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Shape Evolutions of Poincaré Plots for Electromyograms in Data Acquisition Dynamics

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***Abstract*— Poincaré plots (PPs) are a known way of study for complex time series. Such are the majority of medical signals. This method is in use here for the study of verified electromyograms (EMGs). EMGs are records of electrical action of muscular and nervous systems. The shapes of PPs for EMGs as well as its standard descriptors are sensitive to the diagnosis. These last describe the variability of the signals. We have studied the changes in the shapes of the PPs during the taping of EMGs. The changes of the standard descriptors were studied too. Three EMGs were considered for diverse diagnoses. They have varied duration but the same sampling rates. We have found the common shape of the PPs stabilizes itself during about the first third of each record. These shapes can change even further, but already remaining self-similar like the fractals. Standard descriptors are changing within the data acquisition. Still, these changes are smoother and less weighty in the last two thirds of each record.**

Keywords*— *data acquisition dynamics; Poincaré Plots; variability; electromyograms; medical signals

I. Introduction

Electromyograms (EMGs) are records of electric action of muscles. This test is ensuring the high level of diagnosis of the nerves and muscles [1, 2]. It has arisen from the late 1970s by the efforts of American Academy of General Practice. Well-computerized processing is an inherent part in the modern electromyography (EMG) [3]. The database [4] has collected good examples of real EMGs.

Poincaré Plots (PPs) are a kind of return maps. Each result of measurement is plotted as a function of a next one. This simple and effective concept is in use to visualize many complex medical signals now [5]. Long records tapes become visible on a single chart. The longer the record, the more points appear on the chart. One main cloud (or a spot) of points arises as a rule. A shape of the cloud describes the evolution of the system. It allows visualizing the variability of a time series too [6].

There are standard numeric descriptors of PPs shapes, $SD1$, $SD2$ and $R = SD1/SD2$, which have been suggested in [7]. They describe two kinds of the variability of a time series and its randomness. The software [8] presents an example of modern data mining with PPs in cardiology. The mining of EMG data is only starting. Thus, there are now less cutting-edge positions.

The aim of this paper is the study of PPs shapes evolutions in the data record dynamics. We are going to trace the formation of these shapes within the EMGs record. This will to touch standard descriptors as well. Thus, we are paying attention to the evolution of PPs during the EMG record and planning to link it with the real diagnosis.

II. Data and Methods

The data was borrowed from PhysioNet portal [4]. These EMGs were in use earlier in [3, 5] but there were working with truncated datasets. Here we have used the full datasets. The frequency of the discretization was 4 kHz for all records. Hence, the sampling time interval was equal to 0.00025 s and the same for all records. The sizes of the signals were in mV.

Maple 18 was in use in computer handling of all datasets as well as for graphs plotting [9]. The import of the binary files from PhysioNet to Maple has been described in [10].

The standard descriptors were computed like in [11]:

$$SD1 = \sqrt{2} \cdot SD\left(\frac{s_n - s_{n-1}}{2}\right);$$
$$SD2 = \sqrt{2} \cdot SD\left(\frac{s_n + s_{n-1}}{2}\right); \qquad (1)$$
$$(n = 2, 3, .., N)$$

Where $SD(s)$ denoted the operator of the standard deviation for the time series $\{s_n\}_{n=1..N}$.

First of them ($SD1$) defines the short-time variability of the time series. The second one ($SD2$) describes the long-time variability. Its ratio estimates the random impact in the data [5-7, 11].

Each of the datasets has been segmented on the 100 sections of equal duration (so called percentiles). Yet, these percentiles are varied length for different datasets. Besides, the duration of each percentile was much larger than the time sampling interval.

For instance, the shortest of the percentiles for the healthy patient had the duration 0.121715 s that means above 500 samples. It gives over 500 points in the common Poincaré Plot. The percentiles for patients with myopathy and neuropathy were larger about twice, or even threefold. Thus, one or several consequent percentiles may be reckoned as dynamic parts of the signal.

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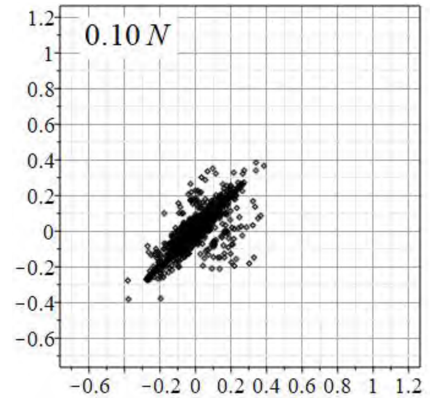
TABLE I. SORT INFORMATION ABOUT PATIENTS [4]

Sex	Age	Short diagnoses	Duration of records, s
male	44	A healthy patient	12.71500
male	57	Myopathy due to long history of polymyositis	27.56425
male	62	Chronic low back pain and neuropathy	36.96450

