A client-entropy measure for on-line signatures

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A CLIENT-ENTROPY MEASURE FOR ON-LINE SIGNATURES

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Abstract— **In this article, we propose an original way to characterize information content in Online Signatures through a client-entropy measure based on local density estimation by a Hidden Markov Model. We show that this measure can be used to categorize signatures in visually coherent classes that can be related to complexity and variability criteria. Besides, the generated categories are coherent across four different databases: BIOMET, MCYT-100, BioSecure data subsets DS2 and DS3. This measure allows a comparison of databases in terms of clients' signatures according to their information content.**

Keywords; On-line signature; entropy; complexity; variability; signature categorization

I. INTRODUCTION

In all the existing biometric modalities, performance evaluation of recognition systems is performed on databases, and systems themselves are tuned in development subsets of data according to a given protocol. This "algorithm evaluation framework" found in Pattern Recognition tasks in general, has made of databases one of the major concerns of the scientific community. As an illustration of this, only in the field of Biometrics, significant efforts have been carried out to collect databases and define evaluation protocols for algorithm comparison in several modalities. This has been done since a long time by the U.S. National Institute of Standards and Technology (NIST) [1] and launched recently in Europe by the European BioSecure Network of Excellence [2].

Now focusing in the Automatic Online Signature Verification field, two international evaluations have been carried out on databases of very different types. One is that of the First International Signature Verification Competition in 2004 (SVC'2004) [3, 4], that was acquired on a digitizing tablet and mixes different cultural types of signatures, namely asian and western signatures; the other is the Online Signature Database of the BioSecure Multimodal Evaluation Campaign in 2007 (BMEC'2007), denoted as DS3 (for Third Data Set of the whole data collection), acquired on a mobile platform thanks to a Personal Digital Assistant (PDA) [5]. These evaluations have been very stimulating and positive for the community; nevertheless, it is still difficult to understand their scope, since the quality of client signatures has not been measured.

Our aim in this paper is to go one step forward in this direction by proposing a novel intra-personal measure of the degree of "disorder" or "chaos" associated to the signature of a person, opposed to its "information content". A possible way to tackle this question is to use an entropy measure [6]. The entropy measure that we propose is not designed to quantify the discriminative qualities of a given signature with respect to other signatures, as a relative entropy measure can do [6]; it is actually designed to assess whether a signature contains or not enough information to be processed by any recognition system. This explains why only client signatures are used to generate the intra-personal entropy measure that we propose in this paper.

Entropy measures the uncertainty related to a random variable, relying on its distribution. The first question raised is how to model an online signature by a random variable; the second question is how to estimate its distribution. The random variable is discrete in this case, and we choose to consider as possible values the raw Cartesian coordinates *(x,y)* as these are the only available features in all types of databases, whether acquired on fixed platforms (as digitizing tablets) or on mobile platforms (as Personal Digital Assistants). Now concerning the second question, as the online signature is piecewise stationary, it is natural to estimate the probability density locally, namely on portions of the signature. To that end, we propose to use a Hidden Markov Model [7] (HMM) as a local estimator of the probability density. To our knowledge, it is novel to measure the information content of an online signature by using the concept of entropy. However, entropy has been exploited in

the document analysis literature to measure the complexity of a character image database [8], by defining the entropy related to each pixel in the image.

Nevertheless, some authors have tried to analyze in terms of other measures than entropy, the variability and complexity in signatures. In [9], both complexity and variability criteria were proposed for off-line signature verification by a human expert. Indeed, a human operator labels signatures according to both criteria and their impact on performance is studied. In [10], off-line signature legibility and complexity were proposed as criteria to categorize signatures manually by a human expert, in 3 or 5 categories respectively. Then, using two machine experts, the influence of such criteria on performance was studied. Both of these works have in common that the labeling of signatures according to their complexity or variability in [9] and the categorization of signatures in terms of legibility and complexity in [10] are carried out by a human expert manually, not automatically. One of the major interest of our approach is to propose a quantitative measure for such categorization, following this way the road opened by other authors with different criteria. Indeed, the stability of signatures is computed in [11] by elastic matching. In the same spirit, measures of the distortion between two dynamic signatures have been proposed [12], involving the concepts of "static" and "dynamic" distortions and merging them by different strategies. On the other hand, signature analysis was also performed by means of fractal geometry leading to the emergence of complexity and legibility criteria [13].

