2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)
Madrid, Spain, October 1-5, 2018

Automatic fall risk assessment for challenged users obtained from a rollator equipped with force sensors and a RGB-D camera

Joaquin Ballesteros[1], Jose Manuel Peula[1], Antonio B. Martinez[2] and Cristina Urdiales[1]

***Abstract*— Fall risk assessments provide a useful tool to prevent morbidity and mortality provoked by falls. Nowadays, these assessments are usually performed manually by the medical staff. This approach has three main drawbacks: i) it is time consuming, so it is only performed a few times per volunteer during their rehabilitation process; ii) it requires supervision by medical staff, so assessment at home or preferred environments is not feasible; and iii) fall risk is evaluated in a global way, so imminent fall risk is not available for decision making in assistive navigation. In this paper we propose an imminent fall risk estimator for rollator's users that can be automatically obtained on the fly. Its main advantages are: i) it can be used in everyday conditions in any environment; ii) it does not require assistance of medical staff; and iii) it is suitable for a variety of users with minimal configuration changes. We have validated our estimator with a set of volunteers (n=10) presenting different physical and cognitive disabilities. Although the number of volunteer is limited, results show that our estimator is coherent to two traditional, well accepted assessments: the Tinetti Mobility Test and the walking speed.**

I. INTRODUCTION

Population is steadily aging [1], leading to an increasing number of elderly people with disabilities. Many of these persons use assistive devices in their every day life. Rollators and walkers are among the most usual devices for mobility assistance. However, falls are one of the most important problems in rollator users. Only in community-dwelling elderly, people fall at least once per year [2]. Furthermore, more than 50% of all unintentional injury deaths in elderly people were produced by falls [3]. Even non-fatal fall related injuries lead to hospitalizations, emergency department visits and the treatment in outpatient settings [4] involving important personal and economical cost.

A fall can be produced by a variety of factors [5]. A high percentage of these factors are related to intrinsic body capabilities and/or to changes in the environments. Specifically, gait and balance disorder or weakness provoke a 17% of falls in the elderly [5]. On the other hand, changes in the environment account for 31% of falls in the elderly due to trips or slips [5]. Fall risk detection in elderly population may reduce mortality and also, injury related personal and economical costs [6].

*This work has been partially supported by the Spanish Ministerio de Educacion y Ciencia (MEC), Project n. TEC2014-56256-C2-1-P and Hospital Regional Universitario of Malaga.

[1]Joaquin Ballesteros and Cristina Urdiales is with Department of Electronic Technology, University of Malaga, Malaga, Spain jballesteros@uma.es peula@uma.es acurdiales@uma.es

[3]Antonio B. Martinez is with the Department of Automatic Control, Polytechnic University of Catalonia, Barcelona, Spain antonio.b.martinez@upc.edu

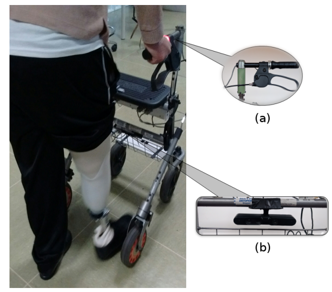


Fig. 1. The onboard sensors on i-Walker rollator: (a) force sensors in handlebars; and (b) RGB-D camera.

There are two different approaches to fall risk detection: manual and automatic assessment. Manual assessment is performed via supervised medical tests. In these tests, a nurse or therapist evaluates different tasks solved by the evaluated person. For example, the well know Tinetti Mobility Test [7] evaluates a person's gait and balance in 17 different tasks (e.g. step symmetry, step continuity, rises from chair, etc). Manual assessments have some drawbacks. First, they require supervision by clinicians; hence, they are only obtained punctually and in controlled situations rather than in everyday life. Besides, they only provide general, condition-related information regarding fall risk, so fall risks provoked by changes in the environments can not be detected.

Automatic assessment approaches rely on information gathered from user-centred sensors to automatically evaluate fall risk. These methods may provide continuous feedback and, hence, they may provide information about imminent falls related to changes in the environments. Automatic fall risk detection methods may be loosely split into three categories depending on the sensors type, namely wearable sensors, ambient sensors and onboard sensors. Wearable sensors based approaches rely on placing embedded sensors in specific limbs, joints or body parts [8], [9]. Ambient sensors based approaches rely on distributing sensors' in the environment to capture the person's activity or posture and, hence, their use is constrained to specific locations [10]. Alternatively, if a person relies on an assistive device, sensors can be placed onboard [11], [12]. Each approach has advantages and drawbacks.

