Toward Non-Invasive Smart Healthcare: Assessing Elderly Motor Function Using Vision-Based Center of Gravity Estimation

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Abstract

This study aims to integrate computer vision technology for human motion capture, elderly exercise test scales, and body composition analysis devices. It specifically focuses on analyzing changes in the center of gravity (COG) during movement to verify the role of computer vision in assessing the motor functions of the elderly, thereby providing support for maintaining their motor functions. This study offers a theoretical and practical foundation for objectively and efficiently evaluating the motor functions of the elderly using computer vision technology, as well as for delaying the decline in their motor abilities.

Keywords

center of gravity, motor, kalman filter, dynamic time warping

ACM Reference Format:
Zhaozhen Tong, Sinan Chen, Yuko Yamaguchi, Kumiko Ono, and Masahide Nakamura. 2025. Toward Non-Invasive Smart Healthcare: Assessing Elderly Motor Function Using Vision-Based Center of Gravity Estimation . In . ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 Introduction

With the increase of age, the elderly often face health problems such as a reduction in skeletal muscle mass and a decline in physical balance [3], which subsequently lead to a decrease in motor function and severely affect their daily life autonomy and independence. In our previous research, we have utilized computer vision models to obtain the feature point data of the elderly during exercise, conducted quantitative analysis of gait movement changes, and inferred their health status by combining body composition indicators[2], providing preliminary verification for the application of computer vision technology based on human motion capture in motor function assessment.

The goal of this study is to further expand and optimize the methods for motor function assessment. By incorporating the index of COG volatility and combining the test results of the Short Physical Performance Battery (SPPB) scale and the body composition analysis device Inbody, a comprehensive analysis will be carried out to explore a comprehensive system of motor function assessment indicators. Specifically, scale normalization, Kalman Filter (KF), and Dynamic Time Warping (DTW) algorithms are employed to calibrate, denoise, and align the motion feature data. Based on the optimized data, the center of gravity index is obtained through weight calculation, and the internal relationships among this index, the performance of SPPB tests, and skeletal muscle-related health indicators are thoroughly analyzed.

The results showed that the volatility index of the COG x-coordin ate was significantly negatively correlated with the score of test 2 (walking test) in SPPB, with a correlation coefficient of -0.43 and a $P<0.05$. It had a correlation coefficient of approximately 0.3 with skeletal muscle-related body composition indices, though this correlation was not significant.

2 Experimental Method

In this study, an experiment is conducted to obtain motion feature coordinate data from walking videos of 19 elderly subjects in Japan, record the SPPB scale test results, and meanwhile use the Inbody body composition analyzer to acquire the elderly subjects' body composition indicators[1]. The specific steps as follows:

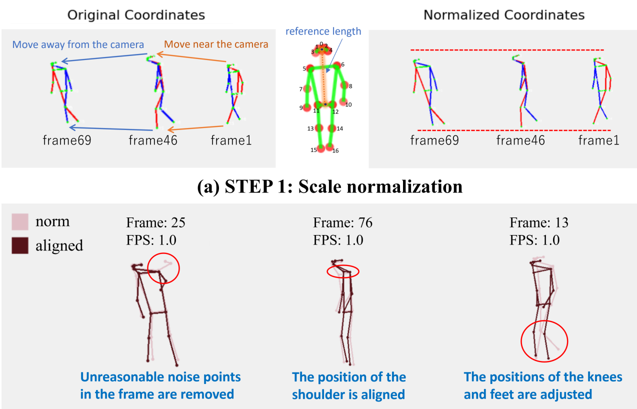
STEP 1: Scale Normalization

First, the Euclidean distance from the nose to the midpoint of the hips is calculated as the reference length. Subsequently, the median of the reference lengths across all valid frames is adopted as

Conference'17, Washington, DC, USA

ACM ISBN 978-x-xxxx-xxxx-x/YYYY/MM
https://doi.org/10.1145/nnnnnnn.nnnnnnn

[1]This survey is conducted after prior ethical review and approval by the Institutional Review Board (IRB) of the Graduate School of Health Sciences, Kobe University (approval number: 1249).