In general, in databases, several instances of a person's signature are available. We may compute entropy on each instance independently or on an ensemble of instances. In this work, as our aim is to study relative quality of databases, we chose to consider a measure of "client-entropy" computed on several instances of a person's signature.

Four databases are used in our study: the most two widely used in the Online Signature Verification literature, BIOMET Signature subset [14] and the freely available subset of 100 users MCYT-100 of MCYT database [15], and two data sets containing the same 104 users but differing by the type of acquisition platform (digitizing tablet vs. mobile platform), the DS3 (mobile) and DS2 (fixed platform) subsets acquired in the framework of BioSecure Network of Excellence. The aim of using these two databases DS3 and DS2 is to analyze the impact of mobility conditions on the client-entropy measure that we propose.

Our methodology is the following: we first analyze signatures in each database in terms of the proposed "client-entropy" measure, generating "categories" of signatures. On the other hand, we compare the distribution of such client-entropy measures across databases in terms of two other criteria based on signature complexity and variability.

This paper is organized as follows: Section 2 presents the client-entropy measure, Section 3 focuses on the analysis of genuine signatures across databases and in particular on the generation of categories of signatures in terms of client-entropy, Section 4 is concerned with database classification in terms of our measure and Section 5 gives the conclusions of our work.

II. MEASURING "CLIENT-ENTROPY" WITH A HIDDEN MARKOV MODEL

As mentioned above, signatures are described by their raw coordinates *(x,y)*. We generate one HMM for each client using 10 genuine signatures and we consider each signature as a succession of portions, generated by its segmentation via the client-Hidden Markov Model (HMM) [7]. Therefore, we obtain as many portions in each signature as there are states in the client-HMM. Then we consider each point *(x,y)* in a given portion as the outcome of one random variable that follows a given probability mass function. Thus, the entropy associated to a given portion of a signature is represented by the entropy of an ensemble of outcomes of a random variable *Z*. Such random variable is discrete since its alphabet *A* has a finite number of values, as many as found in the Cartesian product *XxY* of all possible values of ordered pairs *(x,y)*. The cardinal of *A* is of course related to the resolution of the acquisition surface that may be a digitizing tablet or a Touch Screen in the case of a mobile acquisition platform as a Personal Digital Assistant (PDA). Each outcome of *Z=(x,y)* has a probability value attached to it; if *Z* has as probability mass function $p(z) = Pr(Z = z)$ where *z* belongs to *A*, its entropy is defined as:

$$H(Z) = -\sum_{z \in A} p(z).\log(p(z)) \qquad (1)$$

where log denotes the logarithm to the base 2.

Although the random variable *Z=(x,y)* is discrete, we take advantage of the continuous emission probability law estimated on each portion by the client-HMM. Such density is a mixture of Gaussian components. This choice is motivated by the fact that the discrete version of entropy and the continuous one (called Differential Entropy) are directly related when the density is Riemann integrable [6], which is the case as we have a linear combination of Gaussian densities. Also, a more orthodox version of *H(Z)* could have been computed by quantizing the domain of *Z* in bins and using as probability mass function, the density value obtained by the Mean Value Theorem in each bi-dimensional bin. But as the quantization is actually very fine because of the fine resolution of acquisition devices (at least 1 million pixels), we can assume that the continuous density value is close to the quantized one (the density value obtained by the Mean Value Theorem).