Wearable sensors are usually easy to attach and affordable. However, they may require personal calibration. Besides, they need to be installed in specific body areas, which could be more or less comfortable for everyday use, plus sensors could shift or disconnect while users walk. Ambient sensors typically provide better accuracy than wearables and onboard sensors, but they tend to be expensive and their use is constrained to areas where they are installed. Onboard sensors can be used continuously everywhere as long as people are using equipped assistive devices. However, reported accuracy is usually lower with respect to the other approaches. Nevertheless, if we plan to detect fall risk in everyday situations in a continuous way, ambient sensors can not be used and people would probably fail to attach wearables all the time. Hence, in this work we focus on rollator users (Figure 1). A rollator may be equipped with a variety of onboard sensors [13]. Therefore different approaches can be used to measure the fall risk.

The most common approach to measure fall risk is to analyze the value and/or variation of one or several spatiotemporal gait parameters, e.g. walking speed [14] or the stride-to-stride [1] variability [15]. Also, a person's posture can be used as fall risk estimator too. For example, in [11] posture is used to calculate the person's gravity center and his/her base of support. This method detects fall risk when a person's gravity center is outside of his/her base of support. Other approaches rely on generating user models to detect anomalies, assuming that unusual postures/positions could be provoked by environmental hazards situations or by balance disorders. Both these causes are strongly related with fall risk [5]. In these approaches, fall risk is not binary, but measured as the difference between the person's model and the actual person's position.

The spatiotemporal gait parameters approach can be implemented on a rollator using wheel encoders and force sensors in its handlebars [16], [17]. However, it has been reported that these parameters are not fully reliable to assess fall risk if they are used alone [15] because the fear to fall can alter the values of gait parameters. For example, in order to increase their stability, some users reduce their speed [18], [19]. Alternatively, user's posture can be estimated using range sensors in the rollator [11]. However, their readings depend on the users' clothing rather than on their body alone, plus they do not take into account weight bearing on the device for balance estimation [20]. Other approaches extract a user model from feet position with respect to the rollator [12]. In these methods, it is necessary to model each user first to obtain his/her personal model. Also, they do not take into account weight bearing on the rollator either, e.g, similar feet positions would return similar fall risk, despite how much weight the rollator is supporting. In this work, we propose to combine this model based approach with force sensors on the rollator handlebars to overcome the commented drawback.

This work presents a novel approach to automatically estimate the imminent fall risk in rollator users using on board sensors. The advantage of imminent fall estimation with respect to global indicators is that instead of giving an idea on the general probability of a fall for an individual, they indicate if any given manoeuvre is likely to end in a fall, thus allowing intervention via effectors in the assistive device.

Our methodology has been validated with 10 challenged volunteers presenting a variety o physical and/or neurological disabilities in a rehabilitation center. The global fall risk for all volunteers was provided by doctors via traditional assessment. Results show that our results are coherent when compared with these traditional estimators.

II. Methodology

Our methodology consisted of asking 10 volunteers with different disabilities at Hospital Regional (Malaga, Spain) to move freely with the help of a rollator. The global fall risk of our volunteers was estimated by doctors using a well known manual assessment: the Tinetti Mobility Test [7]. Although global and imminent fall risks can not be compared in a straight way, for validation, we assumed that users with a high global fall risk should have a higher imminent fall risk in average than users with a low global fall risk. This section presents: i) our platform and its sensor onboard; ii) the volunteers selection process; and iii) our test environment.

A. Onboard sensors on i-Walker

We use the i-Walker rollator [21]. It has force sensors in the handlebars and encoders in the wheels (Fig. 1). In addition, we have included a RGB-camera to measure the feet positions[2]. It includes an embedded system (Raspberry Pi) for data filtering and data processing that supports wireless connections.

B. Volunteers selection

It is not recommended, although very usual, to test an assistive device with healthy users, because they do not move nor bear weight the rollator in the same way than a person with disabilities does [22]. For this reason, all our volunteers were patients from an Hospital affected by cognitive and/or physical disabilities. We chose patients who met the following criteria: to be able to walk autonomously with a rollator and support (some) weight on the rollator while walking.

