Data Collection Methods and Predictive Analysis for Fall Prevention in Elderly Populations

Xiao LU
Rehabilitation Department
The First Affiliated Hospital of Nanjing Medical University
Nanjing, Jiangsu, China

Chris Cheng ZHANG
Research and Development Department
Canada Youth Robotics Club
Vancouver, BC, Canada

Yanchang WANG
Faculty of Viaual and Performing Arts, Arts Management and Media
The University of Toronto
Toronto, ON, Canada

Jinhui SHEN
School of Broadcasting and Hosting Arts
Communication University of China, Nanjing
Nanjing, Jiangsu, China

Xinrui DAI
School of Broadcasting TV Editiong and Directing
Communication University of China, Nanjing
Nanjing, Jiangsu, China

Abstract—One of the most severe health risks to elderly populations is the risk of falling. Falls can lead to acute injuries, correlating with a decline in physical health. Recognizing the significance of this issue, the Fall Prevention Project aims to develop an algorithm that can accurately predict and prevent falls in elderly demographics.

Data collection is essential to understanding and predicting falls. This article addresses the data collection methods used in the Fall Prevention Project. By collecting data to train an algorithm, injuries, and fatalities can be modeled to improve the lives of at-risk patients.

For data collection, MediaPipe, a computer vision framework, is combined with an Intel RealSense D435 Camera. After skeleton tracking is completed, a Python code navigates through this data, which is then exported to an Excel file containing the coordinates and velocities for markers on the human body. A machine learning algorithm is used to classify patient movement as either "Risky" or "Safe". From this algorithm, future patient behavior can be analyzed to identify and prevent when a fall is occurring.

Keywords—fall prevention, data collection

I. Background

A. Fall Risk and Assessment

As people age, the risk of falling increases considerably due to the decline in physical and cognitive health. By the age of 65, roughly 35% of adults experience one or more falls a year. Every year, 37.3 million falls require medical attention, and 0.65 million falls result in death [1]. This emphasizes the need for fall risk assessment and prevention tools.

There are existing tools to assess a patient's likelihood of falling. One of the most widely used is the Morse Fall Scale (MFS), which is a survey of 6 items that are scored on scales ranging from 0-15 to 0-30 [2]. By adding up scores for the six categories, patients can be categorized into No Risk (0-24), Low Risk (25-50), and High Risk (51+).

Though this is a useful assessment tool for healthcare workers, it's limited in that it only serves to categorize patient risk but doesn't help to prevent falls from occurring in high-risk patients. The Fall Prevention Project aims to supplement existing predictive tools by providing another tool to classify patient risk and prevent future falls.

979-8-3503-2759-5/23/$31.00 ©2023 IEEE
DOI 10.1109/CSCE60160.2023.00448

II. Project Introduction

Data collection is an essential component of the machine-learning algorithms used as predictive models for patient falls. Machine learning algorithms require large data sets to classify patterns related to risky or safe behavior, which can be used to predict and prevent subsequent falls. For the Fall Prevention Project, data collection involves tracking the coordinate motion of skeleton markers on the human body.

The Fall Prevention Project aims to create a device that can help prevent falls by using cameras coupled with machine learning, which will warn caretakers when patients are at risk of falling before it happens. This will be done by combining a group of 3D camera(s) with Python libraries such as OpenCV and MediaPipe to build accurate 3D representations of each patient, and monitor their locations and poses. From the data collected, a machine learning algorithm is implemented to identify patterns and establish a predictive model.

