Early Diagnosis of Neurodegenerative Diseases by Handwritten Signature Analysis

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Abstract. Handwritten signatures are generally considered a powerful biometric traits for personal verification. Recently, handwritten signatures have been also investigated for early diagnosis of neurodegenerative diseases. This paper presents a new approach for early diagnosis of neurodegenerative diseases by the analysis of handwritten dynamic signatures. For the purpose, the sigma-lognormal model was considered and dynamic parameters are extracted for signatures. Based on these parameters, the health condition of the signer is analysed in terms of Alzheimer disease. The approach is cheap and effective, therefore it can be considered as a very promising direction for further research.

Keywords: Biometrics · Alzheimer Pre-diagnosis system · Handwritten signature · Sigma- lognormal

1 Introduction

Writing is one of the oldest representations of the intelligence of human beings. It arises mainly because of trade, accounting and administration. It represents a graphic reproduction of the spoken language, by means of a set of signs, called graphemes. Writing your own name is one of the first actions that are taught; therefore the signature is a graphic sign that is repeated countless times in everyone's life. The signature contains a huge amount of information related not only to the representation of the name and surname of the signatory, but also to his/her writing system (hand, arm, etc.) and psychophysical state. Therefore, the signature is rightly considered as a biometric trait of extraordinary importance for the verification of digital identity. Also it is the subject of many studies both by forensic experts, computer scientific and even medical doctor [1].

More recently, in view of the extraordinary information of the signer conveyed by his/her signature, it was also considered as a useful means for the pre-diagnosis of neurodegenerative diseases. Among these diseases, the Alzheimer's disease is the

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most common form of degenerative dementia progressively debilitating that leads to loss of cognitive function. Alzheimer's affects, in fact, on a person's ability to carry out the simplest daily activities, going to hit the brain areas that control functions such as memory, thinking, speech and writing; the latter disorder is defined as agraphia.

Therefore, the inability to be able to communicate through writing can be seen as an early manifestation of Alzheimer's disease [2, 3].

For the analysis of a handwritten signature, in this paper the Sigma-lognormal model is used, that is based on the kinematics theory of human movements. This model allows the representation of the information of motor commands and the time it takes the neuromuscular system to produce a complex movement, such as to affix the signature [4, 5]. According to the Sigma-lognormal model, a set of well-defined parameters are extracted from the signature and used for early diagnosis of Alzheimer disease. The experimental tests demonstrate the effectiveness of the proposed approach and some directions for further research.

The organization of this paper is as follows. Section 2 describes the Sigma-lognormal model used for the representation of the signatures. In Section 3 we present the set of features and the classification algorithms that were considered for the early diagnosis. Section 4 presents the system and some experimental results. Section 5 presents the conclusion of the works and some possible directions for future research.

2 The Sigma-Lognormal Model

The kinematic theory of rapid human movement, relies on the Sigma-Lognormal model to represent the information of both the motor commands and timing properties of the neuromuscular system involved in the production of complex movements like signature [4, 5]. In recent years, several scientific contributions demonstrated the utility of such a theory in handwriting signature analysis and processing [6, 7].

The Sigma-Lognormal model considers the resulting speed of a single stroke j as having a lognormal shape Λ scaled by a command parameter (D) and time-shifted by the time occurrence of the command (t0):

$$\left|v_j(t;P_j)\right| = D_j \Lambda(t-t_{oj};\mu_j,\sigma_j^2) = \frac{D_j}{(t-t_{oj})\sqrt{2\pi}} \exp\left\{\frac{\left[\ln(t-t_{oj})-\mu_j\right]^2}{-2\sigma_j^2}\right\} \tag{1}$$

where $P_j=[D_j, t_{0j}, \mu_j, \sigma_j, \Theta_{sj}, \Theta_{ej}]$ represents the sets of Sigma-Lognormal parameters:

- D_j : amplitude of the input commands;
- t_{0j} : time occurrence of the input commands, a time-shift parameter;
- μ_j: log-time delays, the time delay of the neuromuscular system expressed on a logarithmic time scale;

- σ_j: log-response times, which are the response times of the neuromuscular system expressed on a logarithmic time scale;
- Θ_{sj}: starting angle of the circular trajectories described by the lognormal model along pivot;
- Θ_{ej}: ending angle of the circular trajectories described by the lognormal model along pivot.