Our test includes 10 volunteers: 3 men and 7 women. They are in average 61.4 years old (range 46-74 years). Table I shows their physical and/or neurological disabilities. Their therapist provided the user's weight w_0, the user's leg length l_0 and their Tinetti test. This test measures mobility limitation, as directly related to gait abnormalities, balance and fall. It evaluates the user in 17 different items and returns a value from 0 (abnormal gait and unstable) to 28 (healthy user). These items include step symmetry, step continuity, rising from chair, turning 360 degrees, etc. Additionally, we globally evaluate fall risk, using the walking speed, obtained from the rollator's encoders.

C. Tests

After the therapist obtained the Tinetti test for each volunteer, they were asked to walk freely around the main rehabilitation room for 3 minutes (nearly $128m^2$). They were

[1]Stride: differences between a side step and the next step in the same side

[2]A laser sensor for feet detection has been discarded because it the rollator frame creates major occluded regions.

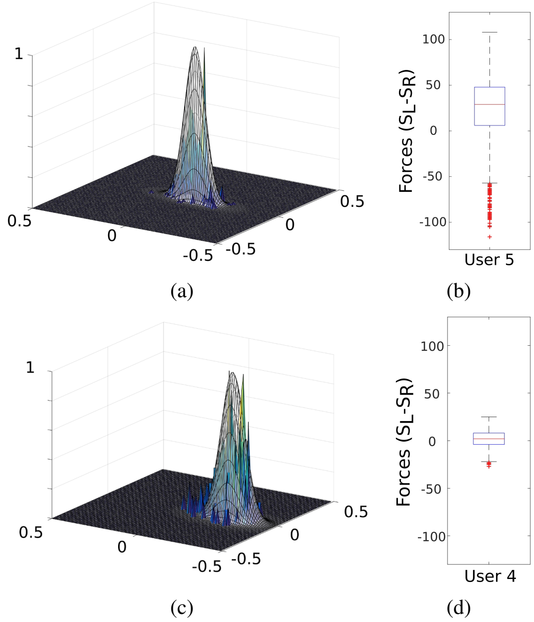


Fig. 2. Users with different Tinetti's value (5-9 for user 5 and 26 for user 4) and a similar bivariate normal distribution, figures (a) and (c). The differences are in the support, figures (b) and (d).

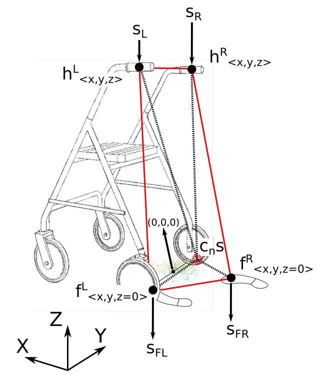


Fig. 3. How calculate CnS in a rollator being: f^L and f^R the feet positions; h^L and h^R the handlebar positions adjusted to the user height; s_L and s_R the support forces in the handlebars and s_{FL} and s_{FR} the support on feet.

suggested to steer left and right, both sharply and smoothly. Also, they were suggested to walk straight ahead for at least ten meters. Other patients and therapists were allowed to walk in the place during the tests.

III. Modeling the user fall risk

In [12], the authors calculate for each person the position of the middle point between their feet using onboard sensors. Then, they obtain the normal bivariate distribution of the frequency of this point in the (x,y) plane with respect to the rollator. Unusual feet positions corresponds to low values of the bivariate normal distribution, which are related to a high fall risk. In order to estimate fall risk, this method sets a frequency threshold, effectively turning the distribution into a planar ellipse: if a given point is outside of this elipse, there is fall risk (binary decision).

Figure 2 shows the bivariate normal distribution associated to our volunteers 4 and 5 (normalised to 1). It can be observed that their bivariate normal distributions are similar -only centered in different places-, so according to [12] they have a similar fall risk. However, these users have very different Tinetti scores ($5-9$ vs 26) and hence, a different expected fall risk. This inconsistency appears because the ellipse model presented in [12] does not take into account weight bearing on the rollator, which affects user's balance [20]. Figures 2(b) and 2(d) show how both users support very different weight on the rollator. Volunteer 5, who has a lower Tinetti score, not only supports more weight in the rollator in average, but also his weight bearing has a larger variance.

