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Automatic Classification of Time-Frequency Plots applied to the Center-of-Pressure rotational components

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Abstract— **Time-frequency plots are widely applied to the non-stationary analysis of signals. These plots may be difficult to interpret, particularly when large data sets have to be considered. The aim of this work is to propose an automatic procedure of feature selection and clustering to be applied to time-frequency plots. We focus on the application of this procedure to plots obtained from a non-stationary analysis of the center-of-pressure signals acquired in upright bipedal stance.**

From a data set of 168 time-frequency plots we obtained 5 different clusters, each characterized by a few distinctive features. We were able to interpret the results of the clustering relating them to the physiological mechanisms underlying postural sway.

I. Introduction

The study of non-stationary signals is often based on the analysis of time-frequency (TF) distributions. However, it is usually difficult to interpret TF-plots, especially in large data sets. In order to overcome the inherent complexity of large data sets, automatic methods of feature extraction and classification were developed in different fields, e.g. seizure detection in EEG signals [1-2], classification of myoelectric signals [3], and automatic speech recognition [4]. However, these studies are focused on the detection of 'already known' characteristics. Our perspective is different, since we are interested not only in developing a method able to automatically recognize specific features, but also to extract information without any a priori knowledge.

The non-stationary problem we are interested in arose from the study of the Center-of-Pressure (COP) signal in human bipedal quiet stance [5-7]. Recently we proposed the 'rotary spectra analysis' to demonstrate the presence of rotational components in the COP signal [8-9]. This allowed us to decompose the COP motion in the plane into its clockwise (CW) and counter-clockwise (CCW) rotational components. Both components showed a marginal spectrum band in the range of 0-1.5 rounds per second (rps), with the highest peaks within the range 0.1-0.2 rps. We hypothesized that these peaks could be related to bursts of the muscle sympathetic nerve activity [9], as the latter is known to modulate postural sway [10]. Furthermore, it is known from the literature that respiration has a considerable impact on the maintenance of equilibrium [11], possibly explaining the component around 0.3 rps found in the rotary spectra analysis of the COP signal. However, our previous analysis did not considered the non-stationary characteristics of the COP signal.

Examining these characteristic frequencies in the TF domain allows assessing their onset/offset time and duration. This may help to understand the physiological mechanisms under postural control in upright stance. To the best of our knowledge, no previous work in literature has ever described this kind of TF-plot.

From the TF analysis of the COP rotational components on a sample of healthy subjects we obtained a large data set of TF-plots. We describe a method for their automatic clustering to find similarities and dissimilarities among them. The aim of this work is to illustrate how the interpretation of this clustering may lead to the discovery of new knowledge.

II. Material and Methods

We describe a two-step procedure based on (a) automatic feature extraction, (b) clustering of TF-plots. We applied this procedure to a large data set of TF-plots obtained from the non-stationary rotary spectra analysis of a sample of healthy subjects.

A. Subjects and Experimental Set-up

We recruited 42 healthy volunteers and asked them to stand quietly, with their arms at their sides, on a force platform (Kistler 9286A, Switzerland). They were tested in two randomized conditions, with their eyes open (OE) and with their eyes closed (CE). All participants gave their written informed consent to be included in the study.

Each acquisition lasted 60 s. The signal was recorded with a sampling frequency of 2 kHz and down-sampled to 20 Hz.

B. Signal processing

We obtained the CW and CCW rotational components of the COP signal as described in [8-9], extending the rotary spectra analysis to the time-frequency domain. Specifically, for each component, we calculated the Choi-Williams distribution, with a kernel $\sigma = 0.5$ [12]. A representative TF-

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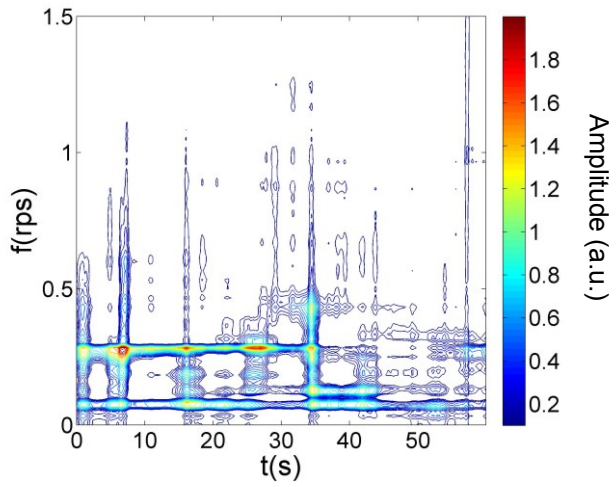

Figure 1. Example of a TF-plot.

plot is shown by Fig. 1. The TF distribution amplitudes are normalized with respect to their maximum value.

