Static Signature Verification by Optical Flow Analysis

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Abstract—**This paper presents a new approach for static signature verification based on optical flow. In the first part of the paper, optical flow is used for estimating local stability of static signatures. In the second part, signature verification is performed by the analysis of optical flow, using an alternating decision tree. The experimental tests, carried out on signature of the GPDS database, demonstrate the validity of this approach and highlight some direction for further research.**

Index Terms—**Static Signature Verification, Local Stability, Optical Flow.**

I. INTRODUCTION

HANDWRITTEN signatures occupy a very special place in biometrics. Unlike other biometric traits, handwritten signatures have long been established as the most widespread means of personal verification. Signatures are generally recognized as a legal means of verifying an individual's identity by administrative and financial institutions. Moreover, verification by signature analysis requires no invasive measurements and people are familiar with the use of signatures in their daily life [1, 2, 3].

Unfortunately, a handwritten signature is the result of a complex generation process. The rapid writing movement underlying signing is determined by a motor program stored into the brain of the signer and realized though his/her writing system (arm, hand, etc.) and writing devices (paper, pen, etc.). Therefore, a signature image strongly depends on the psychophysical state of the signer and the conditions under which the signature apposition process occurs [4, 5].

The net result is that signature variability is one of the most relevant issues that must be faced to develop accurate signature verification systems. In general, two types of variability can be distinguished in signing: short-term variability and long-term variability. Short-term modifications depend on the psychological condition of the writer and on the writing conditions. Long-term modifications depend on the alteration of the physical writing system of the signer (arm and hand, etc.) as well as on the modification of the motor program in his/her brain [5, 6]

In literature, the approaches proposed for the analysis of local stability are mainly devoted to dynamic signatures. A local stability function can be obtained by using DTW to match a genuine signature against other authentic specimens. Each matching is used to identify the Direct Matching Points (DMPs), that are unambiguously matched points of the genuine signature. Thus, a DMP can indicate the presence of a small stable region of the signature, since no significant distortion has been locally detected. The local stability of a point of a signature is determined as the average number of time it is a DMP, when the signature is matched against other genuine signatures. Following this procedure low- and high-stability regions are identified [7, 8, 9] in the selection of reference signatures [10, 11] and verification strategies [12, 13].

A client-entropy measure has been also proposed to group and characterize signatures in categories that can be related to signature variability and complexity. The measure, that is based on local density estimation by a HMM, can be used to access whether a signature contains or not enough information to be successfully processed by any verification system [14, 15, 16].

Other types of approaches estimate the stability of a set of common features and the physical characteristics of signatures which they are most related to, in order to obtain global information on signature repeatability which can be used to improve the verification systems [17, 18]. In general, these approaches have shown that there is a set of features that remain stable over long time periods, while there are other features which change significantly in time [19, 20]. Of course, since intersession variability is one of the most important causes of the deterioration of verification performances, specific parameter-updating approaches have been considered [18, 19, 20].

Concerning static signatures, a multiple pattern-matching strategy has been recently proposed to determine - at local level - the degree of stability of each region of a signature [21, 22, 23]. In this paper the optical flow is used to estimate the local stability of the signature images. In addition, the optical flow is also considered for signature verification, using an alternate decision tree classifier. The experimental results, carried out on signatures of the GPDS database, demonstrate the validity of the approach with respect to other techniques in literature.

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II. STATIC SIGNATURE ANALYSIS BY OPTICAL FLOW

Two categories of signature verification systems can be

identified, depending on the data acquisition method [1]: static (off-line) systems and dynamic (on-line) systems. Static systems perform data acquisition after the writing process has been completed. In this case, the signature is represented as a grey level image I(x,y), where I(x,y) denotes the grey level at the position (x,y) of the image. The results is that static systems involve the treatment of the spatio-luminance representation of a signature image. Therefore, no dynamic information is available on the signing process when static signatures are considered [1, 2]. Notwithstanding, static signature verification is very important for many application fields, like automatic bank-check processing, insurance form processing, document validation and so on. When static signatures are considered, information on local stability is an important parameters for verification aims. In this paper local stability is analyzed by optical flow. Optical flow can be defined as the distribution of apparent velocities of movement of brightness patterns in an image I. As discussed in the excellent paper of O'Donovan [24], optical flow has been used for a variety of computer vision applications like autonomous navigation, object tracking, traffic analysis, image segmentation and stabilization.

