

Template-DTW based on inertial signals: preliminary results for step characterization

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Abstract—In this paper, we present a method for the creation of a library of inertial signals based on Dynamic Time Warping (DTW) for step characterization, with preliminary results in control subjects and patients with neurological diseases. Subjects performed a protocol including a 10 m straight walking, then turn back and walking for additional 10 m. The library is constructed with inertial signals (acceleration and angular velocities recorded in three directions) aligned with the DTW. Templates in the library are obtained for a specific cohort and for the different walking phases of the protocol. They are compared to the signal of a single subject by calculating a Pearson correlation coefficient. The method has been tested on a database of 864 exercises, obtained from 71 healthy controls, 24 patients with Parkinson disease and 48 patients with Radiation Induced Leukoencephalopathy (RIL). Pearson correlation classification reports a precision of about 85% for step detection. For exercise characterization the sensitivity is about 57%, 56% and 82% for Parkinson, RIL and control subjects respectively.

I. INTRODUCTION

Healthy gait is characterized by the repetition of similar patterns, structured into sequential phases. Gait abnormalities can impact either the sequencing of these patterns or the intrinsic structure of the pattern. These alterations can be a consequence of ageing, past trauma or chronic diseases, which can be either localized into the musculoskeletal system (legs, feet) or into the neurological system (brain, spinal cord and inner ear) [1]. Studying these patterns can be useful for diagnosis, follow up and early identification of gait disorders, which is of major importance since they are early predictors of physical disability and are associated with reduced quality of life and loss of independence [2]. Current clinical measures to assess mobility in neurological diseases have no clearly accepted standards [3], [4], except for optical analysis [5]. However, this apparatus is expensive, time consuming and can only be used in large laboratories inasmuch as it requires an entire experimental room. Furthermore, with the rapid development of sensing technology, new gait assessment approaches have appeared recently based on sensors, such as floor sensors, foot-switches, foot pressure insoles and inertial sensors [6]. In particular, Inertial Measurement Units (IMU) including accelerometers and gyroscopes, have

become popular in recent decades being easy-to-use and low-cost solutions. They have been widely used in wearable systems for gait analysis [7]. Also, they have shown good reliability for assessing changes in gait patterns in subjects with neurological diseases such as multiple sclerosis and Parkinson and other diseases such as cardiopathies, stroke and diseases caused by ageing [8]. IMU's can be worn in various parts of the patient's body, most often the lower back, but also the feet, knees, thighs, trunk and head. The signals recorded by these sensors can be used to perform gait analysis and to determine kinematic and kinetic gait parameters for steps, strides or other gait sub phases. Gait patterns can also be identified in the signals by searching for repetitive patterns. These repetitive patterns can be stored as library of templates that can be useful for step characterization [9], [10].

In this paper, a library of templates is extracted from real signals for step characterization purposes. As the sequences we want to detect are variable in duration as well as in amplitude, we use Dynamic Time Warping (DTW) for this purpose. We construct templates for specific pathologies and for specific walking phases in a predefined protocol (exercise). The templates are to be compared to the signal we want to study by calculating a Pearson correlation coefficient. The highest correlation score is used to identify the step. The corresponding template matching algorithm allows not only to associate the detected step to a specific class, but also, to characterize of all the exercise by using a majority voting strategy.

This article is organized as follows: Section II describes the protocol and inertial signal analysis. The methodology for the construction of the step library is presented in section III. Experiments are quantitatively validated and are presented in Section IV followed by discussions and conclusions in Section V.

II. MATERIALS AND METHODS

A. Population

Inertial data was collected from 143 subjects divided into control and neurologic groups. Healthy control subjects had no known medical impairment. The neurologic group is composed of 2 cohorts: Parkinson disease and Radiation Induced Leukoencephalopathy (RIL), which commonly show quite similar small steps and might be difficult to discriminate using the sole clinical examination. Each patient can show unilateral or bilateral disorders. Data has been provided by the Service de neurologie de l'Hôpital d'Instruction des Armées du Val de Grâce, Service de Santé des Armées.

