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Human Gait Modeling and Gait Analysis Based on Kinect

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Abstract—**Real-time monitoring of elderly movement can provide valuable information regarding an individual's degree of functional rehabilitation. Many laboratory-based studies have described various gait detection systems with different wearable inertial sensors, but only limited number of papers addressed the issues by using some non-wearable sensors. A practical method of gait information detection and gait analysis is proposed in the paper using an inexpensive Microsoft Kinect fixed on the midpoint of lower extremity rehabilitation robot. The horizontal distances between Kinect plane and every mark pasted on lower extremity are acquired. Taken the characteristics of gait distance series into consideration, the Autoregressive Moving Average (ARMA) model is established to reflect the changing rule of gait status. Combined with the Kalman filter, gait information reflecting rehabilitation status at next moment is predicted accurately. The method regarding the gait detection and gait analysis is verified by amounts of gait experiments finally.**

I. Introduction

According to the United Nations Population Division statistics, the elderly population has reached 737 million by the end of 2009 accounting for 10.8% of the total population, and then it may account for 15% of the total population in the year 2025[1]. Particularly in the Asia Pacific region the elderly population has grown rapidly. In China, people aged over 60 have reached 178 million, which takes up 13.26% proportion of the total population by the end of 2010. In addition, Thousands of elderly people caught some mournful diseases every year. Aggravation of population aging and high proportion of mechanical injury are causing most people to lose the walking independently, it doesn't only reduce the life level, but also it puts more heavy burden on the society and restricts the rapid growth of national economy.

It is essential for elderly to have a proper rehabilitation training in order to strengthen body function. However, some accidental injuries usually come out and most of them do great harm to the originally weak body in the rehabilitation process, so it is essential to employ diverse sensing devices to monitor the whole rehabilitation process. Moreover, it helps evaluate the rehabilitation level objectively and prevent the accident such as the falls beforehand by combining gait information from sensors. Several efficient methods regarding gait detection and gait analysis using different kinds of sensors have been proposed. Dean M[2] presented a real-time classification system for human movement associated with the data from a waist-mounted tri-axial accelerometer unit and achieved the great performance. Michael R[3] proposed a waist-mounted tri-axial accelerometer system with a remote data collection capability to address the falls detection and falls prevention. S Jiang[4] proposed a fall prediction method based on the gait analysis algorithm (stability and symmetry of gait) by collecting the movements parameters of human walking gait from the tri-axial accelerometer. Devon K[5] proposed a slip-and-fall detection and prediction device designed with Lyapunov method to predict if patient gait balance will become chaotic and unstable, indicating that they may be at risk of fall. M Gabel[6] presented a novel method for full body gait analysis using Kinect sensor, but the Kinect skeleton drifted easily to the side and joint measurements of the features caused relatively larger errors. T Hu[7] presented a systematic approach to modeling a bipedal walker driven by joint moments, the holonomic constraint inside the raw model obtained by Newton's law was gradually eliminated through characterizing ground reaction force and a set of models with no holonomic constraint were obtained for all possible situations in a gait cycle. F Iida[8] presented the two-biped control architecture for the compass gait model used for locomotion in rough terrain and then extended the proposed controller with a sensory feedback by self-stability and gait variability, which enabled the robot to control gait patterns autonomously for traversing a rough terrain.

Several methods of gait detection and gait analysis by some different sensors have been proposed above, but in most of which sensors were dressed on the trainers and it probably led to increasing additional psychological burden, so it is essential to propose some other portable equipment to monitor gait status in the rehabilitation process. The paper proposes a method of gait detection and gait analysis using the Microsoft Kinect, which is fixed on the midpoint of lower limb rehabilitation robot with inductive elements backwards. The horizontal distances between Kinect and every mark pasted on each lower extremity are acquired simultaneously when rehabilitation robot followed by the trainer moves along the scheming path together. The ARMA model is established according to the characteristics of gait distance series and its physical meaning. Moreover, gait information at next moment is predicted accurately by combining dynamic Kalman filter with the output of ARMA model finally.