Additionally, from the hypothesis that every lognormal stroke represents the movement as happening along a pivot, the angular position can be computed as:

$$\phi_j(t;P_j) = \theta_{sj} + \frac{\theta_{ej} - \theta_{sj}}{D_j} \int_0^t \left| \vec{v}(\tau;P_j) \right| d\tau \qquad (2)$$

In this context, a signature can be seen as the output of a generator that produces a set of individual strokes superimposed in time. The resulting complex trajectories can be modeled as a vector summation of lognormal distributions (being N_{LN} the total number of lognormal curves in which the handwritten trace is decomposed):

$$\vec{v}(t) = \sum \Lambda(t) = \sum_{j=1}^{N_{LN}} \vec{v}_j(t;P_j) \qquad (3)$$

For each of the components of the signature, and then for each stroke, it can define some profiles that add information to those already expressed by the parameters of the Sigma-Lognormal.

According to the Sigma-Lognormal model, in this paper a signature S^t is characterized in the generation domain by a sequence of couples

$$S^r = (z^r_1, z^r_2, z^r_3, \ldots z^r_j, \ldots, z^r_m) \qquad (4)$$

where each couple $z^r_j = (t_j, v_j(t_j))$ describes the j-th lognormal curve in which the signature is decomposed (in eq. (6) it is supposed that a signature is decomposed in m lognormal curves).

In this paper, the Script Studio software was used to analyze and graph the signatures through Sigma-Lognormal Model.

3 Alzheimer Pre-diagnosis System Experimental Results

In this work, a set of twelve features to distinguish between pathologic from non-pathologic dynamic signatures are defined as follows: (the label assigned to each feature is shown in brackets):

- Maximum speed of the signing divided by the time of writing (vDIVt);
- Number of log-normal in the signature (N.LogNorm);
- Number of Log-Normal divided by the time (n.logNormDIVt);

- Average and Standard Deviation of the value **μ** (Med_MU, DevSt_MU_);
- Average and Standard Deviation of the value **σ** (Med_Sigma_, DevSt_Sigma)**;**
- Average and Standard Deviation of the value **D** (Med_D, DevSt_D);
- Maximum and minimum speed learned while writing (V.Max, V.Min);
- Number of peaks in the graph speed / time (Peaks);

The selected features are worked out to build a classifier through different machine learning techniques provided by R (a free development environment for statistical analysis).

More precisely, we're considered to distinguish the healthy and non healthy signatures.:

- CART algorithm;
- BAGGING CART algorithm;
- Support Vector Machines(SVM) with linear kernel.

The CART algorithm builds the decision tree in the following way: it starts from the data grouped in a single node (root node) and performs, to each step, an exhaustive search on all possible subdivisions. In each step the best subdivision is chosen, that is the subdivision producing branches as homogeneous as possible. To check if a signature belongs to a pathological case or not, just compare the values in vectors of features of each signature with the conditions present on the branches of the tree. The classification for both trees is carried starting from the root and down to the branch that meets the condition, proceed until there comes a leaf node that indicates the class of the signature.

The BAGGING CART algorithm creates more patterns of the same type obtained from different subsamples of the same group of data. Forecasts of each model are combined together to provide a better result. This approach has proved appropriate for methods with high variance. As before the classification shall be made starting from the root node and go down gradually.