To compute client-entropy, we consider several genuine signatures of a given user or client, namely 10, and a personalized number of states for each HMM, computed as:

$$N = \frac{T_{total}}{M * 30} \qquad (2)$$

where T_{total} is the total number of sampled points available in the training signatures, and $M=4$ is the number of Gaussian components per state.

We ensure this way that the number of sample points per state is at least 120 in order to obtain a good estimation of the Gaussian Mixture in each state (four Gaussian components). Then, we compute following (1) the entropy per portion first (after segmentation performed by the client-HMM), by using all the sample points belonging to each portion across the 10 instances of the person's signatures. We then average the entropy over all the portions of a signature and normalize the result by the average length of the ten signatures considered to generate the client-entropy measure. Indeed, the discrete assumption for the random variable $Z=(x,y)$ makes us consider as alphabet the actual realizations of $Z=(x,y)$ in each portion (when considering the 10 genuine signatures) instead of considering all the possible values of $Z=(x,y)$ per portion.

We compared for client-entropy computation the HMM above described with a Gaussian Mixture Model (GMM) [16]. This interesting study revealed that density estimation with a GMM remains too coarse for a proper characterization of signatures in terms of the entropy measure that we propose. Indeed, the HMM allows a more precise estimation of the required probability density, because it carries out such estimation locally, on portions of the signature, this way complying with the local temporal dependencies existing on signatures. Indeed, with a GMM, the temporal ordering and the resulting local temporal dependencies present in signatures cannot be taken into account because density estimation is carried out globally.

III. ANALYSIS OF GENUINE SIGNATURES IN TERMS OF CLIENT-ENTROPY

A. Databases description

We used four databases in this work: the freely available MCYT subset of 100 persons [15], the BIOMET signature sub-corpus of 84 persons [14], and subsets of the Online Signature Databases acquired in the framework of the BioSecure Network of Excellence [2], DS3 (for Third Data Set of the whole data collection), acquired on a mobile platform, a Personal Digital Assistant (PDA) and DS2 (for Second Data Set of the whole data collection), acquired on a digitizer [5]. The subsets of DS2 and DS3 that we use in this work both contain data from the same 104 persons. The whole BioSecure Signature Subcorpus DS3 and DS2 are not yet publicly available but, acquired on several sites in Europe, they are the first on-line signature multisession databases acquired in a mobile scenario (on a PDA) for DS3 and on a digitizer for DS2. DS3 contains the signatures of 713 persons, acquired on the PDA HP iPAQ hx2790, at the frequency of 100Hz and a touch screen resolution of 1280*960 pixels. Three time functions are captured from the PDA: x and y coordinates and the time elapsed between the acquisition of two successive points. The user signs while standing and has to keep the PDA in his or her hand. Two sessions were acquired spaced of around 5 months, each containing 15 genuine signatures. The donor was asked to perform, alternatively, three times five genuine signatures and twice five forgeries. For skilled forgeries, at each session, a donor is asked to imitate five times the signature of two other persons. In order to imitate the dynamics of the signature, the forger visualized on the PDA screen the writing sequence of the signature he/she had to forge and could sign on the image of such signature in order to obtain a better quality forgery both from the point of view of the dynamics and of the shape of the signature.

On the other hand, DS2 contains data from 667 persons acquired in a PC-based offline supervised scenario and the digitizing tablet WACOM INTUOS 3 A6. The pen tablet resolution is 5080 lines per inch and the precision is 0.25 mm. The maximum detection height is 13 mm and the capture area is 270mm (width) x 216mm (height). Signatures are captured on paper using an inking pen. At each sampled point of the signature, the digitizer captures at 100 Hz sampling rate the pen coordinates, pen pressure (1024 pressure levels) and pen inclination angles (azimuth and altitude angles of the pen with respect to the tablet). This database contains two sessions, acquired two weeks apart. Fifteen (15) genuine signatures were acquired at each session as follows: the donor was asked to perform, alternatively, three times five genuine signatures and two times five skilled forgeries. For skilled forgeries, at each session, a donor is asked to imitate five times the signature of two other persons.

