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A method for detection of functional deficiencies due to unilateral vestibular impairment using the TUG test and IMU sensors

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Vestibular impairments affect movement and can result in difficulties with daily life activities. The main aim of this study is to determine whether a short, simple test such as the Timed Up and Go test (TUG) can be an objective method of assessing balance dysfunction in patients with unilateral vestibular impairments. The TUG test was performed using six MediPost devices. The analysis was performed in three ways: (1) an analytical approach based only on data from one sensor; (2) an analytical approach based on data from six sensors; (3) an artificial neural network (ANN) approach based on data from six sensors. The best results were obtained using maximum angular velocities (MAV) of rotation and total time (TT) for approaches 1 and 2, and using 43 different features for approach 3. The following sensitivities and specificities were achieved: MAV 95% and 70%, TT 73% and 88% for approach 1; MAV 60% and 91% and TT 64% and 98% for approach 2; 88% and 92% for approach 3. The ANN-based six-sensor approach demonstrated the best sensitivity and specificity; however, the one-sensor approach might be used as a simple screening test.

Balance deficits result in difficulties in moving during normal activities, and can adversely affect mobility, even if compensated. Balance disorders affect both the physical and emotional status of patients. Imbalance can be assessed in various ways using dynamic tasks such as the Timed Up and Go test (TUG)[1], and using the Dynamic Gait Index (DGI)[2] and Tinetii scale[3]. In a clinical environment, the investigators typically measure the time needed to complete a task, or assign an appropriate number of points based on its performance. In such cases, the reliability of the assessment is largely dependent on the knowledge and experience of the examiners.

The TUG test consists of walking and turning the body. The patient has to stand up from a chair, walk forward 3 m, turn around, walk 3 m back to the chair and then sit down. The main clinical outcome is the total time taken to complete the test[1]. From the physiological point of view, turning is more difficult for patients with vestibular impairment, who may be able to perform the quick walk quite efficiently[4,5]. As it is difficult to isolate the individual components of the test, viz. walking, turning, getting up from the chair and sitting down, using only a stopwatch, studies have investigated the potential of using inertial sensors.

The use of inertial sensors (IMU—inertial measurement units) in balance tests has been evaluated in previous studies[6,7]. Most of these have used the TUG test, or inertial sensors TUG (iTUG), to screen for fallers and non-fallers[8–10] and predict the possibility of falls in the older people[7,11,12], those with frailty syndrome[13]. They have also been employed in patients with a wide variety of pathologies, such as stroke[14,15], Parkinson's disease[16–21], multiple sclerosis[22,23], muscular dystrophy[24], cerebral palsy[25], and mental status[26,27]. Several studies have also evaluated the potential of TUG in vestibular disorders[23,28–30].

Although imbalance, a symptom of functional impairment, is observed in a number of conditions, its underlying mechanisms vary between individual diseases. By including inertial sensors in the test, it may be possible to identify test features specific to individual diseases. Ortega-Bastidas et al.[31] describe a wide range of technological and TUG test protocol variants, which differ with regard to the numbers of sensors and their location on the body. In the single-sensor assessment, the most frequent choice appears to be at a level of L4-L5, i.e. the location closest to the centre of gravity, or body mass. In contrast, multi-sensor measurements include

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locations such as the sternum, upper limbs and lower limbs, with the limb sensors being mounted on individual segments such as the arm, hand or thigh and shin. Due to this diversity in the protocol and the algorithms used for the calculations, it is not possible to provide coherent sets of data for assessment, even for Parkinson's disease, the most frequently-described condition [17,18,20,32–37].

Vestibular disorders disturb the orientation of the head and body and impair balance during head movement. Mijovic et al.[38] noted that patients with unilateral vestibular deficit required significantly more time to perform most daily activities than controls because they adopted less efficient movement strategies. Similarly, Kim et al.[30] found that the walk/turn ratio determined by iTUG test can be used to distinguish individuals with vestibular loss deafferentation from non-vestibular or healthy individuals.

