Automatic Assessment of a Rollator-User's Condition During Rehabilitation Using the i-Walker Platform

Joaquin Ballesteros, Cristina Urdiales, Antonio B. Martinez, and Marina Tirado

***Abstract*— Patient condition during rehabilitation has been traditionally assessed using clinical scales. These scales typically require the patient and/or the clinician to rate a number of condition-related items to obtain a final score. This is a time-consuming task, specially if a large number of patients are involved. Furthermore, during rehabilitation, user condition is expected to change steadily in time, so assessment may require to run these scales several times to each user. To save time, much effort has been focused on developing clinical scales that require little time to be completed. This is usually achieved by measuring a reduced set of features, i.e., focusing the scales on specific features of a defined target population (Parkinson's disease, Stroke, and so on). However, these scales still require the therapist's intervention and may be tiresome for patients who have to fill them repeatedly. This paper proposes a novel approach to automatically obtain balance scales from the onboard sensors of a robotic rollator. These sensors are used to extract spatiotemporal gait parameters from patients using the rollator for support. These parameters are derived from the user forces on the rollator handles and its odometry. Resulting parameters are used to predict the Tinetti mobility clinical scale on the fly, without therapist intervention. Our approach has been validated with 19 rollator volunteers with a variety of physical and neurological disabilities at Hospital Civil (Malaga) and Fondazione Santa Lucia (Rome). Clinicians provided traditionally obtained Tinetti scores and the proposed system was used to estimate them on the fly. Results show a small root mean squared prediction error. This method can be used for any rollator user anywhere in everyday walking conditions to obtain the Tinetti scores as often as desired and, hence evaluate their progress.**

***Index Terms*— Rehabilitation robotics, assistive technology.**

I. Introduction

IN 2013, a 8.3% of European population over 16 years old declared a severe disability [1]. These users are severely hampered in their daily life by health problems [2].

Manuscript received April 23, 2016; revised January 9, 2017; accepted April 7, 2017. Date of publication April 25, 2017; date of current version November 6, 2017. This work was supported in part by MINECO under Project TEC2011- 29106 and Project TEC2014-56256- C2-1-P, in part by the Fondazione Santa Lucia of Rome, and in part by the Hospital Regional Universitario of Malaga. *(Corresponding author: Joaquin Ballesteros.)*

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Digital Object Identifier 10.1109/TNSRE.2017.2698005

In many of these cases, rehabilitation may lead to skill recovery and allow people to remain autonomous and/or improve their quality of life (QOL). The growing demand for therapists has lead to increased use of assistive devices. These devices can reduce the time spent by the therapist in the rehabilitation process [3].

Therapists recommend a wide variety of assistive devices depending on patient requirements [4]. Some of these devices, like walking aids, improve user autonomy [5], e.g. smart rollators provide effective support to cope with Activities of Daily Living (ADL) [6], and may also help with fall prevention [6]–[10]. Since rollators are used for prolonged periods of time, they are also an excellent tool to monitoring, specially during rehabilitation, when users' condition is expected to change in time [11]–[13]. Condition assessment is useful to evaluate rehabilitation progress, and also to decide how much assistance a given user needs and, hence, decrease the risk of *disuse syndrome* [14].

Traditionally, physical and/or cognitive condition assessment has relied on clinical scales. These scales include a number of items that users and/or clinicians score depending on their appreciation on the user condition. Most scales focus on specific aspects, like gait [15], balance [16], fall risk [17] or mental disorder [18] and are often used in combination with others. The main drawback of these scales is that they take considerable time both from clinicians and users. This is specially tiresome for clinicians working with a large number of patients and for people involved in rehabilitation processes, who would need to score the same scales several times to evaluate their progress.

Alternatively, automatic monitoring has been employed to evaluate users' gait. These algorithms return spatiotemporal gait parameters, usually for specific target populations: walking velocities in elderly people [19]; stride time and length in Parkinson's disease affected users [20]; walking velocity and stride and step length in chronic stroke affected people [21], etc. Most of these studies relate variations in these parameters to different clinical conditions, but they do not provide a global condition assessment like clinical scales do. These parameters can be obtained using external capture systems, wearable sensors, sensorized rollators or any combination of these techniques. External capture systems and wearables typically provide better precision and may return a wider range of parameters. However, they are not practical for continuous monitoring and, due to infrastructure requirements, they are confined to specific enviroments. Wearable sensors are useful for testing, but generally not for everyday use. Hence,

Fig. 1. Volunteer 4 during test with i-Walker platform.

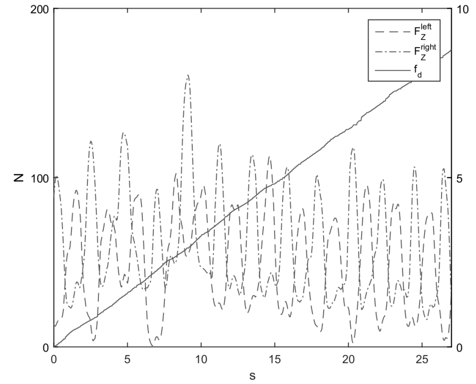


Fig. 2. Handlebar forces by time.

the optimal approach to monitoring would be embedding sensors in the assistive device to measure parameters in a transparent way to the user.

