Timed up and go and 6 minutes walking tests with wearable inertial sensor: One step further for the prediction of the risk of fall in elderly nursing home people

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Abstract: Assessing the risk of fall in elderly people is a difficult challenge for clinicians. Since falls represent one of the first causes of death in such people, numerous clinical tests have been created and validated over the past thirty years to ascertain the risk of falls. More recently, the developments of low-cost motion capture sensors have facilitated observations of gait differences between fallers and non-fallers. The aim of this study is twofold. First to design a method combining clinical tests and motion capture sensors in order to optimize the prediction of the risk of fall. Second to assess the ability of an artificial intelligence to predict risk of fall from sensor raw data only. Seventy-three nursing home residents over the age of 65 underwent the Timed Up and Go (TUG) and a 6 minutes walking tests equipped with a home-designed wearable Inertial Measurement Unit during two sets of measurements at 6 months interval. Observed falls during that interval enabled us to divide residents into two categories: fallers and non-fallers. We show that the TUG test results coupled to gait variability indicators, measured during a 6 minutes walking test, improves (from 68% to 76%) the accuracy of risk of fall's prediction at six months. In addition, we show that artificial intelligence algorithm trained on the sensor raw data of fifty-seven participants reveals an accuracy of 75 % on the remaining sixteen participants.

Keywords: Risk of fall, Elderly, Wearable sensor, Gait variability, Clinical tests

1. Introduction

Falls are an inevitable part of ageing and their prediction and prevention is of paramount importance to health care. According to the World Health Organization (WHO), falls are the second cause of accidental death and approximately 646000 people die every year following falls, particularly people over the age of 65. In the European Union (EU), an average of 35848 elderly people per year (65 and above) are reported to have died from falls [1]. As the population of elderly people in the EU is expected to grow by 60% by 2050, the number of fall-related deaths is expected to increase to almost 60000 per year by 2050, unless additional measures are taken to predict and prevent falls. Additionally, falls result in significant physical and psychosocial costs that have to be incurred by patients and social security. The social security cost for treating fall-related injuries in the EU is estimated to be 25 billion € each year [2].

In nursing homes, falls frequency is higher for elderly people than at home with a yearly rate of falls of 50% [3]. This phenomenon is foreseen to increase in the future in view of the population aging. Risk factors for falls in elderly people are higher among nursing home residents compared to home-based individuals [4]. Those factors are usually grouped in three main categories: intrinsic (age, sex, cognitive disorders, eye-sight impairment, sarcopenia, multiple medication use, sensory impairment, gait disorders, postural instability and neurodegenerative diseases), behavioral (inappropriate footwear, alcohol use), and environmental (slippery surfaces, poor lighting, worn carpeting) [3,4,5].

It is well known that the assessment of the risk of falls is better achieved through screening tools designed for that purpose. One of the most well-known test is the Timed Up and Go (TUG) test [6]. It is considered as the gold standard in fall risk assessment and has numerous advantages. It is simple and easy to describe and to perform, and therefore widely used [7]. It is also recommended by the American Geriatric Society and the British Geriatric Society [8]. The typical time to perform the test is around 20-30 seconds. Unfortunately, this is too short to enable a full assessment of the gait kinematics and more specifically the long-term variability of the stride interval. This is correlated to the risk of fall in home-based older people [9] but requires time series of typical duration of 10 minutes. More recently, TUG test has been performed with patients equipped with an accelerometer. This allowed an analysis focusing on sit-to-stand and stand-to-sit subtasks, which is useful to identify fall risk in home-based fallers versus healthy controls [10]. The findings of this study show that the TUG test allows to identify successfully 63% of fallers and this is increased up to 87% in accelerometer-equipped patients.

Another widely used tool in clinical practice that allows the study of gait for a longer period is the 6 minutes walking test [11]. Similar to the TUG test, accelerometer-based 6 minutes walking test has been used in patients with chronic heart failure [12] and chronic obstructive pulmonary disease [13]. To the best of our knowledge, accelerometer-based 6 minutes walking test has not been performed in elderly people to assess risk of fall.

