Team Number :	APMCM81849
Problem Chosen :	A

2018 APMCM summary sheet

Balance Ability Assessment System

Falls happen with tons of damage which will affect the life level of the elderly. Consequently, it is of great importance to make a balance ability assessment system for them with physical postures while walking and other factors.

Our model firstly extracts 25 indicators **with medical meanings** from the 42 monitoring points by **R-type cluster method and Mahalanobis distance**. Our 25 indicators contain **90.86%** information about the whole body features, with high reliability. And the result makes it possible to measure the basic physical status of each subject.

We then build a balance ability system based on these 25 indicators with **modified Polynomial Curve Fitting method** and we compare the stable pace curve with the experimental pace curve to sculpture one's balance ability. And then our research compares our results with the actual fall times and the **accuracy reaches nearly 80% for all the elderly people who have risks to fall**. However, the accuracy decreases rapidly when applied to the middle-risk elderly people. Due to this phenomenon, our model did some more improvement.

In our improved assessment system, our model considers actual data with **TOPSIS.** We use **7 parameters** coming from the actual data and Annex2's trace data to measure the balance ability of the elderly people. We get **80% accuracy** among nearly all the elderly people comparing with the actual fall times. Moreover, our improved assessment can overall divide those elderly people with high balance ability and low balance ability.

The sensitivity analysis of our improved model proved that small alternation of Age and BMI parameters in our model can slightly influence the result. **A 3% disturbance will influence the rank by only 2.5%. And a 5% disturbance will influence the rank by 7.5%.** Finally, we give some different advice to different kinds of elderly people who have fallen or have low balance ability in medical perspective.

Key words: R-type cluster method, Mahalanobis distance, Polynomial Curve Fitting method (PCF), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

Content

1 Overview

1.1 Background

In the past few decades, the aging degree of our country has gradually accelerated. It is estimated that in 2050, the population over 60 will account for 33% of the total population. And the elders-fallen accidents have increased in a large scale these years.

When old people fall happens, they will be unstable and lose balance, for the elderly, lower muscle recession will lead to lower balance ability, which is insufficient to support the elderly in the fall to lower body; At the same time, due to the decline of the elderly nervous system control ability, nerve conduction is slowed down, and motor response time is prolonged, which will also lead to the elderly in the fall cannot timely adjust the body to maintain balance. In this way, it is essential to measure the elderly's balance ability to give proper advice for them to keep balance and pay more attention to their balance.

In addition, there are few studies on the prediction of elderly balance ability. Moreover, single sensors are mostly used, which have limited detection accuracy and are prone to misjudgment.

1.2 Restatement of the Problem

- Build a model which contains 25 main indicators from given 42 monitoring points. The model needs to be useful to analyze every subjects' steps, the center of gravity, velocity, and acceleration, etc.
- Build a model which is able to assess the balance ability of elderly people based on actual experimental data.
- Analog those elderly people who have fallen years ago and testify to our model whether our models are capable of monitoring their balance ability as lower.
- Give advice to those elderly people who have weak balance ability.

2 Assumptions and Symbol description

2.1 Assumptions

- There is no time difference when recording the trace data.
- The 25 indicators have medical meanings and physical meanings, which is able to predict the center of gravity and other physical parameters.
- The trace data is able to predict the balance ability. Since our R-TYPE CLUSTER algorithm, PCA algorithm, are all based on actual data.

- The trace data is a normal step of each subject, i.e. everyone walks in the lab as they usually walk, especially the same before their fall.
- There is no big physical change during the years that the elders fall and being traced.

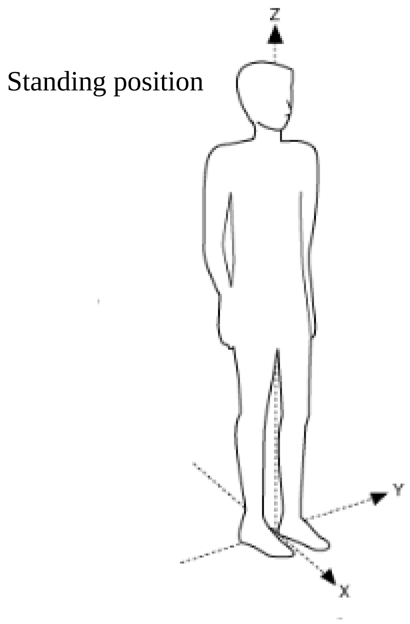
2.2 Symbol description

Definition	Symbol	Definition	Symbol
The height of each elder people	$h(i)$	The steps of each subject	s_i
The weight of each elder people	$G(i)$	The weight of k parameter	$w_k(i)$
Value of X coordinate trace (ahead direction)	$X(i)$	The (resultant) acceleration of each subject at time t and toward the direction x, y, z	$a_i(t, x, y, z, ra)$
Value of Y coordinate trace (width direction)	$Y(i)$	The ratio of the center of gravity to the height of the head in the height direction	$R_i(\mathrm{z})$
Value of Z coordinate trace (height direction)	$Z(i)$	The variance of the k parameter	$\sigma_k{}^2(i)$
The center of gravity of each people	$\mathrm{g}_i(\mathrm{x}, \mathrm{y}, \mathrm{z})$	The length of each people walks in the test	$l_i(t)$

$\boldsymbol{i}$ is the Number of each elderly people, which range from 1 to 76.

k is the variety parameter, such as $\mathrm{g}_i(\mathrm{x}, \mathrm{y}, \mathrm{z})$, $l_i(t)$,$a_i(t, x, y, z, ra)$, etc.

In Annex 2, X-axis is the ahead direction, Y-axis is the width direction of the subject, Z-axis is the height direction of every subject. The schematic diagram is as follows:



3 Extraction Model

We divide the modeling process into three parts. The first step is correcting the data, cleaning the given data and the second step is the extraction process based on annex2 data. We will obtain 25 clusters of indicators to measure the center of the gravity, step length, velocity and acceleration of each subject. Finally, we will build a model to measure the balance risk using these 25 indicators and other physical information we have obtained. In this way, we can clearly identify each persons' walking habits and testify our model in an analog computation.

3.1 The correcting process

➢ **Walking coordinate value $\boldsymbol{X(i)}$,$\boldsymbol{Y(i)}$, $\boldsymbol{Z(i)}$**

There are many given data with big noise, especially the NO.63 elderly, we found him/her trace is regular, only some points have strong noise when he/she walks out/in the trace detection. It may come from the detection system rather than falling data. Due to this phenomena, we decide to use Box-Figure Method to regular these points: if a detection value is upper/lower the adjacent value, we will replace it in $Q3$ or$Q1$. We replace every subjects'$X(i)$,$Y(i)$, $Z(i)$ direction in this way. The correcting **Figure2** shows NO.63 subject walks regular enough to do the following process. And all the correcting data will be used to apply to

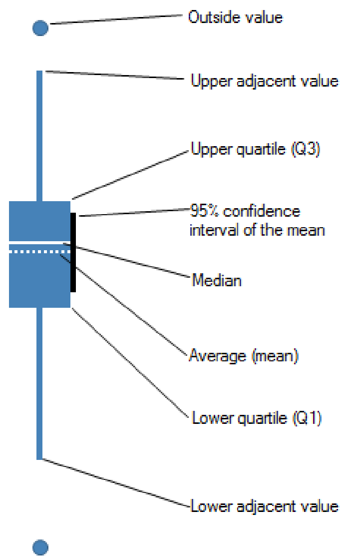


Figure 1 Box-Figure.

assess everyone's balance ability showed in **Annex1**.