In this work we propose a novel approach for automatic user condition assessment using the i-Walker platform (Fig. 1). This platform integrates sensors to measure forces on its handles and its wheels odometry. These sensors readings have been processed to return a number of meaningful spatiotemporal gait parameters. Then, we extract a set of dimensionless variables from these gait parameters to predict the score of the well known Tinetti clinical scale [15]. The proposed approach has been validated working with volunteers under rehabilitation for a 10 weeks period. This approach presents several advantages: i) no therapist is needed to obtain the scale; ii) assessment is transparent to users; and iii) scales can be obtained any time, anywhere as often as desired. Hence, our method is appropriate for punctual user assessment, for condition evaluation during rehabilitation and also to automatically control the amount of help provided to smart rollator-users.

II. Methodology

A. Gait Analysis on the i-Walker Platform

The i-Walker platform is a smart rollator that has been developed for user support and monitoring [22]. It includes force sensors embedded on both handlebars and encoders to measure rotation in both wheels. The system is mounted on a standard MEYRA® frame to minimize the social stigma that some user associate with this kind of platform [23].

In [24], we proposed a methodology to obtain relevant spatiotemporal gait parameters from the i-Walker force and odometry sensors and tested it with several volunteers presenting a variety of disabilities. No external nor wearable sensors were required in the process. Our method was based in the following fact: when heel contact starts, the handlebar force increases in the same side and decreases in the opposite side. Fig. 2 shows this force balance in the i-Walker right and left handlebar sensors. Hence, the user's step can be extracted from the inflection point of the function obtained from difference between left and right handlebar forces.

Using the heel contact timing, we extracted a set of spatiotemporal gait parameters that are frequently used to characterize different clinical conditions (Table I). Side associated parameters like SpL come in pairs, e.g. Spl_{Left} and Spl_{Right}. In order to filter our spurious values, we calculate the mean and standard deviation of each parameter during a time period using a shifting window. In our methodology we work with 18 parameters in total $\{A_1, A_2, \ldots, A_n\}$. These parameters mostly depend on the user's condition, height and weight.

We validated in our tests in [24] that the user diagnosed condition was coherent with the spatiotemporal gait parameters obtained in terms of expected increases and decreases of the parameters values. However, we did not obtain a quantitative condition assessment of the patients. The target of this work is to obtain this assessment by relating our parameters to Tinetti scale scores.

B. Target Population

Volunteer selection is of key importance to validate any methodology for assistive robotic rehabilitation. It is frequent to find research works that are tested with healthy users, often students and scientist involved in the research [9], [10], [25], [26] or under simulation [27]. Other works focus on specific conditions like Parkinson's disease [28] or stroke [21]. Our target is to develop a general methodology to be used with rollator-users presenting any kind of disability. Therefore, we have chosen a set of volunteers at two rehabilitation hospitals: Fondazione Santa Lucia (Rome) and Hospital Regional Universitario (Malaga). These volunteers present a wide variety of physical and cognitive disabilities. Our volunteers had to meet the following criteria: i) to be able to walk with the help of a rollator; and ii) to support some weight on both handlebars while walking with the i-Walker. The first constraint is imposed because in this work the i-Walker does not offer any additional help, it is just used to monitoring. The second constraint is imposed by our commented methodology for gait analysis.

Table II shows our selected 19 volunteers and their physical and/or neurological disabilities. They include 6 men and

TABLE I
GAIT ANALYSIS PARAMETERS ON I-WALKER

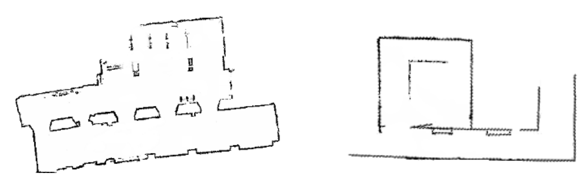
Name	Acronym	Side	Description	Unit
Step Time	SpT	Left Right	Difference in time between one step and the next one	s
Step Length	SpL	Left Right	Difference in distance between one heel contact and the next one	m
Stride Time	SdT	Left Right	Difference in time between one heel contact and the next in the same side	s
Stride Length	SdL	Left Right	Difference in distance between one heel contact and the next in the same side	m
Walking Velocity	WV	-	Number of heel contact per minute	$\frac{m}{s}$
User Support	UrS	Left Right	How much weight users lean on platform	N
Cadence	CAD	-	Number of heel contact per minute	$\frac{step}{min}$

TABLE II
VOLUNTEERS CONDITION AND TINETTI PROGRESSION

During the rehabilitation progress						
Id	Age	Gender	Neurological	Physical	$T_{balance}$	T_{gait}
1	63	Women	-	Hip arthroplasty (Right)	4-5	2-6
2	74	Men	-	Hip fracture, calcaneal and metacarpal (Left)	14-16	8-10
3	68	Women	-	Left above-knee amputation. CREST syndrome	7-12	3-6
4	58	Men	Intellectual disability	Right above-knee amputation	9	7-8