A previous study assessed the value of 360-degree rotation in vestibular impairment patients[39]. The findings indicate that the ANN-based six-sensor approach demonstrated the greatest sensitivity (88%) and specificity (84%); however, the one-sensor approach was judged to be a simple screening test which could be used *inter alia* for rehabilitation purposes, with a sensitivity of 80% and specificity of 60%. The most sensitive and specific measurement parameter was found to be max. angular velocity. Hence, 360-degree rotation (full rotation) in principle, is a different task than the 180 degrees turn (half-turn) used in the TUG. Therefore, the current work evaluates the potential of the half-turn, and the other parts of the TUG test, for identifying vestibular dysfunction.

The aim of the study

The aim of the study was to determine whether the iTUG (Instrumented Time-Up and Go) test can differentiate subjects with unilateral vestibular weakness from those without. In addition, it examines whether the 180 degree rotation used in the iTUG test is sufficient for identification of the most appropriate iTUG measurement parameter for assessing vestibular deficit. It also determines whether using a more elaborate setup with six sensors and an Artificial Neural Network, combining the movement parameters obtained from the sensors as input quantities, yields any improvement in accuracy.

Materials and methods

Study group

The study group consisted of 84 persons, including 44 patients and 40 healthy controls. The characteristics of the groups and inclusion criteria are discussed below. The age distributions histogram is presented in supplementary material (see Supplementary Fig. S1 online). All participants were provided informed consent during the study.

Patients

The study group included patients referred to the balance clinic at least three weeks after the onset of acute vertigo. The inclusion criteria comprised unilateral vestibular impairment, confirmed by Videonystagmography (VNG) caloric test,. Caloric reactivity (defined as the summed caloric responses in the best-responding ear) and asymmetry were calculated by the device. The device's calculations were based on a normative study performed in the same clinical setting, utilizing the same VNG procedure. The study's findings established that CP was considered normal if the difference between both ears was less than 20%. The VSS (Vertigo Symptom Scale) is a tool designed to assess the severity of dizziness by means of a 5-grade scale[40]. The mean VSS score was 18.9 (SD ± 10.2), The computerized dynamic posturography (CDP) used a sensory organization protocol test—SOT (EQUITEST NeuroCom Inc.), which includes composite score, averaged over the 6 tests, is the equilibrium score (ES) parameter. As the posturography results analyzed are standardized, it was possible to label the results as abnormal[41]. Functional assessment indicated by sensory organization test (SOT) was 52.6 (SD ± 15.3) score. The mean age of the patients was 55.7 years (range 29 to 84 years; SD ± 15.3 years).

Healthy persons

This group consisted of healthy adults (volunteers) without dizziness or balance problems. None had any history of dizziness or balance disorders, neurological disorders, musculoskeletal or cardiovascular disorders, migraine or diabetes. The exclusion criteria comprised abnormal results of physical examination, VNG test or dynamic posturography (*SOT*). The mean age of the group was 39.6 years (range 20 to 74 years; SD ± 16.8 years). It consisted of 29 individuals aged between 20 and 43 years and 11 individuals aged between 54 and 74 years. When gathering the data the authors were particularly careful to include healthy older adults.

Methods

All subjects underwent the iTUG test. The test involves getting up from a chair, walking 3 m, turning 180 degrees, walking 3 m back towards the chair, turning 180 degrees and sitting down on the chair (Fig. 1). The authors propose two measurement methods, both using inertial sensors placed on the subject's body: the first employs a single sensor, and the second six sensors. Both methods are based on biomechanical human model which allows selected movement parameters to be calculated.

Measurement data was recorded using a prototype MediPost device. It is a portable, battery-powered, lightweight device controlled by the ESP32 microchip with a Wi-Fi radio module (Fig. 2a). It uses a three-axis inertial measurement unit (IMU) to determine its orientation in space. The IMU (STMicroelectronics LSM9DS1) contains a micromachine system (MEMS) consisting of an accelerometer, gyroscope and magnetometer. During measurement, the device itself uses a sampling frequency of 200 Hz. The signal is then filtered by a low-pass 2nd order Butterworth filter with a 10 Hz cutoff implemented in the device and decimated to 20 samples per second.