In order to fully evaluate support and, hence, balance, it is necessary to take into account weight bearing on the feet, but also on the rollator handlebars. Hand support can be measured using onboard force sensor installed in the handlebars. Single and double support can be approximated depending the relative position of the feet with respect to the rollator. In double support, both feet are touching the ground and separating from the moving rollator. In a single support, only the supporting foot separates from the rollator, whereas the foot in the air follows its movement. If we obtain the left handlebar support (S_L) and the right handlebar support (S_R) using the force sensors (fig. 3), feet support can be estimated as: $< s_{FL}, s_{FR} >=< w_0 - S_L - S_R, 0 >$ or $< s_{FL}, s_{FR} >=< 0, w_0 - S_L - S_R >$ -being w_0 the user's weight- for left and right single support; or $< s_{FL}, s_{FR} >=< (w_0 - S_L - S_R)/2, (w_0 - S_L - S_R)/2 >$ for double support. All four support points are defined in the 3D space (fig. 3). The feet are in f^L and f^R. The hands are in h^L and h^R. Using the four points associated location and support, we can define a centroid of support CnS as:

$$
\begin{aligned}
CnS_x &= \frac{s_L}{w}h_x^L + \frac{s_R}{w}h_x^R + \frac{s_{FL}}{w}f_x^L + \frac{s_{FR}}{w}f_x^R \\
CnS_y &= \frac{s_L}{w}h_y^L + \frac{s_R}{w}h_y^R + \frac{s_{FL}}{w}f_x^L + \frac{s_{FR}}{w}f_x^R \\
CnS_z &= \frac{s_L}{w}h_z^L + \frac{s_R}{w}h_z^R
\end{aligned} \tag{1}
$$

Figures 4(a) and 4(b) show the lateral and the top view of the set of CnS obtained in time from volunteer 3 during his full test. In general, these point clouds in 3D space can not be fitted using a sphere, but rather an ellipsoid. For example, in the case of volunteer 3 there is a lower variation in the positions of CnS in the Y axis (lateral movements in Fig. 3) than in X or Z, meaning that we need to take into account all three axes of an ellipsoid to model the CnS distribution for a person. As proposed in [12] for a ellipse, we can state that there is fall risk if a given CnS is outside of the defined ellipsoid in 3D. Thus, we include in our model weight bearing on the rollator as well as feet position. Furthermore, we could quantify fall risk in terms of the distance to the centroid of this ellipsoid, rather than simply stating that risk exists or not. A larger distance to the center of the set of CnS will be related with an unusual feet position and/or an unusual support, and hence with a higher fall risk. However, we can not simply use an Euclidean

TABLE I

CONDITION AND CHARACTERISTICS PER USERS

Id	Age	Gender	Neurological	Physical	$Tinetti$	$Average_{vel}$	w_0	l_0
1	46	W	-	Prosthesis (Right)	26	0.36 m/s	61kg	0.66m
2	74	M	-	Hip fracture, calcaneal and metacarpal (Left)	23-25	0.336 m/s	57kg	0.85m
3	58	M	Intellectual disability	Right above-knee amputation	16-17	0.2633 m/s	96.7kg	1.1m
4	62	W	-	Meniscus (Left)	26	0.46 m/s	60kg	0.72m
5	63	W	-	Hip arthroplasty (Right)	5-9	0.0987 m/s	86kg	0.96m
6	59	M	Parkinson	-	7	0.35 m/s	75kg	0.79m
7	68	W	-	Left above-knee amputation. CREST syndrome	10-18	0.1173 m/s	56kg	0.95m
8	65	W	-	Periprosthetic femur fracture (Left)	27	0.435 m/s	75kg	0.9m
9	65	W	-	Sacrum fracture (Right)	28	0.5127 m/s	75kg	0.63m
10	54	W	-	Ankle fracture (Left)	24	0.318 m/s	71kg	0.78m

distance from a given CnS to the ellipsoid centroid because we would not be taking into account the shape of the point distribution. Alternatively, we could fit a second ellipsoid to the input CnS point so that is on its surface and it is a scaled version of the user's model. In order to do this, we just need to obtain this scale factor α (eq. 2). Thus, we use the ellipsoid equation as a distance function to calculate α, our fall risk estimator (eq. 3).