Today, the availability of low-cost inertial sensors enables 3D measurement of acceleration and angular speed during human movements. In a recent study, we successfully used an ultra-low-cost wearable inertial sensor to capture rotational movements of the head during a standardized test [14]. Here, we used this sensor to capture locomotor movements during the 6 minutes walking test to increase its predictive power of the TUG test on the risk of falls among elderly nursing home fallers and non-fallers during two sets of measurements at 6 months interval. We present an analysis of kinematic data based on variability assessment and on artificial intelligence (AI) techniques. Current hardware capacities allow to process and manage the huge datasets required for such tools to converge to a solution. That is why these techniques have gained popularity in recent years and are recognized as efficient tools in fall detection in particular [15].

2. Materials and Methods

2.1. Population

Participants to this survey were at least 65 years old or over and lived in 4 nursing homes in the Charleroi area in Belgium. The experiment protocol was designed according to the Helsinki declaration and was approved by the Bioethical Academic Committee (n°B200-2017-144). Exclusion criteria were as follows: lower limb musculoskeletal or cardio-respiratory disorders preventing a 6 minutes walking test or major cognitive disorders preventing a full patient's cooperation. During the experiment, participants who experienced a major illness such as stroke or limb fracture were excluded.

Participants who chose to discontinue their participation, who were admitted to hospital, who had their medication changed thus preventing the continuation of the experiment or who died before the completion of the experiment were also excluded.

Ninety-two individuals started the initial test. Twelve of them were excluded from the survey in view of the above criteria. Seventy-three participants completed the experiment.

Table 1. Main characteristics, comorbidities and medications increasing the risk of fall of the participants. Fallers have been identified according to the fall records between the 6 months interval (t_1 and t_2).

	t_1	t_2
N	80	73
Age (years)	83.2±8.2	83.0±8.3
Male/Female	28/52	28/45
Walking aid required	49	52
Hypertension (%)	44	42
Medications	4	4
Cerebrovascular accident (%)	10	10
Dementia (%)	14	16
Previous heart surgery (%)	21	23
Diabetes (%)	16	15
Hip or knee replacement (%)	16	16
Fallers		23
Timed Up and Go (s)	20 [17-27]	

Age is indicated under the form mean±standard deviation. Medications increasing the risk of fall: Psychotrope, antiarythmic, diuretics [16]. Timed Up and Go (TUG) results are given under the form median [1st quartile-3rd quartile]. Hypertension is defined as a value >140/90 mmHg.

2.2. Protocol

The survey took place between the month of May (t_1) and the month of November (t_2) 2018. At t_1, TUG test was performed in all participants. Participants sat down with their back against a 46 cm high chair rest. When signaled, participants were asked to get up, walk three meters, turn round and sit down again. Participants then performed the 6 minutes walking test with the right to take short pauses as required. Measurements were taken by the two same experimenters (L.C. and R.G.), who always walked aside the patient to prevent any fall in case they lost balance. Six minutes tests were performed by walking a typical distance of 25 m with serial turnarounds. During the 6 minutes walking test, participants were equipped with a homemade sensor collecting several kinematic data. The ultra-low-cost sensor, called DYSKIMOT, was presented in a previous survey [14]. It is based on the Magnetic Angular Rate and Gravity (MARG) sensor LSM9DS1 (SparkFun), composed of 3-axis accelerometer, gyrometer and magnetometer, plus a temperature sensor (Figure 1A and 1B). It is light (10.44 g) and small enough (3 × 3 cm) to be worn by a patient without any disturbance (Figure 1B). Among other quantities, the MARG sensor measures acceleration, $\vec{\boldsymbol{a}}(\boldsymbol{t})$ (in [g], ±16 [g]), and angular velocity, $\vec{\boldsymbol{\omega}}(\boldsymbol{t})$ (in [°/s], ±2000 [°/s]) at a sampling frequency of 100 Hz. The data are transmitted to a PC via an Arduino Uno Rev 3 and a USB cable (RS232 serial link) and then transferred to a home-made acquisition software for further analysis. More details can be found in [14], including a comparison between DYSKIMOT and a gold-standard optoelectronic sensor. This comparison shows that the DYSKIMOT's accuracy is adequate in measuring head rotation during a standardized test. During the experiment, the DYSKIMOT was positioned in the lumbar area of the individual at the level of L4 vertebra (Figures 1C and 1D) in such a way that the sensor's cartesian frame matched with walking directions.