The MediPost system is designed to easily collect data from several sensors at the same time. The device is synchronized and controlled by a program connecting via a predefined Wi-Fi network. Apart from the synchronization signal, if all six sensors are used, and the start of the exercise trigger, all data transmission is

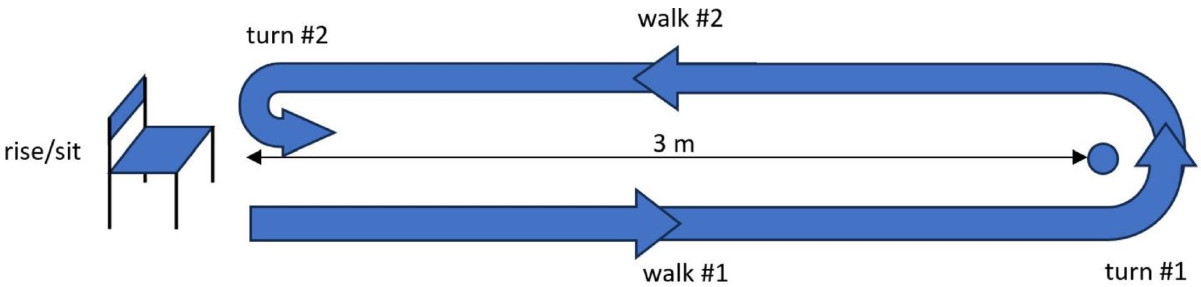

Fig. 1. TUG (Timed Up and Go) exercise schematic diagram.

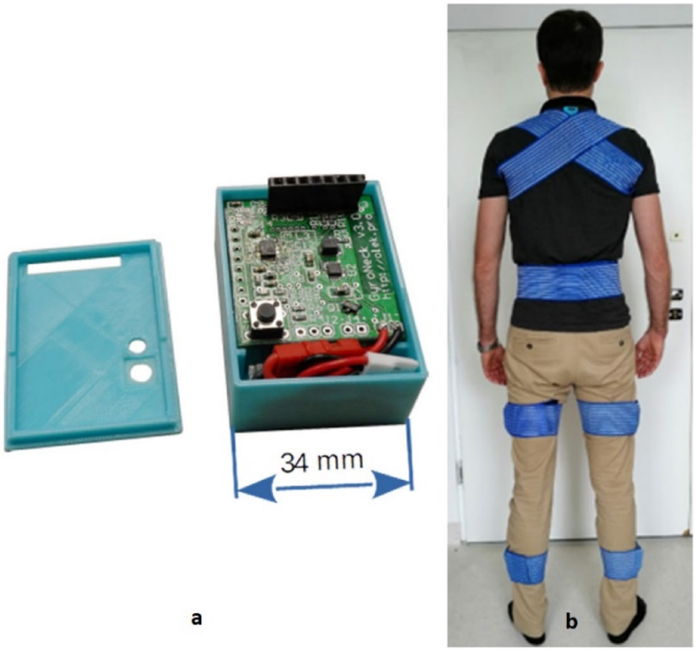

Fig. 2. MediPost device (**a**); MediPost six sensor placement: in the case of single-sensor placement, only the one on the back is used (**b**).

performed after the measurements are completed. All samples are transferred to the PC application and stored in the database; the data consists of information collected from all three IMU sensors in three axes.

The choice of a suitable segmentation strategy also has an impact on the results achieved. The literature indicates describes various algorithms used to calculate individual parameters, these include Weiss etal.[42], the BTS G-Studio platform with segmentation strategy with single-sensor model[31] and the Mellone algorithm[43]. For the present study, the Madgwick algorithm[44] was chosen to determine the angular position of the device. The algorithm is based on the use of quaternions to represent orientation in 3D space and treats the orientation computation task as an optimization problem that is solved using a gradient approach. The Madgwick algorithm yields the angular position of the sensor (pitch, roll and yaw angles) and the translation vector. The algorithm was chosen mainly due to its very low computational overhead; this is an important consideration as it allows the possibility of further work towards implementing processing on a ESP32 microcontroller-based platform. It also provides similar accuracy to the extended Kalman filter[45]. A detailed description of the system can be found elsewhere[46,47].