The following equation defines the surface points $<x, y, z>$ of an ellipsoid centered in (0,0,0) with semi-axes (a, b and c) and a scale factor α:

$$\frac{x^2}{\alpha * a^2} + \frac{y^2}{\alpha * b^2} + \frac{z^2}{\alpha * c^2} = 1 \tag{2}$$

Thus, given an input CnS point $<x_n, y_n, z_n>$ and the ellipsoid's user model ($<a, b, c>$,$<r_1, r_2, r_3>$,$<c_1, c_2, c_3>$), where c and r represent the shifting of the ellipsoid with respect to our center of coordinates (the rollator) and its rotation with respect to the axes respectively, the scale factor α associated with fall risk for any input point $<x_n, y_n, z_n>$ can be calculated as:

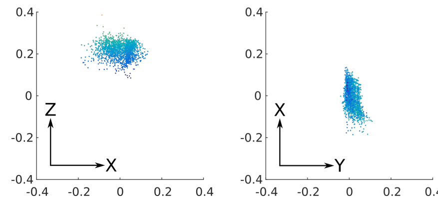
$$\alpha = \frac{x'^2}{a^2} + \frac{y'^2}{b^2} + \frac{z'^2}{c^2} \tag{3}$$

Being $<x', y', z'>$ the new coordinates of the analyzed input point translated and rotated to the user's own ellipsoid axes defined by $<r_1, r_2, r_3>$ and the ellipsoid centroid $<c_1, c_2, c_3>$. The semi-axes can be obtained with the eigenvalues (λ_1, λ_2, λ_3) associated with the CnS covariance matrix as $<\lambda_1^{-1/2}, \lambda_2^{-1/2}, \lambda_3^{-1/2}>$. Translation and rotation can be performed using the eigenvectors (v^1, v^2, v^3) associated with the CnS covariance matrix as:

$$\begin{pmatrix} x' \\ y' \\ z' \end{pmatrix} = \begin{pmatrix} v_1^1 & v_2^1 & v_3^1 \\ v_1^2 & v_2^2 & v_3^2 \\ v_1^3 & v_2^3 & v_3^3 \end{pmatrix} \begin{pmatrix} x_n - c_1 \\ y_n - c_2 \\ z_n - c_3 \end{pmatrix}$$

It can be observed that α scale factor -our $fall\_risk$- creates a new ellipsoid that includes point $<x_n, y_n, z_n>$ on its surface using the user's model parameters (same rotation and proportion among the semi-axes). Our $fall\_risk$ function includes support information in the model.

Figure 5 shows all the ellipsoids that fit the every volunteer's set of CnS in time. Our model shows the support differences between users 4 and 5 (fig. 5(a)), despite the similarity in their feet's positions (fig. 5(b)) that resulted in similar fall risk values in the bivariate method.



(a) Top view (b) Lateral view

Fig. 4. Lateral and Top view of the set of CnS for user 3.

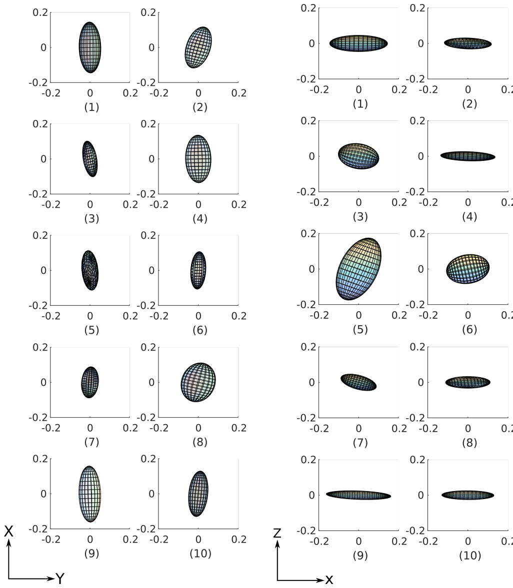
However, like the bivariate approach, our method still needs to model each user. Also a volunteer with a high variance in CnS set, i.e. high fall risk, will have a smoother response to changes than a user with a low variance. Hence, unstable feet position and/or unstable load support could be identified with a medium level fall risk, e.g user 3 load support (fig. 4(a)). In order to solve both problems, we propose to create a normalised ellipsoid model which represent the subset of users with a low fall risk, i.e. users with a high Tinetti values. If fall risk is evaluated against this normalized model, we do not need to obtain a ellipse for each specific user.

