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# Online estimation of rollator user condition using spatiotemporal gait parameters

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***Abstract*— The assistance to people during rehabilitation has to be adapted to their needs. Too little help can lead to frustration and stress in the user; an excess of help may lead to low participation and loss of residual skills. Robotic rollators may adapt assistance. The main challenge to cope with this issue is to estimate how much help is needed on the fly, because it depends not only on the person condition, but also on the specific situation that they are negotiating. Clinical scales provide a global condition based estimation, but no local estimator based on punctual needs. Condition also changes in time, so clinical scales need to be recalculated again and again. In this paper we propose a novel approach to estimate users' condition in a continuous way via a robotic rollator. Our work focuses on predicting the value of the well known Tinetti Mobility test from spatiotemporal gait parameters obtained from our platform while users walk. This prediction provides continuous insight on the condition of the user and could be used to modify the amount of help provided. The proposed method has been validated with 19 volunteers at a local hospital that use a rollator for rehabilitation. All volunteers presented some physical or mental disabilities. Our results successfully show a high correlation of spatiotemporal gait parameters with Tinetti Mobility test gait ($R2 = 0.7$) and Tinetti Mobility test balance ($R2 = 0.6$).**

## I. Introduction

Population is getting older. The elderly are projected to grow by 56 per cent until 2030 [1]. In addition, a high percent of population aged 16 and over declared a severe disability [2]. There are not enough care giving professionals to cover these needs, so in extreme many of these people require to be confine in an institution. Assistive robots may improve the autonomy and the quality of life of people with dependency [3] to avoid these problems. Medical specialists recommend to use a variety of assistive devices depending on the user requirements [4]. In this paper, we focus on smart rollators (Fig. 1) which are a useful support for activities of daily living (ADL).

Walking assistance and fall prevention have been extensively investigated in the field of smart rollators [5], [6], [7], [8], [9]. However, only a few works [10], [11] propose to adjust the amount of assistance. This adjustment is critical for rehabilitation purposes. Unnecessary assistance provokes a decrease of physical and mental activities, increasing the risk of a *disuse syndrome* [12]. Too little help may lead to failure, frustration and stress.

Fig. 1. A user with a right above-knee amputation walks with the i-Walker platform

Some studies define different states depending on the user's posture to adjust the amount of assistance [13]. When unusual states are detected, they reactively change the amount of help. However, they do not analyze how much help different users may need if they are in the same state. Another approach takes into account the user condition as provided by medical staff feedback [10]. They manually adjust some rollator parameters in order to modify the amount of help beforehand. These solutions obviously depend on clinicians' feedback and can not adapt to condition changes or special situations unless a new clinical assessment is performed. [11] excludes clinical intervention by using the center of rotation to evaluate the user's condition. However, this parameter needs to be calibrated from a test without assistance. If it value changes in time, it needs to be recalibrate.

In this work we propose a novel approach to unsupervisedly estimate user condition using only spatiotemporal gait parameters obtained on the fly by the sensors in a smart rollator. We will correlate those parameters with the well known Tinetti Mobility Test [14] while users walk. Thus, we will isolate the most relevant parameters that provide the same information than Tinetti does, only these parameters can be unsupervisedly obtained any time while users walk. The main contributions of this work are: i) normalization and scaling of spatiotemporal gait parameters related to user condition; ii) obtaining a prediction of Tinetti Mobility Test using only spatiotemporal gait parameters; and iii) validation

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with a set of volunteers presenting a diversity of physical and/or cognitive disabilities. Our results have been successful in every case. We expect to use this estimation in the future to adapt the amount of help provided by the rollator to users in a continuous way.

## II. Methodology

### A. The i-Walker platform and our gait analysis algorithm

We use the smart rollator i-Walker [15]. It is a standard rollator frame with force sensors embedded in its handlebars and encoders in both wheels (Fig. 1).