At the end of rehabilitation progress						
Id	Age	Gender	Neurological	Physical	$T_{balance}$	T_{gait}
5	65	Women	-	Periprosthetic femur fracture (Left)	14	11
6	65	Women	-	Hip fracture (Right)	14	11
7	50	Women	-	Ankle fracture (Left)	14	10
8	46	Women	-	Femur prosthesis (Right)	13	9
9	70	Men	Mild Parkinson's disease	-	13	12
10	80	Women	Mild Parkinson's disease	-	14	10
11	63	Men	Moderate Parkinson's disease	-	8	12
12	78	Women	Moderate Parkinson's disease	-	10	10
13	67	Women	Moderate dementia	-	11	10
14	74	Men	Mild parkinson	-	13	12
15	71	Men	Isquemia (Left)	-	12	6
16	71	Women	Mild Parkinson's disease	-	13	11
17	73	Women	Mild Parkinson's disease	-	15	11
18	78	Women	Mild dementia	-	15	11
19	78	Women	Mild dementia	-	16	12

13 women, aged 68 ± 9.25 (range $50-80$ years). The table is divided into two groups of volunteers: those who were at the end of the rehabilitation process and those who were at the middle or beginning of the process. The first group showed little variation in their Tinetti scores. Although they provided a good sample to check wether their predicted Tinetti score matched their real one, they were not adequate to evaluate progress. The second group was monitorized during 10 weeks of their rehabilitation process to evaluate how their Tinetti scores changed.



(a) (b)

Fig. 3. Maps of test areas. (a) Rehabilitation room in Malaga. (b) Rehabilitation corridor and room in Rome.

C. The Tinetti Scale and Associated Evaluation Tests

During our tests, therapists provided the Tinetti clinical scale [15] for each user and test. Tinetti assessment consists of two parts: one to evaluate balance ($T_{balance}$), and another to measure the gait function (T_{gait}). 28 point is the perfect score: 16 point for a perfect healthy balance and 12 point for a perfect healthy gait function. Any score under 18 means high risk of fall. Scores over 24 mean low risk. $T_{balance}$ measures equilibrium and user's fall risk. It evaluates skills like sitting balance, walking with eyes closed or turning 360 degrees. T_{gait} measures how users walk. It evaluates features like foot clearance, step length and height or step symmetry. It can be observed that some features in T_{gait} are clearly related to our spatiotemporal gait parameters. This relationship is not so obvious for $T_{balance}$.

In order to obtain T_{gait} and $T_{balance}$, therapists run all required tasks to score every item in the Tinetti scale. Afterwards, in order to obtain data for our prediction, volunteers were asked to walk freely for 3 minutes around the rehabilitation rooms (Fig. 3) in a non fixed path including at least left and right steering maneouvers and a 10 meter straight walk.

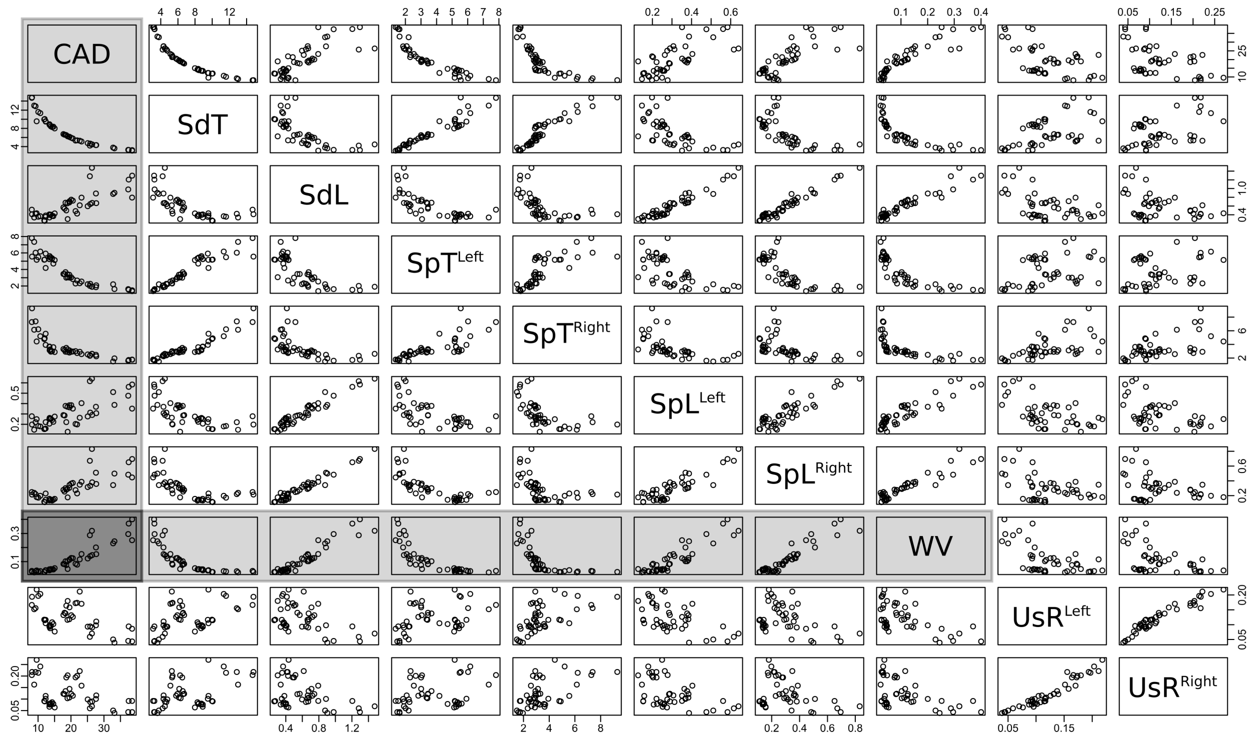


Fig. 4. Pairwise comparison of normalized spatiotemporal gait and forces parameters.