IV. NORMALISED ELLIPSOID MODEL

It can be observed in figure 5, that users with higher Tinetti scores $(1, 4, 8, 9, 10)$ have ellipsoids with similar orientation and similar semi-axes. Therefore, we can obtain our normalised Ellipsoid by generating a new ellipsoid from the merged sets of CnS from users with high Tinetti scores.

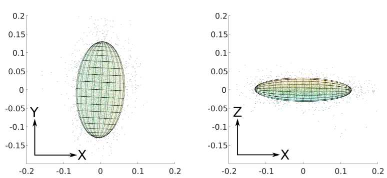
In order to obtain this normalised ellipsoid, we need a normalised centroid (c_1, c_2 and c_3), three normalised semi-axes (a, b and c) and three normalised angles of rotation (r_1, r_2 and r_3). We can not combine the models of users with high Tinetti scores in a straight way. An ellipse center can be affected by the user's body size. The distance between the feet and the rollator could depends on the users height because taller users might walk more separated from the rollator. In addition, the loading support -Z axis- may be affected by the user weight.

Nevertheless, there is a low correlation between the users weight and their weight bearing on the rollator: the Pearson



(a) Top view (b) Lateral view

Fig. 5. Ellipsoids that fit each user's CnS. They are translated to (0,0,0) and scaled to the user's body size for easy visual comparison.



(a) Top View (b) Lateral View

Fig. 6. The normalised ellipsoid model from users with Tinetti scores higher than 26.

correlation coefficient between these variables is equal to 0.42. Similarly, the coefficient is equal to -0.37 for the users height and the distance between their feet and the device. However, users' body size affects the semi-axes, i.e. tall people tend to have a larger stride length than shorter people, and user support clearly depends on user's weight [23]. Hence, the XY axes and Z axes need to be scaled with respect to users' leg length l_0 and weight w_0, as proposed in [23]. Scaling consists of dividing the spatial variable (x,y) by l_0 and the force variable (z) by $9.8 * w_0$.

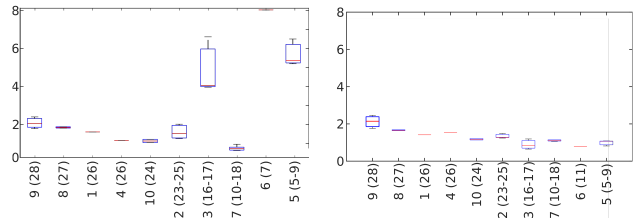
Figure 6 shows the resulting normalised ellipsoid. The normalized ellipsoid must be aligned with the same centroid that the person we are analyzing, which is automatically extracted while the person walks. Using the normalised ellipsoid parameters and the equation 3, our fall risk can be estimated as:

$$\alpha = \frac{x'^2}{(0.1305)^2} + \frac{y'^2}{(0.0658)^2} + \frac{z'^2}{(0.0319)^2} \qquad (4)$$

Being:

$$\begin{pmatrix} x' \\ y' \\ z' \end{pmatrix} = \begin{pmatrix} 0.9958 & 0.0909 & 0.0104 \\ -0.0903 & 0.9947 & -0.0484 \\ 0.0147 & -0.0473 & -0.9988 \end{pmatrix} \begin{pmatrix} x_n - c_1 \\ y_n - c_2 \\ z_n - c_3 \end{pmatrix}$$

In order to confirm that the proposed equation estimates



(a) Ellipsoid model (b) Ellipse model

Fig. 7. Average fall risk estimation per users. Tinetti scores are in brackets.

fall risk correctly, it will be validated with our users in next section.

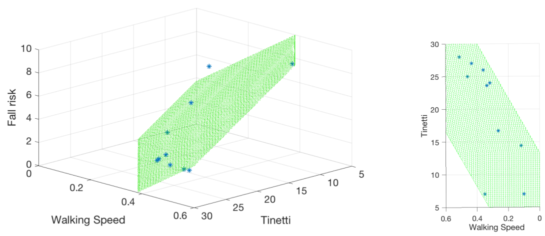
V. VALIDATION

Each volunteer have been evaluated using the Tinetti scale. We have also recorded their average walking speed (table I). As commented, these values are correlated with global fall risk, so we will compare them for each user to validate our risk estimator.

