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Guowei Huang

South China University of Technology

Zikang Zhou

South China University of Technology

Binghong Liang

South China University of Technology

Jinjin Nong

South China University of Technology

Youwei Liu

South China University of Technology

Longhan Xie (✉ melhxie@scut.edu.cn)

<https://orcid.org/0000-0002-5137-1413>

Research

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Individualized Generation of Appropriate Assistance Timings for Active Lower Limb Robots via Machine Learning

Guowei Huang¹ (e-mail: 616126836@qq.com), Zikang Zhou¹ (e-mail: mezikang@mail.scut.edu.cn), Binghong Liang¹ (e-mail: 2498675802@qq.com), Jinjin Nong¹ (e-mail: 591265029@qq.com), Youwei Liu¹ (e-mail: 458386139@qq.com) and Longhan Xie^{1*} (e-mail: melhxie@scut.edu.cn)

¹ Shien-Ming Wu School of Intelligent Engineering, South China University of Technology, Guangzhou, 510640, China

*Corresponding author: Longhan Xie (e-mail: melhxie@scut.edu.cn)

Abstract

Background: Obtaining appropriate assistance timings for individual users of active lower limb assistant robots (ALLARs) is one of the major challenges that limit the practical application of robots since very small assistance timing errors greatly affect the robot's assistance effect. However, neither theoretical nor experimental methods can currently generate appropriate assistance timings due to their respective availability or accuracy limitations.

Method: In this paper, we proposed a new method to generate appropriate assistance timings for individual users of ALLARs via machine learning. The method has the accuracy of theoretical methods and the availability of experimental methods. We established a database of ten static physiological parameters, three dynamic parameters, and theoretical appropriate assistance timings, and mapped the static physiological parameters and the dynamic parameters to the theoretical assistance timings using multilayer neuron networks. Fold-cross validation and determination coefficient were used to test the fit of the model. The root mean square error between generated values and true values of each subject was compared to that between the mean of the sample and the true values of each subject to evaluate the data accuracy of our method. We also set $\pm 2\%$ error as the boundary of the practical accuracy and compared the practical accuracy when using our method to that when using the mean generally.

Result: The model achieved a small standard deviation of the square root error in the 10-fold cross-validation experiment and a large determination coefficient. We reduced the data error of starting and ending assistance timing from 0.0265 and 0.0172 to 0.014 ± 0.000429 and 0.0079 ± 0.000875 , respectively, and improved the practical accuracy of starting and ending assistance timing from 54.93% and 75.49% to 89.54% and 99.95%, respectively.

Conclusion: The proposed method can generate an appropriate assistance timings for different users of ALLARs walking at different speeds. Moreover, a new reference for ending assistance timings is provided and the database can be used as a reference for future research. The practical effect of the method will be tested in future work.

Keywords: Individualization; Assistance timing generation; Lower limb assistant robot; Machine learning

Background

In the past two decades, lower limb assistant robots have been playing an important role in the military, outdoor sports, search and rescue, and rehabilitation due to their ability to enhance human strength and reduce exercise metabolism [1, 2].

Lower limb assistant robots can be classified as

active lower limb assistant robots (ALLARs) and passive lower limb assistant robots (PLLARs), according to the availability of an external power source [3]. ALLARs use external power to assist joint motion of human lower limbs directly, while PLLARs often use a mechanism to improve the human motion[4-7]. Compared with PLLARs, which

are often designed for specific motion, ALLARs have a wide range of motion adaptability in principle. Therefore, most commercial lower limb assistant robots are ALLARs.

In recent years, a large number of ALLARs with different structures, control methods, and interaction concepts have been developed [1, 2, 8]. The lightweight design, human-machine joint coupling, and appropriate assistance force affecting the assistance effect of ALLARs have been further explored and solved. Two representative robots are exosuits developed by Harvard University and the autonomous robots developed by MIT [3, 5, 9, 10]. However, the assistance timings of the robots were rough and general in these studies. They ignored the effect of the differences of subjects and speed on the appropriate assistance timing.

The assistance timing of ALLARs is a key factor affecting their assistance effect. Intuitively, an inappropriate assistance timing will invalidate the assistant effect of ALLARs and even cause an extra burden for users. Results of experiments showed that a small error in assistance timings will greatly reduce the assistant effect of ALLARs. The results of several studies showed that a 10%, 11%, and 6% difference in the starting assistance timing caused an approximate maximum 17%, 88%, and 50% metabolic difference, respectively [11-13]. Therefore, the assistance effect is extremely sensitive to the assistance timing.