During these tests, other patients and therapists were walking in the same rooms, effectively acting as dynamic obstacles. We stored all data from these tests to predict the Tinetti scores based on spatiotemporal gait parameters.

Our original target was to obtain the Tinetti scales once per week during the 10 week rehabilitation period for each volunteer, but time and staff restrictions made it impossible. Therefore, the number of test per patients is variable.

III. Predicting Tinetti Values From Spatiotemporal Gait Parameters

This section describes how to estimate T_{gait} and $T_{balance}$ using only the spatiotemporal gait parameters obtained from the i-Walker while users walks freely in their preferred environment. No additional Tinetti related tasks like sitting up or turning 360 degrees are required for this estimation.

A. Data Preprocessing

As commented, our spatiotemporal gait parameters are affected by the volunteers height and weight, e.g. small people tend to walk with smaller SpL and higher CAD than taller people and UrS clearly depends on weight. Therefore, we use the method in [29] to normalize these parameters with respect to user's weight w_u and leg length l_u:

- Force parameter (UsR) is divided by $\frac{1}{w_u g}$, g being the gravity force.
- Spatial parameters (SpL and SdL) are divided by leg length l_u.
- Temporal parameters (SpT, SdT and CAD) are divided by $\sqrt{\frac{l_o}{g}}$, representing the rate of acceleration with respect to space.
- Spatiotemporal parameter (WV) is an *spatial parameter* divided by a *temporal parameter*, so it is divided by l_u and multiplied by $\sqrt{\frac{l_o}{g}}$.

Scaling returns normalized parameters $\{A'_1, A'_2, \ldots, A'_n\}$.

B. Multicollinearity Reduction

Our target is to predict Tinetti scores based on $\{A'_1, A'_2, \ldots, A'_n\}$. However, the spatiotemporal parameters we use have a high multicollinearity and, therefore, any estimation based on them would be very sensitive to slight changes [30]. Consequently, we have to reduce multicollinearity next.

Figure 4 shows a Pairwise Comparison for our normalized parameters. It can be observed that many of these parameters are strongly correlated. For example, CAD is highly correlated with WV. If WV increases, CAD increases too (Figure 4). In other parameters, correlation depends on the parameter value. Low values of SpT^{Left} or SpT^{Right} are not clearly related to WV, but when WV grows, they decrease smoothly. Some parameters, e.g. force parameters UsR^{left} and UsR^{right} are not related with any other parameters except themselves. These force parameters are the least affected by multicollinearity reduction.

In order to further validate the high correlation degree visually observed in figure 4, we have calculated the data Variance Inflation Factor (VIF): 883.43 in average (Fig. 5). Since any value over 1 means that multicollinearity is high, it is obvious that we need to reduce it.

We have used Principal Components Analysis (PCA) [31] to reduce multicollinearity. PCA applies an orthogonal transformation to input parameters to maximize the variability

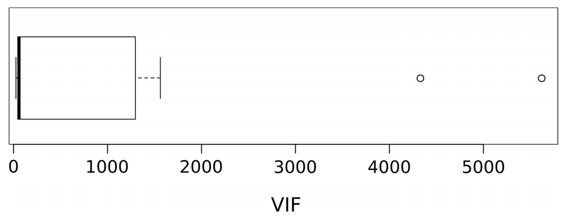


Fig. 5. VIF of gait parameters.

of the new output data. PCA generates factors (**loading**) $\left\{\alpha_1^{C_1}, \alpha_2^{C_1}, \ldots, \alpha_n^{C_m}\right\}$ to transform the normalized spatiotemporal gait parameters for user j $\left\{A_1'^j, A_2'^j, \ldots, A_n'^j\right\}$ to new PCA components (**scores**) $\left\{C_1^j, C_2^j, \ldots, C_m^j\right\}$. The number of components $m \leq n$ can be reduced at expense of the multivariate variability of the output data. In our case, m will be chosen to minimize the regression error. Equation 1 defines the transformation for user j and a component C_k using the spatiotemporal gait parameter $\left\{A_1'^j, A_2'^j, \ldots, A_n'^j\right\}$.

$$C_k^j = \alpha_1^{C_k} A_1'^j + \alpha_2^{C_k} A_2'^j + \alpha_3^{C_k} A_3'^j + \ldots + \alpha_n^{C_k} A_n'^j \quad (1)$$