Figure 7 shows the risk estimation boxplots for all volunteers both in our model (ellipsoid) and in Hirata's ellipse model. As commented, the main difference between both models is that we use support as an additional dimension. We have included the Tinetti score (1-28) for every volunteer in decreasing order. It can be observed that some people, as 2 or 5, did the test several times, whereas others only did it once. Clinicians report a cut in Tinetti scale at 23, i.e. people over 23 have low fall risk and viceversa. This is reflected in both ellipse and ellipsoid models: the first 5 users in the plots have a low fall risk that may change from one to another, but not significantly. However, for people under 23, the proposed ellipsoid model clearly presents a significant increase in imminent fall risk that grows inversely to their Tinetti score. There is an outlier in user 7 that was already commented: she walks extremely slow and, hence, her fall risk is very low despite her score (10-18). In the ellipse model, however, the fall risk does not increase inversely with the Tinetti score and, actually, a slight decrease can be appreciated. This happens because the ellipse model does not take support into account and users with low Tinetti tend to present major variations in weight support while walking.

As commented in the introduction, the walking speed can be used as estimator of fall risk. Typically, given the same person, the faster she walks, the higher the fall risk. The fear to fall can modify this estimator because by decreasing their walking speed users can improve their balance and therefore, decrease their fall risk. In these cases, people with low Tinetti scores may actually achieve low imminent fall risk values in our methodology, even though their balance is not good, by walking very slowly, like volunteer 7 does.

Figure 8 shows the Tinetti score, the walking speed and our fall risk estimator values for all our volunteers. We can observe that points approximately fit a plane in space. If we obtain the plane that minimizes the fitting error using the least square distance, we obtain two significant results. First, its root mean squared error is low (2.7664),



(a) (b)

Fig. 8. Plane fitting for volunteers in the space defined by Tinetti score, walking speed and our fall risk estimator. An increment in fall risk produces a decrement in the Tinetti score or an increment in the walking speed or both.

meaning that there is a relationship between the axes, i.e. the walking speed and the Tinetti score are correlated with our fall risk estimator. Secondly, correlations are coherent with the literature: i) fall risk increases when the Tinetti score decreases -the user has poor condition-; ii) fall risk decreases when walking speed decreases -the user improves his/her balance by moving slower-; and iii) walking speed increases when the Tinetti score increases -the users with good condition walk faster-.

VI. Conclusion and future work

In this paper we have presented a new estimator to assess fall risk in rollator users using only onboard sensors. Unlike other works, our estimator takes into account weight bearing on the rollator, which affects the user's balance. Also, it does not require generating a new model for each volunteer. Instead, it relies on comparing input data with a pre calculated normalised balance model that we have obtained from a set of rollator users presenting high Tinetti scores, i.e. good balance and gait.

The main advantage of our method is that it can be automatically applied anytime, anywhere, plus users do not need to carry any wearables. However, using only onboard sensors in the rollator impose some restrictions. Its main drawback is that feet support needs to be estimated using only the user's weight and the handlebar force sensors. We have solved this issue by assuming that both feet support the same weight, although this is correct only during a short period of time in each step -the double support phase-. Still, results are coherent with more traditional fall risk assessment methods.

The estimator has been validated with 10 challenged volunteers presenting a variety of physical and neurological disabilities. Despite the very limited number of volunteers, results show that our fall risk estimator increases when users' Tinetti scores decrease. Also, results prove that a higher velocity increases fall risk, as reported in other works.

Future work will focus on updating the normalised user model with a much larger number of volunteers. Also, we plan to create a fall risk predictor with partial observable Markov decision process using our estimator as its reward function.

References

[1] D. o. E. United Nations and P. D. Social Affairs, "World population ageing 2015 report," 2015.

[2] A. Tromp, S. Pluijm, J. Smit, D. Deeg, L. Bouter, and P. Lips, "Fall-risk screening test: a prospective study on predictors for falls in community-dwelling elderly," *Journal of clinical epidemiology*, vol. 54, no. 8, pp. 837–844, 2001.

[3] E. Kramarow, L.-H. Chen, H. Hedegaard, and M. Warner, "Deaths from unintentional injury among adults aged 65 and over: United states, 2000-2013." *NCHS data brief*, no. 199, pp. 1–8, 2015.

[4] J. A. Stevens, P. S. Corso, E. A. Finkelstein, and T. R. Miller, "The costs of fatal and non-fatal falls among older adults," *Injury prevention*, vol. 12, no. 5, pp. 290–295, 2006.