II. Information Detection Based on Kinect

The Kinect detection device on the rehabilitation training robot is shown in Fig. 1a, which is mainly composed of three cameras, the middle one is a general RGB camera, through which the RGB information in the view can be obtained, the others are an infrared projector and a CMOS infrared camera, through which the horizontal distances between all pixels in the view and Kinect plane can be obtained directly, namely,

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the RGB-D information of any pixel in the view can be captured by the Kinect. It is fixed on the midpoint of lower limb rehabilitation training robot with the inductive elements backwards in order to realize the gait information detection, which employs the independent wheeled structure and equips with the four stepping motor respectively, so it is used to assist trainer in functional enhancement and rehabilitation, as shown in Fig. 1b. In order to reduce the calculation and storage, several marks are pasted on the frontal surfaces of lower limb and each lower limb has half number, the height above the ground can be adjusted according to the length of lower limbs, and then the horizontal distances between every mark on lower limbs and Kinect plane are detected persistently.

a) The structure of Microsoft Kinect

b) Horizontal distance detection base on the lower limb rehabilitation robot

Figure 1. Distance detection device based on Kinect.

III. Gait Series Modeling

The horizontal distances between every mark pasted on lower limbs and Kinect plane are obtained and regarded as the gait characteristics, and then an applicable ARMA model is established effectively according to the characteristics of gait series itself and its physical meanings.

A. Overall characteristics of gait series

Take the distance from one mark for example in order to describe the characteristics of gait series. As known to all, normal walk activity is carried out with bilateral lower limb moving forward alternately along at the constant drive of the rehabilitation robot, so the distance between every mark in the view and Kinect plane is periodic in theory. However, the amplitude of each lower limb relative to the coronal plane is random due to the positional uncertainty of the homolateral heel striking the ground according to the knowledge of human kinematics, in addition, Kinect contains some uncertain noise inside. Moreover, the whole walk activity of unilateral lower limb is correlative and it can be represented as the linear combination of gait information at previous moment and the corresponding noise. It is applicable to establish a ARMA model for gait series based on the above characteristics.

B. The basic form of ARMA model

The basic form of a common ARMA model is expressed as follows.

$$\Theta(B)\cdot M(B^S)\cdot\Delta^d\cdot\Delta_S^D\cdot X(t)=\Psi(B)\cdot N(B^S)\cdot\varepsilon(t) \tag{1}$$

$$M(B^S)=1-u_1\cdot B^S-u_2\cdot B^{2S}-\ldots-u_P\cdot B^{PS} \tag{2}$$

$$N(B^S)=1-v_1\cdot B^S-v_2\cdot B^{2S}-\ldots-u_Q\cdot B^{QS} \tag{3}$$

$$\Theta(B)=1-a_1\cdot B-a_2\cdot B^2-\ldots-a_p\cdot B^p \tag{4}$$

$$\Psi(B)=1-b_1\cdot B-b_2\cdot B^2-\ldots-b_q\cdot B^q \tag{5}$$

Where B, Δ, d, D, et, X(t) represent the shift operator, the differential operator, the differential order, the seasonal differential order, Gauss white noise with mean 0 and standard deviation 1, original series respectively, $u_1,u_2\ldots u_P$, $v_1,v_2,\ldots v_Q$, $a_1,a_2,\ldots a_p$, $b_1,b_2,\ldots b_q$ represent the seasonal autoregressive parameters, seasonal moving average parameters, unseasonal autoregressive parameters and unseasonal moving average parameters. It is concluded from the above equations that the ARMA model doesn't only eliminate the correlation at an identical moment during different cycles, but also eliminates the internal correlation at different moments in the identical cycle, so it can characterize the changing rules of gait series effectively.

C. Order determination and verification of ARMA model

- Stationary test and non-stationary processing

It is essential for gait series to make a stationary test to examine the stationarity before determining the basic form of the ARMA model. Augmented DF (ADF) test is one of most popular stationary methods. The series is non-stationary if ADF statistical value is larger than those at the significant level of 1%, 5% and 10%, otherwise, the series is stationary. It is necessary to make a differential processing if gait series doesn't satisfy the stationary condition of ARMA modeling, otherwise, the processing is skipped out to get the stationary series. Seasonal differences are carried out if gait series appears a seasonal variation and backward differences are carried out if it appears an increasing or decreasing variation trend on the whole, differential processing aren't stopped until gait series reaches the stationary condition.