Traditionally, gait analysis has been conducted either by using environment sensors, like treadmills or optical systems or via wearables and range sensors [16]. These approaches put constraints on test environments, require intervention of specialized staff to place the sensors and/or operate the system and, in general, can not be performed in everyday situations. Some rollators have relied on Time of Flight sensors to monitorize users' feet and estimate gait parameters. However, parameters can be obtained from simpler, cheaper rollators as long as they include force sensors in the handles and odometers in the wheels. This type of rollators, like i-Walker, can be used anywhere and at any time. Steps can be detected from the force difference between the handlers, corresponding to gait swing. Parameters can be extracted by combining this information with lengths and times returned by the robot odometry and its process unit.

In our previous work [17], we used the i-Walker to obtain meaningful spatiotemporal gait parameters from different challenged users. Our results validated that the chosen set of spatiotemporal gait parameters were coherent with the user diagnosed condition. However, we still did not use the parameters set to estimate how much help each user required because we needed to combine those parameters into a single estimation. In this work, we obtain that estimation using only the handlebar force sensors and the wheels odometry in a smart rollator.

The gait analysis algorithm presented in [17] returns 10 parameters (Table I). We obtain average and standard deviation of each parameter for a period of time. So in total, 18 parameters have been analyzed $\{P_1, P_2, ..., P_n\}$ (Table III).

### B. Test population

Testing assistive devices with users with disabilities is usually challenging, so many works in this area tend to test with healthy [7], [8], [18], [19] or simulated users [11]. Other works focus on specific groups of users, e.g. Parkinson [20] or stroke [21]. Our goal is to define a general estimation of rollator user condition. Therefore, we have chosen a set of volunteers as varied as possible at the Hospital Regional Universitario de Malaga and Fondazione Santa Lucia. Our volunteers had a variety of cognitive and/or physical disabilities (Table II). We imposed only two restrictions to our volunteers, they had to: i) be able to walk with the aid of a rollator; and ii) support some weight while walking on the rollator. With the second restriction, we discarded users who could walk without any aid.

Our tests include 19 volunteers: 13 women and 6 men. They are in average 67.47±9.70 years old (range $46 - 80$ years). Table II shows their neurological and/or physical disabilities. We asked clinicians to provide the Tinetti scale results for every volunteer, so we could correlate gait parameters with Tinetti Balance ($T_{BAL}$) and Gait ($T_{GAIT}$). The table includes body size parameters for each volunteer, because parameters like stride length or user support depends on weight ($w_0$) and leg length ($l_0$) and they need to be normalized. The cognitive disabilities in our volunteers include Parkinson, dementia and intellectual disability. The physical disabilities include amputees and a variety of fractures. The Parkinson and Dementia patients were at the end of their rehabilitation process and their condition did not change.

### C. Mobility assessment and proposed test

In our tests with volunteers presenting disabilities, clinicians provided the Tinetti Mobility Test [14]. This test is divided into two stages: one to measure the balance ($T_{BAL}$), and another to evaluate the gait function ($T_{GAIT}$). $T_{BAL}$ is related with fall risk and equilibrium issues. $T_{GAIT}$ depends on how users walk. A healthy volunteer will obtain a maximum of 28 point: 16 point for a perfect balance and 12 point for a perfect gait function.

Fig. 2. Rehabilitation room map (approximately $128m^2$)

After finishing the Tinetti Mobility Test, volunteers walked freely around the rehabilitation room (Fig. 2) for 3 minutes. They were asked to steer right and left, both smoothly and sharply and and to walk straight at least for 10 meters. Global paths could change during the sessions, depending on obstacles around and users' decisions. Other patients and medical staff were purposefully allowed to walk freely in the same room during tests .

## III. Predicting gait and balance from spatiotemporal gait parameters

This section proposes a methodology to predict the gait and balance indicators proposed in Tinetti Mobility Assessment. It uses only spatiotemporal gait parameters that can be extracted anytime on the fly from the onboard sensors of a smart rollator. The main advantage of this approach is that no medical intervention nor previous training is required to estimate how much help users may need depending on their gait and balance. Thus, this estimation can be obtained in a continuous and unsupervised way.