COP rotational components in the TF domain can be considered as multi-component separable signals, as their components are clearly separated in the TF domain, according to the definition proposed by Rankine et al. in [13]. This means that, generally speaking, a certain component does not shift with time toward a different frequency value (like a "chirp" signal does), but rather it is (discontinuously) present at a specific frequency value.

C. Data set

For each of the 42 subjects, we considered 2 test conditions (EO and EC), and obtained 2 rotary components (CW and CCW) for each condition. Hence we collected a total of 168 TF-plots.

D. Feature Extraction

In order to describe a TF-plot in terms of its frequency components, it is necessary, as a first step, to automatically identify these components. The method we applied, similar to the one proposed in [13], is based on "region growing" [14], an image processing technique for obtaining segmentation. The first step in this technique is to select a set of 'seed points'. Setting a first threshold on the amplitude, *n* seed points are determined. At the exact location of each seed, a region starts to grow from it. The regions are grown from the seed points adding to each region the adjacent pixels, until the amplitude is lower than a second threshold. Both amplitude thresholds are suitably chosen considering the histogram of the pixels amplitudes. Segmenting each TF-plot, we can automatically determine their frequency, amplitude and temporal duration.

The second step is the definition of a set of features. We divided the TF-plane in 3 different frequency bands: from 0 to 0.2 rps, from 0.21 rps to 0.3 rps, and from 0.31 to 0.5 rps. In each band, we evaluated how many frequency components are present, their temporal duration and their energy. The duration of the frequency components was divided in 3 classes, "short", if shorter than 30 s, "medium" if longer than 30 s and shorter than 50 s, and "long" if present for at least 50 s. Similarly, the energy of the component is "low", "medium", or "high" if it contains less than 30%, between 30% and 60%, or more than 60% of the total energy of the TF distribution.

It is important to notice that the energy of each component is expressed as a percentage of the total energy of the TF distribution. In this way, the information relating to the energy absolute value is discarded, as we are interested in the frequency components, and not in its absolute amplitude. This means that we do not include features that are known (a priori) to distinguish between EO and EC conditions, like the COP spectrum power.

Therefore, we defined 27 different features, summarized in table 1.

TABLE I. LIST OF FEATURES

Frequency	Amplitude	Time duration	Feature
0 < f < 0.2 rps	High amplitude	t≥50 s	F1
		30 ≤ t <50 s	F2
		t < 30 s	F3
	Medium amplitude	t≥50 s	F4
		30 ≤ t <50 s	F5
		t < 30 s	F6
	Low amplitude	t≥50 s	F7
		30 ≤ t <50 s	F8
		t < 30 s	F9
0.2 ≤ f < 0.5 rps	High amplitude	t≥50 s	F10
		30 ≤ t <50 s	F11
		t < 30 s	F12
	Medium amplitude	t≥50 s	F13
		30 ≤ t <50 s	F14
		t < 30 s	F15
	Low amplitude	t≥50 s	F16
		30 ≤ t <50 s	F17
		t < 30 s	F18
f ≥ 0.5 rps	High amplitude	t≥50 s	F19
		30 ≤ t <50 s	F20
		t < 30 s	F21
	Medium amplitude	t≥50 s	F22
		30 ≤ t <50 s	F23
		t < 30 s	F24
	Low amplitude	t≥50 s	F25
		30 ≤ t <50 s	F26
		t < 30 s	F27

E. Clustering

Clustering is based on the k-means algorithm [15]. One of the difficulties of k-means is the necessity to define a priori the number of clusters. As we did not have sufficient information to perform this choice, we applied the Iterative Self-Organizing Data Analysis Technique (ISODATA) [16]. ISODATA is an unsupervised algorithm of clustering that iteratively performs a k-means clustering, then it splits every cluster whose samples are sufficiently dissimilar and merges any two clusters which are sufficiently close. The procedure

ends when the cluster centers stop changing or when a maximum numbers of iterations is reached.

We implemented the feature extraction and the clustering algorithm on the described data set.