- Model order determination and verification

Model order is determined in the part after getting the stationary series. First of all, the values of autocorrelation coefficient (AC) and partial autocorrelation coefficient (PAC) at every lagging order are calculated by the Eviews statistic software respectively in order to determine the model order. It is applicable to establish the ARMA model if the PAC is tailed and AC is a seasonal trailing, and then the concrete order of ARMA model is specified by counting the total number of non-zero AC and PAC at the significant level of 5%.

It is necessary to verify the overall stationary and validity of ARMA model after determining the concrete model order. Verification of model residual is employed to calculate the residuals between original series and values obtained by the ARMA model at the corresponding point. The ARMA model is admitted if the probability of Q statistics at every lagging order is larger than 0.05, model residual can be regarded as a random white noise, the model information is effective to reflect the trend and the inverted AR roots as well as MA roots are located in the same unit cycle with smaller probability. Otherwise, ARMA model order needs to be determined again.

D. Model parameters estimation by the least square method

Model parameters are unknown after specifying the model order and need to be evaluated by the least square method due to its smaller calculation and higher precision. The equation of least square method is shown as in

$$H= \min\sum_{i=1}^{n}(y_i-f(x_i))^2 \quad (6)$$

Where y_i and $f(x_i)$ represent the original gait series and the discrete value calculated by the ARMA model at ith point, n represent the total number of date points. The least square method can ensure the smaller error square sum and higher precision from the equation above.

The overall characteristics of original series are described, which is the premise foundation of establishing an effective ARMA model and then stationary test and non-stationary processing are carried out in order to get the stationary series. The model order is determined by calculating the AF and PAF, the validity and stability of ARMA model are verified by the white noise test of residual series and the unknown parameters are calculated by the least square method finally.

Gait series modeling is established effectively according to the characteristics, but it has the following disadvantages of lower predictive precision with low order modeling and high estimated difficulty with high order modeling. Kalman filter can achieve the higher precision by the recursive estimation. However, it causes the difficulty of deducing the state equation and measurement equation. So we combine low order ARMA model with Kalman filter to predict the gait information at next moment dynamically.

IV. Gait Prediction by the Kalman Filter

In order to realize the recursive prediction, the transmation from the ARMA model to the state-space equation must be done at first, and then Kalman filter is employed to obtain the predictive information at next moment.

A. *The linear optimal prediction of Kalman filter*

For a discrete time-invariant linear stochastic system

$$X(t+1)=A\cdot X(t)+T\cdot w(t) \quad (7)$$

$$y(t)=H\cdot X(t)+v(t) \quad (8)$$

First of all, the initial status X(0|0) and initial covariance matrix P(0|0) are specified randomly and predictive equations of Kalman filter are shown as follows.

$$X(1|0)= A\cdot X(0|0) \quad (9)$$

$$P(1|0)= A\cdot P(0|0)\cdot A^T+T\cdot Q\cdot T^T \quad (10)$$

$$X(t+1|t)= (A-A\cdot K(t)\cdot H)\cdot X(t|t-1)+A\cdot K(t)\cdot y(t) \quad (11)$$

$$K(t)=P(t|t-1)\cdot H^T\cdot [H\cdot P(t|t-1)\cdot H^T+R]^{-1} \quad (12)$$

$$P(t+1|t)=A\cdot [P(t|t-1)-P(t|t-1)\cdot H^T\cdot (H\cdot P(t|t-1)\cdot H^T+R)^{-1}\cdot H\cdot P(t|t-1)]\cdot A^T+T\cdot Q\cdot T^T \quad (13)$$

Where y(t), ε(t), K(t), A, Q, T represent the measurement, the white noise, the Kalman gain, the state transition matrix, measurement input matrix, noise input matrix.

Predictive value is obtained with non-linear combination of predictive value at the previous moment, Kalman gain and measurement at current moment according to the equations above.

V. Experiment and Analysis

Some relevant experiments are conducted in order to verify the availability of the ARMA modeling and accuracy of Kalman prediction. Some able-bodied subjects are enrolled voluntarily and asked to simulate the elderly to walk along the scheming straight path. First of all, eight marks are pasted on the lower limbs and each lower limb has half number of marks, the location of every mark on the lower limb is shown in Fig. 2. Every subject does the following activities many times under the same conditions: walk at the speed of 0.34m/s and 0.47m/s in order to do walk activity closer to the elderly and improve the authenticity of experiments.

