On-line Verification for Signatures of Different Sizes

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Abstract

A great number of studies concerning on-line verification systems have been conducted by researchers in the last years. However, investigations on the influence of different signature sizes on the process of signature formation are little. In fact, this kind of analysis for on-line signature verification system is been made for the first time. In this paper, in order to investigate this influence, a database containing signatures of three different sizes was created. The experimental results show that signatures of different sizes are statistically different and they can influence the feature extraction techniques. Thus, a special attention has to be taken in the implementation of global applications that use databases with signatures of different sizes.

Keywords: On-line signature verification, feature extraction and feature selection.

1. Introduction

The use of biometric authentication systems is quickly becoming a reliable alternative to security systems and document authentication. In particular, signature is still one of the most acceptable and less intrusive biometric indicators [1].

There are two types of signature verification systems according to data acquisition: on-line systems, whose data are captured dynamically through a pressure-sensitive device and off-line systems where you only have access to scanned images.

The utilization of global applications which integrate different signature databases requires a special attention due to aspects that can influence the design of the signatures. One of these aspects is the signature size. The analysis of these aspects, done in this paper, is been made for the first time in the literature. Other works have studied the influence of size in signatures; however, using off-line systems [2].

The Section 2 of the paper will show the data acquisition process; in Section 3 will be explained the features used in the system; in Section 4, the enrollment and verification process will be discussed; in Section 5, a description of all the experiments will be done; and finally in Section 6, the conclusion and the future works will be placed.

2. Data acquisition

The data were acquired from a WACOM tablet model CTE-430. A total of 1828 signatures, including forgeries of different sizes, were collected from a group of 20 people containing 6 women and 14 men of different ages. Besides, 10% of the signatures were written by left-handed people. All volunteers contributed with 20 authentic signatures of 3 different sizes: 4 small sizes (7,0cm x 1,0cm), 12 medium sizes (8,0cm x 2,0cm) and 4 large sizes (9,5cm x 4,0cm). These 3 sizes represent respectively the spaces of a Brazilian bank check, an identification document and a credit card. As can be seen in Figure 1, there is a visible difference between the signatures, mostly when we look at the large signatures.

The forgery database was divided into two kinds of forgeries: simple forgeries and skilled forgeries. In the simple forgery the forger only know how to spell the authentic signature. In the skilled forgery the forger can see the genuine signature and he also has time to practice the imitations. This database contains from 10 to 12 medium simple forgeries and 10 to 12 medium skilled forgeries per class.

The raw data available from the tablet consists of X-, Y-coordinates, pressure and time.

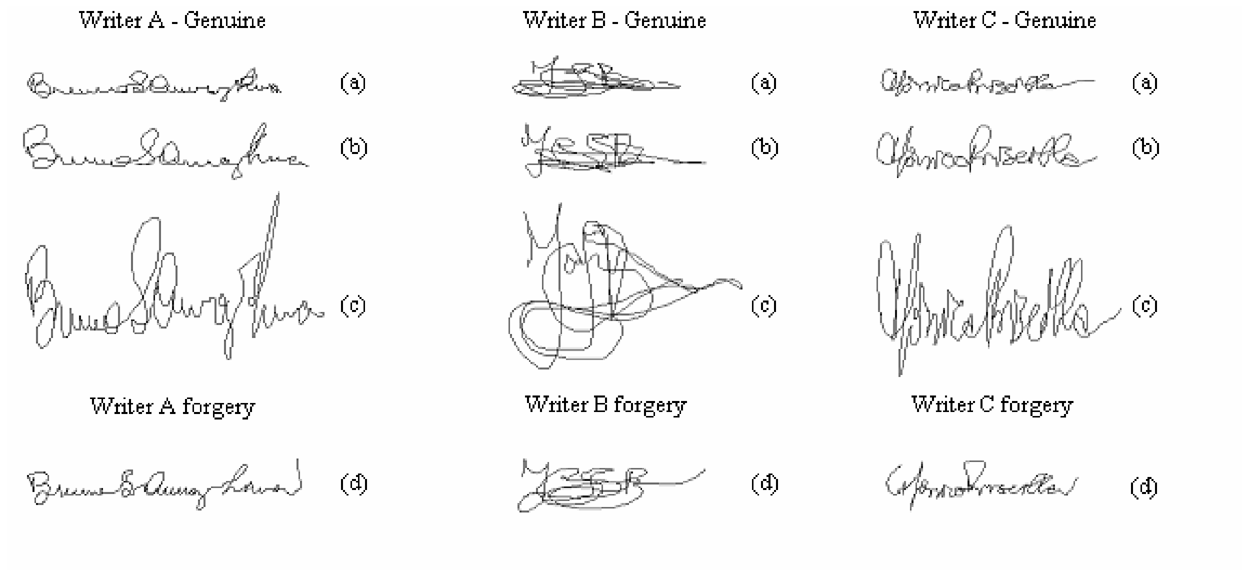

Figure 1. Some signature samples of three different classes. (a) Small signatures. (b) Medium signatures. (c) Large signatures. (d) Forged signatures.