TABLE I

SPATIOTEMPORAL GAIT PARAMETERS

| Name | Acronym | Description | Unit |
|---|---|---|---|
| Cadence | CAD | Number of steps per minute | $\frac{step}{min}$ |
| Stride Time | $SdT$ | Time differences between a side step and the next step in the same side | s |
| Stride Length | $SdL$ | Length differences between a side step and the next step in the same side | m |
| Left Step Time | $SpT^{left}$ | Time differences between a left step and the next right step | s |
| Right Step Time | $SpT^{right}$ | Time differences between a right step and the next left step | s |
| Left Step Length | $SpL^{left}$ | Length differences between a left step and the next right step | m |
| Right Step Length | $SpL^{right}$ | Length differences between a right step and the next left step | m |
| Walking Velocity | $WV$ | The distance walked during the test divided by the test time | $\frac{m}{s}$ |
| Left User Support | $UrS^{left}$ | Amount of weight that users support in the rollator during $SpT_{left}$ | N |
| Right User Support | $UrS^{right}$ | Amount of weight that users support in the rollator during $SpT_{right}$ | N |

TABLE II

USERS CONDITION AND BODY SIZE

| Age | Gender | Neurological | Physical | $T_{BAL}$ | $T_{GAIT}$ | $w_0$ | $l_0$ |
|---|---|---|---|---|---|---|---|
| 65 | W | - | Periprosthetic femur fracture (Left) | 13-15 | 10-12 | $75kg$ | $0.9m$ |
| 63 | W | - | Hip arthroplasty (Right) | 4-5 | 2-6 | $86.4kg$ | $0.96m$ |
| 74 | M | - | Hip fracture, calcaneal and metacarpal (Left) | 14-16 | 8-10 | $57kg$ | $0.85m$ |
| 68 | W | - | Left above-knee amputation. CREST syndrome | 7-12 | 3-6 | $56kg$ | $0.95m$ |
| 58 | M | Intellectual disability | Right above-knee amputation | 9 | 7-8 | $96.7kg$ | $1.1m$ |
| 50 | W | - | Ankle fracture (Left) | 14-15 | 10 | 71kg | 0.78m |
| 55 | W | - | Hip fracture (Right) | 13-14 | 10-11 | 65 kg | 0.9m |
| 46 | W | - | Femur prosthesis (Right) | 10-13 | 8-9 | 70kg | 0.8m |
| 70 | M | Mild parkinson | - | 13 | 12 | $75kg$ | $0.93m$ |
| 80 | W | Mild parkinson | - | 14 | 10 | $63kg$ | $0.75m$ |
| 63 | M | Moderate parkinson | - | 8 | 12 | $91kg$ | $0.97m$ |
| 78 | W | Moderate parkinson | - | 10 | 10 | $61kg$ | $0.81m$ |
| 67 | W | Moderate dementia | - | 11 | 10 | $55kg$ | $0.85m$ |
| 74 | M | Mild parkinson | - | 13 | 12 | $73kg$ | $0.83m$ |
| 71 | M | Isquemia (Left) | - | 12 | 6 | $72kg$ | $0.99m$ |
| 71 | W | Mild parkinson | - | 13 | 11 | $68kg$ | 0.75 |
| 73 | W | Mild parkinson | - | 15 | 11 | $74kg$ | $0.86m$ |
| 78 | W | Mild dementia | - | 15 | 11 | $74kg$ | 0.86 |
| 78 | W | Mild dementia | - | 16 | 12 | $52kg$ | 0.79 |

### A. Data preprocessing

As it was mentioned in section II-A, the spatiotemporal gait parameters $\{P_1, P_2, ..., P_n\}$ are affected by the user's body size, e.g. tall people tend to walk with larger $SpL$ and lower $CAD$ than shorter people and $UrS$ obviously depends on user's weight. [22] proposes to scale all gait data using only user's leg length $l_0$ and weight $w_0$.