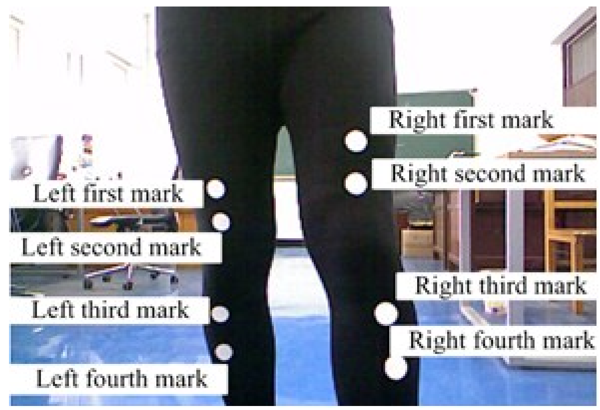


Figure 2. The location of every mark pasted on lower limb.

A. *Normal walk experiments at the speed of 0.34m/s*

The experiments are made after a period of time and then Kinect device is started by the laptop through the USB port, the horizontal distances between every mark pasted on each lower limb and Kinect plane are acquired at the 12 FPS. The distance curves at the speed of 0.34m/s are shown in Fig. 3.

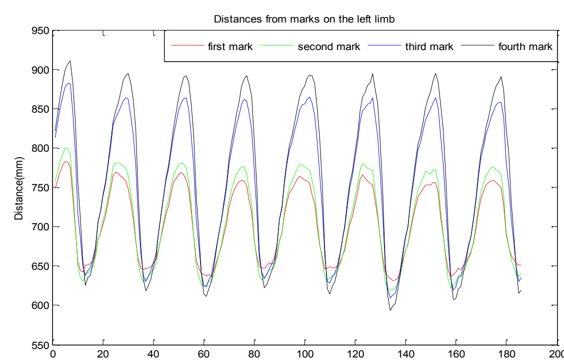


Figure 3. The distance curves of left marks.

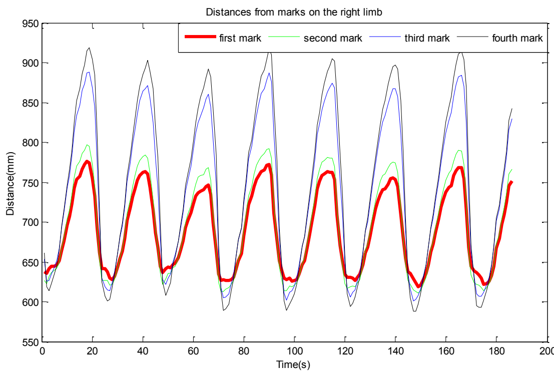


Figure 4. The distance curves of right marks.

The horizontal distance between every mark pasted on left lower limb and Kinect plane is periodic on the whole from the Fig. 3. Amplitude from the first mark pasted on the left limb is smaller than that from the second mark pasted on the left limb, amplitude from the third mark is smaller that from the fourth mark, meanwhile, Amplitude from the third mark is larger than that from the second mark, because the thigh rotates round the hip joint, but the shank doesn't only rotate round the knee joint, but also it also rotates round the hip joint, so its range is severer than the thigh. Meanwhile, the characteristics are applied to the right lower limb, which is shown in Fig. 4.

The series from the first mark on the right limb is taken for example in order to verify availability of gait series modeling and the accuracy of Kalman prediction, which is marked out with red line with the thick width.

B. Normal walk experiments at the speed of 0.34m/s

First of all, stationary test must be carried out in order to obtain the stationary series and the result by the ADF test is shown in the table I.

TABLE I. ADF TEST OF ORIGINAL SERIES

		t-Statistic	*Prob.*
ADF test statistic		-0.466900	0.5119
Test critical values	1% level	-2.578476	
	5% level	-1.942688	
	10% level	-1.615474	

The original series is non-stationary according to the table I, because ADF test statistic value is larger than those at the levels of 1%, 5% and 10%. The gait series have the obvious trend on the whole, so it is very essential to make the seasonal differences for original gait series, the length of differences processing is S=25 and the ADF test of differential processing is shown in table II.