3. Feature Extraction

A total of 35 features were implemented in this paper and they were based on a subset of features used in [3]. This set of features is based on coordinates; average speeds and duration which are confirmed to be among the most consistent features as shown in [4], which makes a comparative study of features used in on-line signature verification systems. The complete feature list can be seen in Table 1.

Table 1. List of features used.

Feature #	**Feature description**
T1	Average writing speed
T2	Maximum writing speed
T3	Time of maximum speed
T4	Total signing duration
T5	Total pen down duration
T6	Minimum horizontal writing speed
T7	Time of min. horizontal writing speed
T8	Total dots recorded
T9	Average dot execution time
T10	Number pen ups
T11	Time of 2nd pen down
T12	Duration of Vx > 0
T13	Duration of Vx < 0
T14	Duration of Vy > 0
T15	Duration of Vy < 0
T16	Average positive Vx
T17	Average negative Vx
T18	Average positive Vy
T19	Average negative Vy
T20	Total Vx = 0 events recorded
T21	Total Vy = 0 events recorded
T22	Maximum Vx – Average Vx
T23	Maximum Vy – Average Vy
T24	Maximum Vx – Minimum Vx
T25	Maximum Vx – Minimum Vy
T26	Maximum Vy – Minimum Vy
T27	Max. X time / total time of pen down
T28	Min. X time / total time of pen down
T29	(Max X - Min X) x (Max Y - Min Y)
T30	Initial X - Minimum X
T31	Final X – Maximum X
T32	Final X - Minimum X
T33	(Max X - Min X)/(Max Y - Min Y)
T34	Standard deviation of X
T35	Standard deviation of Y

All the features are invariant with respect to translation. This aspect is fundamental for our experiment since the signature samples were collected in different areas of the tablet.

4. Enrollment and Signature Verification

In the enrollment phase, a feature vector will be created based on the coordinates, pressure and time, and it will be filled by the features described in Section 3. For each class it will be observed a threshold.

The verification process of our system was totally based on distance measures. The distances we are talking about are the Euclidian distances between the test pattern and the center of the class, which is calculated based on a mean of each feature that belongs to the reference pattern. Before the center calculation all the features are normalized to have zero mean and variation equals to 1.

Patterns that are beyond the threshold delimited for a specific class are considered a fraud. Based on that measure, two types of error rates are calculated: False Reject Rate (FRR) and False Accept Rate (FAR), where the false rejection represents the situation that an authentic user is not considered as being from the class and a false acceptance represents a situation where an impostor is considered as being from the class. These two rates are inversely correlated. In order to compare the performance of the system, we will keep the FAR as being zero.

5. Experiments

All the experiments that will be described bellow have followed the data acquisition, feature extraction, enrollment and verification process described previously.

For all the experiments a total of twenty classes were used. Each class has three different sets of signature, which are the small set (S), the medium set (M) and the large set (L). The dimensions of those three different sizes were described in data acquisition section.

5.1 Signature verification analysis

The first experiment consists of training the system with 8 medium signatures for each class (the enrollment process in described in Section 4). Afterwards, the system will be tested with 3 different sets of signatures S, M and L groups and with a set of medium skilled forged signatures (FS). For the S, M and L group a FRR will be computed and for the FS group a zero FAR will be considered. In order to assure a more consistent result this experiment was repeated 30 times with random training sets and the result of the mean of these experiments are shown in Table 2.

Table 2. Error rates of S, M and L signatures using the complete feature set and trained with 8 signatures. Considering zero FAR for skilled forgeries.