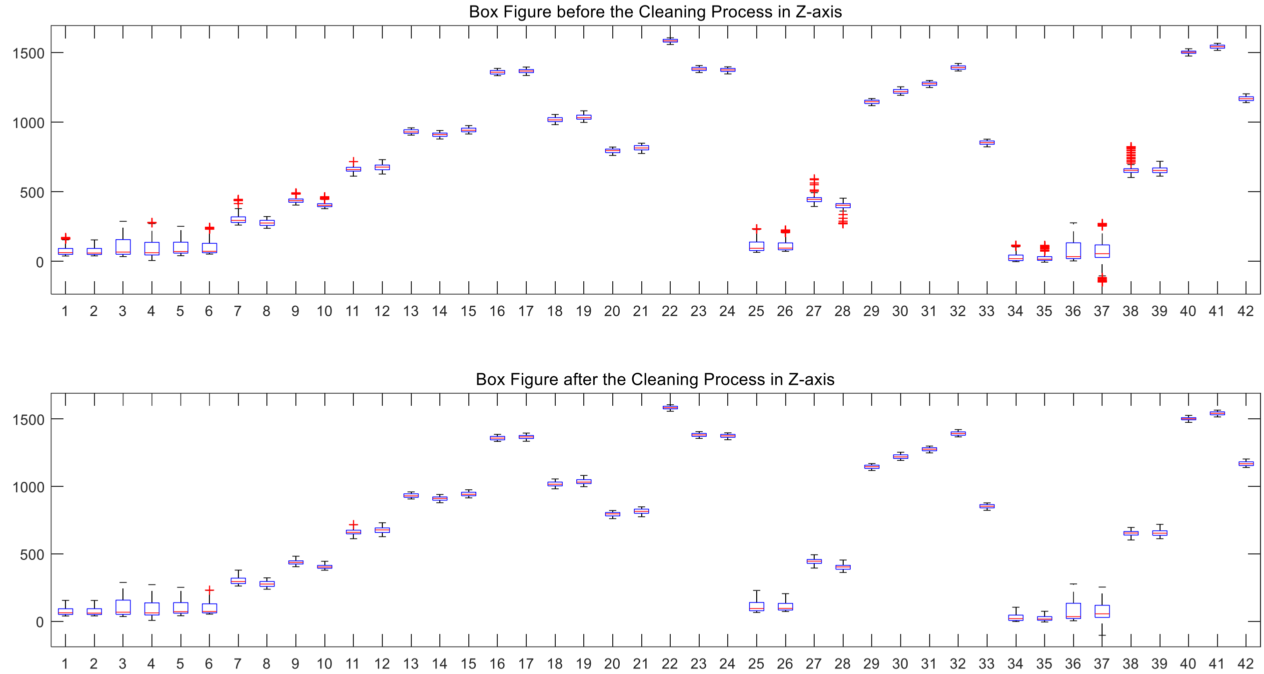


Figure 2 Example box figure in height direction before and after the process

➢ **Unrecorded subjects**

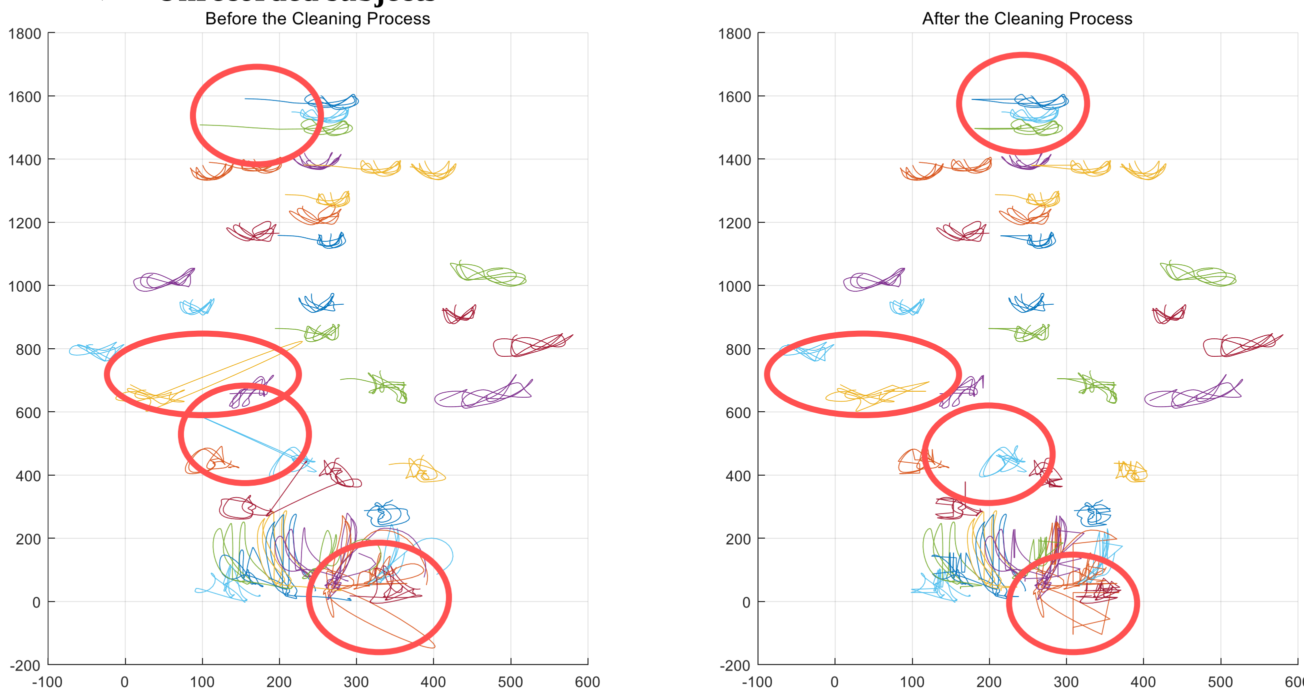


Figure 3 the figure shows that circled data has been replaced. we see this picture in Y-Z coordinate because it represent the volatility.

There are 4 elderly people who have not been traced in the experiment, however, with their basic data, we can only predict their balance risk. We are not able to predict their balance without walking trace. In this way, when we are building the model to measure their balance ability, we will not use their data.

As we can count, among the 80 subjects given in annex I, there are 4 subjects absent in Annex 2, which has been deleted. Besides, after the Box-Figure cleaning process, 65 pieces data were changed in Annex 2.

3.2 An extraction of 25 body indicators

In given data, there are 42 monitoring points which need to be extracted to 25 indicators to measure the center of gravity, acceleration, and steps. And the indicators need to have medical meanings and are able to measure the balance ability with multiple a weight $w_k(i)$. We decided to cluster it in **R-type cluster Method** to divide every part and cluster into 25 indicators. **R-type cluster Method** reaches the minimum square error. When the clustering is dense and the difference between classes is obvious, the effect is better. The steps of the R-type cluster method is as follows:

Step1 Select 25 monitoring points as the initial centroids

Step2 Calculate every centroids' means and calculate the Mahalanobis distance between every monitoring points and the centroids.

Step3 Divide different parts by the shortest Mahalanobis distance to refresh new centroids.

Step4 Until no monitoring points being divided into new clusters. When this happens, $D=\sum_{j=1}^{k}\sum_{x_i\in\omega_i}\left\|x_i-m_j\right\|^2$ reaches the shortest.

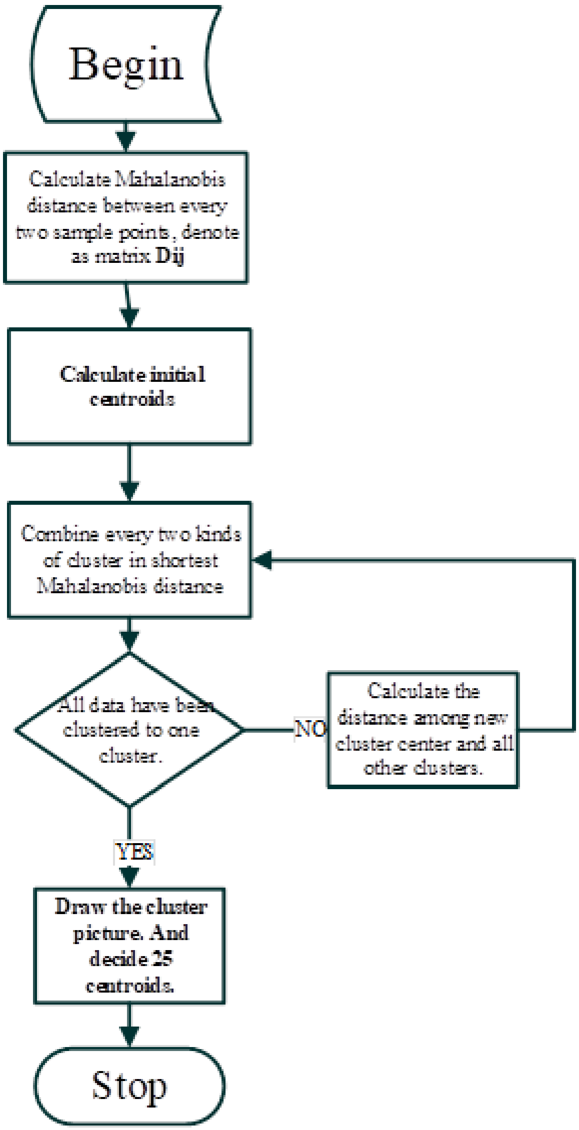


Figure 4 The flow chart of the clustering process

In this process, in aid of Matlab, we obtain every moment's coordinate of every subject. In ahead direction(x), cannot represent the volatility, which is useless to analyze the data, however in width direction(y) and height direction (z), we are able to determine every centroids' coordinate, in which way, and we get **Table 1**. In order to represent the place of each cluster, we take$\bar{x} = x_i(t), \bar{y} = y_i(t),\ \bar{z} = z_i(t)$. And new clusters have been drawn in **Figure5** in Y-Z plane.