TABLE II. ADF TEST OF DIFFERENTIAL SERIES

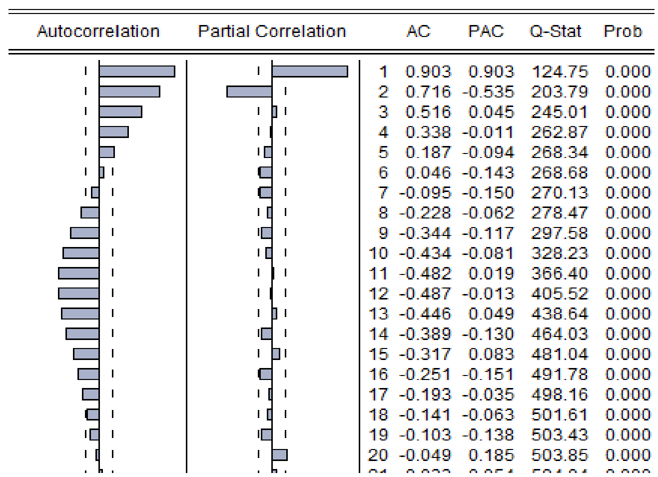
		t-Statistic	*Prob.*
ADF test statistic		-4.867278	0.0000
Test critical values	1% level	-2.580681	
	5% level	-1.942996	
	10% level	-1.615279	

The differential series satisfy the stationary condition from the table II, because the ADF test statistic value of differential series is smaller than those at the levels of 1%, 5%, 10%, where D=1, d=0. Model order is determined by counting the non-zero number of autocorrelation coefficient (AC) and partial autocorrelation coefficient (PAC) at every lagging order after the stationary processing. The autocorrelogram of stationary series is drawn by the Eviews software in the Fig. 5. It is concluded that PAC is truncated after the lagging second order and AC is tailed after the lagging fifth order, so it is applicable to establish the ARMA model, whose concrete form is ARMA(2,0,5)×$(0,1,0)_{25}$, the corresponding equation is shown as follows.

$$(1-a_1\cdot B-a_2\cdot B^2)\,(1-B^{25})\cdot y(t)=$$

$$(1-b_1\cdot B-b_2\cdot B^2-b_3\cdot B^3-b_4\cdot B^4-b_5\cdot B^5)\cdot \varepsilon(t) \qquad (14)$$

Where a_1, a_2, b_1, b_2, b_3, b_4, b_5 are unknown model parameters.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.903	0.903	124.75	0.000
		2	0.716	-0.535	203.79	0.000
		3	0.516	0.045	245.01	0.000
		4	0.338	-0.011	262.87	0.000
		5	0.187	-0.094	268.34	0.000
		6	0.046	-0.143	268.68	0.000
		7	-0.095	-0.150	270.13	0.000
		8	-0.228	-0.062	278.47	0.000
		9	-0.344	-0.117	297.58	0.000
		10	-0.434	-0.081	328.23	0.000
		11	-0.482	0.019	366.40	0.000
		12	-0.487	-0.013	405.52	0.000
		13	-0.446	0.049	438.64	0.000
		14	-0.389	-0.130	464.03	0.000
		15	-0.317	0.083	481.04	0.000
		16	-0.251	-0.151	491.78	0.000
		17	-0.193	-0.035	498.16	0.000
		18	-0.141	-0.063	501.61	0.000
		19	-0.103	-0.138	503.43	0.000
		20	-0.049	0.185	503.85	0.000

Figure 5. The correlogram of differential series.

The model is verified by the residual test of differential series after determining the concrete model order. The result shows that a_3, a_4, a_5 are not significant parameters and the Probability is larger than others, so they should be removed from the equation (14) and the optimal results are shown in the table III.

TABLE III. MODEL PARAMETERS ESTIMATION

Variable	a1	a2	b1	b2
Coefficient	1.82184	-0.87178	-0.51302	-0.38339
Prob.	0.00000	0.00000	0.00000	0.00000
Inverted AR roots	0.91-0.2i		0.91+0.2i	
Inverted MA roots	0.93		-0.41	

It is concluded that the parameters is relatively significant and Probability is very small from the table III, meanwhile, inverted AR roots as well as MA roots are located in the same unit cycle with smallest probability, so the model is stable and effective. The comparison between the original series and ARMA model series is shown in the Fig. 6 finally, from which we can draw the conclusion that ARMA model can reflect the overall trend of gait series, so it is effective for gait series to establish the ARMA model.