However, achieving an appropriate assistance timings is still a great challenge, although some theoretical and experimental methods were proposed [11-14]. The "appropriate" means "accurate, individualized and available". In theory, it is generally believed that it is appropriate for a robot to assist a human when the work of the robot coincides with that of human joints [14]. Therefore, we can obtain the appropriate assistance timings according to the state of the joint work. However, accurate joint power acquisition often requires the aid of motion capture and plantar force measurement

equipment. High equipment cost and limited distance restrict the practical application of theoretical methods. Recently, researchers attempted to experimentally explore appropriate interaction timings through experiments. Ye Ding and his colleague evaluated four different onset actuation timings during loaded walking with a soft hip exosuit in eight healthy participants in 2016 [13]. They claimed that starting assistance at 90% of the gait and exerting a peak assisting force at 17% of the gait achieved a minimal metabolism. Philippe Malcolm measured the metabolic cost of ten subjects walking with a simple ankle exoskeleton in 2012 and found that the optimal starting time for ankle assistance was 43% of the gait cycle [11]. Samuel Galle did a more precise walking experiment with an ankle robot in 2017 and found that the optimal starting time for ankle assistance was 42% of the gait cycle [12]. However, there were still some limitations in these experiments. First, a small number of data samples were not enough to prove the validity of the conclusions. Second, all of these experiments were carried out at a constant speed, ignoring the important influence of speed on gait and assistance timings [15]. It is also difficult to explore appropriate assistance timings for different users walking at different speeds because the number of experiments will greatly increase in this situation. Finally, the experimental method can only obtain a general result that is not an optimal result for every ALLAR user, because different users with different height, weight, gender, and age have different gait; therefore, they require different appropriate assistance timings responding to their individualized gait [16, 17]. Owing to the sensitivity of assistance timings to the assistance effect, these inaccurate experimental methods are also not feasible.

In this paper, we proposed a new method to generate accurate and available assistance timings for ALLARs with the advantages of theoretical and experimental methods. We used the state of joint power to judge the appropriate assistance timings

and expressed it with the corresponding node of the gait cycle. Then, a method of machine learning was used to map dynamic parameters and individualized physiological parameters to the assistance timings. This approach solved the assistance timing generation problems caused by individualized gait, variable speed, and the number of data samples. This idea was inspired by the recent generation of individualized gait in the field of hemiplegia rehabilitation [18, 19]. Different from the field of hemiplegia, where a constant gait is required, in the practical application of an active robot for normal people, the speed and foot-ground interaction will change at any time; therefore, assistance timings should be adjusted dynamically. In this paper, in addition to using the individualized physiological parameters that affect the individualized gait, we also introduced three dynamic parameters: gait cycle, proportion of single support, and proportion of double support to reflect the state of the speed and foot-ground interaction.

Specifically, we collected several individualized physiological parameters and the gait data of 151 people at different self-selected speeds. Dynamic parameters and assisting timings were extracted from the gait data. A multilayer neural network was built to map the static physiological parameters and the dynamic parameters to the assistance timings. The determination coefficient (DC) and root mean square error (RMSE) of the predicted and true values of assistance timings in a ten-fold cross-validation test were used to evaluate the fit of the model. The root mean square error and standard deviation (SD) were used to compare the data accuracy of using the mean and individualized predicted assistance timings. In addition, we set a $\pm 2\%$ assistance timing error as the boundary of practical accuracy, referring to previous experimental results. We compared the practical accuracy of general experimental results with that of individualized predicted results in this paper within the practical application boundary. The result showed that our

method can greatly reduce the error of starting and ending assistance timing by 46.8% and 54.1%, respectively, and increase practical accuracy from 54.93% and 75.49% to 89.54% and 99.95%, respectively. Therefore, our method can generate appropriate assistance timings for individual users walking at different speeds and effectively solve the sensitivity problem of the assistance effect on assistance timings in practical application of active robots.

The contributions of this work are as follows. 1) For the first time, appropriate assistance timings are generated via machine learning, and the contradiction between the sensitivity of the assistance effect to the assistance timings in the practical application and the accuracy and availability of existing methods is addressed, making the selected assistance timings can effectively adapt to different subjects walking at different speeds; 2) a new reference for the end of assistance timing is provided, since most of the studies only provided the reference for the start of assistance timing; 3) dynamic parameters are creatively introduced to reflect the actual motion state, which can generate more accurate assistance timings; and 4) a scarce database of static physiological parameters, dynamic parameters, and assistance timings is developed.

