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Pilot Study for a Robot-Assisted Timed Up and Go Assessment*

Matthew Story, Khaoula Ait-Belaid, Nicola Camp, Roberto Vagnetti, Daniele Magistro, Massimiliano Zecca, and Alessandro Di Nuovo

Abstract— **Falls and fall risk management are challenges that are increasing in an aging society, exacerbated by the decreasing availability of care professionals to provide suitable fall management plans. Technology may provide a solution to this, with robotics and vision systems receiving increased attention. A pilot study was conducted using a vision system mounted on a Turtlebot 4, MoveNet, and different machine learning algorithms to assess a Timed Up and Go (TUG) test. The system was evaluated on the performance of a previously trained action classifier and by comparing times for the different phases of the TUG test from the output of the model with the output from the QTUG test acquired by IMU sensors worn by the participants. The results showed the system could determine if the person was sitting, in transition, or standing with high accuracy (97.09%) with higher levels of consistency for participants between tests than the QTUG. This demonstrates that the system is not only advantageous requiring minimal user input but also can match the performance of wearable sensors that are considered the "gold standard" for TUG tests.**

I. Introduction

The statistics around falls and fall related injuries are staggering, with an estimated one in three people aged over 65 years old experiencing a fall each year [1]. The results of a fall can be as serious as they are varied and can lead to hip and other fractures, spinal, nerve, and brain injury, organ damage, joint dislocation and distortion, soft tissue damage, bruising and cuts, and an increased risk of death [2], as well as depression, reduced social activity, and reduced quality of life as a result of a fear of falling again [3]. A challenge in providing adequate fall risk identification and reduction is the growing gap between the decreasing availability of trained physicians able to administer such procedures and the increasing age of the population. It should be noted that even prior to the COVID-19 pandemic the time constraints on care professionals meant that fall risk screenings were often deprioritized [4].

Technology-based solutions have often been seen as a means of reducing this gap in several sectors such as education [5] and care, especially with recent advances in computer vision, machine learning, and robotics [6], [7]. Although technology-based solutions to fall detection have received attention over recent years [8], reliable technology-based measures to fall risk detection and fall prevention could provide a more fruitful solution to the challenge. After all, it is better to aim for prevention over damage reduction. To improve the efficiency and consistency of fall risk screening and management by healthcare professionals, tools and algorithms have been developed by both the World Health Organisation (WHO) [9] and the Centers for Disease Control (CDC) [4]. Both highlight the importance of gait and balance impairment in the assessment of fall risk, with the Timed Up and Go (TUG) test as the recommended method for evaluation.

The TUG test was designed in the early 90s as a functional mobility test which can provide quantifiable assessment over time [10], and is recognized by both the British and American Geriatric Societies [11]. The TUG test involves the person starting in a seated position, standing up, walking 3 metres, turning around, walking back, and sitting back down. The simplicity of the test can allow for consistent retesting whilst the different phases use common motions that a person would be expected to do during their day (covering 8 out of the 9 features considered important in assessing fall risk [2]). This ease of use also makes it attractive for technology-based analysis, with previous work using vision systems [12], and inertial measurement units (IMUs) [13]. However, these systems either require the user to be able to put on the device independently or fully calibrated (and often expensive) camera set ups.

The aim of this study, therefore, is to evaluate the performance of a low-cost robot-mounted vision system in assessing the TUG test. The main evaluation will be comparing the output from the vision-based algorithm and the wider recognized standard wearable sensors in the time taken to complete the different phases of the test as well as the overall time.

II. Related Work

The tools used for measuring fall risk are varied and even within the same country the tool used differs between trusts and regions [14]. In [15], a review of 20 fall risk assessment tools identified 19 fall risk factors. Of these 19 fall risk factors history of falls (75%), medication (70%) and gait/physical activity (70%) were the most common. The

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latter, gait/physical activity assessment has been identified as risk factor which can be addressed through technology.

A. Wearable Sensors

In wearable sensors, one of the most used devices are IMUs due to their reliability, low cost, and compact size [16]. The feasibility of IMUs for the TUG test has been widely explored and shows great reproducibility, precision, and accuracy [17]. Despite this, the positioning of the IMUs on the person are inconsistent and therefore the reliability of the output from the algorithm may differ if the positioning during testing is inconsistent with the position during training of the model. Common locations include the lower to mid back [13] and on the legs [18], however the placement within studies is variable and lacks sufficient documentation [19]. [20] proposes a multi-IMU approach for optimal lower limb joint angle accuracy however this is not always feasible outside of a clinical/research setting. This represents a common challenge with wearable sensor-based assessment, which requires correct calibration by a trained professional and relies on the user to wear the equipment during the assessment. A potential way around this is the deployment of robotic systems to perform the task.