In this paper we consider the approach of Horn and Shunck for optical flow estimation [25]. In this case optical flow is determined through the minimization of the energy functional [25]:

$$E = \iint \left[(I_x u + I_y v + I_t)^2 + \alpha^2 (\|\nabla u\|^2 + \|\nabla v\|^2) \right] dxdy$$

where

- I_x, I_y and I_t are the derivatives of the image intensity values along the x, y and time dimensions, respectively;
- $[u_{ij}(x,y), v_{ij}(x,y)]^T$ is the optical flow vector;
- α is the regularization parameter.

In other words, the functional E consists of two terms: the first term is the optical flow constraint equation and the second is the smoothness constraint which is multiplied by the regularization parameter α.
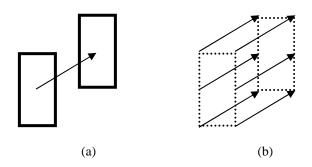

(a)   (b)

Fig. 1. Example of Optical Flow.

Horn and Schunk work out the previous minimization problem using a digital estimation of the Laplacian for the optical flow gradients, to get a large system with two equations for each pixel that can be solved by the Jacobi method [25].

Figure 1 shows an example of Optical Flow: in (a) the movement of a rectangle over two frames is shown; in (b) the optical flow vectors is reported.

III. ANALYSIS OF STABILITY OF STATIC SIGNATURES

In the next section, optical flow analysis is applied to the analysis of regional stability of static signatures. For this purpose, after the preprocessing phase, in which each signature is binarized and normalized to a fixed rectangular area, the identification of the stable regions starts.

In particular, let be:

- I^g_i the set of N genuine signatures of a writer, i=1,2,,...N;
- $[u_{ij}(x,y), v_{ij}(x,y)]^T$ the optical flow between I^g_i and I^g_j.

Now, if we consider the i-th signature I^g_i of a signer, for each pixel $I^g_i(x,y)$ we can consider the sets of optical flow vectors defined as:

$$U_i = \{u_{ij}(x,y) \mid j=1,2,\ldots,N; j \neq i \}$$

$$V_i = \{v_{ij}(x,y) \mid j=1,2,\ldots,N; j \neq i \}.$$

The stability (S) of $I^g_i(x,y)$ can be estimated as:

$$S(I^g_i(x,y)) = \sqrt{\sigma^2_u + \sigma^2_v}$$

being σ_u and σ_v the standard deviation of U_i and V_i, respectively.

IV. SIGNATURE STABILITY BY OPTICAL FLOW

Optical flow provides useful information on local dissimilarity among signature images. In this paper this information is used for signature verification aims. In particular, signature verification is performed by an alternating decision tree (ADT). ADT, that was first introduced by Freund and Mason [26], consists of decision nodes and prediction nodes. Decision nodes specifies a predicate condition, prediction nodes contain a single number. Classification by an ADT is performed by following all paths for which all decision nodes are true and summing any prediction nodes that are traversed. More precisely, in our approach, let be:

- I^g_i the set of N genuine signatures of a writer, i=1,2,,...N;
- I^f_p the set of M forgery signatures of a writer, p=1,2,...,M.

In the enrollment stage the ADT is trained by using the optical flow vectors concerning intra-class and inter-class variability:

- $[u_{ij}(x,y), v_{ij}(x,y)]^T$ the optical flow between I^g_i and I^g_j , i,j=1,2,...,N, i≠j (intra-class variability);
- $[u_{ik}(x,y), v_{ik}(x,y)]^T$ the optical flow between I^g_i and I^g_k , i=1,2,...,N, k=1,2,...,M (inter-class variability).
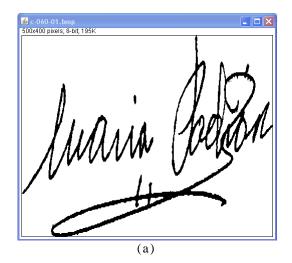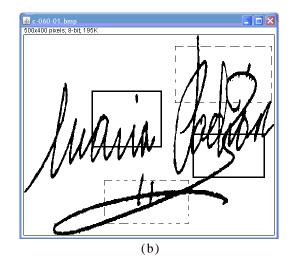
(a)   (b)

Fig. 2. Example Analysis of Local Stability.