[5] L. Z. Rubenstein, "Falls in older people: epidemiology, risk factors and strategies for prevention," *Age and ageing*, vol. 35, no. suppl 2, pp. ii37–ii41, 2006.

[6] S. Heinrich, K. Rapp, U. Rissmann, C. Becker, and H.-H. König, "Cost of falls in old age: a systematic review," *Osteoporosis international*, vol. 21, no. 6, pp. 891–902, 2010.

[7] M. E. Tinetti, "Performance-oriented assessment of mobility problems in elderly patients," *Journal of the American Geriatrics Society*, vol. 34, no. 2, pp. 119–126, 1986.

[8] P. Melillo, R. Castaldo, G. Sannino, A. Orrico, G. De Pietro, and L. Pecchia, "Wearable technology and ecg processing for fall risk assessment, prevention and detection," in *Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE*. IEEE, 2015, pp. 7740–7743.

[9] A. Danielsen, H. Olofsen, and B. A. Bremdal, "Increasing fall risk awareness using wearables: a fall risk awareness protocol," *Journal of biomedical informatics*, vol. 63, pp. 184–194, 2016.

[10] A. N. Aicha, G. Englebienne, and B. Kröse, "Continuous gait velocity analysis using ambient sensors in a smart home," in *European Conference on Ambient Intelligence*. Springer, 2015, pp. 219–235.

[11] Y. Hirata, S. Komatsuda, and K. Kosuge, "Fall prevention control of passive intelligent walker based on human model," in *Intelligent Robots and Systems, 2008. IROS 2008. IEEE/RSJ International Conference on*. IEEE, 2008, pp. 1222–1228.

[12] Y. Hirata, A. Muraki, and K. Kosuge, "Motion control of intelligent walker based on renew of estimation parameters for user state," in *Intelligent Robots and Systems, 2006 IEEE/RSJ International Conference on*. IEEE, 2006, pp. 1050–1055.

[13] M. Martins, C. Santos, A. Frizera, and R. Ceres, "A review of the functionalities of smart walkers," *Medical engineering & physics*, vol. 37, no. 10, pp. 917–928, 2015.

[14] S. Fritz and M. Lusardi, "White paper:"walking speed: the sixth vital sign"," *Journal of geriatric physical therapy*, vol. 32, no. 2, pp. 2–5, 2009.

[15] B. E. Maki, "Gait changes in older adults: predictors of falls or indicators of fear," *Journal of the American geriatrics society*, vol. 45, no. 3, pp. 313–320, 1997.

[16] J. Ballesteros, C. Urdiales, A. B. Martinez, and M. Tirado, "Gait analysis for challenged users based on a rollator equipped with force sensors," in *Intelligent Robots and Systems (IROS), 2015 IEEE/RSJ International Conference on*. IEEE, 2015, pp. 5587–5592.

[17] A. F. Neto, A. Elias, C. Cifuentes, C. Rodriguez, T. Bastos, and R. Carelli, "Smart walkers: Advanced robotic human walking-aid systems," in *Intelligent Assistive Robots*. Springer, 2015, pp. 103–131.

[18] H. G. Kang and J. B. Dingwell, "Effects of walking speed, strength and range of motion on gait stability in healthy older adults," *Journal of biomechanics*, vol. 41, no. 14, pp. 2899–2905, 2008.

[19] S. A. England and K. P. Granata, "The influence of gait speed on local dynamic stability of walking," *Gait & posture*, vol. 25, no. 2, pp. 172–178, 2007.

[20] J. Y. Tung, W. H. Gage, P. Poupart, and W. E. McIlroy, "Upper limb contributions to frontal plane balance control in rollator-assisted walking," *Assistive Technology*, vol. 26, no. 1, pp. 15–21, 2014.

[21] R. Annicchiarico, C. Barrué, T. Benedico, F. Campana, U. Cortés, and A. Martínez-Velasco, "The i-walker: an intelligent pedestrian mobility aid." in *ECAI*, 2008, pp. 708–712.

[22] J. Ballesteros, C. Urdiales, A. B. Martinez, and J. H. van Dieën, "On gait analysis estimation errors using force sensors on a smart rollator," *Sensors*, vol. 16, no. 11, p. 1896, 2016.

[23] A. L. Hof, "Scaling gait data to body size," *Gait & Posture*, vol. 4, no. 3, pp. 222–223, 1996.