Training set = 8 35 features	FRR (%)
(S) Signatures	12,25
(M) Signatures	2,67
(L) Signatures	21,04

The presented results show a great difference among the three sets of signature. The medium (M) set had a low error rate; in contrast, the small (S) set and the large (L) set had higher error rates. These results can be explained by the fact that the system was trained with medium signatures and tested with small and large signatures, which are visually different and also different when it takes in account their features. This experiment is showing that the difference in the size affects the verification error rates. Figure 2 shows the error rates per class. In this graphic, the classes 4, 5 and 16 show a great variation between the medium and small signature and also with the medium and the large signatures. On the other hand, the classes 2, 8 and 10 showed almost no variation between their signatures. It is also realizable that large signatures have a higher error rate than the small ones, which shows that the variation of the large signatures is bigger than the small patterns.

5.2. Statistical analysis

In order to verify the statistical relevance of this result three distances were calculated. The first was the distance between the test signatures of the small group to the center of the medium group. The second was the distance between the test signatures of the large group and the center of the medium group and the last one was the distance between the test signatures of the medium group and the center of the medium group. The mean of all these distances were submitted to a hypotheses test with the significance level of 1%. The limits for the acceptance region of the test for a 99% confidence interval must be greater than 2.58 or less than -2.58 for a normal distribution; since the results for the mean distance of large signatures to medium signatures was $z = -2,8517$ and the mean distance of

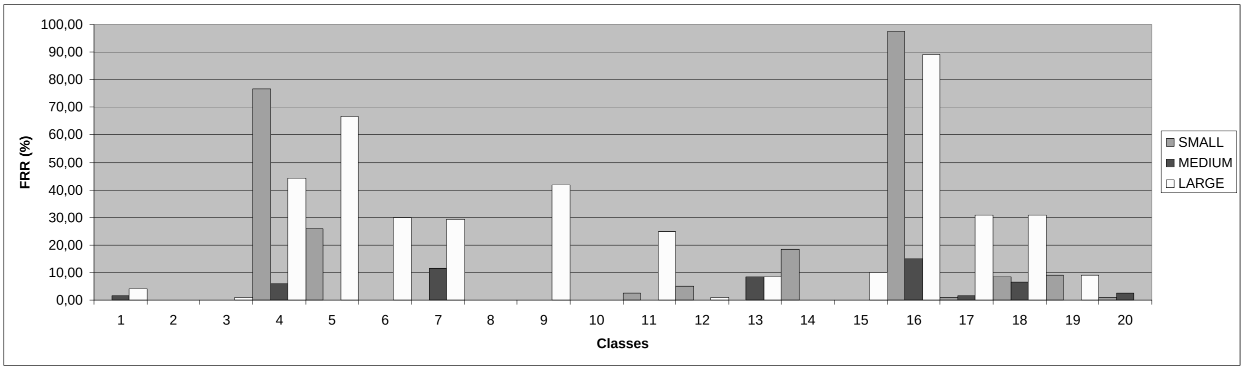

Figure 2. Chart of the error rates per class using the complete feature set and trained with 8 signatures. Considering zero FAR for skilled forgeries.

short signatures to medium signatures was z = -3, 5698, it was verified that these means are very different . (See Table 3).

Table 3. Results of the z-test applied in the mean distances of group S, M and L.

	Complete feature vector			
	M	**L**	**M**	**S**
Signature 1.1	0,2146	0,2789	0,2146	0,2664
Signature 1.2	0,1670	0,2313	0,1670	0,2640
Signature 1.3	0,2685	0,3639	0,2685	0,3061
Signature 1.4	0,2742	0,2907	0,2742	0,2777
:	:	:	:	:
Signature 20.1	0,3112	0,4023	0,3112	0,4681
Signature 20.2	0,2409	0,4408	0,2409	0,3896
Signature 20.3	0,1638	0,3428	0,1638	0,3591
Signature 20.4	0,2616	0,4380	0,2616	0,3644
Mean	**0,2439**	**0,7651**	**0,2439**	**0,4861**
Standard Deviation	**0,2027**	**1,6223**	**0,2027**	**0,5722**
Statistical Test (*z*)	**-2,8517 (test 1)**		**-3,5698 (test 2)**	

The results seen in Table 3 show that even if you use genuine signatures, significant differences will be verified when signatures of different sizes are used in the system. This difference is exactly what it is proved by this statistical test. It says that these signatures are different with 99% of relevance.

5.3. Coefficient of variation analysis

Using the analysis of the coefficient of variation, it is possible to identify the features that have higher dispersion. The coefficient of variation (CV) reveals the dispersion behavior of the data. In an ideal situation these data should be grouped for signatures of the same author and dispersed for signatures of different authors. Thus, the features which present higher variance values are not considered to be good features for verification. The coefficient of variation is obtained by the equation (1):

$$CV = \frac{\sigma}{\mu} \tag{1}$$

where σ is the standard deviation and μ is the mean.