B. Robots

Robots with vision systems have been researched, with recent studies provided more efficient and effective means of gesture and motion recognition [21]. The focus of studies involving robots for fall risk assessment and prevention by gait/physical activity has been as a device which provides physical aid to the user [22]. A scoping review by [23] highlights this preference for wearable/physical assistance robotics in fall prevention, where robots act as a more reactive force to a change in a person's movement/posture that could lead to a fall. This system can benefit greatly people living with frailty, however the risk of falling is still present as even when provided with a walking-aid device the user still has a high risk of falling if they do not use it, be that willingly or otherwise [24]. Therefore, a system which can identify and reduce fall risks with reduced reliance on direct user input may be a more viable means of maintaining a person's independence.

A vision-based robot system would overcome this limitation, as the system is considered passive from a user perspective. Despite studies showing the viability of a vision system-based assessment of mobility [12], [25], [26], there are few studies of how a vision-based assessment of the TUG test on a robotic platform. Most studies used a Kinect sensor, which is a low cost, reliable, and relatively simple system to implement. Whilst useful for feasibility, the platform has been out of production for almost a decade and many of the methods used in these studies are tied to that platform. Furthermore, the studies used the camera in a fixed position, such as on a tripod, limiting the versatility as it requires the person to move within a specific field of view for the assessment [16] (a limitation not shared by mobile robots). Although many social and mobile robot platforms are equipped with vision systems for navigation and social activity recognition, the application in fall prevention has been towards environmental monitoring and clearing of potential trip hazards [27], [28].

Considering previous research, the proposed study investigates the feasibility of a system that is platform agnostic and mobile, whilst still providing a reliable assessment of the TUG test in comparison with more traditional and recognized methods.

III. Materials & Methodology

As identified in [6], one of the barriers to adoption of robots in the home is cost. Therefore, the chosen system would need to be as economical as possible. The Turtlebot 4 was chosen for this as it is a relatively low-cost robotic solution whose design is based off a robotic vacuum cleaner that has received mainstream recognition.

A. Hardware

1) Turtlebot 4:

Developed by Clearpath Robotics, the Turtlebot 4 uses an iRobot Create3 mobile base and a Raspberry Pi 4 running on ROS 2 [29]. For environmental mapping and visual monitoring, the system has a 2D RPLiDAR-A1 and an OAK-D Pro stereo camera. The Standard model includes a mounting plate which gives the robot dimensions of 0.341m x 0.339m x 0.351m (width x length x height). To provide a better field of view, the OAK-D camera was mounted onto a tripod and positioned on top of the mounting plate (see Figure 1).

Figure 1. The Turtlebot4 with the modified camera mount position to provide a better field of view.

2) Kinesis QTUG:

The Quantitative Timed Up and Go (QTUG) by Kinesis is an objective assessment tool of frailty, mobility, and falls risk [30]. The system uses inertial sensors containing a tri-axial accelerometer and gyroscope placed on each leg, just below the knee, and measures 59 gait and mobility parameters during the TUG test [31]. The system has undergone robust assessment in previous studies and has consistently shown reliable performance for measuring gait, mobility, and falls risk [32].

B. Software

To obtain the joint angles of the hips and knees, as well as the relative distance between the ankle and the person's head, the joint coordinates from the frame were required. These were acquired using the MoveNet Thunder FP16 Lite model developed by TensorFlow and Include Health [33]. The MoveNet model was modified to operate as a ROS2 node to enable subscription to the camera output of the Turtlebot 4. The model detects 17 key points with xy coordinates to provide a skeletal overlay of the detected person. The python script for the model was converted to be deployable as a ROS2 node which would subscribe to the "*/oakd/rgb/preview/image_raw*" topic to obtain the 300 x 300-pixel frame.