C. Regression Methods

After multicollinearity is reduced, we perform a regression analysis to obtain the Tinetti scores for user i from the obtained components $\left\{C_1^i, C_2^i, \ldots, C_m^i\right\}$. It needs to be reminded that these components come uniquely from data captured by the i-Walker. The regression procedure returns another set of m coefficients $\{\beta_1, \beta_2, \ldots, \beta_m\}$ that are used to obtain the Tinetti scores for any user. A predicted score for user i with normalized gait parameters $\left\{A_1'^i, A_2'^i, \ldots, A_n'^i\right\}$ is obtained as follows (equation 2):

$$\begin{aligned} &t_{pred}^{gait,bal}(A_1'^i, A_2'^i, \ldots, A_n'^i) \\ &\quad = \beta_0 + \beta_1\left(\alpha_1^{C_1} A_1'^i + \alpha_2^{C_1} A_2'^i + \ldots + \alpha_n^{C_1} A_n'^i\right) \\ &\quad + \beta_2\left(\alpha_1^{C_2} A_1'^i + \alpha_2^{C_2} A_2'^i + \ldots + \alpha_n^{C_2} A_n'^i\right) \\ &\quad \ldots \\ &\quad + \beta_m\left(\alpha_1^{C_m} A_1'^i + \alpha_2^{C_m} A_2'^i + \ldots + \alpha_n^{C_m} A_n'^i\right) \quad (2) \end{aligned}$$

In our case, we need to obtain two sets of coefficients: one to predict T_{gait} and a different one to predict $T_{balance}$.

We have tested three different regression methods: Linear Regression (LR) [31], Ridge Regression (RR) [32] and LASSO regression [30]. Traditionally, PCA and LR are combined into the so called Principal Component Regression (PCR) method [33]. However, PCR results may depend significantly on the number of components selected in PCA m when data is as correlated as ours. Therefore, we also tested RR and LASSO regression, two biased regression estimators. These estimators provide good regression results even when input data still has a degree of collinearity, which could be the case is chosen m is not the most adequate [31]. Both biased regressions have a shrinkage parameter λ to determine how much multicollinearity is allowed. In our case, we select the value that leads to the minimum RMSE.

D. Model Evaluation

Our validation process is based on comparing Tinetti scales obtained from volunteers via the usual methodology ($T_{balance}$ or T_{gait}) with predicted values extracted from data gathered from the rollator while walking (t_{pred}^{bal} and t_{pred}^{gait}). We use the multiple coefficient of determination (R2) [34] and the root mean squared prediction error (RMSEP) [35]. We will use the cross validation (CV) technique [36]. CV split observations into k groups. It iterates k times, choosing $k-1$ groups for learning and the other one for testing. This approach reduces overfitting in obtained models. In this work, we also employed the usual k-fold cross validation with $k = 10$.

Let CV_k be the subset of n^{CV_k} users in the k cross validation test group and Tti_j the response variable for user j (either T_{gait} or $T_{balance}$). The RMSEP using the prediction function t_{pred} is calculated for T_{gait} and $T_{balance}$ as:

$$RMSEP = \sqrt{\sum_{k=1}^{K} \frac{1}{n^{CV_k}} \sum_{j \in CV_k} \left(t_{pred}(A_1'^i, \ldots, A_n'^i) - Tti_j\right)^2} \quad (3)$$

Let Tti be the mean of the predicted variable (either $T_{balance}$ or T_{gait}). The total variation (eq. 6) in the regression is calculated in two parts: one can be explained by the regression equation (eq. 4) and the other one can not (eq. 5). R2 (eq. 7) is calculated as the ratio between the explained variation (eq. 4) and the total variation (eq. 6).

$$EV_{j \in CV_k} = \sum_{j \in CV_k} \left(t_{pred}(A_1'^i, \ldots, A_n'^i) - \bar{Tti}\right)^2 \quad (4)$$

$$UV_{j \in CV_k} = \sum_{j \in CV_k} \left(Tti_j - t_{pred}(A_1'^i, \ldots, A_n'^i)\right)^2 \quad (5)$$

$$TV_{j \in CV_k} = EV_{j \in CV_k} + UV_{j \in CV_k} \quad (6)$$

$$R2 = \sum_{k=1}^{K} \frac{1}{n^{CV_k}} \frac{EV_{j \in CV_k}}{EV_{j \in CV_k} + UV_{j \in CV_k}} \quad (7)$$

R2 has a real value bounded between 0 and 1. RMSEP value is not bounded and it has the same scale as the original values.

IV. Tinetti Score Prediction

We are going to select the best possible combination for the proposed regression methods as well as the best number of components by using the multiple coefficient of determination (R2) [34] and the root mean squared prediction error (RMSEP) [35]. This process has to be performed both for $T_{balance}$ and T_{gait}. Any R2 value close to 1 means that $T_{balance}$ or T_{gait} values can be predicted from the spatiotemporal gait parameters with a minimal error. On the contrary, low RMSEP values mean that the model fits real values correctly. Therefore, given a number m of components, the best multivariate regression will produce the highest R2 and the lowest RMSE.

We have used R language [37] and the packages stat (PCA and LR) [37], glmnet (RR and LASSO) [38] and pls

