Learning Human Interaction using a Smart Rollator, the *i*-Walker

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People tend to slow their gait speed and their balance as they age. In addition, the retirement from the working life, and the consequent reduction of physical and social activity, contribute to the increased incidence of falls in older adults. Moreover, elderly people suffer different kinds of cognitive decline, such as dementia or attention problems, which also accentuate gait disorders.

Assistive technologies (AT) play a key role in today's society, especially when it comes to the older adults. They aim to maintain or improve individual's functioning and independence and to enhance overall well-being. ATs have an impact in their Quality of Life, extending their autonomy and community living, and allowing them to stay active in a safe and independent way. During the last decade, research has focused on developing ATs with sensor systems integrated in the device or located in the human body. Efforts are focused especially on mobility assistance and activity recognition for different targets of population, which could be used, for instance, to monitor elderly population while performing activities of daily living.

This thesis work presents a new methodology to analyse the results obtained from the interaction between a smart rollator, the *i*-Walker, and a group of older adults with high risk of falling as a consequence of physical and/or cognitive impairment. The *i*-Walker is a standard 4-wheeled rollator, equipped with a set of sensors and actuators and is able to collect data for long periods of time (several hours). Force sensors are embedded in both handlers and measure the longitudinal, lateral and vertical forces exerted by the user (X, Y and, Z respectively). Each rear rear wheel contains a motor able to work in 4 different modes, an accelerometer and encoders to calculate the estimated position and orientation of the *i*-Walker. The battery, a RaspberryPi and IMU sensors are placed in a central box under the seat [2]. It has already been tested in post-stroke rehabilitation and fall prevention clinical trials with successful results [1, 3, 4]. The *i*-Walker was used to collect data during the execution of different walking tests and exercises performed by a group of volunteer participants of an international multi-centre study as part of the *I-DONT-FALL* EU funded project [6]. This dataset is formed by 88 older adults that have fallen at least once during the last year. Data were part of the , where each individual was randomly assigned to a training group (motor, cognitive, mixed and placebo) during three months as a fall prevention service. The main objective was to reduce the number of falls, along with the risk and fear of falling. Participants of *I-DONT-FALL* where assessed physically and cognitively before the beginning of the three-months training (motor, cognitive, mixed or placebo) and at the end of this period ($T0$ and $T1$ respectively). The dataset was completed with biological data from each individual, such as age, gender, the number of falls during the last year, if present, as well as some cognitive and physical assessment measures provided by health professionals of each centre. A second group of participants composed by 27 healthy elderly individuals living in a care is the baseline of this work. The inclusion and exclusion criteria were the same for both groups, but people from the latter group had no previous falls before the test. For this PhD we will focus on two of the assessment scales that where used during the evaluations of *I-DONT-FALL*: the 10 Meter Walk Test (10MWT) and the 6 minute Walk Test (6mWT).

For this work, gait parameters are extracted from the interaction between the user and the *i*-Walker, in particular the data extracted from the force sensors located in the handlers of the rollator. In this case, strides are measured in relation to the amount of longitudinal (pushing) hand force exerted at each moment. It has been observed that people, and especially women, present a hip sway during the swing phase in order to balance the weight. When using a rollator, this swaying is accompanied by a pushing force coming from the arm that will allow to move it from one point to another. Hence, we can extract the movements of the *i*-Walker by using its force sensors and, moreover, we might be able to interpret the number of steps performed during an exercise by using the following formula:

$$F_x diff = rhfx - lhfx;$$

where $rhfx$ corresponds to the right hand pushing force and $lhfx$ is the left hand pushing force. Hence, inhere positive values on the resulting signal $F_x diff$ are those where the right hand was exerting a higher pushing force that the left hand, and thus represent a right leg step (see Figure 1). Figure 2 represents the evolution of the step length for each foot while performing the 10MWT.

