Pose estimation för Time up and go (TUG)

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Abstract

Fall risk is a serious issue among the elderly and a leading cause of injuries and hospitalizations. Traditional methods for assessing mobility and fall risk, such as the TUG test, require caregivers and close monitoring, making the process time-consuming and subjective. We have developed an automated system that uses a standard camera and 2D-based pose estimation to conduct the TUG test. The results show that the automated TUG test differs by +/- 1 second in accuracy for each step compared to the manual method.

Introduktion

According to a report from the Swedish Public Health Agency, thousands of elderly people fall each year in Sweden, resulting in significant physical and economic consequences for both individuals and society. Fall-related injuries lead to about 70,000 hospital admissions annually, and falls are among the ten most common causes of death for people over 70 years old [1]. In a study by Shumway-Cook et al. (2000), the Timed Up-and-Go test (TUG) is described as a standardized tool to assess functional mobility and fall risk in the elderly [2].

Traditionally, the TUG test is conducted manually by caregivers, where a nurse or therapist observes a patient's movements and measures the time with a stopwatch. The test involves the patient starting in a seated position, standing up, walking forward, turning around, walking back, turning again, and sitting down. However, this method relies on subjective judgments and manual timing, which can lead to variations in accuracy and results. To improve the process, alternative technical solutions have been introduced. MDPI reports that RGB-D cameras and sensors like Kinect are used to automate motion tracking during the TUG test [3].

These solutions have improved the accuracy of TUG test analysis but often require specialized hardware or deep technical knowledge for implementation.

Ce Zheng describes a system in *Deep Learning-Based Human Pose Estimation* that uses a standard camera and 2D-based pose estimation for automatic, real-time analysis of image data. The software relies on machine learning algorithms to analyze body movements.

The contributions of this paper include the development of a system that uses a standard camera and 2D-based pose estimation to automatically analyze the TUG test. The system uses a web platform and a computer webcam to track body keypoints and segment the test phases. Through visualization in MATLAB, it offers mobility and fall risk metrics, providing a cost-effective solution for clinical evaluation.

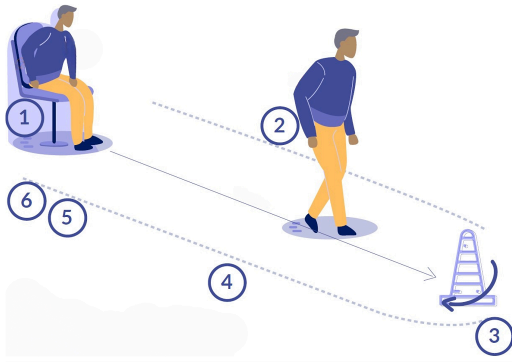

Figure 1. Timed Up-and-Go test (TUG)

Design

Hardware

The pose estimation and skeleton tracking system is built on a combination of hardware and software. The hardware consists of a device with a built-in camera, which can be a computer, mobile phone, or other camera-equipped device. This camera captures real-time images of the individual's movements, which are then processed for further analysis. The hardware is a key component as it provides the visual data of sufficient quality for the software to perform its task correctly.he hardware is a central component as it provides visual data of sufficient quality for the software to perform its task correctly [4]

Software
TensorFlow.js is a JavaScript platform for machine learning that allows models to run directly in the browser, which was used for this project. The PoseNet model tracks keypoints on the body, such as shoulders and knees, enabling real-time motion analysis. The design is built in a 2D system, meaning that motion data and body keypoints are visualized in two dimensions. This approach is simpler to implement compared to a 3D system and is sufficient to analyze the basic angles and positions required to perform the TUG test.

In a 2D system, image data from a single camera angle is used, and the calculations focus on body movements in a plane, reducing complexity while still allowing for effective analysis of movement patterns. By accurately locating these keypoints, the system can segment and identify different movements involved in the TUG test.

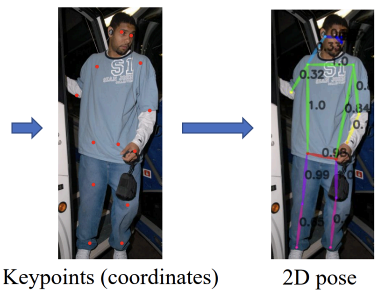

Figure 2. shows key points in 2D position

Integration and Visualization
The system is built to function in a browser-based interface, making it platform-independent and accessible from any device with a compatible browser.

Results and Discussion
After motion data is collected from the hardware and processed by the software, this information is exported to MATLAB, which is used to visualize the collected data through graphs. The graphs show when a person stands up, walks forward, turns around, walks back, turns again, and sits down. The results of five runs and the average can be viewed in Graph 3 on GitHub [5]. MATLAB is also used to validate the program by comparing TUG times between the automated and manual methods. Figure 3 shows the difference between the methods, and the result is that the automated TUG times differ by an average of +/- 1 second.

For the program to function optimally, it is important that the camera is placed in the same exact way for each run to ensure reliable results. During trials, it was determined that the best camera angle is from a slightly diagonal side view. If the camera is placed too far away, the precision in identifying the selected keypoints decreases, which can lead to inaccurate movement and angle analyses. Therefore, a walking distance of 2 meters was chosen instead of the 3 meters usually used in the TUG test.

In trials, the exact endpoint of the walking distance was marked on the floor to enable comparable results between each run. One challenge was maintaining a constant speed and ensuring that all keypoints were registered in every measurement. The conclusion was that a custom-developed PoseNet model would be required to achieve the high precision desired in keypoint detection, but due to time constraints, this could not be implemented within the project's scope.

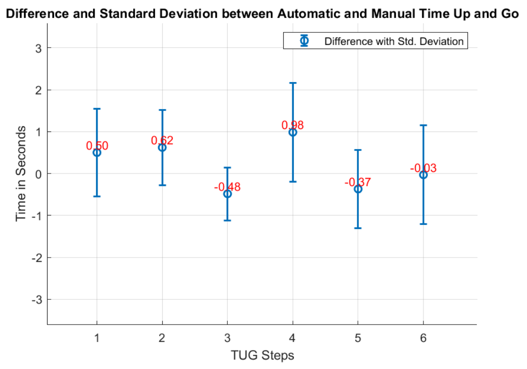

Figure 3. The difference between automatic and manual TUG

Conclusion
A system for automatic TUG has been developed using a standard camera. For future work, it is recommended to extend the system's functionality by developing custom machine learning algorithms tailored to the TUG scenario.

References:

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[5] https://github.com/Annay02/pose-estimation

Figure References:

Figure 1: Ortega-Bastidas P, Gómez B, Aqueveque P, Luarte-Martínez S, Cano-de-la-Cuerda R. Instrumented Timed Up and Go Test (iTUG)—More Than Assessing Time to Predict Falls: A Systematic Review. Sensors (Basel) [Internet]. 2023 [cited 2024 Oct 8];23(7):3426. Available from: https://www.mdpi.com/1424-8220/23/7/3426

Figure 2: Ce Z, Wenhan W, Chen C, Taojiannan Y, Sijie Z, Ju S, et al. Deep Learning-Based Human Pose Estimation: A Survey [Internet]. arXiv [cs.CV]. 2020. Available from: http://arxiv.org/abs/2012.13392

Figure 3: Graph created in MATLAB by the authors.