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Automatic measurement of fall risk indicators in timed up and go test

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ABSTRACT

Fall risk assessment is usually conducted in specialized centers using clinical tests. Most of the time, these tests are performed only after the occurrence of health problems potentially affecting gait and posture stability. Our aim is to define fall risk indicators that could routinely be used at home to automatically monitor the evolution of fall risk over time. We used the standard Timed Up and Go (T.U.G.) test to classify 43 individuals into two classes of fall risk, namely high- vs low- risk. Several parameters related to the gait pattern and the sitting position included in the T.U.G. test were automatically extracted using an ambient sensor (Microsoft Kinect sensor). We were able to correctly classify all individuals using machine learning on the combination of two parameters among gait speed, step length and speed to sit down. Coupled to an ambient sensor installed at home to monitor the relevant parameters in daily activities, these algorithms could therefore be used to assess the evolution of fall risk, thereby improving fall prevention.

KEYWORDS

Fall prevention; timed up and go test; machine learning; depth camera; elderly people

Introduction

Falls are the second most common cause of death reported in the world (World Health Organization. [1]) Even when not lethal, falls of elderly people can have dramatic consequences. An accurate and early assessment of fall risk is essential for preventing falls, and therefore constitutes an important social issue. Clinical tests assess fall risk and identify people for intervention. Even if, according to recommendations, these clinical tests should be performed in prevention and repeated over time,[2] they are, most of the time, performed only after the occurrence of health problems potentially affecting gait and posture stability, e.g., after a fall or a hospitalization. Moreover, these tests aim at evaluating the risk of fall at the time of the test. They may be repeated during rehabilitation but they are seldom repeated over time to monitor the evolution of the risk once the patient has completed the rehabilitation program and returned to their "normal" life. In that context, the development of simplified and automatic methods to assess fall risk would improve falls prevention. Specifically, the risk could be assessed before the occurrence of the first accident, and the evolution of fall risk could be monitored over time. Here we tried to identify parameters which could be measured and monitored in everyday life situations and robustly used to assess fall risk without performing any clinical test. However, when identifying these parameters, we needed to make sure that they were good indicators of fall risk. For that, we needed a standard used as reference regarding the estimated fall risk. Therefore, we compared the risk fall assessment made by physicians and physiotherapists using a clinical test with automated classifications using different subsets of parameters.

The reference clinical assessment performed by physicians and physiotherapists was made using the Timed Up and Go (T.U.G.) test. This test was introduced by Podsiadlo and Richardson [3] and it is recommended by the American Geriatrics Society and the British Geriatric Society. [2] It requires a

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patient to stand up from a chair, to walk 3 m, to turn 180°, to walk back to the chair and to sit down. Fall risk is assessed by the time taken by subject to complete the T.U.G. test. There were several reasons why we chose this test as the reference clinical assessment. First, even if some have critized the T.U.G. test (e.g., some studies have shown that the relationship between T.U.G. time and falls history strongly depends on the gender of the patient, the country he/she is living in, [4] and his/her place of residence in a community dwelling [5]), in practice, it is widely used by healthcare professionals to classify individuals according to their risk of fall. Second, both its sensitivity and its specificity to identify fall risk are excellent (87% in both cases), as shown by testing elderly people who already fell and others who never fell. [6] Third, T.U.G. measurements have high test-retest reliability with intraclass correlation coefficients of 0.96. [7] Last but not least, the T.U.G. test includes the most common types of motor sequences performed in everyday life, such as walking, sitting down and getting up. This makes the T.U.G. test an ideal candidate to identify motor parameters of everyday life tasks that could best be used to automatically assess fall risk. Indeed, it allowed us to directly compare the extracted parameters to the reference clinical assessment of fall risk, which constitutes a necessary validation test in a clinical environment.

So far, research based on the T.U.G. test mainly focused on instrumenting this test with technology in order to objectify the assessment. [8–11] In contrast to this, in this article, we aimed at determining whether in addition to the total duration, some other parameters could be extracted from the T.U.G. test to discriminate high and low fall risk individuals. For instance, Tmaura *et al*, [12] used an accelerometer and angular velocity sensor to segment each phase of the T.U.G. test (the stand up, the walk before the turn, the turn, the walk after the turn, the sit down). They showed that elderly people at high-risk of fall need more time to perform all phases of the T.U.G. test. This study demonstrated that the duration of each phase can be used to classify people. Skrba *et al* [13] used two webcams to automatically extract different parameters in the T.U.G. test. They concluded that the walk duration and the time between turning and sitting back in the chair were the most significant parameters to classify low and high fall risk people.