Between t_1 and t_2, each fall of a participant was recorded by the nursing home staff. The fall records were used at t_2 to categorize participants into fallers and non-fallers. At the end of the survey, 23 fallers and 50 non-fallers were noted.

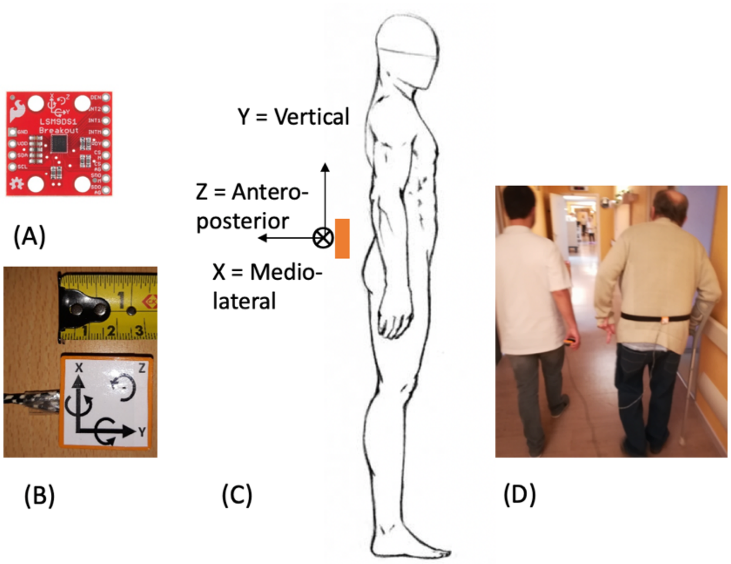

Figure 1. (A) The LSM9DS1 sensor (SparkFun) used to record acceleration and angular speed. **(B)** LSM9DS1 sensor within the DYSKIMOT system. Sensor's cartesian frame is indicated. The curved arrows give rotation's positive direction. **(C)** Schematic placement of DYSKIMOT sensor on a patient. The sensor's cartesian frame matches the walking directions. **(D)** A patient equipped with DYSKIMOT sensor (right) with one experimenter (R.G.) walking aside.

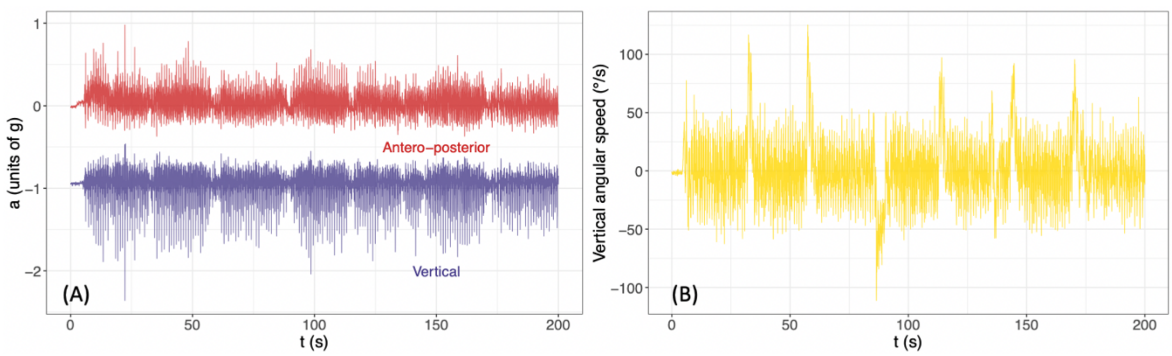

Figure 2. (A) Typical traces of antero-posterior and lateral accelerations measured by the DYSKIMOT during the 6 minutes walking test. **(B)** Typical trace of vertical angular speeds measured by the DYSKIMOT during the 6 minutes walking test. The regularly spaced peaks correspond to turnarounds made by the participants.