Following the guidelines provided by [22], we divided our spatial parameters $(SdL, SpL^{left}, , SpL^{right})$ by the leg length $l_0$. Also, temporal parameters $(SdT, SpT^{left}, SpT^{right}, CAD)$ have been divided by $\sqrt{\frac{l_0}{g}}$. This factor is obtained from the rate of acceleration with respect to space. $WV$ is a spatio-temporal parameter; therefore it has been divided by $l_0$ and multiplied by $\sqrt{\frac{l_0}{g}}$. Also, force parameter $UsS$ has been divided by $\frac{1}{m_0 g}$. After scaling, we have the normalized parameters $\{P_1', P_2', ..., P_n'\}$.

At this point, there is a high degree of correlation in the normalized parameters that we plan to use for prediction. For example, $WV$ depends on $SpL$ and $CAD$. Other parameters like $SdL$ and $SpL$ are also correlated. The Variance Inflation Factor (VIF) for our parameter after scaling is 883.43 in average (Fig. 3). It indicates a high multicollinearity in our data. Multicollinearity reportedly makes estimation very sensitive to slight changes [23].

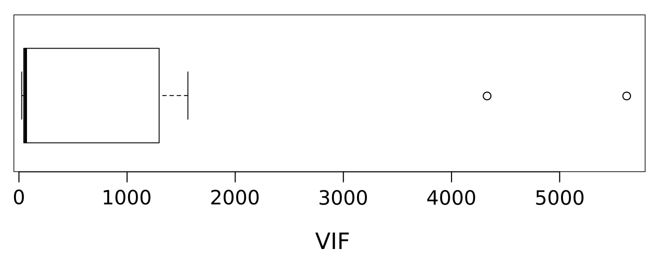



Fig. 3. VIF of gait parameters

### B. Multivariate regression: PCR and PLS

In order to reduce multicollinearity and check the correlation between our gait parameters and Tinnetti $T_{BAL}$ and $T_{GAIT}$, we have analyzed two potential multivariate regression methods: the principal component regression (PCR) [24] and partial least squares (PLS) [24]. These methods have been designed to deal with situations with few samples and correlated dependent variables. We used the *PLS* R package implementation of both methods [25].

PCR is a multivariate regression that uses Principal Component Analysis (PCA) to reduce multicolinearity before applying a linear regression to resulting data. PCA is a statistical procedure that uses an orthogonal transformation to maximize variability in analyzed data by returning a new set of variables called Principal Components. The (chosen) number of principal components $m$ is lower or equal to the original number of parameters $n$. If $m$ increases, then the multivariate variability increases too. In our case, PCA generates linear factors (**loading**) $\left\{\alpha_1^{C_1}, \alpha_2^{C_1}, ..., \alpha_n^{C_m}\right\}$ to transform the scaled spatiotemporal gait parameters for user $j$ $\left\{P_1'^j, P_2'^j, ..., P_n'^j\right\}$ to the new PCA components (**scores**) $\left\{C_1^j, C_2^j, ..., C_m^j\right\}$. Equation 1 shows the transformation for component $C_k$ and user $j$.

$$C_k^j = \alpha_1^{C_k} P_1'^j + \alpha_2^{C_k} P_2'^j + \alpha_3^{C_k} P_3'^j ... \alpha_n^{C_k} P_n'^j \quad (1)$$

Afterwards, PCR does a linear regression using the obtained components. It returns $m$ regression coefficients $\{\beta_1, \beta_2, ..., \beta_m\}$. Using these coefficients, the Tinetti Mobility factors for new user $i$ with scaled spatiotemporal gait parameters $\left\{P_1'^i, P_2'^i, ..., P_n'^i\right\}$ can be estimated using equation 2.

$$\begin{aligned} T_{pred} = \beta_1 \left(\alpha_1^{C_1} P_1'^i + \alpha_2^{C_1} P_2'^i + ... + \alpha_n^{C_1} P_n'^i\right) \\ +\beta_2 \left(\alpha_1^{C_2} P_1'^i + \alpha_2^{C_2} P_2'^i + ... + \alpha_n^{C_2} P_n'^i\right) \\ ... \\ +\beta_m \left(\alpha_1^{C_m} P_1'^i + \alpha_2^{C_m} P_2'^i + ... + \alpha_n^{C_m} P_n'^i\right) \end{aligned} \quad (2)$$

PLS works like PCR, but uses a different approach. PLS searches for directions that have high variance and correlation with respect to the dependent variable, in opposition to PCA which focuses only on high variance [26]. PCR does not take into account correlation between the dependent and the independent variables and hence, it is usually suboptimal for prediction.