Due to the page limit, the whole data are provided in Annex 3.

Table 1 The **average coordinate** of First 10 Clusters of **NO.1** subject

	Cluster1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	Cluster 8	Cluster 9	Cluster 10
$\bar{x}$	1695.422	1772.818	1775.98	1698.211	1783.151	1605.545	1779.691	1594.722	1734.475	1724.957
$\bar{y}$	342.6374	328.3925	248.8436	238.1067	376.4519	516.4507	215.4371	102.106	240.2878	347.0878
$\bar{z}$	68.30856	19.54036	21.19115	77.20021	623.1839	996.6625	638.2322	987.5376	322.1896	325.7501

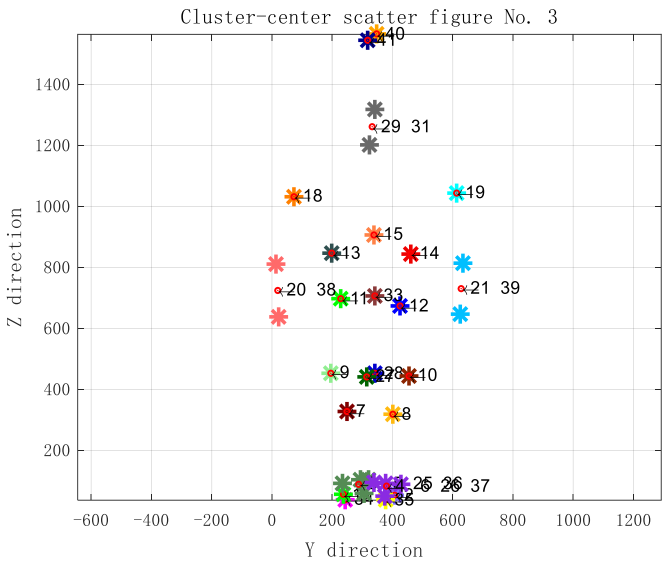


Figure 5 25 clusters-center figure.

The same color stars represent that they were clustered into one cluster. And the centroid is represented in small red circle. And the numbers beside the circle represent the gathering points.

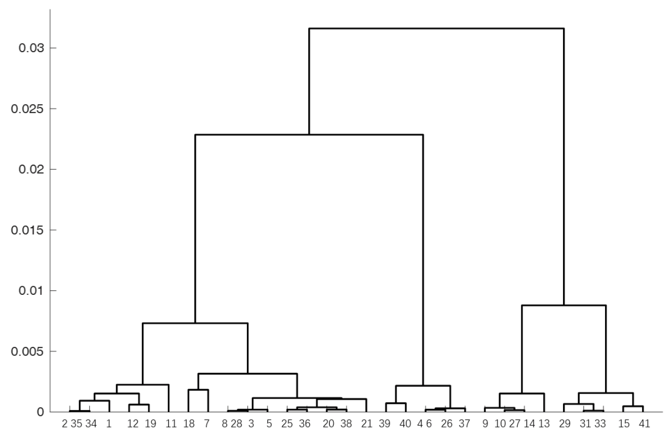


Figure 6 the cluster figure of the extraction system

We need to corresponding indicators with the given points, so we listed **Table 2** and **Figure 7.** In **Table 2**, 42 monitoring points have been clustered into 25 and more indicators. We rank it by the contribution of each indicator, which is calculated as follows:

$$\% = \frac{\sum \lambda_j}{\sum_{i=1}^{76} \sum_{k=1}^{n} \lambda_k} \times 100\% \tag{3.1}$$

In (3.1), i represent every subjects, and λ_k represents the whole point's contribution. λ_j represents the contribution of j points in the $\mathrm{k^{th}}$ cluster.

Its **total contribution** reaches **90.86%** which can fully represent the body features. The other points will be abandoned in order to simplify the model. We also testify our model from medical aspect. According to the essay, we obtain the medical instructions for each cluster. The indicators can be drawn in **Figure 7**.

Table 2[2] the indicators' relations to the indicators and their medical instructions

Indicator	Point1	Point2	Point3	Point4	Contribution %	Medical instruction
1	2				4.00	Ankle Joint, Easy sprain
2	35				4.00	Foot Sole, Hard to fracture
3	34				4.00	Ankle joint, Hard to fracture
4	1				4.00	Foot Sole, Hard to fracture
5	12				3.94	Thigh, fracture after falling down
6	19				3.89	Elbow Joint
7	11				3.89	Thigh, fracture after falling down
8	18				3.82	elbow joint
9	7				3.68	Calves
10	8				3.47	Calves
11	28				2.92	Knee Joint, Easy sprain
12	3	5	25	36	5.92	Chilles Tendon
13	20	38			5.68	Wrist joint
14	21	39			5.79	Wrist joint
15	40				2.95	Skull
16	4	6	26	37	5.95	Chilles Tendon
17	9				4.11	Knee Joint, Easy sprain
18	10				1.89	Knee Joint
19	27				4.00	Knee Joint

20	14				2.53	Muscle Tissue, Hard to fracture
21	13				2.47	Muscle Tissue, Hard to fracture
22	29	31			2.39	Sternal Hilt
23	33				1.96	Abdomen, Hard to fracture
24	15				1.96	Cauda Vertebra, Fracture in the elderly after osteoporosis
25	41				1.65	Skull

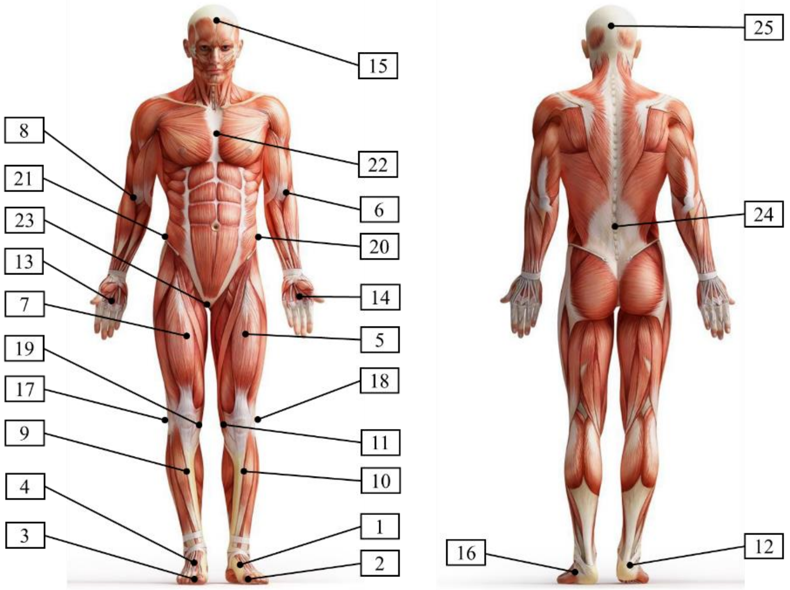


Figure 7 The Refreshed layout of 25 indicators

Comparing with the figure given, we actually extract the foot monitoring points from 12 points to 6 points. And we extract hands monitoring points from 4 points to 2 points and head points from 5 points to 2points. Besides, we abandon 3 points because its contribution is low.

3.3 Physical Parameters

3.3.1 Steps

Steps length($s_i(t)$) plays an important role when determining the balance ability of elderly people. The smaller $s_i(t)$ is, the more careful when the elderly people walks because he/she is afraid of falling. The average $s_i(t)$ of healthy elderly people range from **500 to 650 mm** according to essay[5] . We measured the ($s_i(t)$) in equation (3.2). And **Figure 8** is the schematic diagram retrieved from **NO.3** elderly people's front foot.