(a) STEP 1: Scale normalization

(b) STEP 2: Kalman Filter and Dynamic Time Warping

Figure 1: Preprocessing process: (a) Scale normalization, (b) Kalman Filter and Dynamic Time Warping.

the global reference scale, and combined with the trunk length for perspective correction. All 17 key point coordinates are normalized relative to the midpoint of the hips.

STEP 2: Kalman Filter and Dynamic Time Warping

Following scale normalization, the keypoint trajectories were smoothed using a KF [5]. Its "prediction-update" process first predicts current position from previous frame's position and velocity, then corrects it with current frame's observed coordinates to balance motion laws and observational data reliability.

DTW then aligned left-right symmetric keypoints (shoulders, hips)[1]. The algorithm constructs a distance matrix to measure pairwise point similarity between two sequences, with window constraints to prevent excessive timeline distortion. It calculates cumulative minimum distances to find optimal matching paths, then aligns sequence lengths by linear interpolation when necessary. Meanwhile, Non-symmetric keypoints retain their filtered values in the final aligned output. Figure 1 shows the preprocessing flow.

STEP 3: Construct a Weight-Based COG Index

First, based on human anatomical and kinematic characteristics [4], weights reflecting the mass proportion of corresponding body parts are assigned to 17 key points. Subsequently, using the aligned coordinates of these key points, the x and y coordinates of the center of gravity are calculated frame by frame through a weighted sum of each key point's coordinates and its corresponding weight. Finally, a dataset containing the center of gravity coordinates is generated to quantify the overall spatial position characteristics of human movement.

3 Results and Discussion

Pearson, Spearman rank, and Kendall tau-b correlation analyses are used to explore the correlations among the COG volatility index, SPPB test results, and skeletal muscle-related body composition indices. As showing in Figure 2, the volatility of the COG x-coordinate (`COG_x`) is significantly negatively correlated with the total SPPB score (`test2_score`) ($r=-0.43$, $P<0.05$). During human movement, the COG x-coordinate volatility represents horizontal

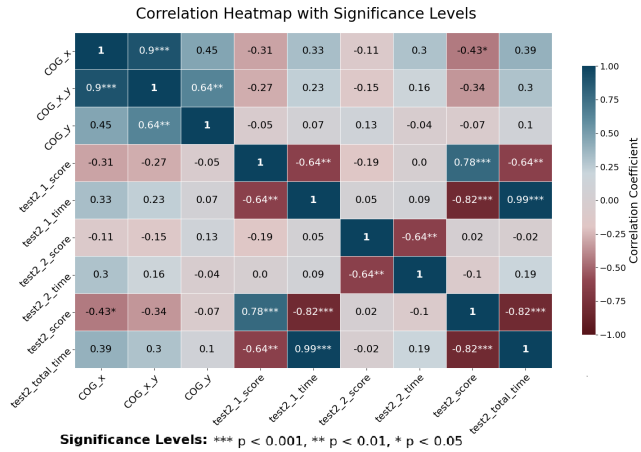


Figure 2: Correlateion analysis via COG and SPPB results.

swing amplitude, indicating body control stability. A negative correlation with SPPB performance shows that higher volatility means poorer performance and weaker control. No significant correlation was found between COG volatility and skeletal muscle-related body composition indices, likely due to a small sample size. However, a positive correlation ($r \approx 0.3$) between COG horizontal fluctuation and these indices offers a research direction for future studies.

4 Conclusion

This study integrated computer vision, SPPB scale, and body composition analysis devices to analyze COG changes during movement of 19 elderly Japanese subjects. It used algorithms to preprocess motion data, constructed a COG index, and explored correlations among the index, SPPB results, and body composition indices.

The results indicate that the significant association between COG and motor ability in elderly subjects provides an effective basis for evaluating motor function. However, due to limited sample size, some correlations have not fully demonstrated. Future studies will explore these associations by expanding sample size and optimizing data accuracy to better reflect movement-health relationships.

Acknowledgments

This research was partially supported by JST SICORP Grant Number JPMJKB2312.

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