2.3. Data analysis

Typical traces of the time series included in $\vec{\boldsymbol{\omega}} = (\boldsymbol{\omega_{ml}}, \boldsymbol{\omega_{v}}, \boldsymbol{\omega_{ap}})$ and $\vec{\boldsymbol{a}} = (\boldsymbol{a_{ml}}, \boldsymbol{a_{v}}, \boldsymbol{a_{ap}})$ (2 times 3 components) are shown in Figure 2. The indices *ml*, *v* and *ap* stand for medio-lateral, vertical and antero-posterior respectively. We recorded for analysis the data at t_1 and t_2 of the 73 participants still included at t_2.

We chose to focus on the assessment of time series variability. As shown in [5], gait variability can be correlated with the risk of fall. Further studies such as [9] have analyzed it using mathematical tools such as fractal dimension and have demonstrated that those tools can discriminate between healthy and disabled individuals, healthy individuals showing a higher fractal dimension. The parameters identified in the present study are the standard deviation (SD) and fractal dimension (D) obtained from the six time series recorded. They were calculated according to the method presented in [17]. Additional mathematical references can be found in the book [18]. SD and D give complementary information about gait variability: SD provides an indication about the magnitude of the fluctuations while D represents the time series complexity, i.e. smooth (D close to 1) or abrupt (D close to 2) relative changes in successive measurements. D is computed using box counting's method.

Due to failed normality tests on data, a Mann-Whitney test was performed with a significance level of 0.05 in order to ascertain potential differences between fallers and non-fallers at t_1.

The TUG test was first analyzed by computing a Receiver Operating Characteristic (ROC) curve. An augmented TUG test (TUG+) was then designed following the methodology shown in Fig. 3. If an individual is recognized by the clinical test as faller, then he/she is assessed a second time by one or more kinematic parameter displaying a significant difference between Fallers and Non-Fallers (according to fall recording). The TUG+ test was chosen after several attempts at designing an augmented TUG test as it provided the best accuracy.

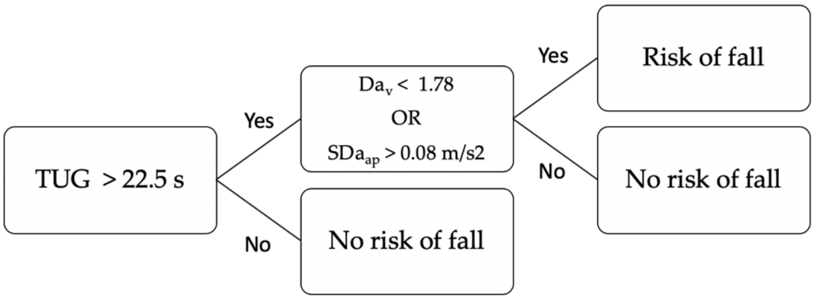

Figure 3. Decision tree illustrating the TUG+ test. TUG's threshold is the one given by the ROC curve, while the other thresholds mentioned guarantee the best accuracy.

The AI algorithm has been designed as follows. The times series related to a participant were divided into fixed-duration frames of 20 s (this value will be discussed in Sec. 3.3) so that the inputs of our model are fixed-size vectors. We used a 10 s overlapping during the frame generation of the train dataset (Figure 4) to increase its size and to remove any bias regarding the starting position of the frames. The obtained dataset has been divided in test/validation datasets and train as a compromise between having enough fallers data for test/validation and for training. The test/validation is made up of 16 participants (8 fallers and 8 non fallers randomly chosen) and the train dataset is made up of 57 participants (16 fallers and 41 non fallers). Models based on Convolutional Neural Network (CNN) + classifier [19] have then been trained and tested to find the optimal accuracy on the risk of fall prediction in the test/validation dataset.

Standard tools belonging to binary classification were then used to characterize TUG test, TUG+ test and AI algorithm: sensitivity ($\boldsymbol{Se} = \frac{TP}{TP+FN}$), specificity ($\boldsymbol{Sp} = \frac{TN}{TN+FP}$), positive ($\boldsymbol{PPV} = \frac{TP}{TP+FP}$) and negative ($\boldsymbol{NPV} = \frac{TN}{TN+FN}$) predictive values, and accuracy ($\boldsymbol{Acc} = \frac{TP+TN}{TP+FP+TN+FN}$) were calculated, with TP the true positives, FP the false positives, FN the false negatives, and TN the true negatives. The positive ($\boldsymbol{LR_+} = \frac{Se}{1-Sp}$) and negative ($\boldsymbol{LR_-} = \frac{1-Se}{Sp}$) likelihood ratios were also computed.