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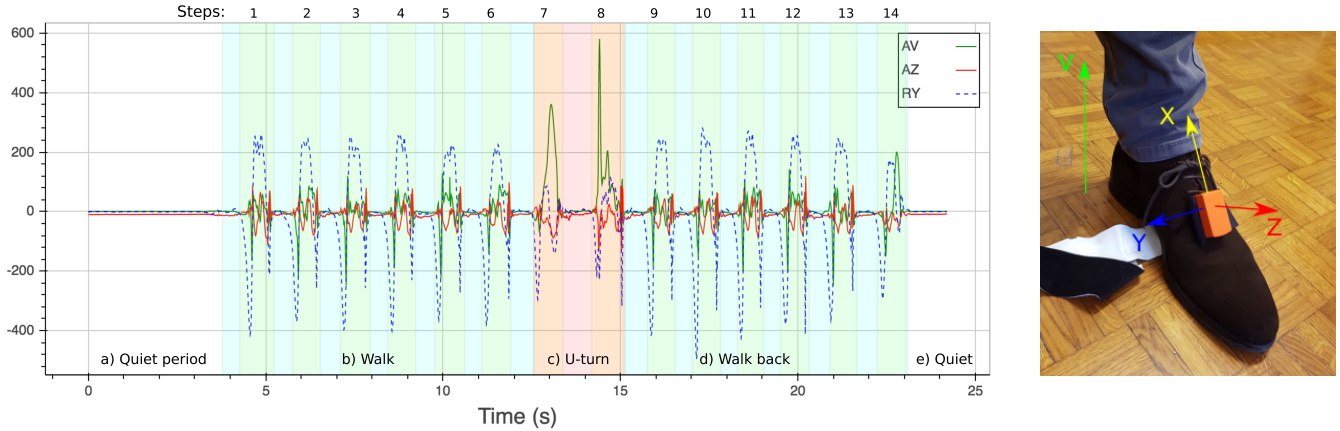


Fig. 1. (Left) Inertial signals obtained with a XSens MTwTM sensor placed in the right foot of a control subject. 3 types of signals are shown: Vertical acceleration (AV), Z-axis acceleration (AZ) and Y-axis angular velocity (RY). The 5 phases of the protocol are shown: a) initial stand quiet, b) walking, c) U-turn, d) walk back and e) final stand quiet. Results of the manual segmentation of steps performed by a specialist can be seen: a total of 14 steps have been manually identified, 6 in the forward walk phase, 2 during the U-turn and 6 in the walk back phase. (Right) Axis definition for XSensTM sensor located at the left foot.

The study was validated by a local ethic comity (Comité de Protection des Personnes Ile de France II, CPP 2014-10-04 RNI) and both patients and control subjects gave their written consent to participate.

B. Acquisition protocol

The protocol includes 2 sensors located at the right and left foot and each of them records, among others, 2 types of signals: 3D accelerations and 3D angular velocities. All signals have been acquired at 100 Hz with wireless XSens MTwTM sensors and fixed using a velcro band designed by XSensTM. The signals obtained with both sensors were automatically synchronized by the acquisition software. During the protocol, subjects walked at their preferred speed and kept their own shoes. The phases of the protocol are: a) stand quiet about 6 seconds, b) walk 10 meters on a level surface, c) make a U turn, d) walk back and walk the same distance and e) stand quiet about 2 seconds. Fig. 1-left shows an example of acquisition from a sensor placed on the left foot for a control subject. In the figure the walking phases of the protocol are highlighted.

C. Inertial signal selection

The inertial signals of acceleration and angular velocity obtained for each sensor are recorded in 3 orthogonal directions, as can be seen in Fig. 1-right. However, for step characterization we only use the Z-axis acceleration (AZ), Y-axis angular velocity (RY) and vertical acceleration (AV) following the recommendations found in the literature [9], [11] and a visual exploratory analysis performed by neurologists.

III. TEMPLATE-BASED DTW CONSTRUCTION

The principle of our step characterization algorithm is to identify the steps in the signals and to associate them with a specific class thanks to a predefined library of labelled templates. We propose to automatically construct this library

from a set of manually annotated signals (steps) in order to retrieve the most typical and characteristic patterns in healthy and pathological gaits. More precisely, we construct a library of descriptive templates for each cohort and for each walking phase of the protocol: forward, U-turn and return.