Our aim was to identify fall risk indicators that could routinely be used at home to automatically monitor the evolution of fall risk over time. For that, we used the T.U.G. test which includes different events performed in everyday life. Subjects performed a T.U.G. test in front of an ambient sensor which automatically extracted different parameters. We combined statistical analysis and machine learning methods to determine which parameters are the most relevant to classify individuals into high and low fall risk. It is important to emphasize here that the parameters that were extracted by our algorithm were non-specific to the T.U.G. test, and that the recordings were performed on T.U.G. sequences only to allow us to directly compare the evaluation respectively performed by our algorithm and that of healthcare specialists.

Method

Subjects

Forty three subjects (27 females, 16 males) aged 61–93 years (mean = 83) were evaluated with the T.U.G. test. We performed the tests in two different places: in a rehabilitation center and in a research laboratory for subjects living at home. The main inclusion criteria were being aged 60–95 years old and being to able to walk at least 10 m straight. Individuals suffering of severe dementia tested with the Mini Mental State Examination score [14] (with comprehension difficulty as aphasia, alexia), visual disorders (advanced macular, degeneration, blindness), or having a questionable cardio-pulmonary status (cardiac failure, pulmonary embolism, oxygen therapy) were excluded. On the other hand, subjects using auxiliary means to ambulate were included, except if they required a wheelchair. Fall history was not included as an inclusion/exclusion criterion. All subjects signed an informed consent and the study was approved by the Vaud ethics committee in Switzerland (reference number: 2015-00035).

Data acquisition

Fall risk was assessed by physicians and physiotherapists using the "classical" evaluation criteria on the T.U.G. test. The same sequences of the T.U.G. test were evaluated both by our algorithm and by healthcare specialists. A standard chair with arms was used. A mark was placed on the ground 3 m in front of the chair to indicate to the subjects the place where they had to turn around. At the beginning of the test, subjects were sitting on the chair. After a signal given by the clinical staff, the subject had to get up from the chair, walk, turn around after passing the mark located on the ground and go sit back on the chair. The clinical staff specified to walk at a normal and comfortable speed. The subjects walked perpendicularly to and at a distance of 4 m from the Kinect sensor. The sensor was positioned at a 1.70 m height and with a tilt angle of 20°. This sensor recorded the movements/locomotion pattern of the subjects. We opted for the Kinect sensor, which in addition to being low-cost, can be used with the silhouette (i.e., using depth points only), which is not considered as intrusive. [15] The clinical staff timed, with a stopwatch, the execution of the test. Each subject performed the T.U.G. test three times with 3–5 min of rest interval between each test.

Preprocessing

Our processing algorithm analyzes the depth images provided by the Kinect sensor, and the silhouette of the individuals is extracted using the background substraction method presented in Dubois and Charpillet. [16] First, the centroid of the person is computed. This centroid corresponding to the average of all points belonging to the silhouette. An algorithm using a Hidden Markov Model is then used to analyse the trajectory of the centroid along the vertical axis. This algorithm identifies the activity an individual is engaged in, such as walking, sitting, etc. [16] Here we used the activity recognition algorithm to identify six types of activity: start-move, start-walk, start-turn, end-turn, start-sit, end-sit (see Figure 1).

T.U.G. test derived parameters

As mentioned above, though we recorded locomotion during the T.U.G. test in order to directly compare the results provided by our algorithm and the visual evaluation of healthcare professionals, our aim was to identify parameters that could be extracted at home during everyday life activities. These parameters were also chosen based on the evaluation criteria that clinicians use when they observe the patient (step length, gait speed, speed to get up or to sit down). Accordingly, based on the six types of activity described in "Preprocessing", we selected the following parameters:

- time to get up (s): time between start-move and start-walk;
- speed to get up (mm/s): maximum vertical upward speed between start-move and start-walk;
- time to sit down (s): time between start-sit and end-sit; and
- speed to sit down (mm/s): maximum vertical downward speed between start-sit and end-sit.