Six MediPost devices are placed on the subject (Fig. 2b). The subjects were allowed to move their arms freely, because the upper limbs were not observed and included in the biomechanical model.

Before performing the tasks, all six sensors were calibrated to eliminate errors associated with gyroscopic sensor drift and to determine the position of the sensors relative to the corresponding body segments. The task was initiated with a sound signal, after which the subject performed the iTUG test.

The turn was performed counterclockwise and the transitions between stages were generally very smooth. The second turn and sitting on the chair are generally combined into one activity.

Data analysis

Two models were developed for data analysis: a model based on data from a single sensor (L4-L5) and a model based on data from six sensors.

Single-sensor model

The single- sensor model provides a clear pattern of changes in the recorded angles over time, which can be used to determine selected movement parameters (Fig. 3). At the beginning of each task, minor angle changes associated with getting up from a chair are observed. After some time, a quick turn of 180 degrees takes place. After a longer or shorter time, a second turn of 180 degrees takes place (consistent or inconsistent with the direction of the first turn), combined with sitting on the chair.

The starting and ending moments of rotation are calculated automatically.

The threshold parameters used to analyze the subject's rotational motion[39] were directly selected for rotations in iTUG. The threshold values for angle change were selected based on measurements of several healthy subjects standing still (for 120 s). The calculations assume that the task is performed correctly by the subject and total turning angle during entire iTUG test is in the range of 300° to 360°; this variation was assumed due to possible errors in angle measurement and some inaccuracy in the subject's performance of the task. Requiring the total rotation angle to be exactly 360° would lead to rejection of some tests as incomplete. The rotation tracking scheme implemented in this way proved to be effective.

The following movement parameters were selected for analysis: the maximum angular velocity, i.e. the value measured during the task (expressed in degrees per second), the mean angular velocity, i.e. value measured during rotation (expressed in degrees per second), and the test duration, i.e. the time between the moment of starting the test and the moment of finishing the second half-turn (value expressed in seconds),

Six-sensor model

By calculating the angular position of each sensor, it is possible to determine the angular position of the body. For the sake of the analysis, the body segments are treated as rigid blocks connected by joints. Additionally, it is assumed that at least one foot must always touch the ground. This allows calculation of not only rotation but also translation, thus reproducing the body position in the software.

The values obtained from the six-sensor model can be analyzed by selecting a single movement parameter and performing a classification using only this parameter (e.g. using ROC curves). This approach is presented in Table 2. Another approach is to analyze all movement parameters collectively.

To combine different movement parameters describing the task from different perspectives, an artificial neural network (ANN) was implemented[48]. The employed network was based on the Multi-Layer Perceptron concept, i.e. the neurons were organized into layers, with the data flow being unidirectional and only possible between adjacent layers. Various network sizes were tested to find the best performing networks. Rigorous leave-one-out cross-validation was performed; this means that the learning process was performed from scratch 84 times (i.e. the number of records in the database); each time, 83 records were used for learning and one for validation. The reported performance metrics are calculated for the validation samples only.

The six-sensor model uses the Madgwick algorithm to calculate the angular position of each sensor, which in turn, is used to determine the angular position of body segments (calibration is particularly important here). As in the previous model, the body segments are treated as rigid blocks connected by joints, and at least one foot was assumed to always be in contact with the ground. This allows calculation of not only alignment but also segment shifts, thus reproducing the body position in the software. The six-sensor model offers a number of advantages; most importantly, it allows movement parameters to be calculated assessing the body as a whole, it