The joint angles were obtained from the coordinates of different joints to reduce the impact of changes in distance from the camera which will occur during the TUG test. During sitting and standing behaviour the joints which have the most significant difference are the knees and the hips [34], [35], therefore these were selected as the most reliable indicators of if the person were sitting or standing. The joint angles (left and right) were calculated using the equations for determining the angle between two vectors, where the hip angles (see Eq. 1) used the xy coordinates from the shoulder (sh_{xy}), hip (hip_{xy}), and knee (kn_{xy}), and the knee angles (see Eq. 2) used the xy coordinates for the hip, knee, and ankle (an_{xy}). The head height was also obtained by determining the y-distance between the nose joint and the ankle with the lowest y-coordinate value.

$$\theta_{hip} = cos^{-1} \frac{(sh_{xy} - hip_{xy}) \cdot (kn_{xy} - hip_{xy})}{(\sqrt{sh_{xy} - hip_{xy}}) * (\sqrt{kn_{xy} - hip_{xy}})} \quad (1)$$

$$\theta_{knee} = cos^{-1} \frac{(hip_{xy} - kn_{xy}) \cdot (an_{xy} - kn_{xy})}{(\sqrt{hip_{xy} - kn_{xy}}) * (\sqrt{an_{xy} - kn_{xy}})} \quad (2)$$

The four joint angle values and the head height value were stored in a CSV file for the data analysis.

C. Data Collection

A total of 18 TUG tests were recorded between 5 physically able people (4 male, 1 female, age range 27-43 years old). Prior to the TUG test, the participant had the two sensors for the QTUG strapped to their legs, just below the knee. For the TUG test, the person began in a seated position and when instructed the participant would stand up, walk to a cone placed 3 metres in front of the chair, turn around, walk back to the chair, and sit down. At the same time as the participant being given the instruction to begin the test, a member of the research team would start the QTUG and then stop once the participant was sat back down. The robot would begin side on to the person to provide the optimal viewing angle for the knee and hip joint angles whilst seated, at a distance of 2 metres perpendicular to the participants motion of travel. As the person moves, the robot was moved by a member of the research team (using teleoperation) in an arc forward/backward to keep the person in frame. The typical robot movement would be 0.3 metres in the x and y directions with a rotation of 45 degrees, therefore the participant was <5 metres from the robot and the vision system. Each participant was asked to complete the TUG test 3 times. Due to camera errors, two of the participants recorded multiple data sets. The camera errors occurred during the walking phase; therefore, the datasets were included as they could still provide an accurate time estimation for the completion of the TUG test. Ethical approval for this study was granted by Sheffield Hallam University Ethics Committee (ID: ER60410080).

D. Data Analysis

The output from the skeletal tracking algorithm was stored in a CSV file and trimmed to include the timestamp, left and right hip angles, left and right knee angles, head height. After trimming the datasets where a person was not in the frame, the TUG phase was labelled by one of the researchers based (where 0 = sitting, 1 = transition, 2 = standing/walking) on the 4,670 joint skeleton output images. The action classifier models were trained and tested using videos collected previously, with the model trained on just joint angles and head height performing better for this dataset. The three modes (Support Vector Machine (SVM) model, Random Forest Classifier (RFC), and K-Nearest Neighbour (KNN) models) were tested against the labelled dataset to determine the most accurate model to use in the next step of data analysis. These models were selected as they are computationally low-cost, with one of the aims of the system being affordability, therefore the models would need to be able to run quickly on low-powered GPUs. These models can also perform well with smaller datasets and datasets with a lot of noise.

The data was also trimmed so that the vision system output timeframe lined up with the QTUG output timeframe. This data also had the TUG phase labels removed and would be determined by the model selected in the previous step. To obtain the times for the different phases of the TUG test the following equations were used based on the action classifier outputs (where [0] represents the first label of that phase and [last] represents the last label of that phase):

$$t_{total} = t_{trans[last]+1} - t_{trans[0]-1}$$

$$t_{sittostand} = t_{walk[0]} - t_{trans[0]-1}$$

$$t_{standtosit} = t_{walk[last]} - t_{trans[last]-1}$$

$$t_{walk} = t_{walk[0]} - t_{walk[last]}$$

The output from the QTUG gave 65 data outputs per test, which was refined to 7: TUG recording time, Time taken to stand, time taken to sit back down after walking, walk time, pre-turn time, post-turn time, and time taken to turn. The test date and time was also kept to match the skeletal tracking algorithm output with the QTUG output.