PLS also represents dependent variables using a new base with $m$ components. It also has a **loading** factor to transform scaled spatiotemporal gait parameters into the **scores**. Then, it uses these scores to find a linear regression model.

### C. Evaluating our models

An important aspect when modelling a response variable is the cross validation (CV) technique. CVs split observations into two sets: one for learning purposes and another for testing purposes. These techniques limit overfitting in the resulting models. In this paper, we apply a k-fold cross validation with $k = 10$ to evaluate the regression with all users [27]. We have 19 volunteers, so, the learning group will be in average $19 * 9/10$ and the testing group will be in average $19 * 1/10$. These groups rotate 10 times, so, each volunteer will be 9 times in the learning group and 1 time in the testing group.

We are going to evaluate 2 models ($T_{BAL}$ and $T_{GAIT}$) using 2 multivariate regressions (PCR and PLS) with a number of components $1 \leq m \leq 18$. We are going to use the Root Mean Squared Error Prediction (RMSEP) [28] and the multiple coefficient of determination (R2) [25] to select the best possible combination.

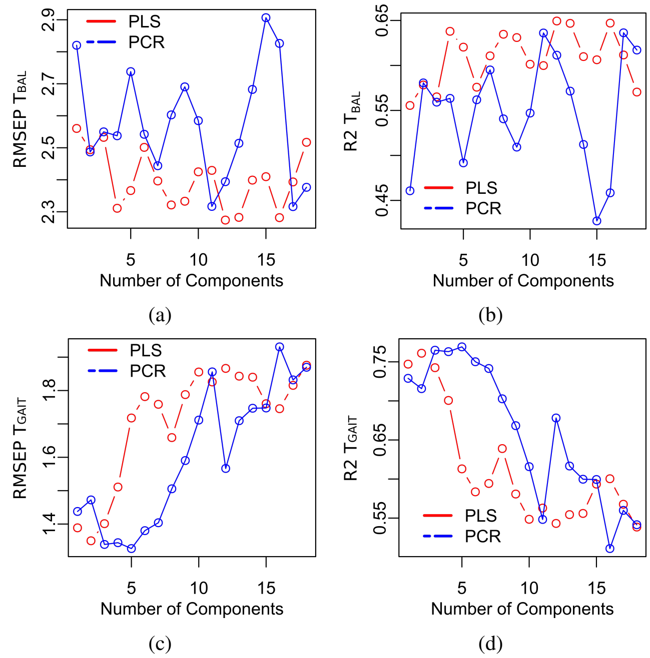



Fig. 4. R2 and RMSEP metrics for $T_{BAL}$ and $T_{GAIT}$ using PCR and PLS with all posible number of components

Let $T_{pred}$ be the prediction function for PCR or PLS, $L_k$ the test set in our k-folder cross validation, $\left\{C_1^j, C_2^j, ..., C_m^j\right\}$ the independent variables and $y_j$ the response variable. The RMSEP is calculated as:

$$RMSEP = \sqrt{\sum_{k=1}^{K} \frac{1}{|L_k|} \sum_{j \in L_k} \left(T_{pred}(C_1^j, ..., C_m^j) - y_j\right)^2} \quad (3)$$

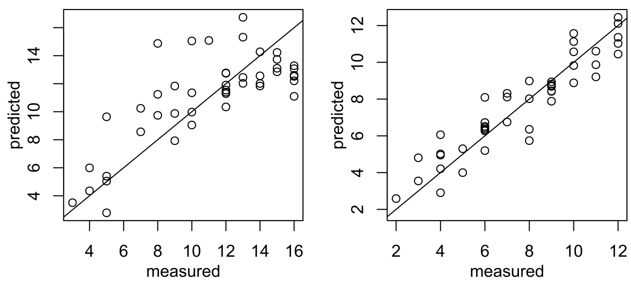
Let $\bar{y}$ be the mean of the response variables. The R2 is defined as the ration between the variances of the fitted values and real values of the dependent variable:

$$R2 = \sum_{k=1}^{K} \frac{1}{|L_k|} \frac{\sum_{j \in L_k} \left(T_{pred}(C_1^j, C_2^j, ...) - \bar{y}\right)}{\sum_{j \in L_k} (y_j - \bar{y})} \quad (4)$$