Last classifier used is a SVM with linear kernel. A SVM uses a representation of the pattern examples as points in space, mapped so that the examples of the separate categories are clearly (linearly) divided. This means that the gap between categories should be as wide as possible. When additional test examples are considered, they are mapped into that same space and are classified according to the side they belong.

Finally, a user-friendly interface was developed for Alzheimer Pre-diagnosis, which exploits the handwritten signature after the Sigma-Lognormal parameters extraction. It has been so named "APs" (Alzheimer Pre-diagnosis System).

4 Experimental Results

For the experimental test of the system, a set of dynamic signatures was considered belonging to a private database.

The set consists of sixty-two signatures divided into two groups: Patologic and Healthy (Figure 1). The first group is composed of twenty-nine signatures, the second group is composed of thirty signatures.

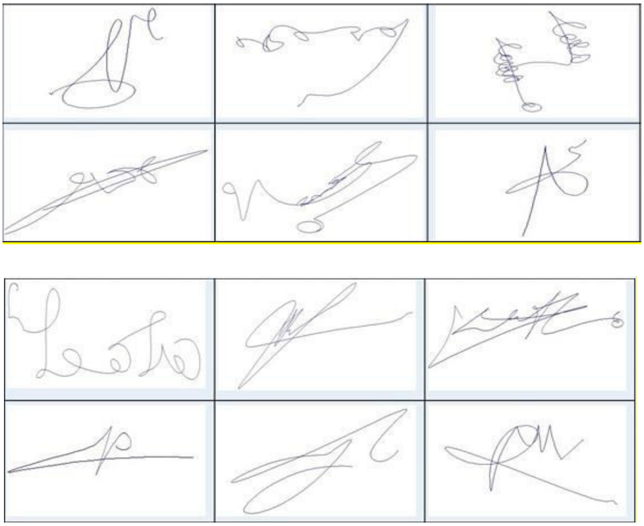

Fig. 1. The first table contains examples of pathological signatures, instead the second contains healthy.

Figure 2 and 3 show the decision trees obtained from the training data using the CART and the BAGGING CART algorithm, respectively. Figure 4 shows the result obtained using the SVM algorithm (with linear kernel), when the features Peaks vs logDIVt are considered (we chose these features since they are the best to separate the two classes).

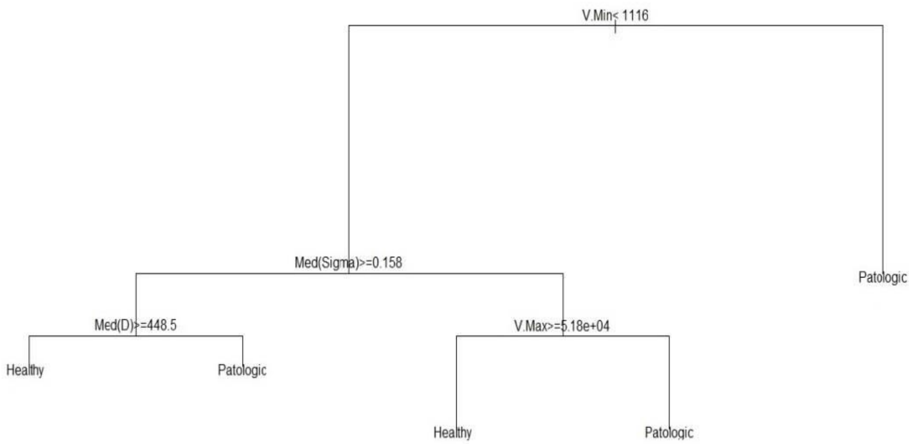

Fig. 2. Decision Tree: CART.