Sigmaplot (v. 11.0) and R (v. 3.5.0) softwares were used to perform the statistical calculations. AI algorithm has been designed by using the standard softwares Keras over Tensorflow 2.0.

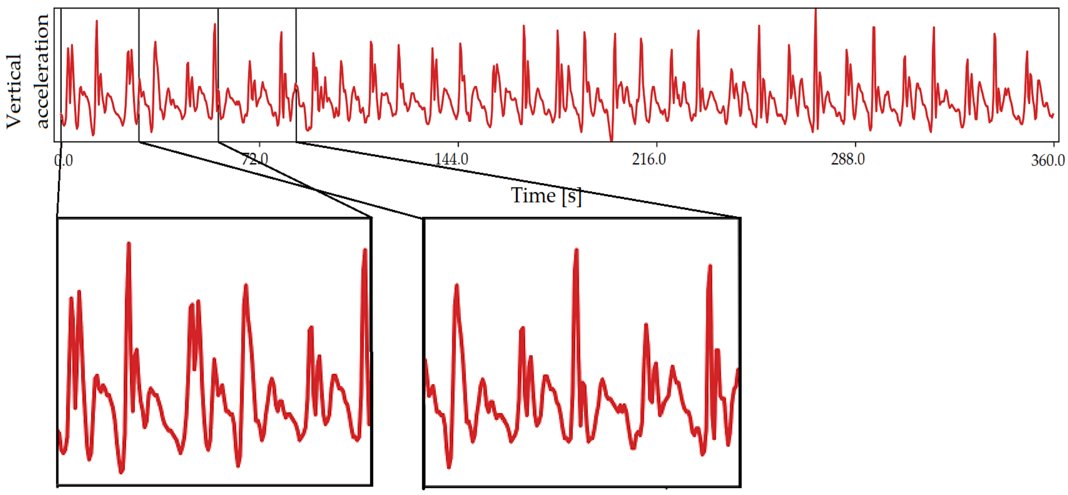

Figure 4. Example of sequence splitting for the train dataset. A duration of 20 s is chosen with 10 s overlapping.

3. Results

3.1. Variability indices

The variability indices (SD and D) computed from the six time series recorded during the 6 minutes test are shown in Table 2. The medians are compared and the p-values are indicated. Two parameters are significantly different for the Fallers and Non Fallers : SDa_{ap} is significantly larger for Fallers and Da_v is significantly smaller. The fractal dimensions are globally smaller for Fallers than for Non Fallers. Those parameters will then be selected in the TUG+ test.

Table 2. Comparison between variability indices of Fallers and Non-Fallers at t_1. Data are given under the form median [1st quartile-3rd quartile]. SD = standard deviation, D = fractal dimension. These indices are followed by a subscript labeling the time series from which it has been obtained. Results of the TUG test are given in the last line. Significant differences are written in bold font.

	Fallers	**Non-Fallers**	**p**
SDa_v (m/s^2)	0.0949 [0.0810-0.149]	0.101 [0.0868-0.130]	0.245
SDa_{ml} (m/s^2)	0.0864 [0.0752-0.109]	0.0950 [0.0747-0.109]	0.891
SDa_{ap} (m/s^2)	0.120 [0.0901-0.173]	0.0900 [0.0753-0.120]	**0.010**
$SD\omega_v$ (°/s)	17.4 [15.5-20.2]	18.4 [15.0-21.9]	0.957
$SD\omega_{ml}$ (°/s)	15.8 [12.3-20.3]	13.7 [11.1-19.2]	0.480
$SD\omega_{ap}$ (°/s)	8.29 [6.77-11.6]	8.79 [7.44-12.6]	0.487
Da_v	1.78 [1.73-1.82]	1.81 [1.77-1.85]	**0.044**
Da_{ml}	1.78 [1.66-1.81]	1.81 [1.77-1.83]	0.088
Da_{ap}	1.73 [1.68-1.80]	1.79 [1.73-1.83]	0.072
$D\omega_v$	1.71 [1.67-1.76]	1.74 [1.69-1.76]	0.376
$D\omega_{ml}$	1.74 [1.71-1.78]	1.78 [1.72-1.82]	0.098
$D\omega_{ap}$	1.81 [1.75-1.83]	1.82 [1.78-1.85]	0.149
TUG (s)	23 [19-31]	19[16-25]	**0.035**