A machine learning technique to model the risk of falling prediction for an individual was also applied to the *i*-Walker data generated during the 10MWT exercises at $T0$ and $T1$. Several variables have been selected for the 10MWT exercises from the study sample using the *i*-Walker. These variables combined raw data with other calculated variables. They correspond to the average values

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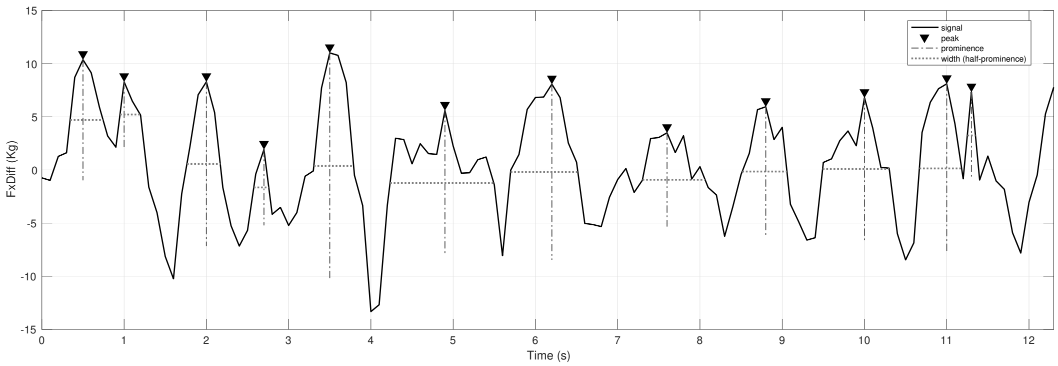

Figure 1: Right leg strides, pushing force increments and average pushing time within peaks

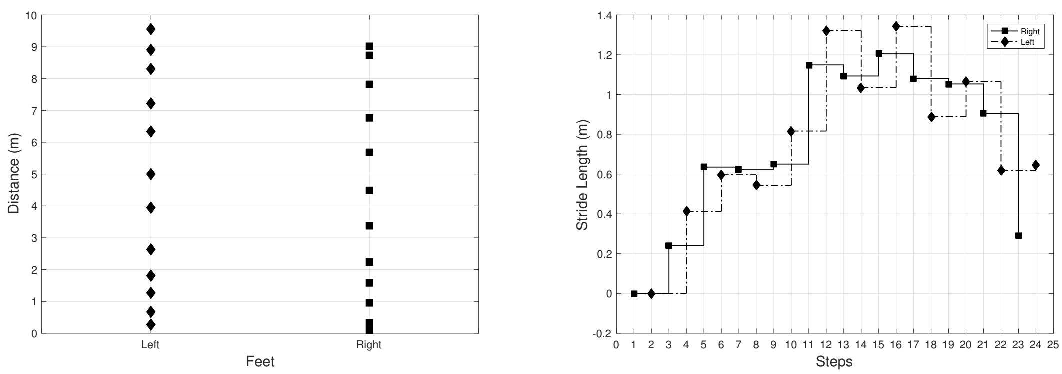

Figure 2: Evolution of an individual's stride length during the 10MWT: (a) Estimated feet position; (b) Stride length for each foot

from the force sensors (X, Y and, Z directions) of both hands and the average speed. The dataset has a total of 20 variables. The average was computed for all the 10 meters of the exercise and also for the values discarding the first and last two meters (the central part of the exercise). The reason of discarding values from the beginning and the end of the exercises was to reduce noise from acceleration and deceleration phases and focusing on the stable regime of the exercise [5]. The exercises were divided in two datasets, containing the 10MWT exercises performed at $T0$ and $T1$ respectively. The former is used as a training set to obtain a predictive model for the risk of falling, while the second is used as test to detect if the population has changed their status as an effect of the treatment.

To obtain the model for fall risk, a logistic regression was performed using L_1 regularization, first with all the variables, and then selecting only the relevant ones, by discarding all variables that were assigned zero weight by the regularized logistic regression. From all the variables only 10 were used by the model that included variables for all the exercise (average speed, mean force on the X direction, right hand force on the X direction and left hand forces on the three directions) and only for the central part (left hand forces on the X and Z directions and right hand forces on the Y and Z directions). A Support Vector Machine (SVM) model with linear kernel was also computed, obtaining identical results. It is clear that the information obtained from the force exerted by the user to the *i*-Walker is essential to characterise its walking behaviour. The best accuracy obtained from the model measured using 10-fold cross validation was 0.88 with standard deviation 0.1. The accuracy of the model for all the data was 0.95. Preliminary results of both studies are published in [2]

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