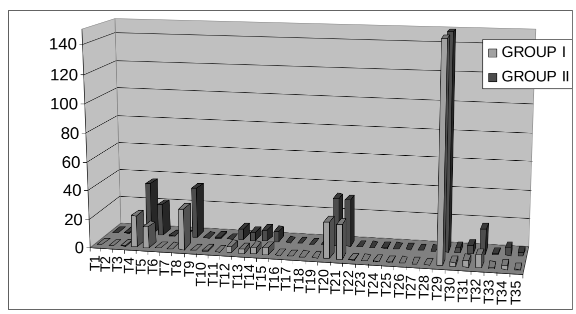

Figure 3. Mean of the coefficient of variation of each feature considering GROUP I as been a group formed by medium signatures and GROUP II as been a group formed by signatures of different sizes.

For that experiment we have defined two different groups. Group I containing 12 medium signatures for each class and group II also containing 12 signatures; however, of these 12 signatures, 4 are medium, 4 are large and 4 are small. For each group it was calculated the CV for each feature. These coefficients will be compared between the two groups. If the value of the CV in group II is bigger than the value in group I, it means that the signatures in group II are more dispersed then in group I. In fact, the features of group

II, which contains signatures of different sizes, have more dispersed signatures as shown in the Figure 3. This observation shows that the quality of the features is affected by the size variation. We can also see that the feature T29 is feature that has the highest CV, which shows that in both groups this feature has great variation.

5.4. Feature selection

Based on the results of the previous experiment, a second experiment was performed in order to verify if there is a specific group of features that can give similar results for signatures of different sizes.

A new set of features was assembled but this time using only the 20 features of less coefficient of variation, which are, T1, T2, T3, T6, T7, T9, T10, T11, T16, T17, T18, T19, T22, T23, T24, T25, T26, T27, T28 and T33. Observing the results in Table 4, it was verified that we have almost the same error rates as the experiment using the complete feature set. Indeed, we had an increase in the large signatures error rates, but on the other hand, we had a decrease in the medium and small signatures error rates, which basically haven't alter the final result. (See Figure 5)

Table 4. Error rates of S, M and L signatures using the 20 features of less coefficient of variation. Considering zero FAR for skilled forgeries.

Training set = 8 20 features	FRR (%)
(S) Signatures	14,87
(M) Signatures	4,79
(L) Signatures	16,54

5.5. Local Feature Selection

Due to the fact that we haven't found a common feature set that gives a similar and lower rate, we have decided to generate a feature vector for each class. A new set of feature was created for each class with the objective of minimizing the error rates per class. For each class we separated the first 20 features of less standard deviation. This experiment was also performed 30 times with different training sets.

Observing Table 5, it is easy to see the evident improvement in the results. The M error rate was kept almost at the same level. The S and L error rates, on the other hand, have dropped to 5,63 and 4,67 respectively, which make them similar error rates. (See Figure 6)

Table 5. Error rates of S, M and L signatures using the 20 features of less coefficient of variation for each class. Considering zero FAR for skilled forgeries.

Training set = 8 20 features	FRR (%)
(S) Signatures	5,63
(M) Signatures	2,54
(L) Signatures	4,67

Thus, the results of this experiment show that it is possible to find a feature vector that minimizes the error rates for the three sizes of signatures. This observation shows that it is possible to have good results even if you use different sized signatures. This also indicates that some features are not influenced by the difference of sizes. One aspect that can be observed in Figure 4 is that, even using local feature selection, the classes 4, 9 and 16 remained having high error rates
as was verified in the first experiment (Figure2), which shows that these classes have a great inter class variation. Looking at the frequency of the features for each class, we can observe that their distribution doesn't indicate a convergence for a specific group of features, which demonstrate that a unique feature vector will not give good results. The distribution of the features can be seen in Figure 4.

From Figure 4 we can also see that the features T29 and T35 were not important in this experiment that we are verifying signatures of different sizes.

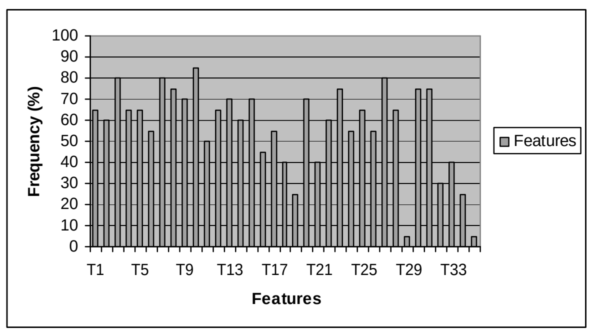

Figure 4. Number of times that each feature was used considering local selection.