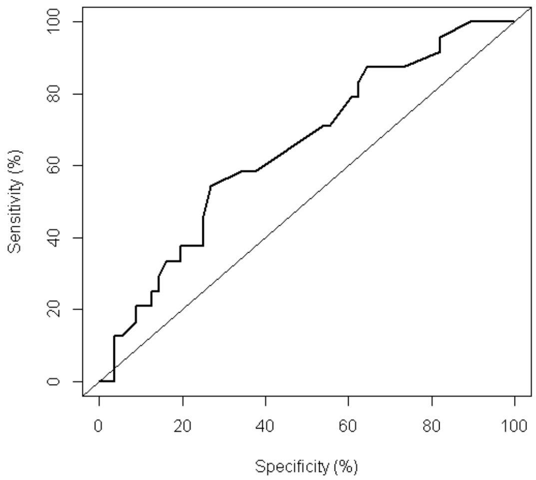

Figure 5. ROC curve for TUG test. An area under curve of 0.648 is obtained, a Youden's J of 0.273 and a threshold of 22.5 s.

3.2. TUG and TUG+ tests

Fallers perform the TUG test significantly slower than Non-Fallers. ROC curve and confusion matrix for the TUG test are shown in Figures 5 and 6. Related parameters are shown in Table 3. Youden's statistics for the TUG test leads to an optimal threshold of 22.5 s. An individual performing the TUG test over that threshold is likely to be considered as presenting a risk of fall in our population. The threshold of 22.5 s is chosen in the TUG+. The SDa_{ap} and Da_v thresholds were adjusted in order to maximize the TUG+ test's accuracy. The TUG+ test has a better accuracy (73.9%) than the TUG test. See detailed comparison in Table 3. Confusion matrix for the TUG+ test is also shown in Figure 5.

	Faller	Non-Faller
Risk of fall	TP	FP
No risk of fall	FN	TN

← Fall records

↑ Test (TUG, TUG+, AI)

(A)

TUG	Faller	Non-Faller
Risk of fall	9	11
No risk of fall	14	39

(B)

TUG+	Faller	Non-Faller
Risk of fall	8	7
No risk of fall	15	43

(C)

AI	Faller	Non-Faller
Risk of fall	6	2
No risk of fall	2	6

(D)

Figure 6. Confusion matrices in our study. **(A)** General definitions. TP = True Positives, FP = False Positives, FN = False Negatives, TN = True Negatives. **(B)** Results for the TUG test. **(C)** Results for the TUG+ test. **(D)** Results for the AI classification. The validation data set has 16 participants.

Table 3. Characterization of the TUG and TUG+ test. The following parameters are displayed: sensitivity (Se), specificity (Sp), positive (LR_+) and negative (LR_-) likelihood ratios, positive (PPV) and negative (NPV) predictive values, and accuracy (Acc). Improvements of TUG+ and AI methods with respect to TUG are emphasized in bold font.

	TUG	**TUG+**	**AI**
Se	0.541	0.521	**0.750**
Sp	0.732	**0.860**	**0.750**
LR_+	2.02	**3.72**	**3.00**
LR_-	0.627	0.556	0.333
PPV	0.481	**0.631**	**0.750**
NPV	0.782	**0.796**	0.750
Acc	0.657	**0.739**	**0.750**

3.3. AI classification

Models have been trained and tested for the following window sizes: 1, 2, 5, 10, 20 and 60 s. 20 seconds windows showed the best convergence rate as shown in Fig. 7. We have then performed a random search hyperparametric study to optimize the accuracy of our AI algorithm [20].