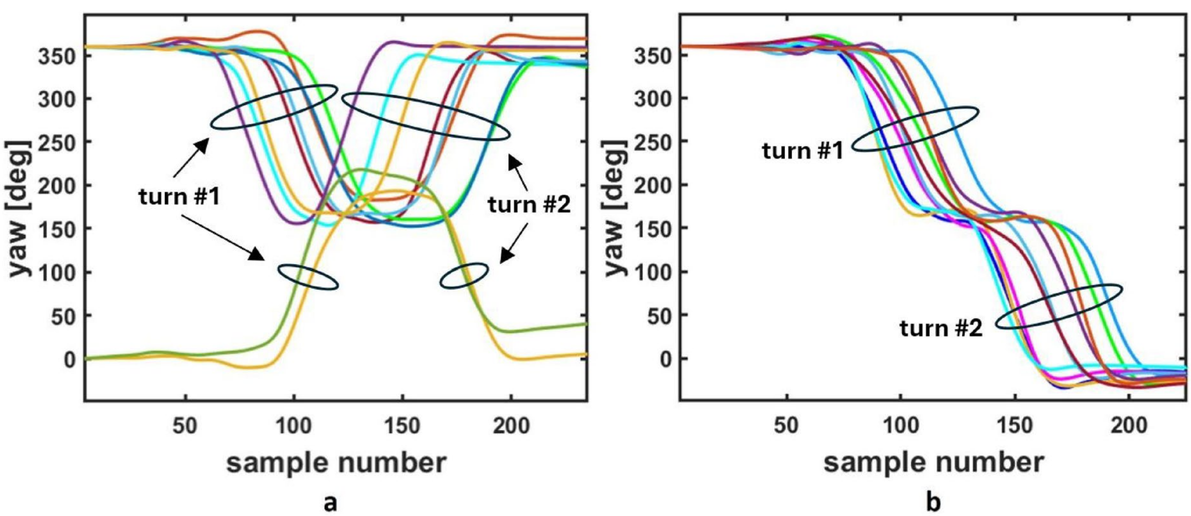

Fig. 3. Angles obtained from 20 example subjects during the iTUG test: 360-180-360 or 0-180-0 (**a**) and 360-180-0 (**b**).

Parameter	Healthy	Patients	*p*-value
Total time (one sensor)	7.36 ± 1.08 s	9.34 ± 1.70 s	< 0.01
Maximum angular velocity (one sensor)	192.62 ± 19.72 deg/s	153.92 ± 25.28 deg/s	< 0.01
Mean angular velocity (one sensor)	111.42 ± 32.72 deg/s	91.54 ± 21.04 deg/s	< 0.01
Total time (six sensors)	8.22 ± 0.78 s	10.08 ± 1.95 s	< 0.01
Maximum angular velocity (six sensors)	153.53 ± 22.26 deg/s	132.68 ± 20.84 deg/s	< 0.01
Mean angular velocity (six sensors)	136.19 ± 19.72 deg/s	115.79 ± 19.50 deg/s	< 0.01

Table 1. Comparison of healthy controls and patients according to selected parameters in iTUG test.

Parameter	AUC	*p*-value	Accuracy (%)	Sensitivity (%)	Specificity (%)
First half-turn time	0.5849	0.15	62	89	33
Second half-turn time	0.7537	< 0.01	74	68	80
Second walk time	0.6787	0.04	69	50	90
Total time	0.8591	< 0.01	80	73	88
Maximum angular velocity	0.8881	< 0.01	82	95	70
Mean angular velocity	0.7057	< 0.01	73	53	91

Table 2. Single-sensor model results based on ROC analysis.

can effectively analyze leg movement; however, the single-sensor model is far simpler to calibrate, with no such procedure being needed in some cases.

The following parameters have been proposed as a way to summarize body movements: total duration of the entire exercise, the time to perform the individual stages of the exercise (viz. standing up, walking, turning, walking, sitting down), the maximum angles and angular speeds for each segment during each exercise stage, and latency, i.e. the time from the buzzer signaling the start of the task to the moment when the subject started to get up from the chair (expressed in seconds).

The values obtained from the six-sensor model can be analyzed by selecting a single movement parameter and using it to classify subjects as impaired or not (e.g. using ROC curves). This approach is presented in Table 3. Another approach is to analyze all movement parameters collectively.

It is hypothesized that the six-sensor approach could achieve better results because it allows various movement parameters describing the task from different perspectives to be combined. For this purpose, an artificial neural network (ANN) was implemented.