Low values of RMSEP represent a better model, i.e. fitted values are more similar to the real ones and it is not bounded. On the other hand, R2 is bounded between 0 and 1 and any value close to 1 means that the dependent variable can be predicted from the independent variables with a minimal error.

Fig.4 shows R2 and RMSEP metrics for $T_{BAL}$ and $T_{GAIT}$ using PCR and PLS with all possible numbers of components. The best combination is the one which presents the highest R2 value and the lowest RMSEP value.

PLS provides better results for $T_{BAL}$. A low RMSEP value and high R2 value indicates that the depended variables can be predicted with an acceptable error. We observe four



(a) $T_{BAL}$ prediction $m = 4$ (b) $T_{GAIT}$ prediction $m = 3$

Fig. 5. Cross validated prediction for Tinneti mobility test

possible $m$ values in R2 priority (Fig. 4(b)): 4, 12, 13 and 16. In RMSEP we also observe the same four possible $m$ values (Fig. 4(a)). The error difference from selecting 4 components to selecting more is less than 1% in R2 and less than $0.0368$ in RMSEP. These small improvements do not compensate an increase in the number of components, so we set $m = 4$.

PCR provides better results for $T_{GAIT}$. We observe three possible $m$ values in R2 priority (Fig. 4(d)): 3, 4 and 5. In RMSEP we observe the same three values (Fig. 4(c)). As in the previous case, the difference between selecting 3 components or more is less than 0.5% in R2 and less than $0.0123$ in RMSEP. Therefore, we set $m = 3$.

Fig. 5 shows the prediction using the selected number of components in both cases. $T_{GAIT}$ predictor outperforms $T_{BAL}$ predictor. It has a lower RMSEP value and a higher R2 value. This difference was expected. We are using spatiotemporal gait parameters to measure equilibrium and fall risk in $T_{BAL}$, whereas $T_{GAIT}$ focuses on the user gait, and hence, it can be predicted more accurately by using these parameters.

### D. Extracting the model

Once the number of components for $T_{GAIT}$ and $T_{BAL}$ are selected and results have been validated, our model for estimating a new dependent variables using the proposed spatiotemporal gait parameters can be obtained. Using the loading $\alpha_n^{C_m}$ and the regression coefficients $\beta_m$ values we can rearrange the equation 2 in order to obtain a compact version:

$$\begin{aligned} T_{pred} = P_1'^i & \left( \sum_{r=1}^{m} \beta_r \alpha_1^{C_r} \right) \\ + P_2'^i & \left( \sum_{r=1}^{m} \beta_r \alpha_2^{C_r} \right) \\ & \dots \\ P_s'^i & \left( \sum_{r=1}^{m} \beta_r \alpha_s^{C_r} \right) \end{aligned} \tag{5}$$

It only needs to store the $\left(\sum_{r=1}^{m} \beta_r \alpha_s^{C_r}\right)$ values to use the predictor function with the scaled parameters. Table III shows these factor for $T_{GAIT}$ and $T_{BAL}$ prediction function. Any new user condition could now be estimated as the product of their scaled spatiotemporal gait parameters (obtained at any moment of a walk using a time shifting window) by the factors described in table III.