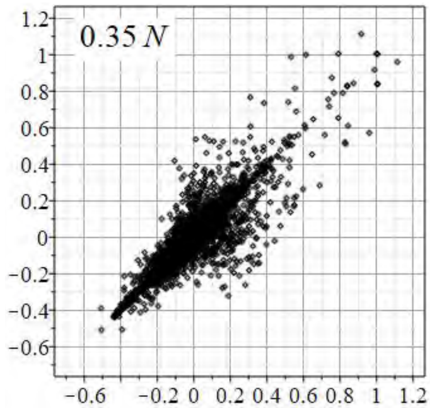
III. RESULTS AND DISCUSSION

A. *Healthy Patient*

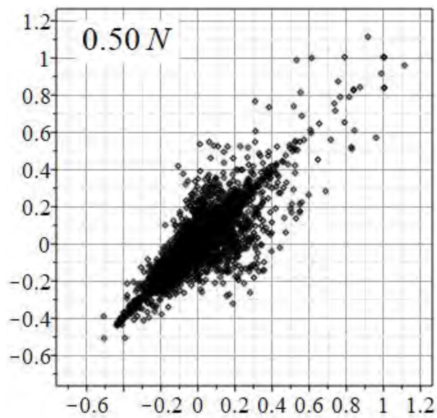
The full record consists of $N = 50860$ samples. Fig. 1 shows the dynamic of the shapes for PPs with varied numbers of points. The typical "comet shape" is observed.



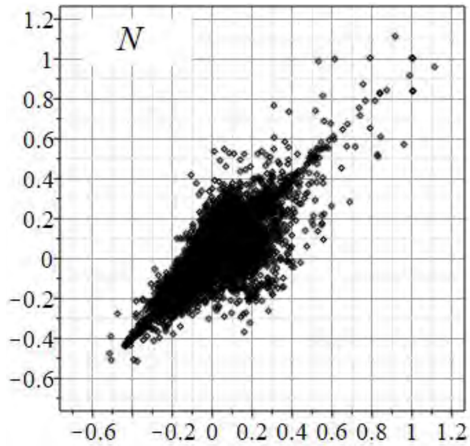
a)



b)



c)



d)

Fig. 1. The changes of Poincaré Plot shape in the process of data acquisition for healthy patient. The number of points is equal to: a) $0.1\times N$; b) $0.35\times N$; c) $0.5\times N$; d) N

One can see the self-similarity of PPs, especially for three last images. Note the numbers of points on these images vary more than twice. The self-similarity was gone only for the PPs with small enough numbers of points (roughly less than $0.15\times N$, see Fig. 1a).

Fig. 2 presents the dynamics of the standard descriptors for healthy patient.

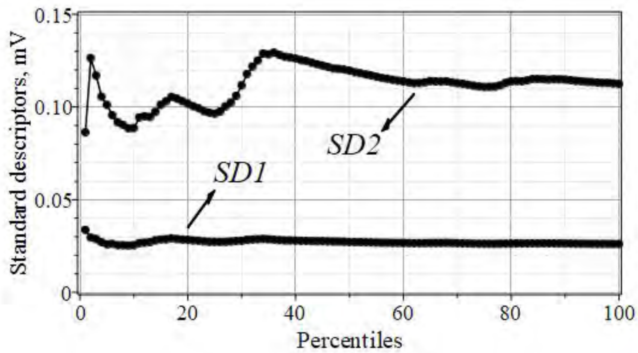


Fig. 2. The dynamics of the standard descriptors for healthy patient PPs

B. *Patient with Myopathy*

The record consists of $N = 110337$ samples. The self-similarity of the PPs was even clearer expressed, like to the above case, although the shape of PPs was definitely another. That is why we give here only the complete Poincaré Plot and the dynamics of the standard descriptors on the Fig. 3. The location of curves is alike to the Fig. 2.

C. *Patient with Neuropathy*

This record consists of $N = 147858$ samples. The self-similarity of PPs is inherent in this case too. However, the dynamics of the standard descriptors looks not as smooth as in above sections. The reader can see also specific shape of complete Poincaré Plot in this case (Fig. 4). The location of curves is alike to the Fig. 2 and Fig. 3.

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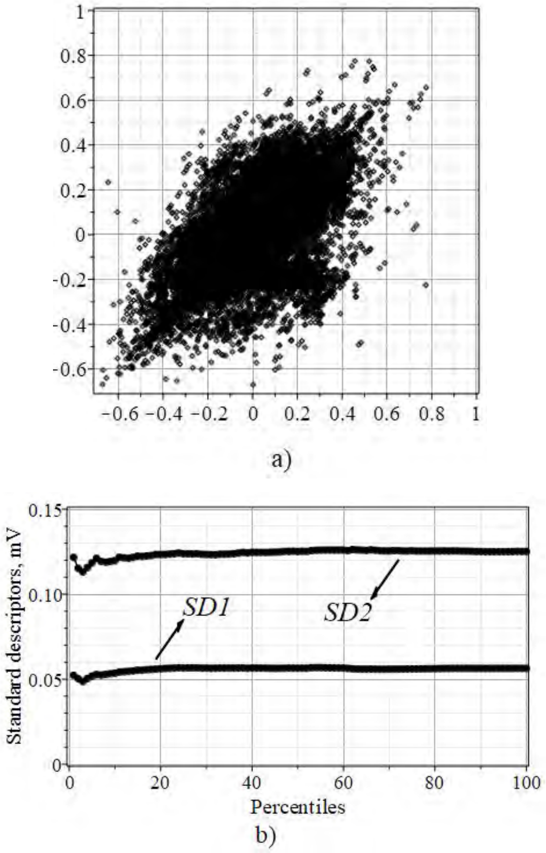

Fig. 3. The results for patient with myopathy: a) the shape of complete Poincaré plot; b) the dynamics of the standard descriptors.