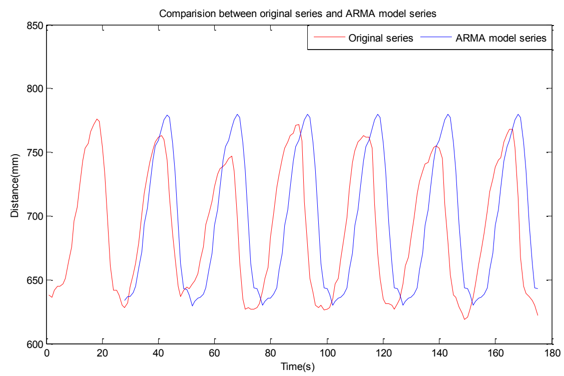


Figure 6. Comparison between original series and ARMA model.

C. Gait prediction by the dynamic filter

In order to realize the recursive prediction, Kalman filter is employed to obtain the predictive value at next moment after gait series modeling. First of all, the transformation from the ARMA model into state-space model must be conducted, and then the curves of original series and Kalman predictive series are shown in the Fig. 7.

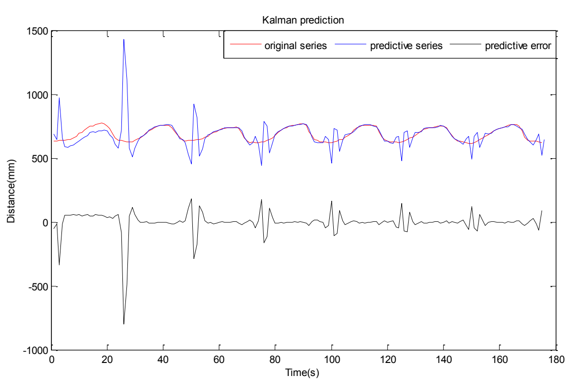


Figure 7. Comparison between original series and predictive series.

Predictive error is relatively large at the beginning from the Fig. 7, especially when every lower limb moves to the nearest location to the Kinect, predictive error reaches the maximum, but it reduces to 0 gradually with the time. Because the initial status X(0|0) and covariance matrix P(0|0) are specified randomly, so the precision is lower at the first, but Kalman predictor can recursively predict the gait information beforehand due to its characteristic of dynamically modifying the weight. On the other hand, measure precision is low when the object is nearer to the Kinect, moreover, gait is uncertain in the rehabilitation process due to the body functional decline.

It is applicable for gait series to establish the ARMA model and realize the gait information prediction based on the ARMA modeling according to the experiment at the speed of 0.34m/s.

D. Normal walk experiment at the seed of 0.47m/s

Normal walk experiment at the speed of 0.47m/s is conducted in order to verify the rationality of gait series modeling and accuracy of Kalman filter further. We compare with the characteristic variation at the different speed finally. The experiment is mainly composed of two sections too. Take the distances from first mark pasted on the right lower limb for example in order to describe the characteristic of gait series, which is marked out with red line with the thick width.

E. Gait series modeling

The curves from four marks on the right limb at the speed of 0.47m/s are shown in Fig. 8. The horizontal distances from every mark are still periodic on the whole and the relative relationships between every two mark have been described above, because the former condition is applicable to the latter.

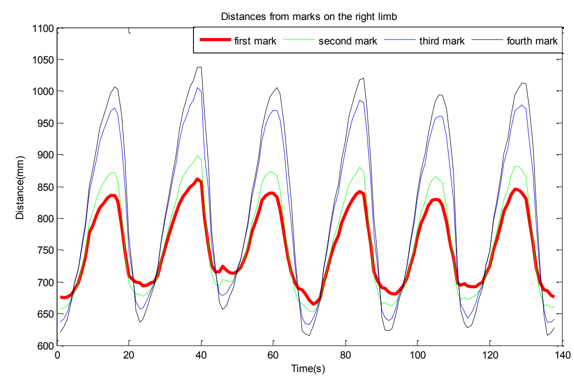


Figure 8. The distance curves from right marks.