TABLE III
LOADING FACTORS

| $Pmter.$ | $T^{gait}_{pred}$ | $T^{bal}_{pred}$ |
|---|---|---|
| $CAD$ | 0.2707 | -1.7109 |
| $SdT_{av}$ | -0.3089 | -0.2942 |
| $SdT_{sd}$ | -0.2852 | -0.7359 |
| $SdL_{av}$ | 0.3216 | 0.6483 |
| $SdL_{sd}$ | 0.0642 | 0.5542 |
| $SpT^{Left}_{av}$ | -0.3256 | -0.3405 |
| $SpT^{Left}_{sd}$ | -0.2625 | -0.1382 |
| $SpT^{Right}_{av}$ | -0.2527 | -0.2129 |
| $SpT^{Right}_{sd}$ | -0.2878 | -1.0209 |
| $SpL^{Left}_{av}$ | 0.2109 | 0.9142 |
| $SpL^{Left}_{sd}$ | 0.0606 | -0.0529 |
| $SpL^{Right}_{av}$ | 0.2314 | 0.4968 |
| $SpL^{Right}_{sd}$ | 0.0626 | 0.1038 |
| $WV$ | 0.2338 | 1.4451 |
| $UrS^{Left}_{av}$ | 0.1128 | 0.5096 |
| $UrS^{Left}_{sd}$ | -0.0545 | -0.7104 |
| $UrS^{Right}_{av}$ | 0.1202 | 0.6676 |
| $UrS^{Right}_{sd}$ | -0.0669 | -1.0508 |

We noticed in our tests that the model fitted volunteers affected by neurological disability ($RMSE(T^{gait}_{pred}) = 1.51$ and $RMSE(T^{bal}_{pred}) = 1.97$) better than the rest ( $RMSE(T^{gait}_{pred}) = 2.3$ and $RMSE(T^{bal}_{pred}) = 3.4$). This happens because all people in the neurological disability group were tested at the end of their rehabilitation process. At that point, they were already better and their physical condition allowed them to walk almost like healthy users ($T_{GAIT} = 10.56 \pm 1.94$, $T_{BAL} = 12.44 \pm 2.51$). The other volunteers had poorer parameter values ($T_{GAIT} = 7.05 \pm 2.6$, $T_{BAL} = 10.84 \pm 4.07$) and a much larger parameter variance, because they were at different states of recovery. Hence, the model provides a better fit for the neurological disability group in average.

## IV. Conclusion and Future Work

In this paper we have presented a methodology to estimate user condition from gait parameters in challenged people using a rollator equipped with force sensors and odometry. Unlike other works, our method does not require feedback from medical staff and the estimation can be performed unsupervisedly, at anytime and when users are performing any ADL. Our methodology imposes a single restriction to rollator users: they must support some weight on the platform. This is a loose restriction because, otherwise, they would not need the platform to walk. Our rollator can be used for long term monitoring and during the whole rehabilitation process.

Our method is not as accurate as medical staff feedback. It has two errors in the response variable. The first one is introduced by the gait analysis algorithm, which has a small error associated to the spatial $3.53 \pm 0.0068\%$, temporal $67.26 \pm 50.38 ms$ and support $0.98N$ parameters. The second one is introduced by the regression, the RMSEP values are $T_{GAIT} = 1.34$ and $T_{BAL} = 2.31$. Our Tinetti estimation is not as precise as a true clinical scale. However, it is enough to modulate how much assistance we provide to a given user as long as we split the scale into bins larger than the estimation error. Indeed, in many works it is proposed to establish as little as two bins in the scale to determine the user's condition [29]. We have also checked that our estimation is valid for a wide range of conditions and disabilities, since our volunteers were chosen to be as varied as possible.

Results have successfully proven that user condition prediction can be defined using the Tinetti Mobility Assessment, i.e. we could provide continuous assessment of $T_{GAIT}$ and $T_{BAL}$ to users and/or medical staff and we could use those values to adjust assistance on a need basis in the future. Hence, these results validate our proposal to estimate the user condition using only the spatiotemporal gait parameters on a rollator.

Future work will focus on extending this method to other mobility assessment tests as Berg Balance Scale [30] or balance evaluation system test [31], so we can explore the full potential of smart rollators as unsupervised evaluation tools. Also, it will focus on working with a much larger number of volunteers to cluster them by gait abnormality. This would allow us to reduce the variance of their spatiotemporal gait parameters and, hence, RMSE in the lower values estimation. We will also use the user condition prediction in a collaborative control system [32] to continuously adapt the amount of help provided to users to their needs.

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