Online estimation of rollator user condition using spatiotemporal gait parameters

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Abstract— **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 sucessfully 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 institutionalization. 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. Adjustment is critical for rehabilitation purposes. Unnecessary assistance provokes a

Fig. 1. The user 8 walks with i-Walker platform

decrease of physical and mental activities, increasing the risk of a *disuse syndrome* [12]. Too little help may lead to failure, frustration and stress.

Some works on help adjustment define different states depending on user posture [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 condition. However, this parameter needs to be calibrated from a test without assistance. If its value changes in time, it needs to be recalibrated.

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 robot 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 with a set of volunteers presenting a diversity of physical and/or cognitive disabilities. Our results have been successful

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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).

In our previous work [16] we used i-Walker to obtain meaninful spatiotemporal gait parameters from different challenged users. Our results validated that the chosen set of spatiotemporal gait parameters is coherent with the user diagnosed condition. However, we still did not use the parameter 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. Unlike other solutions which include cameras or wearable sensors, estimation can be obtained anywhere, in everyday conditions and for extended periods of time.

The gait analysis algorithm presented in [16] returns 7 parameters (Table I). Some parameters as $UserSupport$ or $StepTime$ depend on body side. We obtain average and standard deviation of each parameter for a period of time. It total there are 18 features to be analyzed $\{P_1, P_2, ..., P_n\}$.

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], [17], [18] or simulated users [11]. Other works focus on specific groups of users, e.g. Parkinson [19] or stroke [20]. 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 ± 8.86 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

As commented, clinicians provided the Tinetti Mobility Test[14] for our volunteers. This test is divided into two steps: 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 can obtain a maximum of 28 point: 16 point for a perfect balance and 12 point for a perfect gait function.
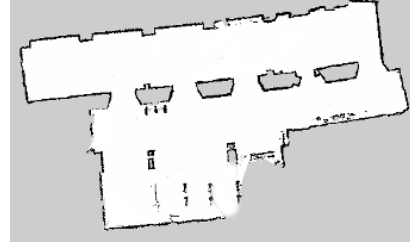

Fig. 2. Rehabilitation room map (approximately $128m^2$)

After finishing their Tinetti Mobility Test, volunteers walked freely around in the rehabilitation room (Fig. 2) for 3 minutes. Their paths needed to include steering right and left at least once smoothly and once sharply, plus a 10 meter straight walk. Further than that, the path changed during the sessions, depending on obstacles around and users' decisions. Other patients and the medical staff were allowed to walk freely in the same room during tests on purpose.

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 using 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, unsupervised way.

A. Data preprocessing

As commented, 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 smaller people and UrS obviously depends on the people weight. [21] proposes to scale all gait data using only leg length l_0 and user weight w_0.

Following the guidelines provided by [21], we divided our spatial parameters (SdL, SpL) by the leg length l_0. Also, temporal parameters (SdT, SpT, CAD) have been divided by $\sqrt{\frac{l_o}{g}}$. 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 $\sqrt{\frac{l'_o}{g}}$. Also, force parameter UsR has been divided by $\frac{1}{m_0 g}$. After scaling, we have normalized parameters $\{P'_1, P'_2, ..., P'_n\}$.

TABLE I
SPATIOTEMPORAL GAIT PARAMETERS

Name	Acronym	Description	Unit	Side
Cadence	CAD	Number of steps per minute	$\frac{step}{min}$	No
Stride Time	SdT	Time difference between one step and the next in the same side	s	Left Right
Step Time	SpT	Time difference between one step and the next one	s	Left Right
Stride Length	SdL	Length difference between one step and the next in the same side	m	Left Right
Step Length	SpL	Length difference between one step and the next one	m	Left Right
Walking Velocity	WV	Number of steps per minute	$\frac{m}{s}$	No
User Support	UrS	Amount of weight that users support in rollators. Directly related with weight-bearing.	N	Left Right

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	$96.7kg$	$1.1m$
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	$61kg$	$0.0.81m$
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

At this point, there is a high degree of correlation exist 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 indicate a high multicollinearity in our data. Multicollinearity reportedly makes estimation very sensitive to slight changes[22].
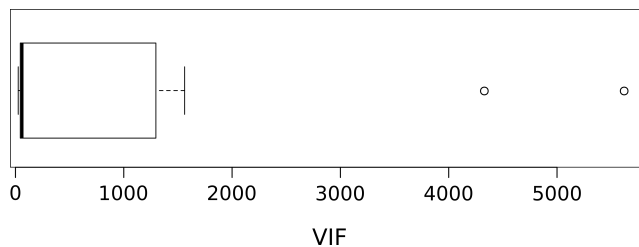

Fig. 3. VIF of gait parameters

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) [23] and partial least squares (PLS) [23]. These methods

have been designed to deal with situations with correlated dependent variables and few samples. We use the *pls* R package implementation of both methods [24].

PCR is a multivariate regression that uses principal component analysis (PCA) to reduce multicollinearity 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.

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

Afterwards, PCR does linear regression using the obtained components. A m regression coefficients are obtained from the linear regression $\{\beta_1, \beta_2, ..., \beta_m\}$. 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.