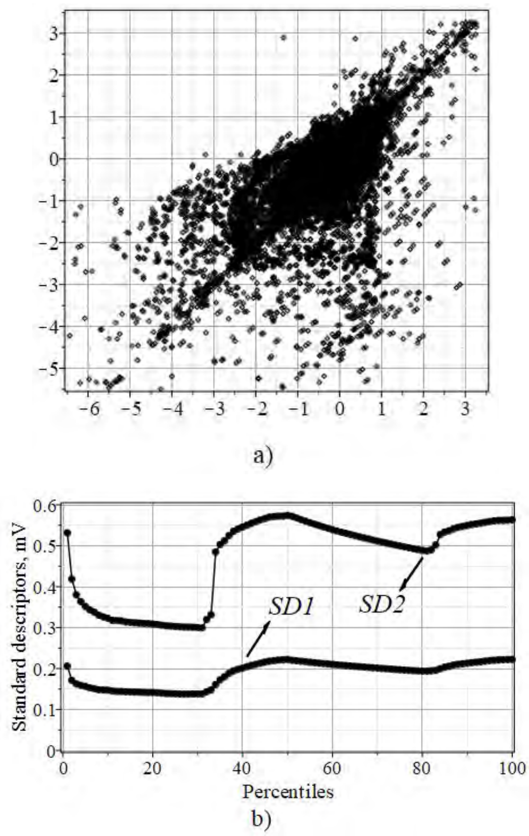

Fig. 4. The results for patient with neuropathy: a) the shape of complete Poincaré plot; b) the dynamics of the standard descriptors

D. Discussion and Comparisons

First, we point out that the shapes of PPs are most likely linked with the diagnosis (see Figures 1, 2 and 3). These specific shapes are very difficult to confuse. This idea needs further testing, yet, it may be useful for diagnosis and clinical decision-making.

We should to point out the similar dynamics of these shapes in the process of data acquisition (see Fig. 1). The shapes of PPs have stabilized after the gathering of about the third of data capacity. It looks as general rule, despite of the difference of shapes and the big difference in the numbers of samples for each data set.

The shape of the each PPs remains self-similar if data is collected further. This suggests the fractal nature of the PPs. Thus, a large enough part of the Poincaré Plot, let us say a half, or one third, is statistically equal to the complete Poincaré Plot [12, 13]. Here we say 'a half, or one third' keeping in the mind the number of points in a cloud.

This property permits the digital filtering of PPs with Haar wavelet filters for instance. Filtered PPs will be equal to unfiltered due to the own fractal nature. Haar filters can divide the data set on the two almost independent halves. One of them is the high frequency part of signal while the second one presents the low frequency part. Their scatter plot may be even more informative and convenient as the classic Poincaré Plot.

The behavior of the standard descriptors (se Fig. 2, 3 and 4), in general, confirms that above said. The more or less smooth dependences are inherent in the latter two third of signals. Still, the sizes of the descriptors and the smoothness of their changes with the data capacity are quite dependent on diagnoses.

Let us compare also the randomness of the datasets by the statistical box-plot (Fig. 5). Note that the random effects for the EMG of a healthy patient are clearly not as great as in pathological cases.

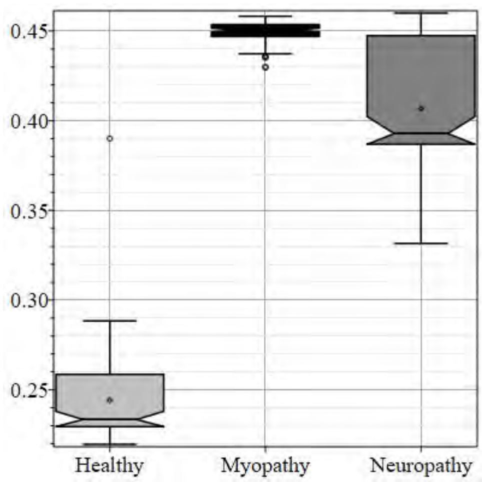

Fig. 5. Statistics box-plot for the ratios $R = SD1/SD2$. These ratios estimate the randomness of each signal.

IV. Conclusions

Let summarize the results of this study in several points:

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- Shapes of PPs for EMGs become steady after the first third of a data set. The diagnosis and the number of samples in the data did not have much weight for this rule.
- PPs have demonstrated self-similarity, behaved like typical fractals, in the process of further data gathering. Similar results have been reported earlier for the PPs of instantaneous heart rhythm [14].
- The dependences of standard descriptors of PPs on the number of samples have confirmed the above conclusions.

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