The vertical trajectory of the centroid allowed us to identify the step of the person. As shown in Figure 1, asterisks correspond to the local maxima detected during the walk. One step corresponds to the interval between two local maxima. Step lengths were estimated from the corresponding 3D coordinates of the centroid. This information allowed us to obtain other T.U.G. test parameters which can be extracted at home:

- mean and median step length (cm): mean or median of the distances between two local maxima;
- coefficient of variation (C.V.) of mean and median step length (%): standard deviation of the step length divided by the mean or median step length;

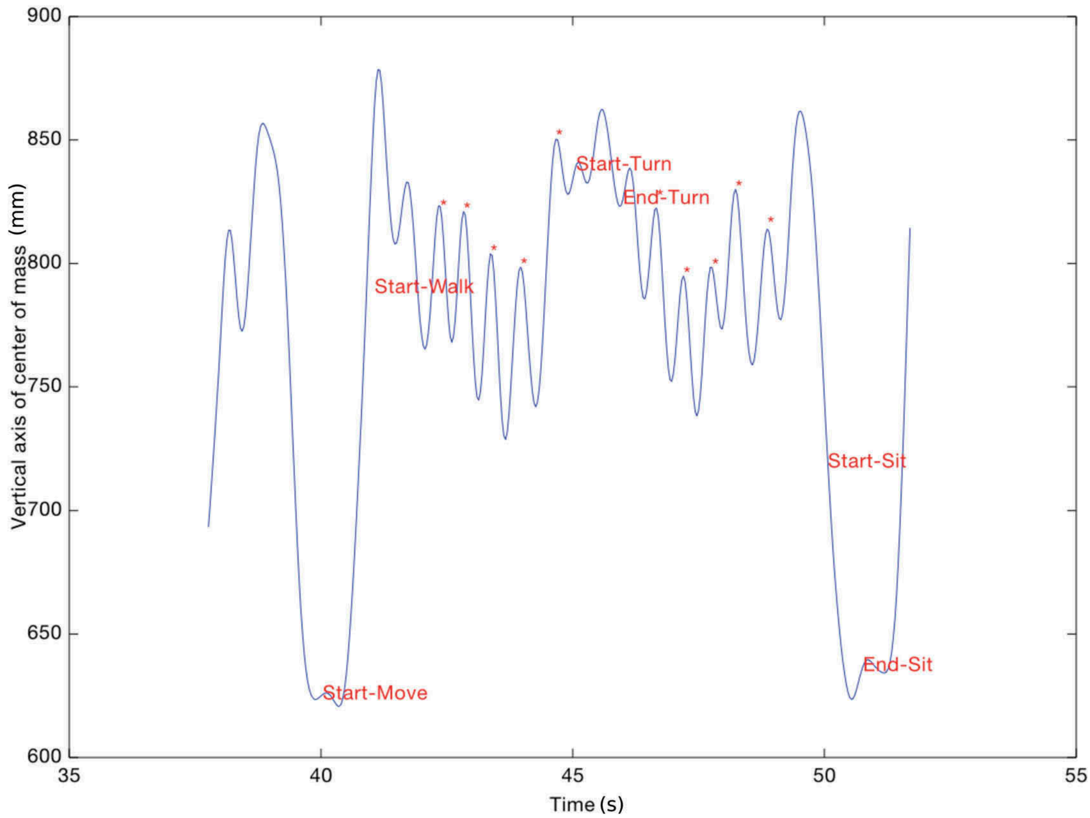

Figure 1. Trajectory of the centroid of a subject and automatic detection of six types of activity.

- mean and median step duration (s): mean or median of the duration between two local maxima;
- C.V. of the mean and median step duration (%);
- mean and median cadence of walking (steps/min): cadence was calculated as 1 divided by the step duration, mean or median of cadence of the two walking sequences (forth and back);
- C.V. of the mean and median cadence (%); and
- gait speed (during the two walking sequences, cm/s): sum of step lengths divided by the sum of step durations.

The algorithm used to determine the gait parameters is detailed in Dubois and Charpillet. [17] Previous studies showed that the algorithm used in this study measures accurately the step length, the step duration, the cadence and the gait speed compared to the GaitRite system [17] and to the OptiTrack system. [18]

Data analysis

We used the best time of the three trials to classify the subjects since the best performance reflects the subject's capacities as it is usually done by healthcare professionals. Twenty two subjects performed the test in less than 15 s and were considered as having a low-risk of fall whereas 21 other subjects needed more than 15 s and were considered as having a high-risk of fall. Table 1 presents the statistics of the low and high fall risk group. In the literature and in clinical practice, the threshold time used to discriminate between low- and high-risk of fall does not reach a consensus.

Table 1. Statistics of times to performed T.U.G. test obtained with the low and high fall risk group.