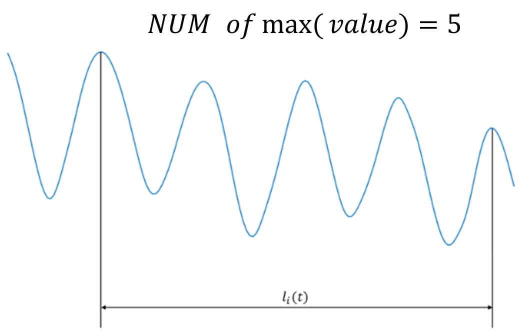


Figure 8 schematic diagram on how to calculate the $s_i(t)$

$$\overline{s_i(t)} = \frac{l_i(t)}{NUM} \tag{3.2}$$

He walks 5 steps and in these 5 steps (NUM=5), he walks in a whole length of $l_3(t)$, and we can obtain his $\overline{s_\iota(t)}$ by using equation (3.2). We chose indicator 24 as the monitoring point since it stays near the center of gravity and can fully represent the steps. In this way, we can obtain every single elderly people's $s_i(t)$. In **Table 3**, we give out the 10 smallest steps subjects. And the whole data are provided in **Annex3**.

Table 3 The Top 10 smallest $s_i(t)$

NO.i Subject	Name	Steps length(s_i) (mm)	NO.i Subject	Name	Steps length(s_i) (mm)
2	Wenyanfang	298.762176	6	hujiawei	412.734457
10	Jiashengpu	334.19008	20	renweiyi	418.047596
73	litongsheng	376.757392	29	Xuxiuyun	426.628618
51	Aizhenjiang	381.165191	71	Weixiurong	441.583232
43	Xingjunmiao	395.310528	26	tianguilin	447.550773

3.3.2 Center of gravity

Usually, we humans have a 3-dimension coordinate to represent his/her center of gravity. In our model, we actually concentrate on the height direction (Z). We can calculate our $g_i(x,y,z)$ using 25 indicators by equation (3.3). In equation (3.3), ω_i is determined by the average weight of elderly people. And $x_i(x,y,z)$ represents every indicators' position. According to the essay, we got equation (3.3) to measure the position of every elderly people.

$$g_i(t,x,y,z) = \sum_{i=1}^{n} \omega_i \times \left(\frac{x_i(t,x,y,z)}{N}\right), \quad N = 1,2,\ldots,25 \tag{3.3}$$

ω_i is the weight distribution of different parts of the elderly people' s, which we find and summary in Appendix.

However, we care more about the center of gravity from height direction because it can roughly refer your balance ability. We determine a parameter in equation(3.4).

$$R_i(t,z) = \frac{g_i(t,z)}{h(i)}, \quad R_i(z) = \overline{R_\iota(t,z)} \tag{3.4}$$

If $R_i(z)$ is large, your center of gravity is higher, which is not good for your balance ability according to the physics knowledge that if we want to keep the balance we always lower our center of gravity. When people are

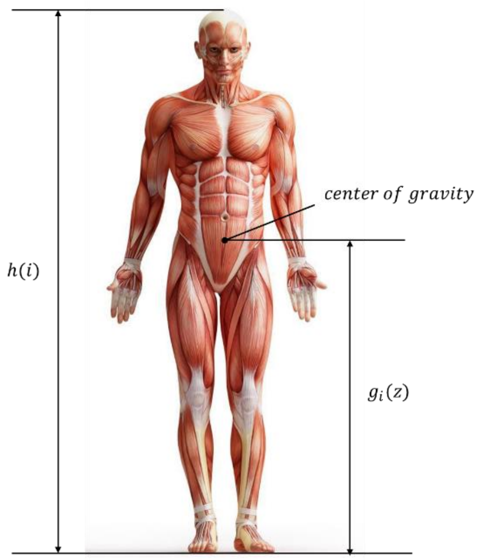


Figure 9 The instruction picture of equation (3.4)

normally walking, $R_i(z)$ranges from 0.41-0.48, according to the essay. If the center is lower or higher than this range, you may lose your balance, in which way we can determine as low balance ability. The $R_i(z)$results are given as follows in **Table 4** with randomly 10 elderly people, the whole data are given in **Annex3**.

Table 4 the average center of gravity in height direction while walking of 10 subjects

Number	Name	$R_i(z)$	Number	Name	$R_i(z)$
51	aizhenjiang	0.487082	69	cuixiulan	0.462587
33	baiqingquan	0.559306	39	cuizhenhua	0.473142
9	baiyulin	0.421556	30	fujianying	0.428312
46	cangyongli	0.426392	15	gengxiulin	0.508803
38	chenfue	0.484044	34	guanpeihua	0.506725

3.3.3 Motion(acceleration)

Acceleration is the best reference to reflect the change of motion of the object. And when somebody falls, the average impact force is:

$$F = q\frac{mv}{\Delta t} = q \cdot ma \tag{3.5}$$

In (3.6), v is the impact velocity and results in 0 at the end of the falling process. And $q \in [1,2]$, According to the elasticity of collision, when q =1, the body does not bounce; when q = 2, the body bounces completely.

The larger the $\mathrm{F_0}$ is, the stronger the discomfort of the human body will be, and the balance risk will be higher when $\mathrm{F_0}$ gets higher. q is determined by the nature of the contact surface and is not easy to measure. In order to make the fall prediction method more universal, measurable quantities less related to individual characteristics should be studied. Therefore, the fall process can be identified by studying the change of acceleration a.

In the static state, due to gravity, human body's breathing and other physiological movements, noise interference and so on, we focus on the organs of the **upper body** (indicators 20, 21, 22, 24) in the direction of X axis, Y axis and Z axis changes in a small range. We average the acceleration of different parts' acceleration.

The acceleration can be obtained using the given data. And the motion model of the human body can be abstracted as a rigid body. Normally, we can calculate $a_i(t,x)$, $a_i(t,y)$, $a_i(t,z)$simply in equation(3.6)

$$a_i(t,x) = \frac{dx^2}{d^2t} = \frac{dv}{dt} = \frac{\frac{dx}{dt}}{dt} \tag{3.6}$$

And due to the given data, the average $\Delta t = 0.015$, $\Delta t \to 0$, using the limit knowledge, we can replace (3.6) in:

$$a_i(t,x) = \frac{\frac{\Delta x}{\Delta t}}{\Delta t}$$

So as the Y direction and Z direction.

Finally, we can obtain the resultant acceleration **(ra),** $a_i(t,ra)$ in the following equation:

$$a_i(t,ra) = \sqrt{a_i(t,x)^2 + a_i(t,y)^2 + a_i(t,z)^2}$$

For goodness to build a balance ability system, the maximum acceleration represents the most unbalance point, and represents him/her tends to fall, so we simplify acceleration as in (3.7):

$$a_i(ra) = max(a_i(t,ra)) \tag{3.7}$$

We listed NO.1 elderly people's acceleration of each direction and resultant acceleration and drew it in **Figure10**. We listed And the whole data are provided in **Annex3**.

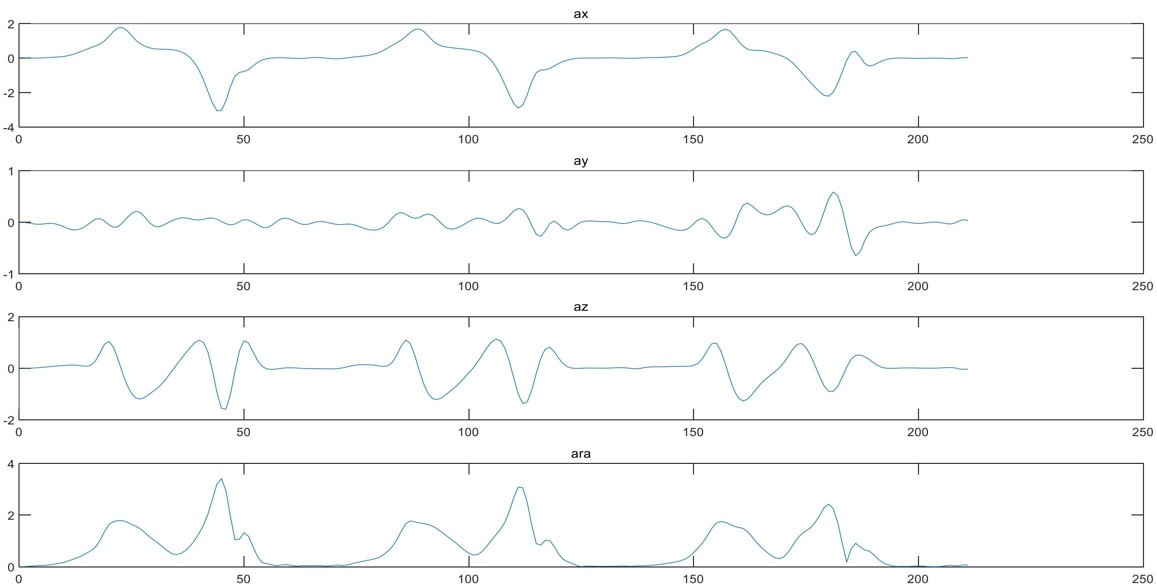


Figure 10 No.1 elderly's acceleration based on sequence in X-axis, Amplify in Y-axis.