The employed network was based on the Multi-Layer Perceptron concept, i.e. the neurons were organized into layers, with the data flow being unidirectional and only possible between adjacent layers. Various network sizes were tested to find the best performing networks. Rigorous leave-one-out cross-validation was performed, i.e. the learning process was performed from scratch 84 times (the number of records in the database), with 83 records used for learning each time, leaving one for validation. The reported performance metrics are calculated for the validation samples only.

ROC curves
When single movement parameters were analyzed, the sensitivity and specificity of each approach was determined using ROC curves. The area under the ROC curve (AUC) was calculated and statistical significance was set at 0.05. The cut-off point was calculated using the Youden index. ROC curves were calculated for all listed parameters. Data were checked for normality using the Shapiro–Wilk test.

Results
A comparison of the mean values of rotation parameters between the patients and the healthy group is presented in Table 1. Significant differences in parameters were found between the groups.

Single-sensor model analysis
ROC curve classification revealed that maximum angular velocity demonstrated the greatest accuracy and sensitivity when differentiating between vestibular and healthy subjects. Although total time also offered high accuracy, its sensitivity was markedly lower (Table 2).

Six-sensor model analysis
The classification results for the six-sensor approach when a single movement parameter was used for analysis are shown in Table 3. The analysis did not show any significant advantage over the single-sensor model.

Six-sensor ANN-based model analysis
For the six-sensor ANN-based approach, the network structure consisted of a single hidden layer of 10 neurons with a bipolar sigmoid activation function and an output layer of one neuron with a linear activation function.

Parameter	AUC	p-value	Accuracy (%)	Sensitivity (%)	Specificity (%)
Movement start time (latency)	0.7455	< 0.01	71	59	85
Rise duration	0.5940	0.45	61	70	52
Sit duration	0.6122	0.14	61	68	53
Turn duration	0.7517	0.09	73	83	63
First walk duration	0.7750	< 0.01	73	52	95
Second walk duration	0.7955	< 0.01	73	52	95
Total time	0.7983	< 0.01	80	64	98
Maximum angular velocity	0.7591	< 0.01	76	60	91
Mean angular velocity	0.7710	< 0.01	76	65	86

Table 3. Six-sensor model results based on ROC analysis.

Inputs	Number of inputs	Accuracy (%)	Sensitivity (%)	Specificity (%)
Durations of stages of the exercise plus total duration of the exercise	6	89	95	83
As first, plus maximum and mean rotation speed for the trunk segment	8	90	95	85
As first, plus mean angular velocities of all body segments, separately for each stage	41	90	88	92

Table 4. Six-sensor model classification results.[A]

Parameter	TEST	Accuracy (%)	Sensitivity (%)	Specificity (%)
Maximum angular velocity (one sensor)	iTUG	82	95	70
Total time (six sensors)	iTUG	80	64	98
Neural network taking into account durations of stages of the exercise plus total duration of the exercise plus mean angular velocities of body segments, separately for each stage (six sensors)	iTUG	90	88	92
Maximum angular velocity (one sensor)	Rotation*	73	80	60
Maximum angular velocity, taking into account all segments (six sensors)	Rotation*	74	61	85
Neural network taking into account all segments (six sensors)	Rotation*	86	88	84

Table 5. Comparison of different methodologies for the analysis of rotation; the table presents the findings with the greatest classification accuracy, sensitivity or specificity. *The comparison data come from a previous work[39] using full rotation (360 deg).

This simple structure proved to be sufficient; neither more complex structures nor more elaborate activation functions resulted in better performance. The Levenberg–Marquardt algorithm was used for training and leave-one-out cross-validation for validation of results. Sample results obtained for various combinations of inputs to the network are given in Table 4. The best-performing networks delivered an accuracy of 90%. Using a large set of input quantities improved accuracy only marginally, but provided a better balance between sensitivity and specificity.

Table 5 summarizes the best results of the six-sensor ANN network compared to previous findings obtained from iTUG tests with 360-degree rotations.

Discussion

Patients with unilateral vestibular dysfunction may suffer from difficulties daily activities due to experiencing vertigo and lack of balance, especially during body movement and rotation. In the present study, the diagnosis of unilateral vestibular dysfunction was confirmed by objective questionnaires, together with videonystagmography and dynamic posturography as objective tests.