It is clear, based on that results that for each signature exists different features set that brings better results.

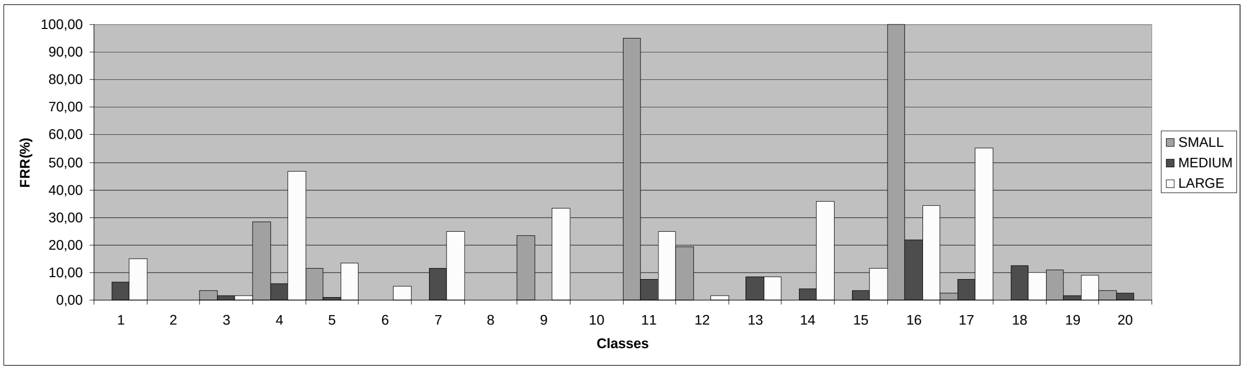

Figure 5. Chart of the error rates per class using 20 features of less coefficient of variance. Considering zero FAR for skilled forgeries.

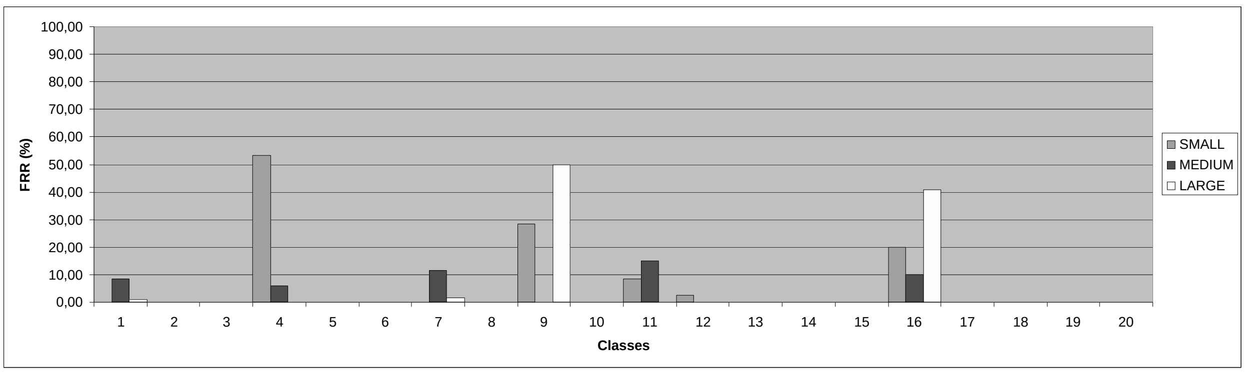

Figure 6. Chart of the error rates per class using a local feature set and considering zero FAR for skilled forgeries.

6. Conclusion and future work

Based on our experiments and on statistical tests, it was verified that there is a substantial difference between medium, small and large signatures. The small and large signatures have influenced the results of the verification process when compared to medium signatures. We can imply from this that signing in areas of different sizes can alter the way a person writes his name, as a consequence, the feature extraction is also influenced. This conclusion can strongly affect the way the verification systems are built.

One aspect that must be investigated is a way of manipulate the signature before the feature extraction. One possibility is use only the body of the signature, in other words, the central region of the signature which seems to have a less variation.

Another aspect that can be considered in a future work is to also perform training with small and large signatures.

Finally, more signatures must be collected in order to have a more representative database with more testing signatures of small and large sizes.

7. References

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