V. EXPERIMENTAL RESULTS

The experimental results have been carried out using static signatures of the GPDS database. The database contains 16200 signatures from 300 individuals: 24 genuine signatures and 30 forgeries for each individual [27]. The result here reported concerns only twenty-five signers since other experiments are still in progress. For each signer the stability analysis is performed, according to the approaches described in Section III. Figure 2 shows a genuine specimen (a) and the result of the stability analysis obtained by optical flow (b). High stability regions are marked by continuous-line rectangles, low stability regions are marked by dotted-line rectangles. In this case the stability analysis has been achieved by considering the three optical flows in Figure 3, obtained by computing the optical flows between the signature in Figure 2a and other three genuine specimens.
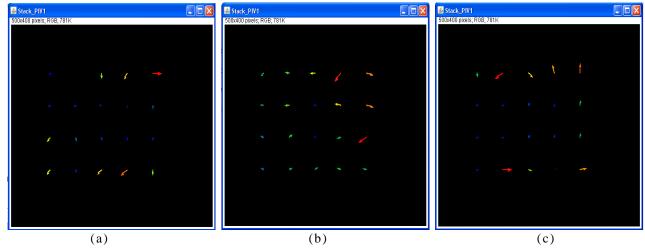
Signature verification has been carried out by considering, for each signer, N=5 genuine signatures (I^g_i, i=1,…,5) and M=4 forgeries (I^f_i, i=1,..,4) for training the ADT. Therefore,
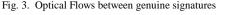
$\binom{N}{2}=10$ optical flows between genuine signatures and N·M=20 optical flows between genuine signatures and forgeries are used for training. For testing, fourteen genuine and fourteen forged signatures are considered. In the testing stage, the optical fields $[u_{ti}(x,y), v_{ti}(x,y)]^T$ between the test signature I^t and each genuine signature I^g_i, i=1,2,…,N, are computed. Each one of the N optical flows is provided to the ADT that returns a verification results r_{ti}. The N results are combined according to the majority vote strategy, in order to define the final verification result for the test signature I^t.

The results, in terms of Type I - False Rejection Rate (FRR) and Type II - False Acceptance Rate (FAR) are reported in Table 1. On average we register a Type I error rate equal to 23% and a Type II error rate equal to 20%. Figure 4 shows an example of optical flow between two genuine specimens. Figure 5 shows the optical flow between a genuine specimen and a forgery. The great amount of deformation is clearly visible when the optical flow is performed between a genuine signature and a forgery.

(a)   (b)   (c)

Fig. 3. Optical Flows between genuine signatures

TABLE I
Experimental Results

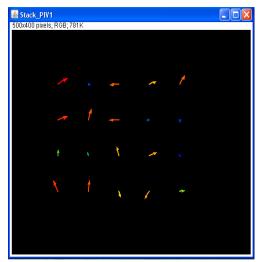| Author	PERFORMANCE	
n.	FRR	FAR
1	14%	36%
2	0%	0%
3	29%	0%
4	43%	57%
5	29%	14%
6	29%	43%
7	0%	0%
8	57%	14%
9	29%	57%
10	0%	0%
11	21%	29%
12	14%	0%
13	29%	50%
14	21%	14%
15	0%	7%
16	14%	14%
17	57%	29%
18	43%	36%
19	0%	0%
20	21%	7%
21	14%	0%
22	14%	14%
23	57%	36%
24	36%	43%
25	14%	7%

Fig. 5. Optical Flow: genuine vs false

VI. CONCLUSION

In this paper optical flow is considered as a tool for static signature analysis. In the first part of the paper local stability in static signatures is analyzed by optical flow analysis. In the second part, optical flow vectors between test signature and genuine specimens are considered to verify the authenticity of a test signature, using an alternate decision tree. Some results carried out on static signatures extracted from the GPDS database demonstrate the new approach is worth consideration for further research. Of course, more experimental results are necessary to verify the effectiveness of the proposed approach and - in particular - to determine the capability of the Optical Flow in recognizing short-term and long-term variability as well as for evaluating the extent to which stability depends on the signature type and signer characteristics.

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Fig. 4. Optical Flow: genuine vs genuine

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