	Low risk of fall	High risk of fall
Number	22	21
Mean (s)	12.03	25.76
Standard deviation (s)	2.07	5.89

This time varies from 10 s to 25 s. Shumway-Cook *et al* [6] consider that a cut-off of 13.5 s constitutes a good criterion to discriminate low and high fall risk individuals. Okumiya *et al* [19] showed that the T.U.G. test was a predictor of falls with a cut-off of 16 s. In our study, we used 15 s as threshold because it is the threshold used by the clinicians in the institute where we performed the T.U.G. test. Importantly, supplementary data analyses performed as control revealed that cut-off thresholds set between 13.5 s and 16.5 s do not alter the classification results.

The Kinect-extracted parameters were evaluated with statistical tools. We tested simultaneously the 17 parameters (gait speed, speed to sit down, etc) using a multivariate analysis of variance (M.A.N.O.V.A.) with two groups, high and low fall risk. For each parameter, the difference between the two groups was analyzed using either a Student *t*-test or a Wilcoxon Rank Sum test (when the distribution of values deviated from normality or when variance was not homogeneous between groups). Significance level (i.e., alpha) was adjusted for multiple comparisons using Bonferroni correction. Moreover, we assessed the correlation between each Kinect-extracted parameter and the T.U.G. test duration used to classify subject into low or high fall risk. We used the Spearman's correlation coefficient because our parameters were non-normally distributed.

We used supervised machine learning methods to classify the 43 subjects of the database in two classes (low- vs high-risk of fall). We generated all the combinations of one to two features from the parameters described in section "T.U.G. test derived parameters" (such as mean and median step length, gait speed, time to sit down, etc). Each combination was evaluated using state of the art classifiers. We used the scikit-learn implementation [20] of Nearest Neighbors, Linear S.V.M., R.B.F. S.V.M., Gaussian Process, Decision Tree, Random Forest, Neural Net, AdaBoost, Naive Bayes, Quadratic Discriminant Analysis and the k-fold validation procedure to compare the classification performances based on the different subset of features. The k-fold cross validation procedure was performed by dividing the database in 43 partitions corresponding to the 43 subjects' so that each subject could never be simultaneously in the testing and training set. All three subject's trials were kept in a same fold. We used the average performance calculated on the k partitions to evaluate the classifier. It is important to mention here that the clinical "classification" as performed by the clinicians based on the T.U.G. test duration was used as classifier output in the learning phase, but the T.U.G. test duration was never used as input of the classifier.

Results

Statistical analysis

The M.A.N.O.V.A. showed a significant effect of class ("Low risk of fall" vs "High risk of fall") on the different parameters, $F(17, 107) = 38$, $p < 0.001$.

Regarding the results of the Student *t*-tests and Wilcoxon Rank Sum tests, all *p*-values were below 0.001, indicating that for all parameters, the values recorded in the "High risk of fall" group were significantly different from those recorded in the "Low risk of fall" group.

The Spearman's correlation coefficient between Kinect-extracted parameters and T.U.G. test duration are shown in Table 2. All parameters significantly correlated to the T.U.G. test duration, with $p < 0.001$ in each case. The correlation was strong for all parameters (r_s always above 0.61) except those related to the coefficient of variation for which the correlation was weaker (r_s between

Table 2. Relevance of the extracted parameters as classification criterion. Spearman's correlation coefficient was calculated for each parameter. The best score among classifiers tested with a single feature is shown in the third column. The maximum best score obtained from the different combinations of a given parameter with another feature is presented in the forth column. The fifth column displays the mean best score for models with two parameters. The mean best score corresponds to the quality of the parameter as classification criterion. The sixth and seventh columns indicate the maximum and mean best score for models with two parameters excluding "Gait speed".

Parameters	Spearman's rho	Best score single feature	Max best score two features	Mean best score two features	Max best score two features excluding "Gait speed"	Mean best score two features excluding "Gait speed"
Gait speed	−0.97	0.99	1	0.994		
Mean length	−0.92	0.96	1	0.979	1	0.977
Median length	−0.90	0.96	0.992	0.975	0.992	0.973
Speed to sit down	0.61	0.88	1	0.930	1	0.926
Median cadence	−0.82	0.90	1	0.917	1	0.914
Speed to get up	−0.70	0.84	1	0.911	0.967	0.909
Time to sit down	0.83	0.90	1	0.916	0.977	0.910
Median duration	0.82	0.90	0.992	0.913	0.992	0.907
Mean duration	0.81	0.86	1	0.906	1	0.900
Mean cadence	−0.76	0.84	1	0.904	1	0.899
Time to get up	0.78	0.87	0.992	0.897	0.969	0.892
CV of mean length	0.51	0.66	0.992	0.828	0.977	0.818
CV of median length	0.49	0.64	0.992	0.817	0.984	0.808
CV of mean cadence	0.46	0.72	0.992	0.816	0.969	0.803
CV of median cadence	0.47	0.63	0.992	0.815	0.977	0.804
CV of mean duration	0.39	0.61	0.992	0.817	0.969	0.804
CV of median duration	0.37	0.60	0.992	0.818	0.961	0.808

0.37 and 0.51). We can see that "Gait speed" was the parameter that correlated the most with T.U.G. test duration, $r_s = 0.97$, $p < 0.001$.