Table 5 the average resultant acceleration of indicators in the upper body of the first 10 elders.

NO(i)	Name	Resultant acceleration	NO(i)	Name	Resultant acceleration
1	aizhenjiang	3.4235	6	cuixiulan	3.6221
2	baiqingquan	3.10892	7	cuizhenhua	4.00751
3	baiyulin	3.27565	8	fujianying	3.8146
4	cangyongli	3.39113	9	gengxiulin	3.49987
5	chenfue	4.13762	10	guanpeihua	2.8821

3.4 Conclusion

We used Box-Figure method to correct some testing error or mechanical record error, which may represent wrong information to sculpture elderly's walking process and we deleted 4 elderly people who have no walking test data because we cannot measure their balance ability in our extraction model.

In the extraction process, we extract 25 indicators from 42 monitoring points in R-type cluster method, which **contributes 90.86% to the body features**. And their total **showing frequency** among 76 subjects reaches **79%**. Besides, these 25 indicators have their medical meanings, which is able to measure the elderly people's balance ability. And 25 indicators contain 75.6% monitoring points. Comparing with the figure given, we **clustered 14 monitoring points and abandon 3 irrelevant points**. However, these 25 indicators can fully represent all the body features.

When we are calculating the physical parameters, we obtain every subject's step length, the center of gravity and the ratio of the height of gravity center and height, every direction's acceleration of the 25 indicators and max resultant acceleration.

3.5 Error Analysis

We have listed the error value and their origins in **Table 6.**

Table 6 the error percentage, origin and methods to correct in the future work

	Error	Error origin& method to correct
Correcting process		We correct the data out of limits in the top quarter or the bottom quarter. From this process, the data might not be very accurate.
25 Indicators	Frequency 23%	We have abandoned 3 points and cluster 14 points to obtain 25 indicators, the frequency loss is tolerable since we focus more on the contribution rate.

	Contribution 9.14%	The contribution reaches 90.86%, and enough to represent all the monitoring points of the body features.
Center of gravity		The **weight chosen** might influence our method much. Depending on the different individual, we should change the weight accurately, however, we determine it on average, in which way, will not influence our results that much. If every individual's parts of weight can be accurately measured, we can obtain the center.
Steps	0.51%	The beginning point may affect step length to some extent. We calculate the subjects' real step length $s_r(i)$, and $\overline{err}(i) = \frac{s(i)}{s_r(i)} = 0.51\%$, the average error is 0.51%
Resultant Acceleration		The error comes from 2 parts. The first is a **systematic error**, $\Delta t = 0.015$ is small, however, if it can be smaller, the result can be more accurate. The second part is the **monitoring error** since we obtain our data in distance and time, the distance measurement and timing measurement may lead to error. In the future, we can obtain acceleration in hardware method since the acceleration sensor can transfer exact acceleration.

4 A System to Assess the Balance Ability of Elderly People

4.1 Model

We build our model in **Polynomial Curve Fitting method (PCF**) to calculate the variance $\sigma_k{}^2(i)$ based on the existing 25 indicators. We see the fitted polynomial curve as stable and in this way, we can calculate the variance $\sigma_k{}^2(i)$ between the walking curve and the stable curve. And $\sigma_k{}^2(i)$ is able to measure the balance ability of i^{th} individual's one direction. And we can obtain a total variance by combine the two variance. If one has a low balance ability, he/she might fall in width direction and height direction since ahead direction has been concerned in the change of the center of gravity. No matter which directions he/she may fall, combine two $\sigma_k{}^2(i)$ is able to represent the balance ability. And our PCF method is done in **Figure 11** and steps:

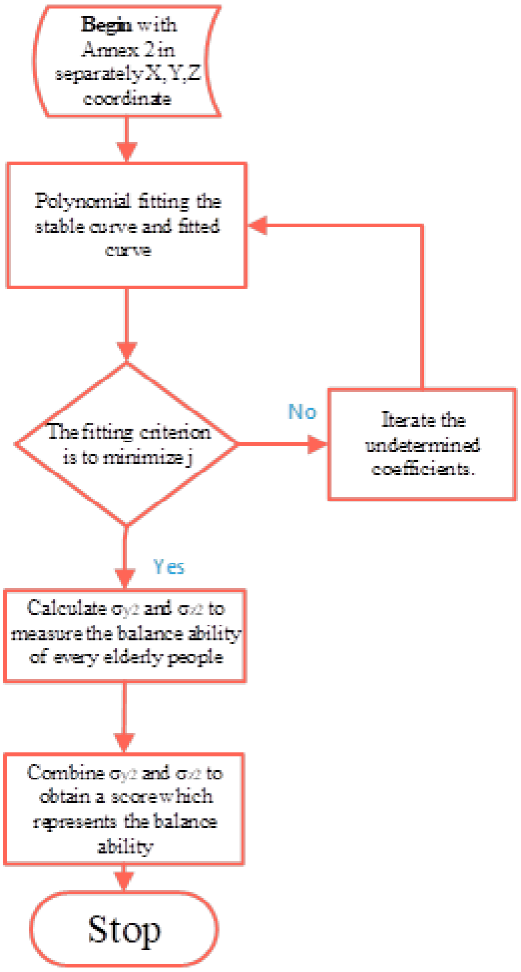


Figure 11 The flow chart of PCF

Step1 Set $f(x) = a_1r_1(x) + a_2r_2(x) + a_3r_3(x) + \cdots + a_6r_6(x)$

Step2 Determine $r_i(x)$ is polynomial equations (it fits much better than Trigonometric functions) and polyfit the stable curve until $J_{i(x,y,z)}(a_1, a_2, \dots, a_n) = \sum_{i=1}^{n} \delta^2_{i(x,y,z)}$ is minimal.

Step3 Iterate every subjects' walking coefficients and plot his/her trace curve in every direction.

Step4 Calculateδ^2_{iy} and δ^2_{iz} to measure the balance ability of every elderly people of one direction.

Step5 Combine $\delta^2_{iy} + \delta^2_{iz}$to measure the balance ability of an elderly people. (we chose not to use δ^2_{ix}, because it varies very large since it is the ahead direction.)

Aided of Matlab, we obtain every elderly people's own $f(i,x) = a_1r_1(x) + a_2r_2(x) + a_3r_3(x) + \cdots + a_6r_6(x)$

We scratched NO.55's indicator 15 (head).

$f(55, z) = 280 + 1155z - 600z^2 + 11672z^3 - 11046z^4 + 5433z^5 - 1334z^6 + 129z^7$

The polynomial fitting results can be plotted in **Figure12,** the result is given in **Annex3**.

In this model, we calculate everyone's variance between the walking curve and the stable curve in width direction $\delta^2_{iy}$and height directionδ^2_{iz}. We sum the two variance to a final variance $\delta^2_{it}$and the total variance is able to represent the balance ability of an elderly people. i.e. If one has a high variance, he/she has a bad balance ability. On the contrast, if he/she has a low variance, he/she has a good balance ability.

We compare us δ^2_{it} results with the given fallen times, then we

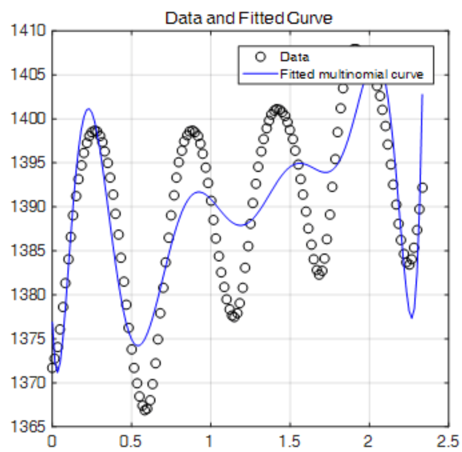


Figure 12 polynomial fitting results

rank the balance ability by the numeric size of δ_{it}^2. We gave out the first 10 elderly people who have the best balance ability and the last 10 elderly people who have the worst balance ability in **Table7**. The whole data are listed in **Annex3**.