III. Results

Applying feature extraction and clustering to the whole set of 168 TF-plots, we obtained 5 groups. The first group contains 15 plots, the second 57 plots, the third 33 plots, the fourth 27 plots, and the fifth 36 plots. Fig. 2 shows how the features (columns) are distributed in the 5 groups (rows). Squares are black-colored when a feature is present in at least 60 % of the group elements.

Each group has a few features which discriminate it from the others. Since these "main features" are never common to different groups, they can be considered as representative of the characteristics of the group. The first group shows a high prevalence of features F5 and F18. The second group is represented by features F1. The third group is characterized by feature F3. The fourth group is characterized by feature F4. The last group is characterized by features F6, and F15. There are no groups represented by features ranging from F19 to F27, i.e. from frequency components higher than 0.5 rps.

IV. Discussion

We defined 27 features to describe each TF-plot in terms of its frequency components. These features were formulated to help us understanding the physiological meaning underneath the detected frequency components. Clustering the 168 TF-plots obtained from the sample of healthy subjects, we found 5 well separated groups. Each of them was characterized by 1 or 2 features, never overlapping with those of the other groups. Hence, we can consider these features as the main characteristics of each group. This means that we were able to identify 5 'templates', i.e. 5 different typologies of recurrent types of behavior pertaining the frequency components' characteristics.

All of the 5 groups were characterized by a low frequency component ($f < 0.2$ rps). This component may have different time durations (short, medium or long) and/or amplitudes (medium or high), but it is always present. This result is in accordance with our previous hypothesis that human postural sway is influenced by the bursts of muscle sympathetic nerve activity [8, 9]. In group 2 (which is the most populated) and in group 3, the low-frequency component shows a high amplitude. However, in group 2 this component can be considered continuous in time, while in group 3 it is present only in short bursts. This 'dissimilarity' in the time duration could distinguish two different patterns of activation of the muscle sympathetic nerve. In groups 1, 4 and 5 the low-frequency component shows a medium amplitude, with short bursts in group 5, and medium and long bursts in group 1 and 4, respectively. Furthermore, groups 1 and 5 show an additional feature of short duration in the frequency range $0.2 \leq f < 0.5$ rps. This has low amplitude in group 1 and medium amplitude in group 5.

Hence, all the groups seems to be characterized by the activity of the sympathetic nervous system. Only two groups show an influence of the parasympathetic activity (respiration) for periods of time shorter than 30 s.

A posteriori we verified that each group included almost the same number of TF-plots referring to OE and CE conditions, and CW/CCW rotational components, i.e. they are evenly distributed. This is not surprising, since we didn't find any spectral difference between the CW and CCW rotary components of healthy subjects [9]. Furthermore, in our description we considered the energy of each component as a percentage of the total energy, discarding the information about its absolute value. This means that we did not expect (a priori) to see any difference between OE and CE conditions, since it is known that they mainly differ for the power of the spectrum density of the corresponding signals [17-18].

V. Conclusion

We developed an automatic method to analyze and classify the time-frequency distributions of the COP rotational components and demonstrated its applicability to a data set gathered on healthy volunteers. This automatic method allowed us to analyze similarities and dissimilarities of a high number of TF-plots, rapidly and in a repeatable way. Moreover, we were able to interpret the results of the clustering and to relate them to physiological elements. This demonstrates that the method could be used both to classify TF-plots and for knowledge discovery.

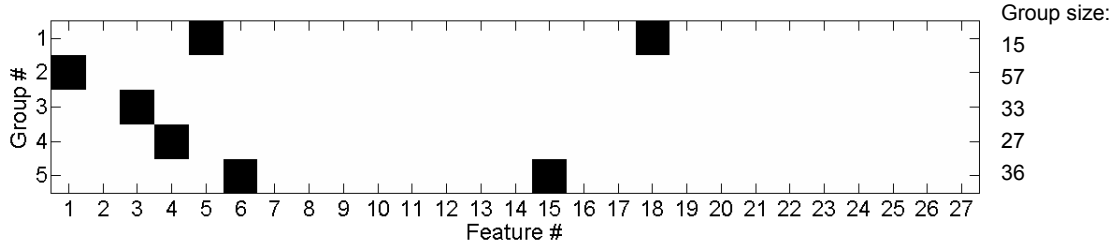

Figure 2. Results of the clustering algorithm applied to the data set. Each row represents a group, each column represents a feature. Squares are black-colored when a feature is present in at least 60 % of the group elements. The number of TF-plots clustered in each group is reported on the right side of the graph.

Due to its characteristics the method can be easily adapted to analyze other typologies of TF-plots.

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