The main aim of this study was to determine whether an objective iTUG test can accurately identify patients with balance instability due to unilateral vestibular weakness. It also examines whether the method based on minimal time and resources, i.e. a single inertial sensor (IMU-based MediPost device) is also sufficient for the purpose.

In common clinical practice, the TUG assessment is performed by visual observation, i.e. without a computer system. The outcome is the total time taken to complete the task. The procedure has been used to assess the risk of falls risk in patients with vestibular disorders. Whitney et al.[49] propose a TUG cut-off point as 11.1 s, with a sensitivity of 80% and a specificity of 56%; these findings were found to offer enhanced accuracy in differentiating those with vestibular impairment. However, the measurements are usually taken by stopwatch, and as such, the data can be acquired only for the entire test, rather than its component stages; in addition, human error when capturing the beginning and end of a rotation can significantly affect the results. The computerized iTUG procedure provides more possibilities for dividing the test into parts and assessing other parameters.

Our findings confirm that the iTUG (MediPost) is a useful tool for assessing imbalance in symptomatic patients with unilateral vestibular weakness. The test used two measurement methods: the first employing a single sensor attached at L4, and the second with six sensors attached to various parts of the body (Fig. 2b). The data from the six-sensor model was also analyzed using ROC curves and an advanced neural network. While each method obtained satisfactory results, the data varied significantly depending on the method of analysis and the analyzed test parameter.

In both our models, max angular rotation was found to be one of the most suitable parameters for differentiating the vestibular patients from the control group. In the single-sensor model, maximum angular velocity demonstrated exceptional resistance to all kinds of calibration problems, measurement inaccuracies, drifts and errors in the execution of the exercise; as such appears to be the best differentiating parameter. It can only be automatically recorded, which further justifies our use of instrumental measurements (iTUG). The six-sensor model provides a more accurate representation of the mechanics of movement and minimizes any inaccuracies in measuring movements, as data collected synchronously from a larger number of sensors.

Interestingly, when max angular velocity was used as the main outcome, it demonstrated high sensitivity in the single-sensor model but high specificity with quite low sensitivity in the six-sensor model. This difference may have two possible explanations. Firstly, the single-sensor model is based solely on observing the rotation angle. The phases in which the subject does not rotate are not distinguishable from each other, viz. the latency, standing and first walk phases, and the total time associated with the end of sitting down is also unobservable in this model. Secondly, the individual phases of the iTUG test typically merge during its performance: the start and stop conditions are determined differently for the assessment of rotational movement and differently for the measurement of body angles (in the six-sensor model). For this reason, the single-sensor model tends to extend the rotational phases at the expense of the first and second walk in the iTUG test.

Hence, the single-sensor model, which was found to demonstrate very high sensitivity and markedly lower specificity in the ROC analysis seems to be useful for screening patients with vestibular deficit.

The greatest sensitivity and specificity was observed in the third method, i.e. the six-sensor model based on an artificial network. The six-sensor approach did not exhibit acceptable sensitivity (60%) when a single movement parameter was used for analysis. Combining a larger number of sensors with ANN processing significantly improved the detection capabilities of the entire approach, obtaining a sensitivity of 88% and specificity of 92%.

Maximum angular velocity appears to offer greater value than static posturography (sensitivity 61.3% and specificity 58.3%)[50], suggesting its potential use for functional assessment in patients with vestibular disorders. A previous study by Picardi et al.[51] based on a single lumbar-mounted sensor found angular velocities from sit-to-walk (duration of rising) to be an important parameter for characterizing people with Parkinson's disease; however, this approach did not achieve significant results in the present research. It is also worth noting that the iTUG test and rotation test achieved similar results when similar groups of patients for selecting the best detection parameter. However, it should be noted that neither the maximum angular velocity nor other movement parameters provided both high sensitivity and specificity when the single-sensor modeling approach was chosen.