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

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 focus only on high variance [25]. 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 a number of components m. 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 modeling a response variable is the cross validation (CV) technique. CVs split observations in two: a part for learning purposes and another part 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 [26].

We are going to evaluate 2 models (T_{BAL} and T_{GAIT}) using 2 multivariate regression (PCR and PLS) with a number of components $1 \leq m \leq 18$. We are going to use the root mean squared prediction error (RMSEP) [27] and the multiple coefficient of determination (R2) [24] to select the best possible combination.

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
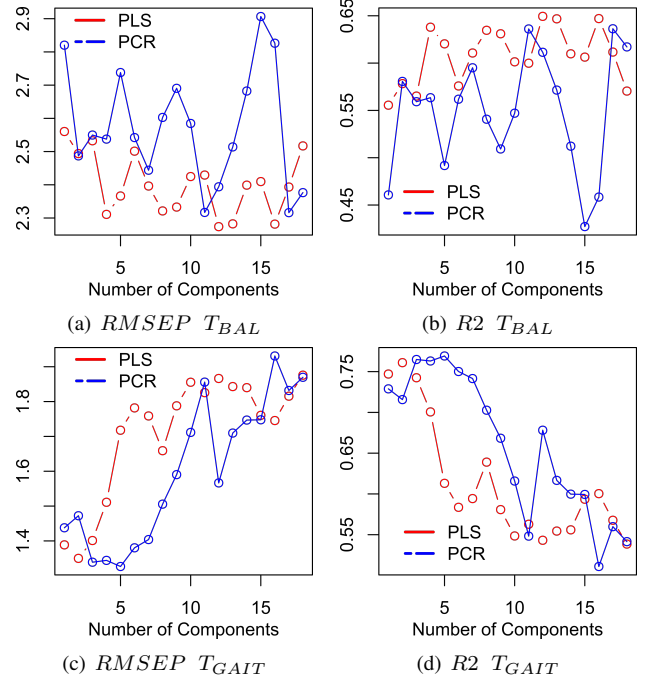

Fig. 4. R2 and RMSEP metrics for T_{BAL} and T_{GAIT} using PCR and PLS with all posible number of components

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 presenting the highest R2 value and the lowest RMSEP value.

For T_{BAL}, PLS provides better result. A low RMSEP value and high R2 value indicates that the depended variables can be predicted with an acceptable error. We observe four 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 for $m = 4$.

For T_{GAIT}, PCR provides better results. 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 for $m = 3$.

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}, wheras T_{GAIT} focuses on the user gait, and hence, it can be predicted more accurately by using these parameters.
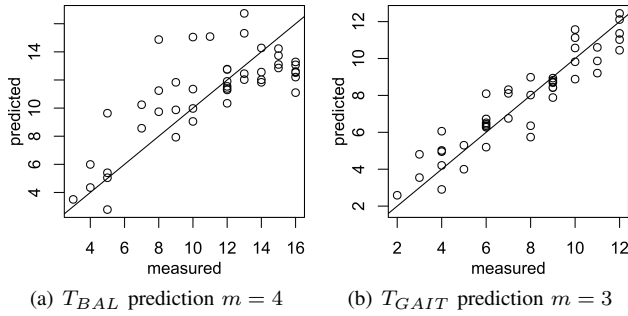
(a) T_{BAL} prediction $m = 4$ (b) T_{GAIT} prediction $m = 3$

Fig. 5.   Cross validated prediction for Tinneti mobility test

Pmter.	T_{pred}^{gait}	T_{pred}^{bal}
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_{av}^{Left}	-0.3256	-0.3405
SpT_{sd}^{Left}	-0.2625	-0.1382
SpT_{av}^{Right}	-0.2527	-0.2129
SpT_{sd}^{Right}	-0.2878	-1.0209
SpL_{av}^{Left}	0.2109	0.9142
SpL_{sd}^{Left}	0.0606	-0.0529
SpL_{av}^{Right}	0.2314	0.4968
SpL_{sd}^{Right}	0.0626	0.1038
WV	0.2338	1.4451
UrS_{av}^{Left}	0.1128	0.5096
UrS_{sd}^{Left}	-0.0545	-0.7104
UrS_{av}^{Right}	0.1202	0.6676
UrS_{sd}^{Right}	-0.0669	-1.0508

D. Extracting the model

Once the number of components for T_{GAIT} and T_{BAL} is 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 β_m values we can rearrange the equation 2 in order to obtain a compact equation:

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

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 the 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.

We noticed in our tests that the model fitted volunteers affected by neurological disability ($RMSE(T_{pred}^{gait}) = 1.51$ and $RMSE(T_{pred}^{bal}) = 1.97$) better than the rest ($RMSE(T_{pred}^{gait}) = 2.3$ and $RMSE(T_{pred}^{bal}) = 3.4$). 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 estimation can be performed unsupervisedly, 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 $T_{BAL} = 2.31$. Nevertheless, results have proven that estimation is valid for a wide range of conditions: it has been validated with 19 volunteers presenting a variety of cognitive and physical disabilities.

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 [28] or balance evaluation system test [29], so we can explore the full potential of smart rollators as unsupervised evaluation tools. We will also use the user condition prediction in a collaborative control system [30] to continuously adapt the amount of help provided to users to their needs.

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