B. Analysis of genuine signatures: client categories

We performed on the four databases a *K*-Means for different values of *K* and reached a good separation of signatures with $K=3$ on all databases as shown in Figures 1 to 4, respectively on MCYT-100, BIOMET, DS2 and DS3. We notice visually that on the four databases, the first category of signatures, those having the highest client-entropy, contains short, simply drawn and not legible signatures, often with the shape of a simple flourish. At the opposite, signatures in the third category, those of lowest client-entropy, are the longest and their appearance is rather that of handwriting, some are even legible. In between, we notice that signatures with medium client-entropy (second

category) are longer and sometimes become legible, often showing the aspect of a complex flourish.

This categorization of signatures by client-entropy shows a link with the complexity of the hand-draw and the variability of instances of signatures. In the next section, we formalize this remark by defining two criteria.

C. Complexity and Variability criteria for comparison

The first criterion that we use in our comparative analysis with the proposed client-entropy measure is related to the complexity of the signature. It consists of a vector of five components: the number of strokes obtained by computing the number of local extrema (points where the speed estimation in the y-direction is zero), the number of cusps (points where both speed on the x and y directions are zero), the number of crossing points, the length of the signature, and the number of changes in pen direction. We consider the Euclidean norm of the vector as the indicator of complexity for each signature. We then average such measure on the 10 genuine signatures in order to generate a complexity measure for a given client.

The other criterion is related to the variability of a client's signature. We use Dynamic Time Warping [6] to this end because it uses a local paradigm to measure distortions. We compute the distances between all the possible couples of genuine signatures (45 as we consider 10 genuine signatures) and average the obtained distances to get the indicator of signature variability.

The plots in Figure 5 show for the four databases client-entropy vs. the complexity criterion and the variability criterion. We notice that signatures of highest client-entropy are highly variable according to our DTW-based criterion and of rather low complexity (spread along the variability axis). At the opposite, signatures of lowest client-entropy are more complex (spread along the complexity axis) and more stable (show low variability). We observe this is true for all the databases here considered.

Figure 1: Examples of signatures from MCYT-100 of (a) highest, (b) medium and (c) lowest client-entropy

Figure 2: Examples of signatures from BIOMET of (a) highest, (b) medium and (c) lowest client-entropy

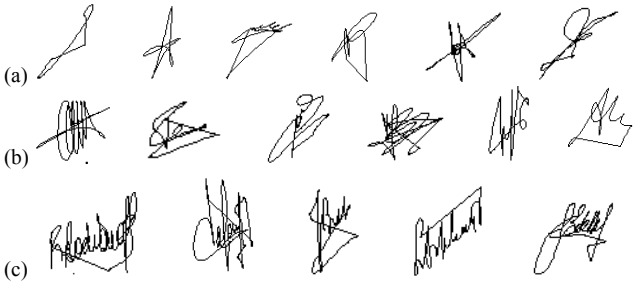

Figure 3: Examples of signatures from DS2 of (a) highest, (b) medium and (c) lowest client-entropy

Figure 4: Examples of signatures from DS3 of (a) highest, (b) medium and (c) lowest client-entropy

IV. DATABASE CLASSIFICATION ACCORDING TO CLIENT-ENTROPY

A. Fixed platform (DS2) vs. mobile platform (DS3)

We recall that BioSecure DS2 and DS3 subsets contain signatures from the same users. This allows us to analyze the impact of switching from a fixed platform to a mobile one in terms of client-entropy.

Table 1 shows that the distribution of the same users in the three entropy-based categories differs in the two data sets with 46% of users who switched categories. Indeed, some users that had a low client-entropy when signing on the fixed platform (digitizing tablet) have a higher client-entropy when signing on the mobile platform (PDA). We show in Figure 6 an example of two users that do not belong to the

same category in terms of client-entropy when signing on a fixed platform or a mobile one.