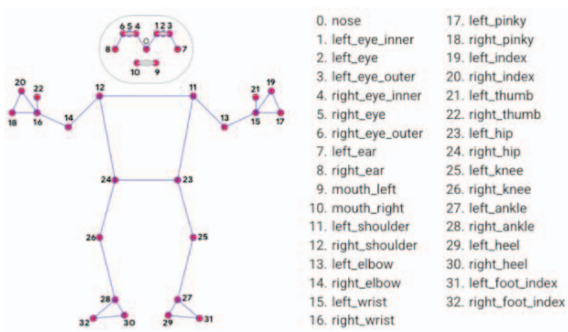

Figure 1: Skeleton Tracking Model of the Human Body [5]

III. Data Collection

A. Using MediaPipe and OpenCV

Data Collection for the Fall Prevention Project uses the Intel RealSense D435 camera or similar product [3], a depth camera frequently used in robotics and virtual reality applications. MediaPipe, a computer vision framework used in Python [4], is combined with the depth camera to obtain motion data throughout a patient's fall. Markers are placed on the user's shoulders, wrists, elbows, hips, knees, and ankles in order to track their coordinate motion.

When the code is executed, a window containing real-time frames of the subject from the camera is displayed. This setup is designed to monitor the subject's movements. In the event of a fall or near-fall, MediaPipe is used for skeleton tracking to record the tracked poses in a video. The code leverages the Pandas Python library for data analysis, enabling the user to append and manipulate columns, rows, and datasets, and import the data into an Excel file. Furthermore, the OpenCV (Open Source Computer Vision) library is utilized for computer vision and image processing. Open CV facilitates object detection and tracking, generates motion capture markers for data collection [6], and processes the video captured by the camera for subsequent skeleton tracking purposes.

B. Global and Local Frames

For data collection, the origin is set to the average coordinate between the hips. The positive X axis is to the right (as seen on the camera frame), the positive Y axis is vertical, and Z is extruding from the camera frame. To convert information from the depth camera into usable information, the X, Y, and Z coordinates for markers must be transformed from global into local frames. This is done using a transformation matrix. The distances from the origin to important markers are changed into vector form to build a coordinate frame. From this, the vectors are normalized to create a transformation matrix. If the necessary points aren't available, an identity matrix is used so as not to change the coordinates.

C. Assigning Results

After data is collected, results are assigned to each of the poses. A new camera frame is opened where the user can replay the video and assign the poses in each frame to either "Safe", "Risky", or "Fallen". The user can rewind, slow down, or fast-forward the video. The pose data and risk classifications are uploaded into an Excel sheet.

The Excel file displays the patient's data related to X, Y, and Z coordinates for each of the points used for motion tracking. It also displays the height from the floor and velocity. Velocity data is obtained by determining the distance between the initial and final coordinates using the Euclidean distance formula and dividing by the time differential dt. Table 1 below displays pose data for the velocity, height, coordinates, and risk classification observed.

$$distance = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2}$$

Figure 2: Euclidean Distance Formula

CH	CI	CJ	CK	CL	CM	CN	CO	CP	CQ	CR
31: X	31: Y	31: Z	31: Height	31: Velocity	32: X	32: Y	32: Z	32: Height	32: Velocity	Risky Position?
0.089	-0.87	-0.329	0.207	0.076	-0.257	-0.864	0.082	0.066	0.205	Safe
0.116	-0.853	-0.337	0.202	0.235	-0.251	-0.871	0.051	0.07	0.076	Safe
0.034	-0.817	-0.448	0.204	0.502	-0.241	-0.87	0.022	0.074	0.287	Safe
0.015	-0.822	-0.394	0.202	0.507	-0.257	-0.888	0.013	0.081	1.461	Safe
0.09	-0.873	-0.224	0.208	0.503	-0.18	-0.872	0.153	0.093	1.179	Safe
0.075	-0.865	-0.202	0.207	0.334	-0.203	-0.899	0.039	0.124	1.614	Safe
0.157	-0.855	-0.088	0.205	0.404	-0.124	-0.876	0.08	0.155	0.668	Safe
0.195	-0.862	0.004	0.211	0.489	-0.119	-0.874	0.083	0.18	0.711	Safe
0.209	-0.857	-0.073	0.21	0.237	-0.12	-0.872	-0.083	0.199	0.557	Safe
0.22	-0.867	0	0.216	0.234	-0.11	-0.901	-0.08	0.207	0.98	Safe
0.188	-0.883	-0.072	0.21	0.234	-0.154	-0.902	-0.164	0.208	0.308	Safe
0.156	-0.889	-0.096	0.217	0.462	-0.204	-0.911	-0.174	0.218	1.273	Safe
0.145	-0.869	-0.208	0.22	0.276	-0.235	-0.9	-0.244	0.225	0.505	Safe
0.164	-0.865	-0.264	0.217	0.275	-0.202	-0.866	-0.281	0.22	1.286	Safe
0.169	-0.849	-0.317	0.222	0.247	-0.194	-0.86	-0.265	0.219	0.257	Safe