Intuitively, a template can be interpreted as an average step. However, since steps have different durations and amplitudes, it is not possible to compare and merge them with simple averaging methods. We therefore propose, before averaging the signals, to warp them nonlinearly in time dimension so that they match each other as closely as possible. More precisely, we propose to use the Dynamic Time Warping (DTW) [12]. Given a reference time series R of length $|R|$ and a test signal T of length $|T|$, the aim of DTW is to stretch or shrink signal T by repeating or averaging some samples so that T fits signal R . The process is performed by finding the optimal path in a 2D $|R| \times |T|$ cost matrix D of accumulated distances:

$$D(i, j) = \min[D(i-1, j-1), D(i-1, j), D(i, j-1)] + d(i, j) \quad (1)$$

with

$$d(i, j) = \|R(i) - T(j)\|_2^2 \quad (2)$$

The DTW uses dynamic programming to find the minimum cost path through the matrix of local costs. The temporal warping for signal T is obtained by using the path output from DTW.

As a preliminary step, a training subset of exercises is selected. Then, the signals in the subset are manually segmented by an expert, who identifies the beginning and the end of each step (cf. Fig. 1-left). Signal segments corresponding to steps (right and left foot) are then processed to construct the library:

- 1) The duration (step lengths) of all the annotated steps in the training subset of exercises are calculated.

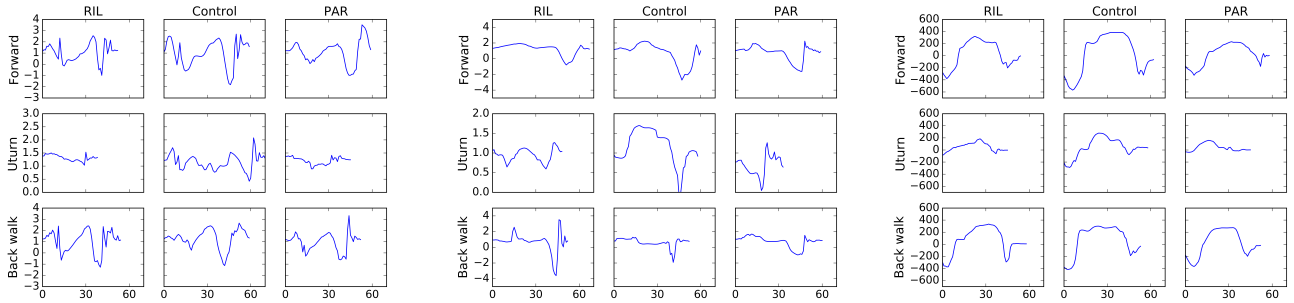


Fig. 2. Example of templates using the vertical acceleration AV ($m.s^{-2}$) (left), Z-axis acceleration AZ($m.s^{-2}$) (middle) and angular velocity RY ($rad.s^{-1}$) (right) signals in the different phases of the protocol

- 2) A K-means clustering algorithm is applied to the step lengths in order to identify the K most representative step lengths.
- 3) For each cluster, we extract a reference signal. This signal is the one whose length is the closest to the average length in the cluster.
- 4) All signals in the cluster are temporally realigned to the reference signal by using the DTW.
- 5) For each cluster all the realigned signals are averaged so as to form the template.

This process is applied independently for each cohort (Control, PAR, RIL), each walking phase (forward, U-turn and return) and each component signal (AV, RY, AZ).

IV. EXPERIMENTS AND RESULTS

Each subject performs the walking protocol (exercise) between 1 and 4 times. A total of 864 exercises was collected, each one with a different number of steps. Subject's characteristics are shown in Table I. In total, the database is composed of 34556 steps (17301 extracted on the right foot and 17255 on the left foot).

TABLE I
SUBJECTS' CHARACTERISTICS.

Group	Exercises	Subjects	Sex (M/F)	Age (std)
Control	350	71	35/17	38.79 (19.6)
Parkinson	154	24	26/27	58.95 (14.9)
RIL	360	48	80/45	74.02 (10.84)

The average walking speed in these experiments was 1.18 (0.19) m/s in the control group, 0.79 (0.24) m/s for the RIL group and 0.85 (0.23) m/s for the Parkinsonian group. These values are in concordance with values reported in the literature in which gait speed in neurological patients are lower than those of healthy people [13]. For training, the subsets are composed of 5 exercises (left and right foot), which constitutes a good compromise between complexity and performance. The final library of templates is composed of 162 templates: with $K=6$ templates per phase (forward, U-turn, walk back), signal (AV, RY, AZ) and cohort (Control, PAR, RIL), i.e. $6 \times 3 \times 3 \times 3$. The number of clusters $K=6$ was chosen so as to avoid the presence of unrepresentative

steps or outliers (which can be due to incorrect segmentation).