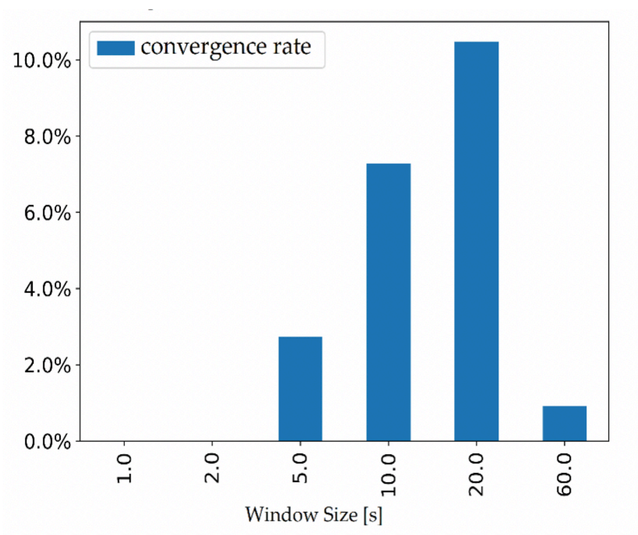

Figure 7. Convergence rate of the AI-algorithm versus window size. The convergence rate is the ratio of models that reached a precision of at least 65% on test data and the total amount of models trained for a specific window size.

We have kept the solution presented in Fig. 8, leading to the confusion matrix displayed in Fig. 6D. It showed the maximal accuracy while being equally specific and sensitive (Sp=Se). One solution with higher accuracy was found (Acc=81%) but at the expense of sensitivity (Se=62.5%) and was therefore not kept.

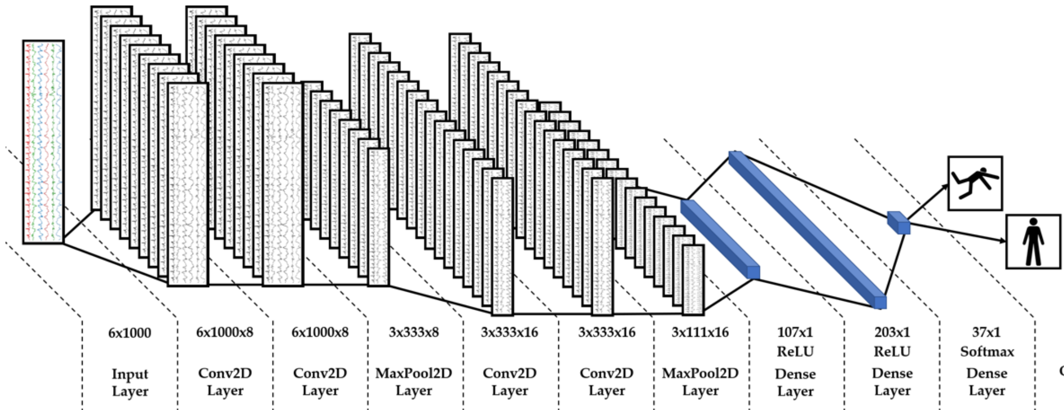

Figure 8. CNN-based AI algorithm used to predict the risk of fall. The input layer receives a 20 s frame from the 6 inputs of the DYSKIMOT sensor. The convolutional layers (Conv2D Layer) extract meaningful features from its input and present it to the next stage. Pooling layers (MaxPool2D Layer) reduce the dimension of the feature space by retaining the meaningful inputs of its layer only. After several convolutional stages, the remaining features are injected in a three layers neural network (Dense Layer) in order to classify the participant's frames (Output Layer). The risk of fall is the mean (ranging from 0 to 1) of prediction on all frames of participant's sequence. A mean greater than 0.5 denotes a participant with risk of fall.

4. Discussion

We report here for the first time on the increase of accuracy of TUG+ compared to TUG in predicting falls in elderly nursing home people. The novelty of this TUG+ is to combine TUG stopwatch-based duration results to gait variability indicators measured during a 6 minutes walking test instrumented with an ultra-low-cost inertial sensor. Furthermore, TUG+ accuracy results were very close to those obtained with an AI algorithm trained on the sensor raw data collected among elderly participants, demonstrating the performance of TUG+.