Table 1: Sample Pose Data and Risk Classifications

Using data from the Excel sheet, the user can choose from one of three machine-learning algorithms to analyze the pose data. The machine learning algorithms build a predictive model, which is used to classify the fall risk of subsequent poses.

IV. Future Research

In the future, implementing multiple sensors, such as an accelerometer, gyroscope, or magnetometer to measure angular acceleration, roll, pitch, or yaw data could be used to improve the machine learning algorithm. This would supplement the camera data, which could be used to provide more biomechanical information to the algorithm to improve the existing model.

In addition, collecting data from patients of diverse demographics could improve the machine learning algorithm. One major limitation of the study so far is that the data thus far was generated primarily from young and healthy patients, which is not representative of the population that's most at risk of falling. Creating a comprehensive database with a wider demographic of ages, genders, and physiologies will ensure the algorithm works for a more inclusive sample of the population, and for those most vulnerable to fall-related injuries and fatalities.

Finally, applying the patterns obtained from the Fall Prevention Project to create a wearable device that can signal to caregivers when a patient is about to fall is the next step to be taken. This will ensure that caregivers or people nearby are aware when someone is falling. Ultimately, this will help reduce the occurrence of dangerous or life-threatening falls.

V. Conclusion

The Fall Prevention Project addresses the health risks associated with falls in elderly populations by creating an algorithm to predict and prevent falls. This will prevent serious and potentially life-threatening injuries from occurring.

To accomplish this, a depth camera is combined with using MediaPipe and OpenCV, both of which are computer vision frameworks. By tracking the motion of X, Y, and Z coordinates of markers on the shoulders, wrists, elbows, hips, knees, and ankles, a transformation matrix is used to convert the local frames into global frames.

Next, results are assigned to each of the poses in an Excel sheet. Poses are labeled, “Risky”, “Safe”, or “Fallen”. This information is uploaded into a machine learning algorithm that builds a predictive model of the poses, allowing for poses to be classified before the user falls.

For future development of the Fall Prevention Project, implementing additional sensors such as an accelerometer or gyroscope would provide additional data about falls. Furthermore, expanding the dataset to include more patients from a variety of ages, risk categories, and physiologies could improve the predictive algorithm. Finally, implementing these findings into a wearable device has the potential to warn caregivers when a fall is about to occur, which would further decrease the risks associated with falls in elderly populations.

References

1. S. Usmani, A. Saboor, M. Haris, M. A. Khan and H. Park, "Latest Research Trends in Fall Detection and Prevention Using Machine Learning: A Systematic Review," *MDPI,* 2021.
2. V. Jewell, K. Capistran, K. Flecky, Y. Qi and S. Fellman, "Prediction of Falls in Acute Care Using the Morse Fall Scale," *PubMed,* 2020.
3. Intel RealSense, "Intel RealSense Depth Camera D435," [Online]. Available: https://www.intelrealsense.com/depth-camera-d435/. [Accessed 12 June 2023].
4. J. Fernandez, "MediaPipe Instant Motion Tracking," GitHub, [Online]. Available: https://github.com/google/mediapipe/blob/master/docs/solutions/instant_motion_tracking.md. [Accessed 12 June 2023].
5. J.-W. Kim, J.-Y. Choi, E.-J. Ha and J.-H. Choi, "Human Pose Estimation Using MediaPipe Pose and Optimation Method Based on a Humanoid Model," *MDPI,* 2023.
6. Open CV, "About," [Online]. Available: https://opencv.org/about/. [Accessed 12 June 2023].