Table 7 The comparison analysis of Total fall times and δ_{it}^2

Number	Name	δ_{it}^2	Total fall times	Number	Name	δ_{it}^2	Total fall times
57	xieshuli	50.528	0	37	qijianming	183.948	0
56	xiangxu	59.269	1	2	baiqingquan	186.576	2
59	xuxiuyun	61.212	0	55	wujinzhan	196.889	2
7	cuizhenhua	69.101	0	63	yangxijin	209.398	3
1	aizhenjiang	71.768	0	15	hujiawei	212.223	2

In **Table7**, the left chart is the elderly people who have good balance ability and in the right chart, it is those who have worse balance ability.

In **Figure 13**, we drew all the elder people's data. We can see that when δ_{it}^2 is small, the elderly people fall less and when δ_{it}^2 reaches high, the possibility of fallen rise rapidly. The line is the trendline polynomialed.

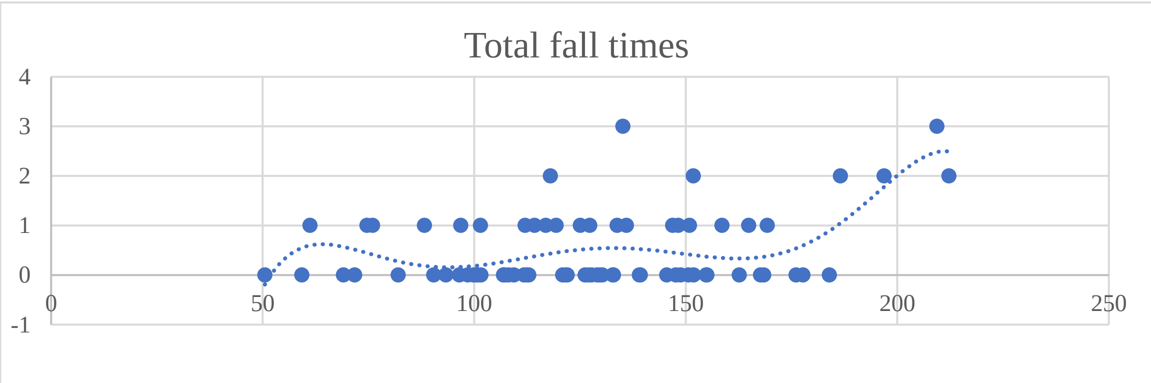


Figure 13 The relevance between δ_{it}^2 and the total fall times

4.2 Conclusion

The balance ability assessment system based on the 25 indicators is good to evaluate one's balance ability. If he/she gets a higher δ_{it}^2 though our system, he/she may have a low balance ability and have high risk of falling down. When we are comparing the first 5 and the last 5 balance ability elderly people in **Table7**, the **accuracy reaches nearly 80%**. However, in the middle δ_{it}^2 part, where most normal elderly people reach, the accuracy goes rapidly lower, which means the system is not stable and needed to be improved.

We can see from **Figure 13**, it is hard to analyze the balance ability and the risk of fall of the elderly people simply by analyzing his/her walking δ_{it}^2 based on these 25 indicators. We need to analyze more factors contributes to the problem thoroughly. In this way, we build a new system which not only contains 25 indicators but other factors as well.

From the system's perspective, we give one advice: the first is when testing the subjects, test them with acceleration sensors, which will lead to more accurate acceleration and other parameters.

5 An Improved System to Measure the Balance Risk of Elderly

5.1 Model

The **Technique for Order of Preference by Similarity to Ideal Solution** (TOPSIS) is a multi-criteria decision analysis method. TOPSIS is based on the concept that the chosen alternative should have the shortest geometric distance from the positive ideal solution (PIS) and the longest geometric distance from the negative ideal solution (NIS).[4]

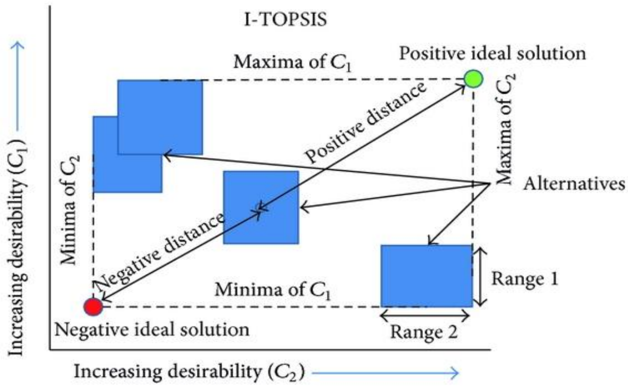


Figure 14 Graphical representation of TOPSIS

Information entropy is a quantity used to describe information disorder degree in information theory. The higher the entropy value, the higher the information disorder degree, and the higher the corresponding information efficiency. Here are the steps to determine the weight needed in TOPSIS.

We use the concept of **information entropy** to determine the weight of the evaluation index, **avoiding the influence of subjective factors,** which is our aim, to some extent. Information entropy is a measurement method to measure information uncertainty by using mathematical probability theory, which indicates that the more dispersed the data distribution, the greater the uncertainty. The information entropy of each index can be used for decision information. The steps are as follows:

Step1 The data matrix X is normalized to obtain the calculated matrix Y

$$y_{ij} = \frac{x_{ij} - \bar{x}_{.j}}{max(x_{.j}) - min(x_{.j})}$$

Step2 Calculate the entropy

$$H_{.j} = -\frac{1}{\ln n}\sum_{i=1}^{n} a_{ij}\ln(a_{ij})$$

Step3 Calculate the weight of every characteristic

$$w_{\cdot j} = \frac{1 - H_j}{n - \sum_{j=1}^{m} H_j}$$

Step4 Enter the positive, negative, and interval criteria $J_i^+,\ J_i^-\ \ and\ \ J.$

Step5 Calculate the distance between the target and the optimal solution, if the distance$S_{iw} = 1$, it is the most optimal solution. Rank by the distanceS_{iw}.

We use 7 criteria ($\delta_{it}^2,\ R_i(z),\ a_i(ra)$, Complaint value, drop, Age, BMI, and s_i) listed in **Table 9** to test our TOPSIS algorithm. The parameters have been calculated in the former article or have been processed in Annex 1. However, the medical value needs to be quantitated in **Table 8** according to its possible contribution to the falling or the falling severity of those who have those complaint. And Table8 is presented according to some essay we have listed in Reference.

Table 8[5] the quantitative value of the given complaint

CVD	Hypertension	Drug/alcohol withdrawal symptoms	Osteoporosis	Bone fracture history	Neuropathic disorder
2	2	1	5	5	3
Anoxia	Sarcopenia	Visual impairment unadjustable by lenses	vestibular disorder	Head trauma	
2	4	4	5	3	

Table 9 the different varieties' explanation and optimal intervals in TOPSIS

Criteria	**Explanation**	**Property**	**Optimal**	**Lower unbearable**	**Upper unbearable**
δ_{it}^2(mm)	The variance originated from 25 indicators which can analyze elderly's trace habits.	Negative criteria	Smallest		
$R_i(z)$	The ratio of center of gravity and height based on 25 indicators.	Interval criteria	[0.41,0.48]	0.35	0.52
$a_i(ra)$ (m/s^2)	The maximum resultant acceleration of the 25 indicators.	Interval criteria	[2.5,5]	2	5.8
Complaint Value	We numeric the complaint declared in Annex1.	Negative criteria	Smallest		
Age	Age of every elderly people	Negative criteria	Smallest		
BMI	BMI of every elderly people	Interval	[19,28]	17	32

		criteria			
s_i	The steps length of each subject based on 25 indicators	Positive criteria	Largest		

The results are as follows in **Table 10** and **Table 11**. We find that depending on TOPSIS, complaint value, Age and BMI play an important role when analyzing the elders' risk of falling down and the balance ability. And the total 25 indicators and its deuterogenic occupation reach **62.7%.** And the last **37.3%** are occupied by the given Annex1. In **Table11,** we obtain the positive and negative optimal solution.

Table 11 The weight of different characteristic's weight by TOPSIS

Characteristic	δ_{it}^2	$R_i(z)$	$a_i(ra)$	Complaint value	Age	BMI	s_i
Weight	0.113	0.261	0.163	0.135	0.102	0.135	0.09

Table 12 The optimal solution of the balance ability

Positive optimal solution Cstar	0.0210	0.0348	0.0202	0.0744	0.0151	0.0167	0.0133
Negative optimal solutionC0	0.0050	0	0	0	0.0092	0	0.0058

5.2 Results Analysis

Being tested by our improved system to measure the Balance Risk of elderly using TOPSIS, we obtain the rank value which represents his/her balance ability.