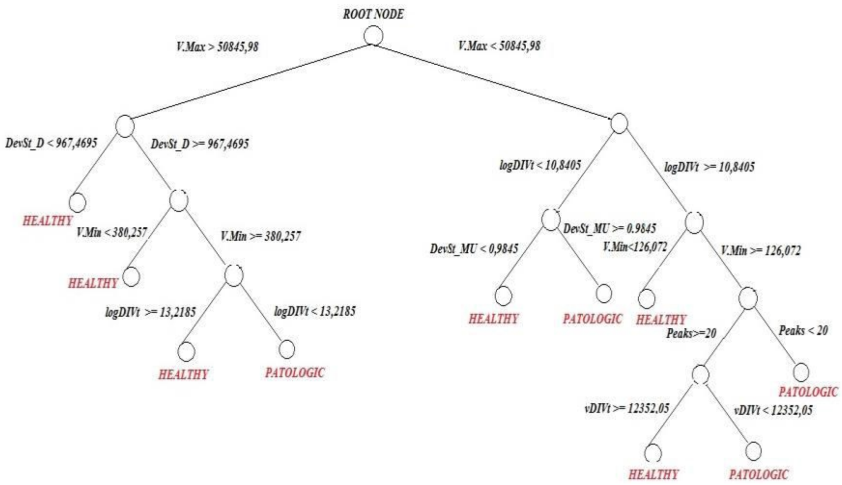

Fig. 3. Decision Tree: BAGGING CART.

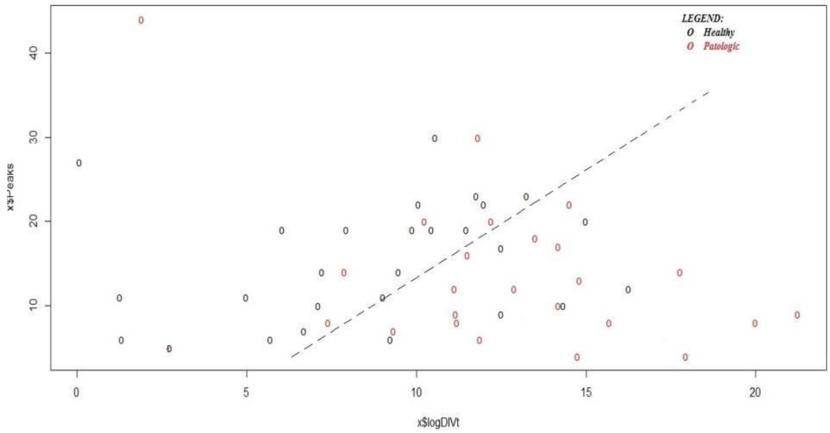

Fig. 4. Decision Tree: Bagging Cart algorithm.

Table 1-3 reports the classification results.

Table 1. Decision Tree (Cart Algorithm)

	Healthy	Patologic
Healthy	24	8
Patologic	7	22

Table 2. Decision Tree (Bagging Cart Algorithm)

	Healthy	Patologic
Healthy	31	1
Patologic	1	28

Table 3. Support Vector Machines

	Healthy	Patologic
Healthy	25	7
Patologic	10	19

Table 4 reports the False Acceptance Rate (FAR) and the False Rejection Rate (FRR) for the three classifiers.

Table 4. Experimental Results

	FAR	*FRR*
Decision Tree (CART)	25%	24%
Decision Tree (Bagging)	3%	3%
SVM	21%	34%

As the result demonstrates, the algorithms to generate decision trees are more efficient (in our case) than SVM. In particular, in our test, the Bagging Cart outperforms significantly both the Cart decision tree and the SVM classifier.

5 Conclusions

This paper addresses the possibility to use handwriting signatures to predict neurodegenerative diseases. For the purpose, the Sigma-Lognormal model was considered for handwritten signature analysis and specific key-features are used for the early diagnosis of Alzheimer, using a bagging cart classification tree.

Some experimental results show that this approach allows a fast pre-diagnosis, inexpensive and non-invasive. Of course, more research is still necessary to evaluate the effectiveness and robustness of the approach using other data sets, also to evaluate the extent to which this approach can be used as a screening standard routine for the early diagnosis of Alzheimer disease.

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