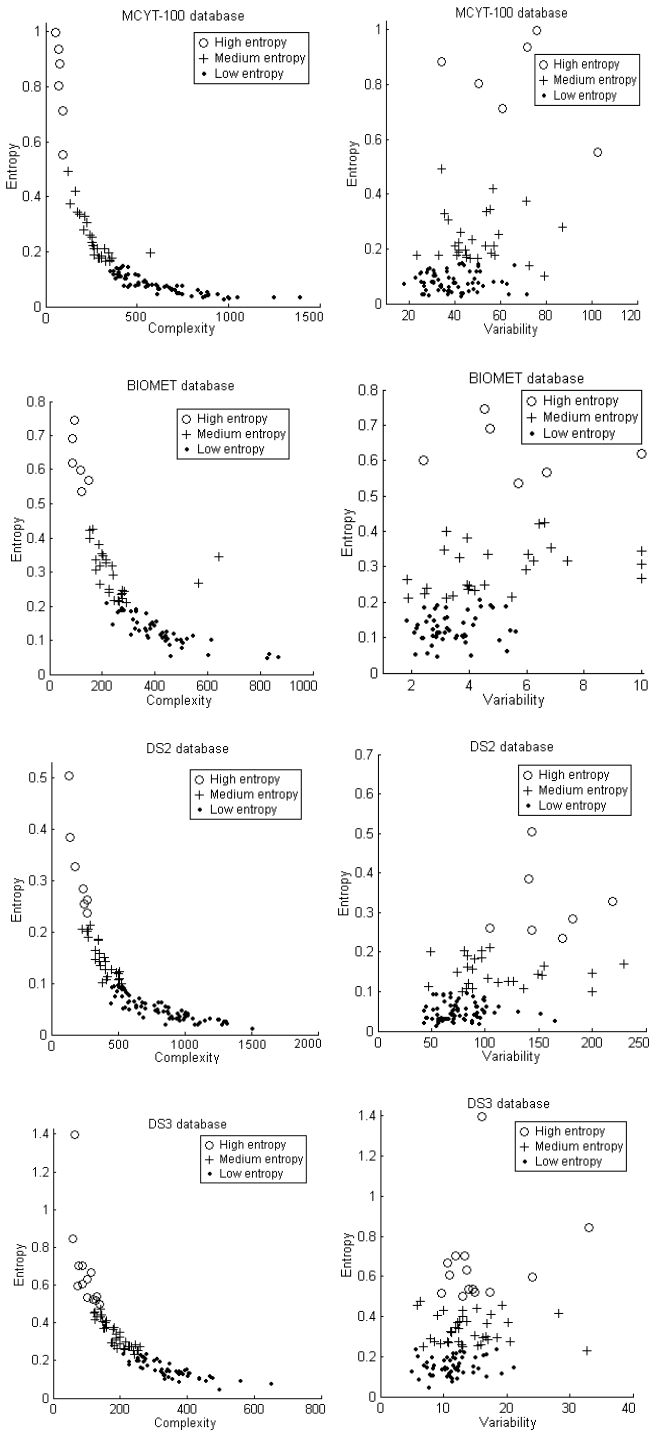

Figure 5: Client-entropy vs. Complexity (left) and Client-entropy vs. Variability (right) on the 4 databases MCYT-100, BIOMET, BioSecure DS2 and DS3 subsets for the 3 client-entropy categories : (o) stands for highest, (+) for medium, (.) for lowest client-entropy

To go further, as shown in Figure 7, the complexity of signatures in DS2 is far more important than that of DS3. Indeed, signing on a mobile platform shortens the signatures, makes them more variable and favors less complex hand-draw.