First of all, we also do the stationary test by the ADF statistic test and make a differential processing when the series is non-stationary. Model order is determined by counting the non-zero number of AF and PAF at a significant level of 5%. It is concluded that PAC is truncated after the second order and AC is tailed after the eleventh order, so it is reasonable to establish the ARMA model according to characteristic above, the corresponding equation is shown in the (15).

$$(1-a_1\cdot B-a_2\cdot B^2)(1-B^{23})\cdot y(t)=$$
$$(1-b_1\cdot B-b_2\cdot B^2-b_3\cdot B^3\ldots-b_{11}\cdot B^{11})\cdot\varepsilon(t) \tag{15}$$

Where a_1, a_2, b_1, …, b_{11} are unknown model parameters. The model is verified by the residual test of differential series after determining the concrete model order. The result shows that $b_2,\ldots b_{11}$ are not significant parameters and the Probability is larger than others, so they are removed from the equation (15) and the surplus parameters are estimated by the least square method in the table IV.

TABLE IV. MODEL PARAMETERS ESTIMATION

Variable	a1	a2	b1	b6
Prob.	0.0000	0.0001	0.0350	0.0001
Inverted AR roots	0.78-0.27i		0.78+0.27i	
Inverted MA roots	0.81+0.41i	0.81-0.41i	0.07-0.83i	
	0.07+0.83i	0.67+0.42i	0.67-0.42i	

It is still concluded that the model is stable and effective from the table above and then the comparison between the original series and ARMA model is shown in the Fig. 9, from which we can draw the conclusion that it is applicable for gait series to establish the ARMA model to reflect the overall changing rule.

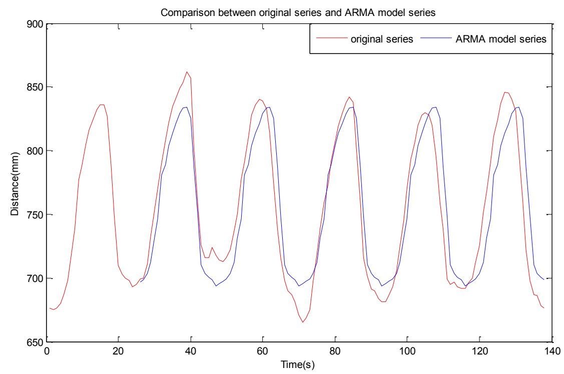


Figure 9. Comparison between original series and ARMA model.

F. *Gait prediction by the dynamic filter*

Kalman filter is employed again to obtain the predictive information at next moment after the gait series modeling and curves of original series and predictive information are shown in the Fig. 10.

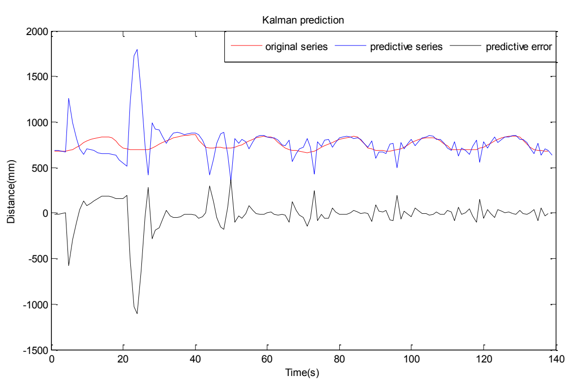


Figure 10. Comparison between original and predictive series.

Predictive error is relatively large at the beginning, but it reduces gradually with the time, because Kalman filter can recursively predict the gait information beforehand due to the superior characteristic of dynamically modifying the weight.

It is similarly applicable to establish the ARMA model and realize the recursive prediction based on the ARMA model according to the experiment at the speed of 0.47m/s.

G. *Characteristic comparison at different speed*

It is concluded that the ARMA modeling according to the characteristic of gait series itself can reflect the overall trend reasonably at the speed of 0.34m/s and 0.47m/s, although the number of data points in a cycle is discrepant at different speed and the model order is different. Meanwhile, the differences in a cycle due to the different speed can be used to identify the motion characteristic.

VI. CONCLUSION

A method of gait information detection and gait analysis is proposed in the paper by using an inexpensive Microsoft Kinect, the horizontal distances between Kinect and every mark on each lower extremity are acquired simultaneously and accurately in the rehabilitation process, and then ARMA model is established in terms of the characteristics of gait distance series and its physical meaning. Combined with the Kalman filter, gait information at next moment is predicted by the model output and the great performance is verified by two kinds of experiments finally.

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