The TOPSIS Value is high means the distance between the target and the positive optimal solution if the distance $\boldsymbol{S_{iw}} \rightarrow \mathbf{1}$, which means his/her **balance ability is great**, he/she has a lower possibility to fall down. At the same time, if the distance $\boldsymbol{S_{iw}} \rightarrow \mathbf{0}$, which means he/she has a **lower balance ability**, he/she has a high risk of falling down. Besides, we compare our model with the given fall times. We obtain the list as following in **Table13,** and more data are provided in Annex3.

Furthermore, we drew **Figure 15** to clearly show our model. In **Figure15,** the x-axis represents TOPSIS value which ranges from 0 to 1 and the Y-axis is the fall times among all the given elderly people. And the trend line clearly shows that those with high distance to the positive optimal solution have more actual fall times. On the contrast, those who have a low distance to the positive optimal solution have nearly 0 actual fall times or even some disease. We can tell from **Figure15** that if one's TOPSIS value is lower than 0.7, he/she might fall down with a high possibility and if his/her value is higher than 0.9, he/she might fall down with low risk.

From **Table12**, we get 80% accuracy in the first 5 and the last 5 elderly people, and we get nearly **80% low balance ability elderly people with lower value**, and only several elderly people are ranked in the middle of the list. More data are provided in Annex3.

Table 13 the comparison of Topsis value's and the total fall times

NO	Name	TOPSIS Value	Total fall times	NO	Name	TOPSIS Value	Total fall times
14	haoyubin	0.96	0	8	Fujianying	0.60	0
23	lirenfan	0.96	1	24	Lishuhau	0.48	1
57	xieshuli	0.95	0	56	Xiangxu	0.39	2
25	litongsheng	0.95	0	48	Wanghancai	0.38	1
11	hanjianshe	0.94	0	2	Baiqingquan	0.24	2

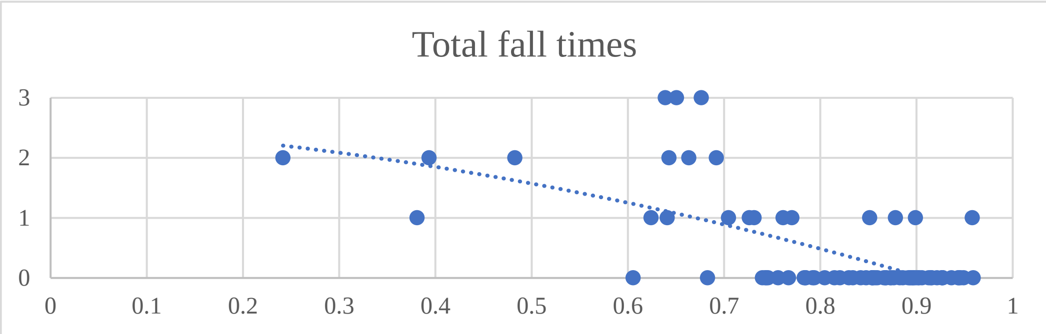


Figure 15 The relevance between the distance S_{iw} and the total fall times

6 Sensitivity Analysis

In this process, we measure the sensitivity of our model, we changed BMI, Age, and Complaint value while other value stay unchanged to test the sensitivity of the TOPSIS method. In **Table 14,** we analyze the change of the actual data's influence to the final rank of each subjects' balance ability. The change ratio relatively high when someone has less disease, because when the value decrease 5%, one's balance ability can be much higher than before, his/her risk of falling down lowers 10% to others' data.

Table 15 the sensitivity analysis of actual data

	Sum Changes	change ratio
BMI decreased by 3%	2	2.6%
BMI increased by 3%	2	-2.6%
Age increased by 3%	1	1.3%
Age decreased by 3%	6	-7.8%
Complaint value decrease by 5%	8	-10.4%
Complaint value decrease by 5%	3	4.1%

Besides, in **Table 16**, we analyze the limit change's influence to the whole rank. We analyze all the interval criteria, and select the biggest influence to list. More analysis needs to be done in the future work.

Table 17 the sensitivity analysis of the TOPSIS criteria limit

	changes in the top 20	changes in the last 20	sum	change ratio
band broaden by 3%	5	3	8	20.00%
band broaden by 5%	4	5	9	22.50%
Lower limit decrease by 3%	0	1	1	2.50%
Lower limit decrease by 5%	0	2	2	5.00%
The upper limit decrease by 3%	2	3	5	12.50%
The upper limit decrease by 5%	5	4	9	22.50%

7 Advice for Elderly People

For elderly people who have a lower risk of falling down, they have better balance ability (in our improved, those whose s_{iw} ranges from **0.9-1**). However, they need to pay attention while walking as well, because their volatility (the variance between stable pace and their testing pace) while walking is higher. Some of them suffer from vision impairment unadjustable by lenses, osteoporosis, and hypertension. Therefore, they should pay attention to taking moderate exercise to keep fit. In order to reduce the incidence of osteoporosis, sarcopenia, visual impairment, and vestibular disorder.

For elderly people who have the middle-balance ability (in our improved, those whose s_{iw} ranges from **0.8-0.9**), they have a moderate risk of falling. They may have some diseases listed in the Annex1. They should keep diet to lower blood pressure which is the most common disease of them. They should take more calcium and other trace elements to prevent or alleviate osteoporosis. In addition, increasing muscle strength can also improve their balance ability.

For elderly people who have a high risk of falling down or even those who have fallen (in our improved, those whose s_{iw} is lower than **0.8**), they have poor balance ability and physical quality. **80% of them suffer from osteoporosis and hypertension**, which affect their balance ability. Therefore, they should also keep diet, take more calcium and other trace elements to alleviate osteoporosis and increase muscle strength. At the same time, they should also pay attention to the height and step of walking, regular gait is conducive to improve the balancing force.

For all the elderly people, from medical perspective, the knee joint (indicators11, 18) is not a solid bone structure except for patella. However, due to long-term wear and tear, the meniscus is seriously damaged and easy to be damaged. Therefore, fast running and climbing higher stairs are not recommended after for them. Especially for the elderly who have osteoporosis and the bones are extremely prone to fracture after falling down. If they don't have enough muscle reserves, and exercise often, your muscles will age faster than if you exercise regularly.

According to the **Table10,** the balance ability is measured with different weight. we can analyze the weight to decrease our possibility of falling down. We should not move sharply because δ_{it}^2 contributes a lot to the balance ability. And due to the height $R_i(z)$ contribution, we should exercise more to tense our leg muscles in which way, can increase our reflectivity before falling down.

8 Strengths and Weaknesses

8.1 Strengths

- ✓ We obtained 25 indicators by clustering method with medical meanings rather than with mathematical meaning only. The analysis of the problem is **comprehensive**.
- ✓ TOPSIS can make full use of all the original data, in which way we can demonstrate each parameters' contribution to the balance ability.
- ✓ Our model can evaluate multiple objects at the same time, the results are **objective**, **reasonable and applicable**, and of high medical value and mathematical meaning. Even with some slight disturbance, our model can stay **stable**.
- ✓ We considered every parts' of our body's contribution if one has bone fracture history, his complaint can be considered in our model. Ones' health status has been considered in our model.

8.2 Weaknesses

- × When we deal with problems, we did not take into account the difference in left and right step sizes in elderly people. But different left and right step sizes can affect the elderly's ability to balance.
- × We did not take into account the process of the elderly to go upstairs and downstairs, because the situation is more complex than the flat floor, judging the balance ability is better.
- × TOPSIS only considers the role of the main factors, but ignores the secondary factors, so that the evaluation results are not comprehensive enough.
- × We determine everybody's body weight distribution is on average, in which way, will influence our results slightly. If every individual's parts of weight can be accurately measured, we can obtain more accurate results.

- With calculating method to obtain the acceleration is inaccurate, however, if we use sensors to measure the acceleration in each direction, we will measure elderly people's balance ability more accurate.

9 Conclusion

Our model efficiently extracts 25 indicators with medical meanings from the 42 monitoring points by using **R-type cluster method**. Our 25 indicators contain 90.86% information about the whole body features, which makes it possible to measure the basic physical status of each subject. Our research measured three basic physical data: the step length, center of gravity in two main direction(Y and Z) and acceleration towards different direction and the resultant acceleration in order to obtain the subjects' whole information. The error of steps reaches 0.51%, which is accurate enough. However, if we can use more accurate measurement to collect these data, our results will be better.