The present study focuses on turnover; gait assessment will be the subject of further analyses in later studies. Previous research has confirmed the clinical value of iTUG tests including walking and rotation as the main tasks for assessing patients suffering from disturbed balance[7,17,42]. Based on the clinical presentation of the patients, it would be expected that the greatest disturbance would occur during the rotation and immediately afterwards. Therefore it is important to assess turnover, i.e. rotation, in patients; hence the iTUG test was selected for the study.

Research has found 360 degree rotation to be an appropriate task for identifying patients lacking fully-compensated vestibular impairment[39]; however the iTUG test included in the present study only used a 180 degree rotation, i.e. a half turn. Our present findings indicate that the half turn test was more effective than the full-turn. This could be due to the fact that during the turn, the vestibular system is mostly stimulated at the beginning of the rotation and after stopping: these are the key points at which a dysfunctional vestibular system can cause balance problems. In the half-turn, the start and stop are closer to each other, and as such, the stress stimuli activity may overlap, thus triggering a balance reaction even in partially-compensated individuals. These findings suggest that the turn stage of the iTUG is the most prone to disruption in vestibular dysfunction patients.

The single-sensor model is less time consuming to install than a multi-sensor model, but yields less information. In addition, the single sensor seems to be adequate for screening purposes. The six-sensor model also requires a more advanced mathematical approach, and the cost of equipment could be about six times higher due to *inter alia* the multiplication of sensors; the test procedure could also be significantly longer: even though the patient performs the same task in the same way, the total procedure requires more time to install, calibrate and remove the sensors.

However, the six-sensor multi-parameter analysis is far more effective when coupled with artificial intelligence methods, such as ANN. In this case, the classifier is able to exploit interactions between movement parameters, giving markedly better results than can be obtained from any of the parameters taken individually.

As in every study, the presented research has some inescapable limitations. In this case the most important is related to the study group itself. The presented research has been subjected to constraints characteristic of clinical studies, which necessitate appliance of very narrow inclusion criteria. These constraints contributed to a relatively small size of the study group. Moreover, the age distribution in the two groups of interest (healthy subjects, patients) is imperfectly matched (cf. histogram in the supplementary material). This issue has been induced by the natural difficulty in accumulating a representative sample of older people subjects of perfect health. For many subjects, the diagnostic tests revealed significant changes in central nervous system performance parameters, despite no earlier reports of any associated symptoms. This resulted in exclusion of these candidates from the healthy subjects group. Such composition of the study group may introduce bias in the models: while age was not a parameter taken into account in the model, more frequent prediction of younger people as healthy may occur, while healthy older patients may be subject to more false positive reports. Removing some subjects from the healthy group in order to match the age distribution has been considered, however, due to the overall small size of the study group the idea was abandoned. Consequently, further research must focus on confirming the findings of this study on a larger group. Once such a group is available, it may also be advisable to develop separate classifiers for the young and old subjects, or include the age as an input parameter.

Conclusions

1. Both the single-sensor and six-sensor models are effective for differentiating the symptomatic vestibular patients from the controls. However, the results indicate significant differences between the methods.
2. In both models (single-sensor and six-sensor), maximum angular rotation speed seems to be the most appropriate parameter to differ the vestibular from the control group. However, this parameter demonstrates high sensitivity in the single-sensor model, and high specificity in the six-sensor model. The highest sensitivity and specificity were obtained in the six-sensor model employing the ANN network.
3. The 180 degree half-turn seems to be a more accurate, sensitive and specific task for identifying vestibular patients than the 360 degree full turn, regardless of the number of sensors and analysis method.

Data availability

The data that support the findings of this study are not openly available due to reasons of sensitivity and are available from the corresponding author upon reasonable request. Data are located in controlled access data storage at Lodz University of Technology.

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M.K.: conceptualization, methodology, investigation, writing—original draft. R.K.: formal analysis, methodology, software, writing—original draft, figures preparation, review and editing. W.T.: investigation, writing—original draft, review, supervision. M.J.: data collection, writing—original draft, review. E.Z.-S.: review and editing. M.J.-K.: review and editing.

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Declarations

Ethical approval
All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. The study was approved by the Bioethics Committee of the Nofer Institute of Occupational Medicine, Lodz, Poland (No of protocol 17/2014).

Competing interests
The authors declare no competing interests.

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