IV. Results

A. Machine Model Accuracy

The three previously trained models performed with high accuracy, with the SVM (97.09%) performing significantly higher than the RFC (95.61%) and KNN (95.59%). As with previous tests of the models both the sitting (≥95.41%) and walking (≥97.74%) had the highest accuracies, with the transition phase having the lowest accuracy (≥88.49%). The main errors occurred when labelling transition datasets as sitting (≤9.71%), which can be attributed to the challenges of distinguishing when a person has begun standing.

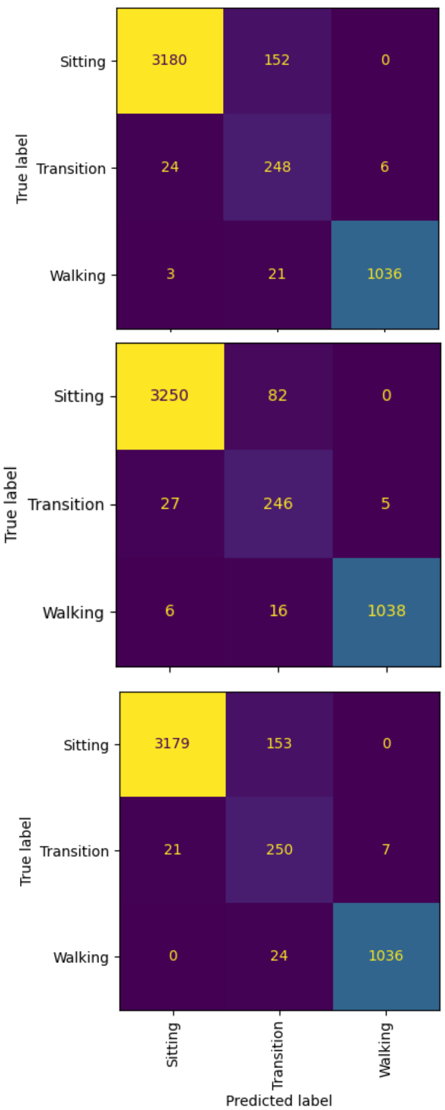

Figure 2. The confusion matrices for the SVM (Top), KNN (Mid) and RFC (Bottom) models on the labelled data. The x-axis labels represent the predictions and the y-axis represent the researcher's label.

B. Time difference in phases

The time outputs for the different phases of the TUG test from the different measures showed that the SVM model could record the total time taken with similar levels of deviation across all tests (0.36s average) as the QTUG (0.54s average). The time taken during the walking phase was the most consistent between the three measures with the average walking time difference being 0.543s±0.252 for the SVM compared to QTUG (see Table 1).

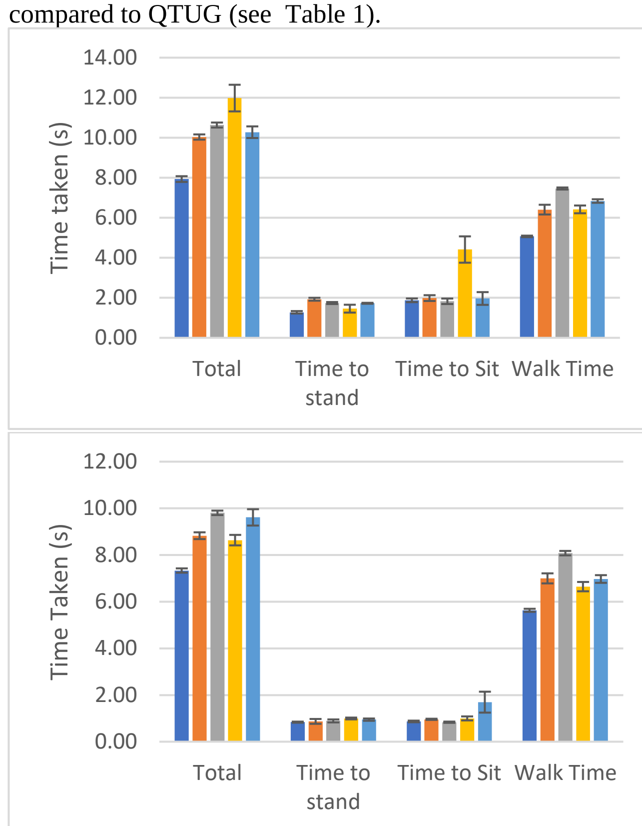

Figure 3. The average times for each participant (represented by the different bars) to complete the different phases of the TUG test for the QTUG (top), SVM (bottom).