A. Template analysis

Fig. 2 shows an extract of the library with different templates among the different phases and cohorts in study. For example, in Fig. 2-left, patterns from walking phases in forward and back directions in the AV signal are similar but they differ from patterns in the U-turn phase. As we can see, in the example shown in Fig. 2-right, signal templates in the RY signals do not differ a lot among cohorts of subjects: it seems that these patterns have a similar shape but different amplitudes. Another important observation is that the length of each pattern is different among cohorts. Subjects with neurological diseases have usually shorter steps and therefore change their templates as can be seen in Fig. 2-middle in the U-turn phase in the template for the parkinsonian cohort.

B. Step detection

As sequences we want to detect are variable in amplitude, we use the Pearson correlation coefficient to measure goodness of fit that is independent of the scale. For each type of template, a sliding-window of size equal to the length of a template $|T|$ is applied to each exercise (with an overlapping of $|T|-1$ samples) in the corresponding signal of the template to generate n signal segments S (possibly steps). Then, an array of n correlation coefficients between the template and each signal segment is obtained by calculating:

$$r = \frac{cov(T, S)}{std(T)std(S)} \quad (3)$$

We detect a step in the exercise if the Pearson coefficient associated to a signal segment S is higher than a threshold chosen by heuristic and fixed to 0.75. Furthermore, as a step can be detected using templates from different cohorts, we select the template with the highest coefficient of correlation providing the corresponding class of step. A total of 34480 steps between left and right foot have been detected. Results have been obtained with a precision of 84.66% and a recall of 87.05%.

C. Step characterization

Preliminary results for step characterization are shown in Table II. It should be noted that the ground truth here is given by the global status of the subject. For example, all the segmented steps from a specific subject in one class are catalogued with the same class of the subject. This criterion could be biased by the fact that in pathological subjects, some steps present normal dynamic whereas others are abnormal.

TABLE II
CONFUSION MATRIX FOR STEP CHARACTERIZATION

		Predicted			Total
		RIL	PAR	Control	
True	RIL	8383 (0.49)	6743 (0.40)	1860 (0.11)	16986
	PAR	1291 (0.19)	3850 (0.57)	1662 (0.24)	6803
	Control	2211 (0.21)	1409 (0.13)	7071 (0.66)	10691

As can be seen in Table II, for each cohort the highest score of prediction is achieved in the same original class, which reflects some moderate robustness of the method. Results show that the highest score is obtained in the control group with 66% of sensitivity. For the RIL group, 40% of the steps were attributed to the Parkinsonian group which suggests some similarity among the templates in subjects from the neurologic cohorts.

TABLE III
CONFUSION MATRIX OBTAINED AFTER MAJORITY VOTING (MV) FOR EXERCISE CHARACTERIZATION

		Predicted			Total
		RIL	PAR	Control	
True	RIL	204 (0.56)	57 (0.16)	99 (0.27)	360
	PAR	30 (0.19)	88 (0.57)	36 (0.23)	154
	Control	27 (0.08)	34 (0.09)	289 (0.82)	350

Table III shows the result after performing a majority voting strategy. Specifically, we try to characterize all the exercise instead of focusing on each step in the exercise. In this case, if more than half of the steps examined in one exercise is classified in a specific cohort, then, the entire exercise is assigned to that cohort. This rule is applied independently for each foot. A good classification is achieved in control subjects with a sensitivity of 82%. Exercise characterization for the RIL group increased from 49% to 56% of sensitivity. This improvement could be explained by the fact that the pathology could affect only one side of the body. Other characteristics such as the age of the patient could explain the similarity of gaits to a healthy, when compared to other older Parkinson and RIL patients.

V. CONCLUSIONS

We presented a method that is able to characterize different steps for patients with neurological troubles and control subjects. The method is based on the construction of a library based on DTW from inertial signals. It has been applied with a database composed of 864 acquisitions from 71

healthy controls and 72 patients with neurological troubles. Preliminary results have shown that by using a small quantity of templates, step detection and characterization could be performed. Furthermore, in order to characterize the entire exercise the majority voting strategy brings useful information. The method could be improved by evaluating disorder severity of the subject at each step foot and subtracting possible normal steps of neurological groups to obtain a pure neurological template pattern. A wide analysis in the phases of the protocol is also needed as well as a study of the different patterns in the library. Future research effort should focus on testing different classification techniques with cross-validation. The dynamic of each subject step is a crucial factor to characterize other subject's steps because each subject has his own way of walking.

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