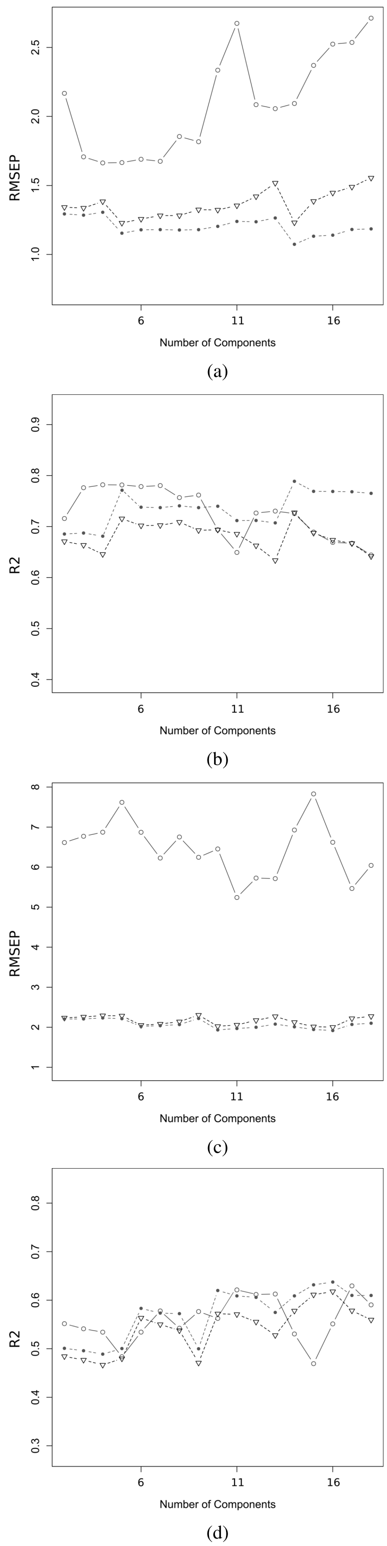


Fig. 6. Regression quality metrics using PCA plus LR (– ○ –), RR (– ▽ –), LASSO (– • –) for: T_{gait}: a) RMSEP; b) R2; and $T_{balance}$: c) RMSEP; d) R2.

(RR and RMSE) [34] for our statistical analysis. Figure 6 shows R2 and RMSEP for PCA combined with LR, RR and LASSO for every m between 2 and 18. The best T_{gait} regression according to RMSEP is obtained using PCA and LASSO (Figs. 6(a)). The best results are obtained using $m = 14$ components, followed by $m = 5$. Both values are also the best choices according to R2 for PCA and LASSO (Fig. 6(b)). Since $m = 14$ returns better RMSEP and R2 values than $m = 5$ we settle for the PCA and LASSO regression with 14 components for T_{gait}.

PCA and LASSO also provides the best regression for $T_{balance}$ in terms of RMSEP (Fig. 6(c)). In this case, the best number of components are, in order, $m = 10$ and $m = 16$. These values are also the best choices in terms of R2 (Fig. 6(d)). Hence, we settle as well for PCA and LASSO regression for $T_{balance}$, only this time with 16 components.

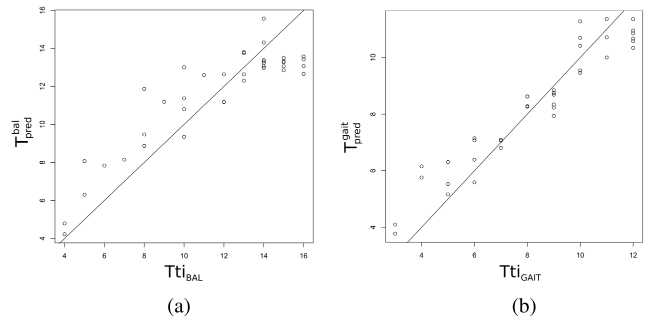


Fig. 7. Estimation of Tinetti mobility test. (a) $T_{balance}$ prediction $m = 15$. (b) T_{gait} prediction $m = 13$.

A. Model Extraction

After the best number of components m_{best} is selected, we can calculate the prediction functions t_{pred} for gait and balance. Given a user i, equation 2 can be rearranged using the loading $\alpha_n^{C_m}$ and the regression coefficients β_m to obtain a compact form (equation 8). Prediction depends on a sum of spatiotemporal gait parameters $\left\{A_1'^j, A_2'^j, \ldots, A_n'^j\right\}$ scaled by factors $F(p)$.

$$t_{pred}(A_1'^i, A_2'^i, \ldots, A_n'^i) = \beta_0 + \sum_{p=1}^{n} A_p'^i F(p)$$

$$F(p) = \sum_{k=1}^{m_{best}} \beta_k \alpha_p^{C_k} \tag{8}$$

Table III shows our $F(p)$ for balance prediction (t^{bal}_{pred}, $m = 16$) and gait prediction (t^{gait}_{pred}, $m = 14$). We can observe how the different spatiotemporal factors contribute positively or negatively to increase predicted Tinetti scores. Some of these contributions are validated by several research works. WV, for example, contributes positively to both scores, meaning that a higher velocity is related to a better physical condition, as stated in [39]. On the contrary, user support UrS contributes negatively to both scores: it was already stated in [40] that higher weight bearing implies worse user condition. Cadence (CAD) contributes positively to t^{gait}_{pred}, but very negatively to t^{bal}_{pred}. When people find it hard to keep balanced, they tend to move in fast, small steps. This effect is particularly evident in people with vestibular disorder [41].

