Real-time Training Model for Elderly People Balance Ability

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Abstract. Falling happens when people’s body (excluding feet) unexpectedly touches the ground, which causes serious injuries for old people. Therefore, it is of great significance to assessing old people’s balance characteristics and help them prevent form falling. Based on this, we constructed a feature extraction model and obtained 25 factors that have the greatest influence on body balance by our model. We found that the most influential parts mainly distribute on people’s trunk, left arm, right foot and head, which can be applied in further study of falling prevention and balance supervision.

1. Introduction

Falling, as defined as to drop down suddenly to a lower position [1], widely happened among the elder population. Because of its serious harm to elders’ health and the heavy burden brought on their families and society, falling prevention and balance analysis has been highly concerned by scientist. Up to now, considerable efforts have been made. Some of them focused on the danger warning system based on cameras or sensors, such as Tang Y and Ma B, who developed a video surveillance system based on IDVS[2], plus, Niazmand designed a smart cloth for body status monitoring[3]; some of studies contributed to activity prediction models construction with actions gathering analysis, like Yiping Tang along with his team, they built an elder’s activity model with remote monitoring system for action information collecting[4]; and some people were trying to detect people’s body status through positioning technology, like Yaning Du[5]. In summary, oost of the researches can be categorized into fall detection algorithm and detection algorithm based on pattern recognition [6]. However, palpable demerits of inconvenience, high study cost or action restrictions exist as well [7]. Therefore, to further benefit falling studies, we investigated falling influence factors by establishing a feature extraction model, which has a realistic comprehensive meaning for falling analysis.

2. Data Source

We collected the data from a research institute, where a random sampling test was made by deploying 42 monitoring points on the elders’ bodies. The distribution of the points is shown in Figure 1.
3. Establishment of the feature extraction model
Since the balance of body correlates to the gravity center position and the area of bearing surface, we viewed the 42 monitoring points as movement features, and regarded the changes of human body’s gravity center as the gait characteristics of trunks’ balance ability, by gait analysis. The coordinates of the gravity center at different time were obtained with the data in Annex II and moment synthesis method. Then we got the accelerations of gravity center and each point. Finally, we calculated the most influential 25 characteristics through motion analysis, with points’ gravity center and correlation of the accelerations. A characteristic extraction model was established.

3.1. The measurement of human barycentric coordinates
Human barycentric coordinates related to the distribution of body weight based on Bravin-Fischer Model. So with the weight ratios of different body parts to the whole body (shown in Figure1), we divided the human body into 14 parts: head, torso, upper arm, forearm, arms, legs, calves (except head and torso, the left and right sides of are regarded as two parts). Then, we obtained the barycentric coordinates \((X'_i, Y'_i, Z'_i)\) of the i testee at time \(t\) with Torque synthesis method, shown in Formula 1:

\[
X'_i = \sum_{k=1}^{14} w_k a'_k, \quad Y'_i = \sum_{k=1}^{14} w_k b'_k, \quad Z'_i = \sum_{k=1}^{14} w_k c'_k
\]

(1)

Among them: \(w_k\) is the ratio of the k part to body weight with \(k = 1, 2, \ldots, 14\), \(a'_k, b'_k, c'_k\) represent the specific coordinates of k part. For the left upper arm, it’s coordinated calculation process of the center position is shown as follow:

\[
da'_i = \frac{x'_{17,i} + x'_{19,i}}{2}, \quad b'_i = \frac{y'_{17,i} + y'_{19,i}}{2}, \quad c'_i = \frac{z'_{17,i} + z'_{19,i}}{2}.
\]

Figure 1. The 42 monitoring points on the body of the elders
Table 1. Relative weight of various parts of the human body in Bravin-Fischer Model

| Part                | Relative Weight | Part                | Relative Weight |
|---------------------|-----------------|---------------------|-----------------|
| Head                | 0.07            | Left foot           | 0.02            |
| Torso               | 0.43            | Right upper arm     | 0.03            |
| Right thigh         | 0.12            | Left upper arm      | 0.03            |
| Left thigh          | 0.12            | Right forearm       | 0.02            |
| Right leg           | 0.05            | Left forearm        | 0.02            |
| Left leg            | 0.05            | Right hand          | 0.01            |
| Right foot          | 0.02            | Left hand           | 0.01            |