Machine learning

Each model was evaluated using the k-fold cross validation score representing the good classification rate. First, we tested the classifiers with a single feature. The result was that no parameter provided a model which classified without error the subjects, the clinicians classification being used as a reference. "Gait speed" was the parameter with the best classification score as shown in third column of Table 2 representing the best score for each parameter obtained among all the classifiers.

Then, we trained the classifiers with two parameters. For each parameter combination, we only considered the score of the classifier giving the best result, denoted as "Best score". The maximum "Best score" and the mean "Best score" of a given parameter were calculated from the "Best score" of all the combinations of this parameter. These values are presented in the forth and fifth columns of Table 2. We can see that the mean "Best scores" are greater than 0.93 for "Speed to sit down", "Mean step length", "Median step length" and "Gait speed", meaning that these parameters provided the best models. From the maximum "Best score", we found that six combinations gave a perfect model, three of those including the "Gait speed" parameter. These six combinations were "Mean step length" coupled with "Mean step duration" (with Naive Bayes and Neural Net), "Mean step length" coupled with "Mean cadence of walking" (with Linear S.V.M.), "Speed to sit down" coupled with "Median cadence of walking" (with Neural Net), "Speed to get up" coupled with "Gait speed" (with Q.D.A.), "Time to sit down" coupled with "Gait speed" (with Random Forest) and "Mean step duration" coupled with "Gait speed" (with R.B.F. S.V.M.).

The "Gait speed" being a parameter strongly correlated with the T.U.G. test duration, as shown in subsection "Statistical analysis", we also trained our classifiers with two parameters excluding "Gait speed". The sixth and seventh columns on Table 2 represent the maximum and mean "Best scores" of each parameter combinations excluding "Gait speed". In agreement with previous result, the parameters with the mean "Best score" greater than 0.92 were "Speed to sit down", "Mean step length" and "Median step length".

The different algorithms used to classify the data were all more or less effective, and there were no real differences in their outcome. Figure 2 shows a graphical representation of the data and the treatment performed by each classifier. An example of combination of two parameters ("Gait speed" and "Speed to sit down") for which the classification by the different algorithms was good is shown in Figure 2 a). A clear boundary separating the two classes can be observed. This suggest that we can make robust and reliable classifications from these two parameters. In contrast, Figure 2 b) shows an example of combination for which no clear separation is to be seen and for which the model built with the chosen parameters ("C.V. of mean step duration" and "C.V. of mean step length") made mistakes.

Discussion

Our aim was to identify parameters that could be extracted in everyday life activities and could be use to predict fall risk. These parameters were extracted and selected from sequences of individuals performing the T.U.G. test in front of an ambient sensor. The locomotion sequences were simultaneously evaluated by healthcare professionals who classified subjects as having either a high- or low-