Figure 7 plots our predicted Tinetti scores t^{bal}_{pred} and t^{gait}_{pred} versus the traditionally obtained ones $T_{balance}$ and T_{gait} for all out 19 volunteers using equation 8 with the factors

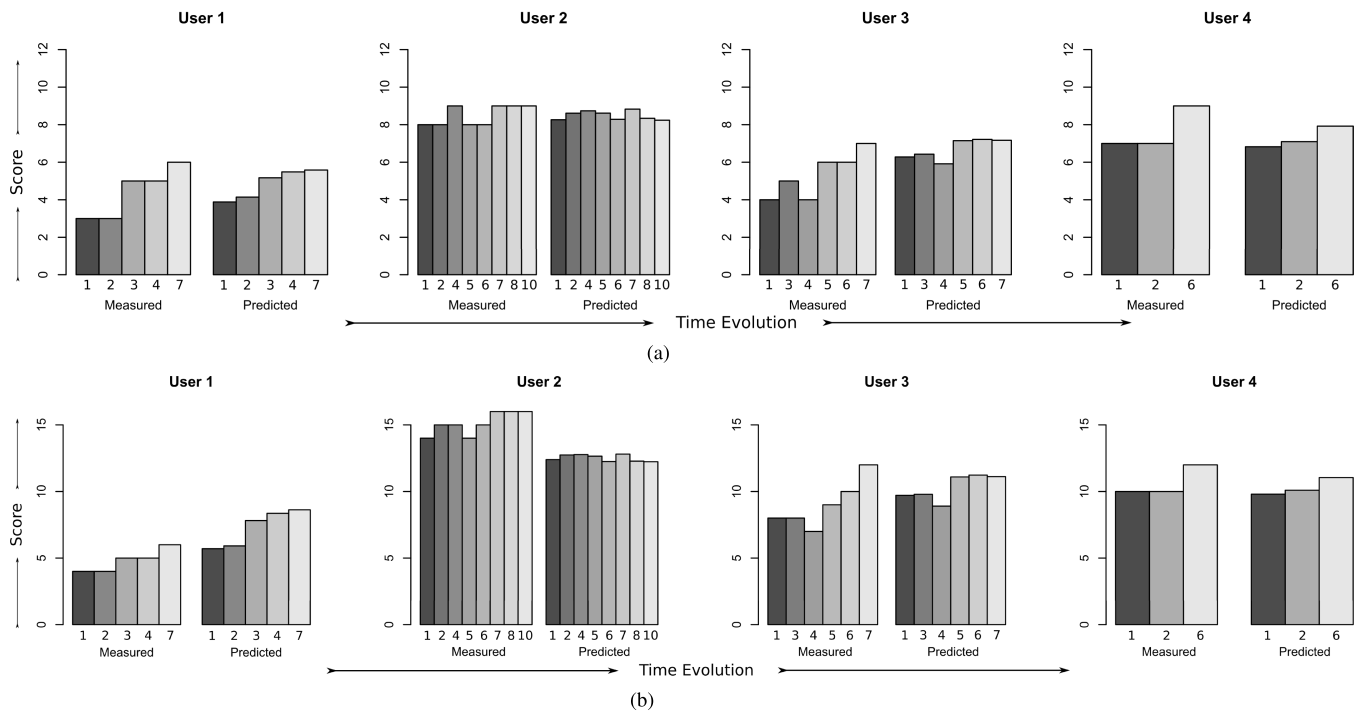


Fig. 8. Estimated user condition during a rehabilitation process per week. (a) Tinetti gait rehabilitation progress. (b) Tinetti balance rehabilitation progress.

TABLE III
THE NEW FACTORS: $F(p)$

$Pmter.$	t^{gait}_{pred}	t^{bal}_{pred}
CAD	0.0526	-0.2879
SdT_{av}	-1.1757	-3.8643
SdT_{sd}	-0.4755	-1.7448
SdL_{av}	-0.0194	1.1836
SdL_{sd}	0.0222	-0.7616
SpT^{Left}_{av}	-0.0520	-0.9794
SpT^{Left}_{sd}	-0.1495	0.1813
SpT^{Right}_{av}	-0.1827	1.7535
SpT^{Right}_{sd}	-0.1473	-2.9284
SpL^{Left}_{av}	0.0035	0.1668
SpL^{Left}_{sd}	0.0098	-0.6387
SpL^{Right}_{av}	0.0073	0.4265
SpL^{Right}_{sd}	0.0096	0.1764
WV	0.0048	0.7014
UrS^{Left}_{av}	-0.1909	-0.0387
UrS^{Left}_{sd}	-0.0128	-0.4584
UrS^{Right}_{av}	-0.2194	-0.4291
UrS^{Right}_{sd}	0.2719	-0.0562
β_0	8.2894	11.5789

in table III for estimation. We can observe that t^{gait}_{pred} provides a better fit than t^{bal}_{pred} predictor. This was expected, because it has higher R2 and lower RMSEP values (Fig. 6). These results are coherent with the nature of the predicted parameters. T_{gait} can mostly be explained by the spatiotemporal gait parameters we use in our regression. $T_{balance}$, however, includes more specific fall risk and equilibrium features that are harder to extract from gait parameters.

V. Evaluation of Rehabilitation Progress

Rehabilitation progress typically depends on the patient's pathology. Neurological diseases are usually associated to the slowest rehabilitation processes, where progress may take years [42]. Amputees usually need at least half year in order to complete their rehabilitation process [43]. The fastest rehabilitation process is associated to fractures: after surgery, people may complete their rehabilitation process in a few months [44].