3.2. The measurement of acceleration at barycenter and the monitoring points

In physics, acceleration is the change rate of velocity with respect to time: \( \frac{\Delta v}{\Delta T} \). In this model, we regarded the average acceleration \( (v_{m,t}^i) \) of m point from period \( T_i \) to \( T_{i-1} \) as its instantaneous velocity at \( T_i \). Thus, the accelerations \( a_{m,t}^i \) of barycenter and 42 monitoring points mentioned above are as Formula 2:

\[
\begin{align*}
    v_{m,t}^i &= \sqrt{(x_{m,t+1}^i - x_{m,t}^i)^2 + (y_{m,t+1}^i - y_{m,t}^i)^2 + (z_{m,t+1}^i - z_{m,t}^i)^2} \\
    a_{m,t}^i &= \frac{\Delta v}{\Delta T} = \frac{v_{m,t+1}^i - v_{m,t}^i}{T_{m,t+1} - T_{m,t}}
\end{align*}
\]

\( x_{m,t}^i, y_{m,t}^i, z_{m,t}^i \) respectively represent the coordinates of the m point at \( T_i \) time, with \( m = 1,2,\cdots,42 \) and \( v_{G,t}^i \) and \( a_{G,t}^i \) respectively mean the velocity and acceleration at \( T_i \) time.
3.3. Calculating correlation coefficient

Our model calculated respectively the correlation coefficient $\rho^i_{Gm}$ between every participant's gravity acceleration and corresponding 42 monitoring points' accelerated speed:

$$
\rho^i_{Gm} = \frac{\text{cov}(a^i_G, a^i_m)}{\sqrt{D(a^i_G)D(a^i_m)}}
$$

As a big covariance indicates a strong relative relationship, the monitoring points with a large correlation coefficient have a large impact on gravity acceleration.

4. Empirical analysis of key feature extraction model

4.1. Analysis of the change of gravity center acceleration with time by gender

From our calculation result, we found that both older men and women have gravity center acceleration less than $2.5g$ ($g$ is the gravity acceleration and $2.5g$ is about $24500 \text{mm/s}^2$), exhibiting that 76 subjects did not fall into the experimental range. It can be inferred from Figure 3 that the change trends of average barycenter acceleration of elders are basically same.

![Figure 3. the average acceleration of Female and Male](image)

Note: since the time interval between adjacent moments of each observer are with minimal difference, the abscissa in this figure is defined as the time ID number, and the intercept range of average acceleration value is subject to the one with the smallest monitoring time ID number.

4.2 Extraction of 25 key feature points

Figure 4 displays the 25 key monitoring points with the highest correlation with the acceleration of the gravity center extracted according to the value of the phase relationship. Taking Ai Zhenjiang as an example, in Figure 5, the variation trend of Ai Zhenjiang's gravity center and the acceleration of some monitoring points with time. Among them, left knee and right hand have little correlations with gravity center acceleration. At the same time, left hand, top of head and right foot are points that highly correlated with gravity center acceleration.
Figure 4. The distribution of body balance features

Note: The red point is 25 key feature points.

Figure 5. The acceleration of some points on the elderly subjects named Ai Zhenjiang

Note: Left knee, right hand, left hand, top of head and right foot are 8, 38, 39, 22 and 34 respectively.

It can be seen from Figure 5 that the acceleration of the top of the head has the smallest fluctuation while that of the left knee (double of the top of head) and right foot are the biggest. This explains in some ways that knees and feet are the main sources of energy during walking as they move a lot, while the hand swing fluctuates in small degree and the head maintains relatively stable.
5. Conclusion
In order to investigate the factors that may influence body balance and result in the elderly’ falling, we built a feature extraction model to find the most important parts that may lead to old people’s fall which can generate realistic and accurate result for understanding old people’s falling. According to mechanics theory: balance maintains when the resultant force on an object is zero, we calculated the acceleration of the elders gravity center and the that of each monitoring points. In detail, we firstly calculated the coordinates of the gravity center of the elders; then, calculated the acceleration of each monitoring point and gravity center; finally, we extracted 25 key points that have the largest influence on trunk’s balance, according to the correlation of each monitoring point’ acceleration and gravity center. The results show that the parts have great impacts on body balance mainly distribute on trunk, left arm, right foot and head. which has very practical meanings for further falling prevention studies and balance researches.

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