TABLE 1: THE 4 DATABASES (MCYT-100, BIOMET, BIOSECURE DS2 AND DS3 SUBSETS) IN TERMS OF NUMBER AND PERCENTAGE OF USERS IN THE 3 CLIENT-ENTROPY CATEGORIES

Number and percentage of clients	MCYT -100	BIOMET	DS2	DS3
with highest entropy	6 (6%)	6 (7.14%)	7 (6.73%)	16 (15.38%)
with medium entropy	27 (27%)	26 (30.95%)	26 (25%)	33 (31.73%)
with lowest entropy	67 (67%)	52 (61.91%)	71 (68.27%)	55 (52.89%)
Number of clients	100	84	104	104

Figure 6: Signatures of two users that change of category on DS2 and DS3; (a) from medium (left) to high client-entropy (right) and (b) from low (left) to medium client-entropy (right)

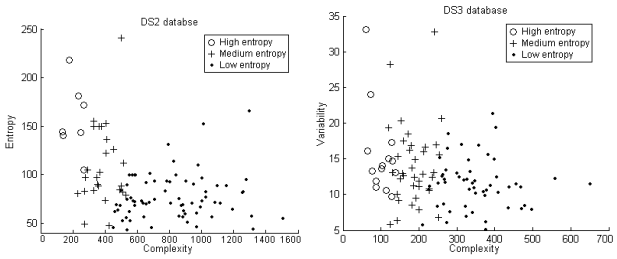

Figure 7: Variability vs. Complexity on DS2 (left) and DS3 (right) for the 3 client-entropy categories: (o) stands for highest, (+) for medium, (.) for lowest client-entropy

B. Comparing MCYT-100 and BIOMET databases

These two databases are the most widely used in the online handwritten Signature Verification literature nowadays. Our aim is to compare them in terms of client-entropy. Table 1 shows that the percentage of users with the highest client-entropy is almost twice more important in BIOMET database than in MCYT-100 database; also, the percentage of users with the lowest client-entropy is more than half of the population in MCYT-100 while it represents only one third of the population in BIOMET.

From this entropy study, we can infer that signatures in BIOMET are more variable and of lower complexity than those of MCYT-100. This is confirmed by the plot in Figure8. This makes of BIOMET a more difficult database

in terms of modeling intra-class variance compared to MCYT-100.

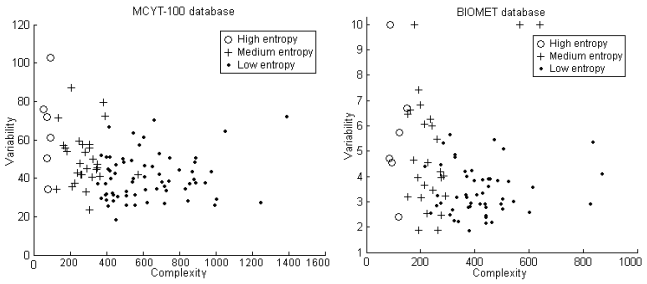

Figure 8: Variability vs. Complexity on MCYT-100 (left) and BIOMET (right) for the 3 client-entropy categories: (o) stands for highest, (+) for medium, (.) for lowest client-entropy

V. CONCLUSIONS

We have proposed in this work a novel measure of client-entropy based on Hidden Markov Model. Such measure allows obtaining categories of signatures which are coherent across several databases of different sorts. Three main categories appear opposing in the extremes highly variable, short and low information content signatures (high client-entropy) to stable, longer and complex signatures with the aspect of handwriting (low client-entropy). This interpretation is the outcome of the link that we made between client-entropy on one side and complexity and variability measures on the other side. The same behavior is observed on BIOMET, MCYT-100 and BioSecure sub-corpuses DS2 and DS3. Also, the impact of shifting from a fixed acquisition platform to a mobile one was measured in terms of increase of client-entropy on the same persons, when measured on DS2 and DS3.

Finally, we compared the client-entropy on MCYT-100 and BIOMET data sets, the most used databases in the literature. We conclude that BIOMET, as it mostly contains users showing rather high client-entropy, makes client characterization more difficult than MCYT-100.

Future work will focus on other ways of estimating client-entropy.

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