We have followed the rehabilitation process of volunteers 1-4 (Table II) for 10 weeks. Volunteers 5 to 19 were at the end of their rehabilitation process, so their Tinetti scores did not change much and we do not have their data for such a long period. Our original target was to run tests, including data capture and traditional Tinetti scores, on a weekly basis, but due to typical hospital schedules constraints, the number and the periodicity of tests vary for each volunteer, e.g we only run three tests with volunteer 4, but we run 8 with volunteer 2. Figure 8 shows all Tinetti scores and the predicted values for each volunteer during the rehabilitation period. It shows in which week tests were run for every volunteer. For example, volunteer 4 does not improve drastically from one week to the next: we can observe that there is actually a 3 weeks gap between his last two tests. From a general point of view, both T_{gait} and $T_{balance}$ are expected to grow along the time period. Typically, improvement should be faster in volunteers 1 and 2 than in volunteers 3 and 4 because, as commented, progression for amputees is slower. However, volunteer 1 had a complete hip replacement and, consequently, her Tinetti scores are consistently low. Also, volunteer 2 had already been under rehabilitation for more than two months when we started our 10 weeks supervision period. Hence, his scores are high and do not improve much from one week to the next. All in all, we can not evaluate tendencies with such a small number of volunteers. Instead, we focus on evaluating the quality of our regression.

Regarding our methodology, we can observe how the predicted models preserve the progression of the scored values for gait and balance. For example, volunteers 1, 3 or 4 improve T_{gait} and $T_{balance}$ scores during the rehabilitation progress. t^{gait}_{pred} and t^{bal}_{pred} progress in an analogous manner, i.e. score evolution presents a similar shape. As commented, there are approximation errors. These errors are more noticeable in balance prediction. This was expected, because we are extracting both predictions from spatiotemporal gait parameters. Nevertheless, as proven in section IV prediction results are also good for balance.

We have observed that sometimes predicted and traditional scores may not match due to the discrete nature of the Tinetti scale. This may happen with users in advanced periods of their rehabilitation processes, like volunteer 2. In these cases, therapists may score some scale skills one point higher or lower depending on minimal changes. We have observed in practice these situations for skills like step symmetry or turning 360 degrees. When Tinetti scores are high, these differences provoke some oscillations in final results, that are not captured in our models because they cope directly with continuous data extracted from action rather than from human perception. This problem typically appears when a given skill score is in the limit between two discrete values.

VI. Conclusion and Future Work

In this paper we have presented a methodology to automatically estimate the Tinetti scale scores for gait and balance using spatiotemporal gait parameters extracted from a robotic rollator while the user is walking. These gait parameters are extracted from the rollator wheels odometry and force on its handlebars. Clinical scales typically require a therapist intervention and patient's time to complete a number of tasks for evaluation. In our methodology, assessment can be performed any time, while people are performing their ADL, without therapists' intervention and in a transparent way to the rollator-user. Also, unlike previous works on assessment, our methodology is extendable to a wide variety of physical and cognitive conditions because it is not focused on specific effects of any particular condition but rather on generic gait features. Our only restriction for evaluation is that people must support some weight while walking with i-Walker platform. This condition is met by most people who really need a rollator to walk.

We have evaluated different regression methods to extract our models. The best results in terms of RMSEP and R2 have been achieved by a combination of PCA -to reduce multicollinearity- and LASSO both for gait and balance score prediction, with 14 and 16 components respectively.

Our model has been tested with 19 volunteers presenting a variety of disabilities. Most these volunteers were at the end of the rehabilitation process, so we only had one run to predict their Tinetti scores. We followed volunteers 1-4 during a 10 week rehabilitation process to evaluate their progress. One of the main advantages of the proposed methodology is that we can predict Tinetti scores automatically, anytime, anywhere. However, we asked clinical staff to obtain their Tinetti scores each time we run new tests for benchmarking. Results prove that predicted scores and traditionally obtained ones follow the same trends in all four cases.

Our model is affected by a number of errors. First, there is some error in the gait analysis algorithm, that returns the spatiotemporal gait variables to feed the model. We have estimated the following errors: i) $67.26 \pm 50.38ms$ in temporal estimations; ii) $3.53 \pm 0.0068\%$ in spatial estimations; and iii) $0.98\ N$ in support estimations. Regression also introduces some error. The RMSEP value for $t^{bal}_{pred} = 1.98$ and for $t^{gait}_{pred} = 1.15$. It can be observed that, despite all commented errors, these values are low.

In some cases, we observed that some differences between predicted scores and human obtained scores in people whose condition is practically stabilized may be due to very small variations in some Tinetti skills, e.g. gait symmetry. Therapists may provide a higher or lower score depending on this minor variation from one test to the next. Our prediction tends to filter these minor variations because we are not using discrete scores.

This methodology can be used for continuous monitoring and patient assessment, but also to modulate the amount of help provided by active assistive devices like a robotic rollator. Adaptation of assistance is of key importance to prevent frustration and/or loss or residual skills.

Future work will focus on extending the proposed methodology to balance specific clinical scales like the Balance Evaluation Systems Test [45] or the Berg Balance Scale [16]. This may require additional input parameters for specific balance evaluation to reduce commented balance prediction errors. We also plan to introduce this methodology for user assessment in the collaborative control system proposed in [46] to adapt assistance provided by our rollator to each specific user's needs.

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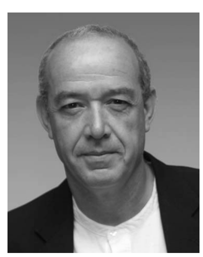

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