We then build a balance ability system based on these 25 indicators with **Polynomial Curve Fitting method and variance method,** we compare the stable pace curve with the experimental pace curve. In order to sculpture one's balance ability, we select the largest variance as the criteria since the largest variance means he/she is in the most unstable status. And then we compare our results with the actual fall times and make an analog computation, the accuracy reaches nearly 80% in highest and lowest risk elderly people. All the elderly who have fallen many times have been ranked with a high variance, which means they walk very unstable. However, the accuracy decreases rapidly when applied to the middle-risk elderly people. Due to this phenomenon, our model did some more improvement.

In our improved assessment system, our model considers actual data with Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), our research selected 7 potential parameters to measure the balance ability of the elderly people, and we get 80% accuracy among nearly all the elderly people comparing with the actual fall times. And the trend line actually fits the results. Moreover, our improved assessment can overall divide those elderly people with high balance ability and low balance ability. And we rank them by using the elderly people's 'distance' to the positive optimal solution to measure their balance ability.

The sensitivity analysis of our improved model proved that small alternation of Age and BMI parameters in our model can slightly influence the result. A small disturbance (3%) will influence the rank by **only 2.6%.** And a small disturbance (5%) of optimal solution's limits will influence the rank by **12%.**

Finally, we give some advice to elderly people who have fallen or have low balance ability in medical perspective. To those who haven't fallen or have better balance ability, we give some advice too, according our 25 indicators' medical instructions.

Reference

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【5】 Steffen, T. M., Hacker, T. A., & Mollinger, L.. (2002). Age- and gender-related test performance in community-dwelling elderly people: six-minute walk test, Berg balance scale, timed up & go test, and gait speeds. Physical Therapy, 82(2), 128.

【6】 Tong Lina. (2011). Human Fall Recognition Method based on Mechanical Information Acquisition System. (Doctoral dissertation, University of Science and Technology of China).

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【8】 Mei-Zhen, Z. , Feng, Y. , & Yi-Chun, B. . (2016). The relationship between anthropometric indexes and slip-related falls risk factors in older adults. Journal of Beijing Sports University.

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Appendix

```
clc, clear
%% initial
%25cluster
data3=[1        2       0       0       0
            2       35      0       0       0
            3       34      0       0       0
            4       1       0       0       0
            5       12      0       0       0
            6       19      0       0       0
            7       11      0       0       0
            8       18      0       0       0
            9       7       0       0       0
            10      8       0       0       0
            11      28      0       0       0
            12      3       5       25      36
            13      20      38      0       0
            14      21      39      0       0
            15      40      0       0       0
            16      4       6       26      37
            17      9       0       0       0
            18      10      0       0       0
            19      27      0       0       0
            20      14      0       0       0
            21      13      0       0       0
            22      29      31      0       0
            23      33      0       0       0
            24      15      0       0       0
            25      41      0       0       0];
%% import data
      resultvar_yy=[];
      resultvar_zz=[];
```

```
A = dir(fullfile('*.trc'));
for iiii=1:1:76
    data1=load(A(iiii).name);
  result_yy=[];result_zz=[];
    resultfit_yy=[];resultfit_zz=[];

  data2=data1(:,3:end);%matrix1*126

  for i=1:1:25%row
      yy=[];zz=[];
      for ii=2:1:5%column
          if data3(i,ii)~=0
              yy=[yy,data2(:,3*data3(i,ii)-1)];
              zz=[zz,data2(:,3*data3(i,ii))];
          end
      end
      result_yy=[result_yy,mean(yy,2)];
      result_zz=[result_zz,mean(zz,2)];
      yytofit=result_yy(:,i);
      zztofit=result_zz(:,i);

  % Create the model.
    fun = @(x,xdata)x(1)+x(2)*xdata+x(3)*(xdata).^2+x(4)*(xdata).^3 +x(5)*
(xdata).^4 +x(6)*(xdata).^5+x(7)*(xdata).^6+x(8)*(xdata).^7;
      tdata =data1(:,2);
      m0  =  1.0e+04  *[0.0280         0.1155       -0.6000         1.1672       -1.1046
0.5433      -0.1334        0.0129];
  % Solve the bounded fitting problem.
      my1 = lsqcurvefit(fun,m0,tdata,yytofit);
      my2 = lsqcurvefit(fun,my1,tdata,yytofit);
      yyfitted=fun(my2,tdata);

      mz1 = lsqcurvefit(fun,m0,tdata,zztofit);
      mz2 = lsqcurvefit(fun,mz1,tdata,zztofit);
```

```
            zzfitted=fun(mz2,tdata);
            resultfit_yy=[resultfit_yy,yyfitted];
            resultfit_zz=[resultfit_zz,zzfitted];
            difference_yy=abs(resultfit_yy-result_yy);
            difference_zz=abs(resultfit_zz-result_zz);
            var_yy=var(difference_yy,0,1);
            var_zz=var(difference_zz,0,1);
        end
        resultvar_yy=[resultvar_yy;var_yy];
        resultvar_zz=[resultvar_zz;var_zz];
 end

%%CLUSTER
clc, clear all
%read in circle
A = dir(fullfile('*.trc'));
resultfinal=[];
for i=1:1:2
    data1=load(A(i).name);
    [m,n]=size(data1);

    a=[];
        for ii=1:1:42
            X=[data1(:,3*ii+1),data1(:,3*ii+2)];
             a(:,ii)=pdist(X,'mahal');
        end
        %%
        b=zscore(a); %standard the data
        r=corrcoef(b); %coefficient matrix
        d=pdist(b','correlation'); %计算相关系数导出的距离
        z=linkage(d,'average');   %按类平均法聚类
        figure
            h=dendrogram(z);   %画聚类图
      set(h,'Color','k','LineWidth',1.3)   %把聚类图线的颜色改成黑色，线宽加粗
```

```
        T=cluster(z,'maxclust',25);    %cluster into 25 catagory
        results= [];
        for iii=1:25
            tm=find(T==iii);    %find the ith coatogory's subjetct
            tm=reshape(tm,1,length(tm)); %in row
results=[results;tm,zeros(1,15-length(tm))];
        end
        resultfinal=[resultfinal;results];

end
%% topsis
clc, clear
data=load('datatopsis.txt');
[m,n]=size(data);
fun=@(qujian,lb,ub,x)(1-(qujian(1)-x)./(qujian(1)-lb)).*(x>=lb &
x<qujian(1))+(x>=qujian(1) & x<=qujian(2))+(1-(x-qujian(2))./(ub-
qujian(2))).*(x>qujian(2) & x<=ub);
%properties trans
qj2=[0.41,0.48]; lb2=0.35; ub2=0.52;
data(:,2)=fun(qj2,lb2,ub2,data(:,2));
qj3=[2.5,5]; lb3=2; ub3=5.8;
data(:,3)=fun(qj3,lb3,ub3,data(:,3));
qj6=[19,28]; lb6=17; ub6=32;
data(:,6)=fun(qj6,lb6,ub6,data(:,6));

for j=1:n
    b(:,j)=data(:,j)/norm(data(:,j));    % normalize the matrix
end
%% weight
% data analysis in 1
maxdata=repmat(max(data),m,1);
mindata=repmat(min(data),m,1);
max_min=maxdata-mindata;
```

```
stddata=(data-mindata)./max_min;
%calculatee the weight
f=(1+stddata)./repmat(sum(1+stddata),m,1);
e=-1/log(m)*sum(f.*log(f));
d=1-e;
w=d/sum(d); %  权重向量
%%
c=b.*repmat(w,m,1);           %求加权矩阵
Cstar=max(c)        %求正理想解
Cstar(1)=min(c(:,1)); Cstar(4)=min(c(:,4));
Cstar(5)=min(c(:,5));
Cstar(7)=max(c(:,7)); %属性 1,3,5,6 为成本型，属性 2 为效益型
C0=min(c)            %q 求负理想解
C0(1)=max(c(:,1));    C0(4)=max(c(:,4));
C0(5)=max(c(:,5));
C0(7)=min(c(:,7)); %属性 1,3,5,6 为成本型，属性 8 为效益型
for i=1:m
    Sstar(i)=norm(c(i,:)-Cstar);    %求到正理想解的距离
    S0(i)=norm(c(i,:)-C0);          %求到负理想的距离
end
f=S0./(Sstar+S0);
[sf,ind]=sort(f,'descend');            %求排序结果
Y=[ind',sf'];
```