We confirm that the TUG test is efficient to predict falls. However, the TUG area under ROC curve was equal to 0.648 and shows that the test has a low to medium discriminatory power between Fallers and Non-Fallers. Its accuracy shows that only 65.7% of our sample was correctly predicted. We do not observe sensitivity and specificity as high as in [21] (Sp and Se of 87%). This could be explained by the fact that their sample only included 30 individuals. Our findings are closer to that of [13] performed with 1200 individuals with an area under ROC curve of 0.61. Furthermore, a difference of 3.9 s between Fallers and Non-Fallers is observed in our survey, which correlates with that of [22] (difference of 3.59 s). The threshold defining the risk of falls varies between 13 and 32.6 s according to the studies quoted by [22]. Our value of 22.5 s is intermediate. This latter study shows that the TUG test is a test that allows a better division between Fallers and Non-Fallers when they are nursing home residents but not when they are home-based. This conclusion is shared by [23].

Kinematic analysis of the 6 min walking test reveals that the magnitude of antero-posterior acceleration's fluctuations is significantly larger in Fallers. It is coherent with the findings of [24] showing that elderly people who have already fallen have longer deceleration periods during a walking cycle than healthy young people. This behavior aims at reducing the swing phase to shorten unstable periods during the walking cycle. Fallers also present smaller fractal dimensions. This observation can be related to the optimal complexity framework of [25]. They argued that physiological signals recorded in a healthy individual have a maximal complexity (*e.g.* high fractal dimension or entropy). A loss in complexity is associated to aging or disease. For instance, a smaller complexity in the walking pattern of healthy aged participants has been observed in [26]. In our population fallers are less able to perform quick modifications of their walking pattern and show a less complex behavior than Non-Fallers.

The study [27] is an attempt to improve the TUG test by increasing the walking distance and by timing each phase of this move (chair lifting, walking time, turnaround time) in order to get more information during the test. Others, like [28], chose to complement the TUG test with additional sensors in order to improve its effectiveness. In [29] the TUG test is specifically coupled with inertial sensors and shows an accuracy of 88%. In another survey, the same authors combined a questionnaire-based clinical evaluation with kinematic data measured by an inertial sensor during the TUG test. They obtained accuracies of 68% for clinical evaluation alone, 73% for inertial sensors alone, and 76% for combined evaluation. Those results are similar to ours: We find that the TUG test combined with kinematics from 6 minutes walking test (TUG+ test) is a better way to predict the risk of falls in the elderly. Firstly, the specificity of the test is increased by moving from the TUG to the TUG+ test. The latter has a specificity of 86%. It is more efficient to identify that an individual classed as presenting no risk of fall will indeed not fall. Finally, we managed to increase the accuracy of the TUG test by 9% (Table 1). Using the TUG+ test, 74% of the individuals on our sample were correctly categorized.

According to the review [30], techniques combining sensors and clinical tests are encouraging but the protocols used have yet to be standardized (sensor position, choice of clinical tests, data analysis). It is therefore possible to find combinations of clinical tests and kinematic parameters with an accuracy between 47.9% and 100% in a given sample [30]. The choice of the TUG test appears adequate in view of its intensive use in the field of geriatric rehabilitation and simplicity to perform. This test provides important information to predict the risk of fall when combined with kinematic data. The position of the inertial sensor in the lumbar area is relevant as it is close to the body center of mass. Studies such as [31] show that it is at this position that the best information can be gathered in order to differentiate between Fallers and Non-Fallers. Furthermore, our choice of a 6 minutes walking test with an inertial sensor provides long term information about individual's gait. Such information is not available with the TUG test alone. It appears from our study that the TUG test combined with kinematic parameters such as SCa_{ap} and Da_{v} collected during the 6 minutes walking test improves the accuracy in predicting falls.

We finally have built a complementary approach: AI analysis of 6 minutes walking kinematical time series in view of predicting the risk of fall. AI techniques are nowadays able to detect falls in real time [32,33,34]. The particularity of our first attempt is to focus rather on a six-month prediction. The obvious weakness of our AI classification, based on a convolutional neural network, is the size of our data set. Still it shows the feasibility of risk of fall prediction from the kinematic data of an elderly walking 6 minutes, with an accuracy, specificity and sensibility of 75%. Such a technique, combined to a wearable sensor, gives hope that relevant home tools monitoring the risk of fall of home-based elderly will become available in a near future.

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Conflicts of Interest: The authors declare no conflict of interest.

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