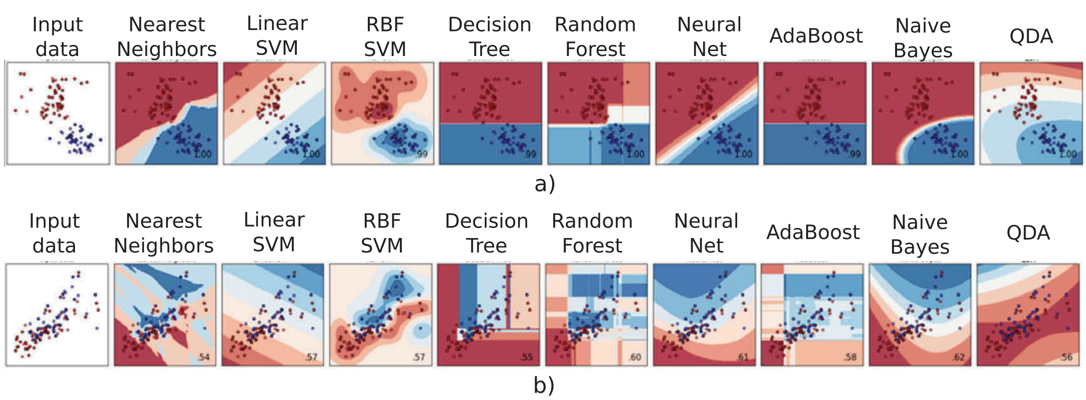

Figure 2. Estimation of the risk of fall. Different machine learning algorithms were used to classify the subjects into those who have a low (red) or a high-risk of fall (blue). Red and blue areas correspond to the classifier decision function. (a) The classification relies on the combination of two parameters, "Speed to sit down" (on the *X*-axis) and "Gait speed" (on the *Y*-axis). Individuals are clearly "split" into two distinct categories. (b) The classification relies on the combination of two parameters, "Coefficient of variation of mean step duration" (on the *X*-axis) and "Coefficient of variation of mean step length" (on the *Y*-axis). These two parameters do not allow to clearly classify the individuals.

risk of fall using manual estimation of T.U.G. test duration. From the ambient sensor, several parameters were automatically extracted. Combining machine learning tools and statistical analyses, we identified four parameters that were highly relevant, namely “Speed to sit down”, “Mean step length”, “Median of step length” and “Gait speed”. We then showed that a model built on one of these four parameters combined with any other can be used to correctly classify individuals in “High-risk of fall” or “Low-risk of fall” classes during T.U.G. test.

In the introduction of this article, we mentioned that Skrba *et al* [13] concluded that the walk duration and the time between turning and sitting back in the chair were the most significant parameters to classify people into high- and low-risk of fall categories. We have not included these parameters in our study because our aim was to extract parameters that are not specific to the T.U.G. test. Rather, we focused on more “generic” parameters that could be extracted at home in everyday life activities. The parameters identified as relevant in our study (“Speed to sit down”, “Mean step length”, “Median step length” and “Gait speed”) all match this criterion as they can technically be extracted in more general conditions than the T.U.G. test (even if the values could be influence by the situation). We showed that a combination of two parameters is sufficient to obtain a classification without error. According to our analysis, “Gait speed” stands out as the most relevant parameter. One might argue that velocity is a proxy measure of T.U.G. test duration as measured by healthcare professionals to make the classification. This indeed was confirmed by the high-correlation between T.U.G. test duration and “Gait speed” ($r_s = -0.97$). However, it is important to highlight that the classifiers also gave excellent results when excluding the “Gait speed” parameter. In particular, coupling “Speed to sit down” with “Median cadence of walking” gave rise to an excellent classification score, even if those two parameters were less correlated with T.U.G. test duration ($r_s = 0.61$ for “Speed to sit down” and $r_s = -0.82$ for “Median cadence of walking”). In addition, we believe that gait speed is the parameter whose value is the most likely to be affected if measurements take place at home. Specifically, in the T.U.G. test, people walked straight, in an uninterrupted way and without being perturbed by objects or obstacles as furniture. Such straight paths devoid of obstacle is less likely to occur in a furnished home environment. Therefore, we propose to couple a gait-related parameter (other than gait speed) with a parameter related to the sitting position (e.g., speed to sit down).

Fall risk represents a human, economic and societal issue. Currently, fall prevention mostly relies on clinical tests, and notably the T.U.G. test, performed in healthcare institutions by expert clinicians. Our long-term goal is to develop a system with which fall risk could automatically be assessed at home, before the occurrence of the first accident. This system would allow an “early” identification of people having a “critical” fall risk, so that these persons could be included as soon as possible in rehabilitation programs allowing them to stay autonomous longer. This would also contribute to highly reduce fall-induced healthcare costs. In this study, we automatically extracted motor parameters from individuals performing the T.U.G. test. We notably showed which parameters could be used to assess fall risk in everyday life. The next step will consist in automating the acquisition of the identified variables with the system placed at the tested individuals’ home in order to validate the current results and identify the parameter combinations that are the least subject to environment variations. The next step should consist in a longitudinal study taking into account the fall history of the tested persons.

Conclusion

We have used an ambient sensor in order to identify parameters that could be extracted automatically at home for assessing the evolution of fall risk. Machine learning methods allowed us to determine which parameters are the most relevant to predict the T.U.G. test result. We concluded that a gait-related parameter (other than gait speed) combined with a parameter related to the sitting position allowed to correctly classify individuals.

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Declaration of interest

The authors in this study declare that there is no conflict of interest.

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