The sit to stand phase also had a low average time difference for the SVM (0.692±0.329). The largest discrepancy was during the stand to sit motion, which in turn had a knock-on effect to the total time as well. The largest contribution to the differences in the stand to sit and total time come from the data from one participant, and removing the data gives the mean difference for total time as 0.811±0.713.

Table 1. The average time differences between the SVM model and the QTUG across the different phases

Phase	Average Time Difference (s)
Sit to Stand	0.692±0.329
Walking	0.543±0.252
Stand to Sit	1.746±1.309
Total	1.515±1.532

V. Discussion

The management of fall risk is a key factor in reducing the number of falls globally, especially amongst those experiencing frailty. However, the gap between the number of people requiring management and the number of people able to provide this is increasing. One means of assessing fall risk is the Timed Up and Go (TUG) test, which has seen increased research into the adoption of technology to perform the test [16]. Despite the use of robots for tackling different aspects of fall risk [23], [27], [28], a method for assessing the TUG test using a vision system on a robotic platform has, to the author's knowledge, not been tested. This paper represents the findings from a pilot study to address this gap by evaluating the performance of a vision system on a robotic platform against a more recognized IMU sensor (QTUG). The evaluation was split into two elements: firstly, to determine the accuracy of a pre-trained model in classifying the different phases of the TUG test, and secondly to compare the performance of the vision system output with that of the QTUG.

The action classification models all performed with high accuracy (>95%) with the SVM model performing the highest, which may be expected when using an imbalanced dataset. The main source of error was in the transition phase (sit-to-stand or stand-to-sit) however this still had a high overall accuracy (>88%). This error may prove difficult to remove completely due to the subjective nature of when someone can be considered no longer sitting but transitioning to standing (and vice versa). Furthermore, the amount of data available for this phase of the TUG test is less as this phase typically takes ≈1-2 seconds, as verified by the QTUG results. Therefore, the action classifier can be considered viable for the next stage of evaluation.

For the comparison between the SVM model and the QTUG, the time taken to complete the different phases and the overall TUG test were compared. As the tests were performed by able bodied adults consecutively, deviation between the times measured was used to determine performance as the times taken would be expected to be similar. The average standard deviation in the overall time taken for each participant differed by 0.18s between the SVM and QTUG outputs, highlighting that the SVM can measure the TUG test with similar levels of consistency and repeatability. This is a key aspect of the TUG test as it measures changes over time, therefore any changes detected need to be because of the user and not the system. The average time differences for the different phases also showed a negligible difference between the two systems, which was reduced further when the potentially anomalous data was removed. The source of the anomaly also appears to be in the QTUG data, as can be seen in Figure 3, where the stand-to-sit time and standard deviation for participant 4 is significantly higher than for the other participants. The anomaly could be attributed to incorrect sensor placement or unexpected sensor movement during the first test for this participant. Removal of this from the data reduces the standard deviation by half and brings the QTUG data for this participant more in line with the other participants. Errors because of sensor placement highlight one of the benefits of the vision-based robotic system which was able to provide more consistent datasets by avoiding this potential user error.

The vision-based approach is not without limitations, however. One of the key challenges for vision-based systems is occlusion and data loss because of the person not being within the frame. Whilst this can be minimised by removing anomalous data through a rules-based approach (significant changes in limb length and unfeasible changes in acceleration for example) there is still potential for error. The Turtlebot 4 also had limitations in this study, including the field of view of the camera, movement speed of the robot, and bandwidth for transmitting data. These were the main source of data loss during the study, although they were not during the transition phases and therefore did not affect the times obtained.

This pilot study shows the developed system for a robotic TUG assessment is capable of not only matching but outperforming the wearable sensor-based testing. Whilst only using one robotic system in this study, the design of the algorithm is to be platform agnostic, improving the versatility and potential viability of the system. A more expansive study involving a larger pool of participants and different robotic systems will give a more robust assessment. The proposed system shows initial steps for developing a system that can provide robust, accurate assessments for older people in their homes. The high accuracy of the action classifier in the different phases of sitting, standing, and transitioning between the two also opens the possibility for other applications, including monitoring of sedentary behaviour. The next steps to fulfil this ambition will be to demonstrate the system can operate independent of platform, as the current robot may not be suitable for certain environments and success is this field requires flexibility. Further automation is also required for successful deployment, including automating keeping the person within the frame. However, this pilot study shows that a vision-based robotic assessment of the TUG test is not only feasible but may prove to be more reliable than current methods.

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