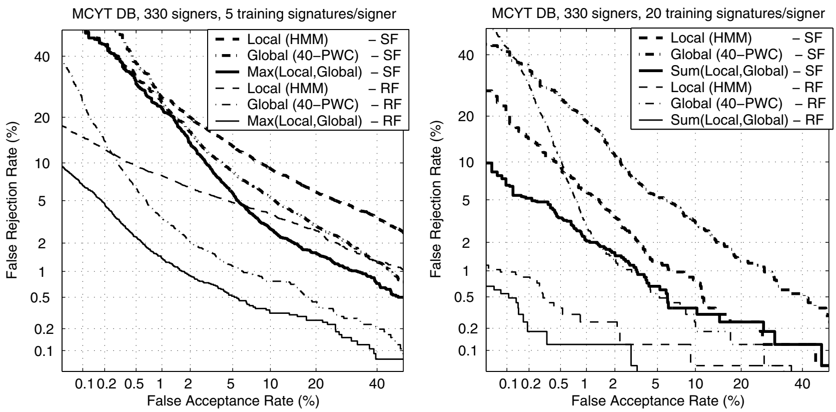


Fig. 4. Verification performance for *a posteriori* user-independent decision thresholding

four conditions depicted in Fig. 3 when using the first 40 ranked features for the global approach. This is highlighted with a vertical dashed line. Detection trade-off curves for this working point are given in Fig. 4.

Verification performances of individual and combined systems for *a posteriori* user-independent and user-dependent decision thresholds are given in Tables 2 and 3. User-dependent decision thresholding leads to error rates significantly lower than user-independent decision thresholding. This effect has also been noticed in previous works [7, 14]. When using user-dependent thresholds and for the four conditions considered, the local approach is found to outperform the global one and the sum rule performs better than the max rule. Also remarkably, the global approach is found to be robust to the score misalignment produced by the strong user-dependencies found in signature recognition, as performance difference between using user-dependent and user-independent thresholds is not as high as the one found for the local approach.

6 Conclusions

An on-line signature recognition system based on fusion of local and global analysis of input signatures has been described. Global analysis is based on a novel feature-based description of signatures and non-parametric statistical modeling based on Parzen windows. Local analysis relies on a function-based approach and parametric statistical modeling through Hidden Markov Models.

Feature selection and performance experiments are conducted on the large MCYT database comprising 16500 different signatures from 330 contributors. Verification performance on random and skilled forgeries has been given for user-specific and global decision thresholds. The machine expert based on global information is shown to outperform the system based on local analysis in the case of small training set size and user-independent thresholds. It has been also found to be quite robust to the severe user-dependencies encountered in signature

Table 2. Verification performance with **5 training signatures** for *a posteriori* user-independent and user-dependent decision thresholding. Average EERs in %

	skilled forgeries		**random forgeries**	
	user-indep.	user-dep.	user-indep.	user-dep.
Local (HMM)	9.39	2.51	4.86	0.59
Global (40 Feat. + PWC)	6.89	5.61	2.02	1.27
Combined (MAX)	**5.29**	2.39	**1.23**	0.41
Combined (SUM)	6.67	**2.12**	2.14	**0.24**

Table 3. Verification performance with **20 training signatures** for *a posteriori* user-independent and user-dependent decision thresholding. Average EERs in %

	skilled forgeries		**random forgeries**	
	user-indep.	user-dep.	user-indep.	user-dep.
Local (HMM)	2.60	**0.51**	0.39	0.0041
Global (40 Feat. + PWC)	5.21	2.38	1.58	0.3180
Combined (MAX)	2.30	0.53	0.33	0.0064
Combined (SUM)	**1.70**	0.55	**0.18**	**0.0005**

recognition. The two proposed systems are also shown to give complementary recognition information which has been exploited with simple rules. Relative improvements in the verification performance as high as 44% (for skilled forgeries) and 75% (for random forgeries) have been obtained as compared to state-of-the-art works[1].

Future work includes applying feature subset selection methods to the proposed set of global features, and exploiting the user-dependencies found in the global and and local approaches through target-dependent score normalization procedures [14] and user-dependent fusion approaches [22].

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[1] The local system has participated in SVC 2004 (with minor modifications regarding score normalization [14]), where was ranked as the system in first and second place, for random and skilled forgeries, respectively [21].

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