Method

Data collection

A total of 151 subjects were invited to participate in the data collection experiments. The subjects were confirmed to have no history of neurological, musculoskeletal, visual or proprioceptive diseases or injuries. To make the results generalizable, the subjects were invited randomly to participate in the experiment, except the gender distribution was kept uniform. The static physiological parameters related to individualized gait were recorded, including age, gender, and 10 body parameters (Fig. 1) [18]. The dynamic parameters included gait cycle, proportion of single support, and proportion of double support, which were measured by four reaction force plates (Bertec,

portable force plate, FP4060-05-PT, USA; 1000HZ) in this paper, and can be also measured easily by foot switches or inertial measurement units found in most of the active robots [12, 20]. A motion capture system (Vicon, Oxford Metrics, UK; 250 Hz) with 10 infrared cameras was used to collect the gait data. Sixteen markers were adhered to the responding anatomic landmarks according to the plug-in gait model. The plug-in gait model is a virtual lower limb model of the motion capture system (Vicon, Oxford Metrics, UK; 250 Hz), which is based on the model established by Kadaba [21]. The subjects were asked to walk five times at five conscious speed levels on a 10 m runway. The software (Nexus, Oxford Metrics, UK) of the motion capture system (Vicon, Oxford Metrics, UK; 250 Hz) recorded the markers position data and calculated the joint kinematics and kinetics with the plug-in gait model (Fig. 2).

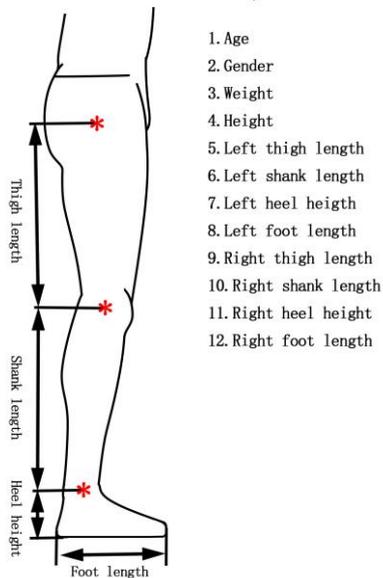


Fig. 1 A total of 12 physiological parameters significantly affected the individualized gait. Age and gender were recorded by a questionnaire. The weight and height were obtained via a weight and height measurement instrument. The thigh length was defined as the distance from the center of rotation of the hip joint to that of the knee joint. The shank length was defined as the distance from the center of rotation of the knee joint to that of the ankle joint. The heel height was defined as the distance from the

center of rotation of the ankle joint to the ground. The foot length was defined as the length of the sole. These lengths were measured by a tape, and the measurements were conducted by a specific operator for a stable measurement errors.

Data preprocessing

Raw data containing joint motion and power of lower limbs and ground reaction force was collected by the motion capture system (Vicon, Oxford Metrics, UK; 250 Hz) and the reaction force plates (Bertec, portable force plate, FP4060-05-PT, USA; 1000Hz), respectively. A gait cycle was considered to be the time interval between the ipsilateral heel striking the ground. The single support phase refers to the state when only one foot touches the ground, while the double support phase refers to the state when two feet touch the ground [22]. Accordingly, we obtained the gait cycle, the proportion of single support phase, and the proportion of double phase support phase from the raw data of reaction force plates (Bertec, portable force plate, FP4060-05-PT, USA; 1000HZ). Then, the joint motion and power corresponding to the gait cycle were selected. The selection of the joint depended on the type of the ALLARs. In this paper, we took the ankle active robot as an example, but the method adapts to all kinds of ALLARs. In theory, the best time for assistance was considered to be consistent with the time of ankle joint positive work [14], so we recorded the starting timing and ending timing of the positive work in a gait cycle as the beginning assistance timing and ending assistance timing, respectively. Then, the assistance timing was normalized by the gait cycle. All these operations were conducted automatically by a computer program in Matlab (The MathWorks Inc., USA).

Multilayer neural networks

Multilayer neural networks were used to map the physiological and dynamic parameters to assistance timings. Structurally, multilayer artificial neural networks are composed of many single neurons [23]. A single artificial neuron mimics the

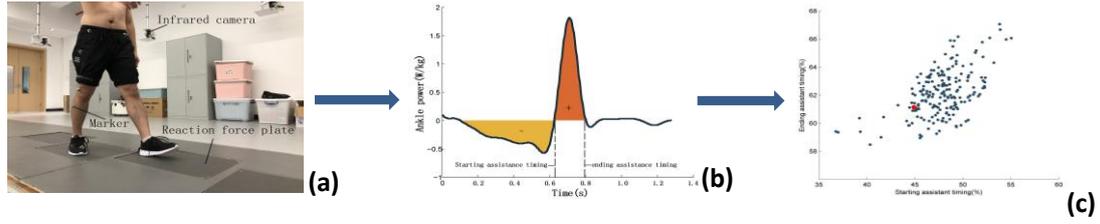


Fig. 2 (a) Raw data collection from the motion capture system (Vicon, Oxford Metrics, UK; 250 Hz) and reaction force plates (Bertec, portable force plate, FP4060-05-PT, USA; 1000HZ). The markers were stuck to the lower limbs and two Velcro strips were used to tie the shorts to the thigh to reduce the shaking of the markers. **(b)** Acquisition of assistance timings. The orange refers to the positive power and the yellow refers to the negative power. The starting timing and the ending timing of the positive work in a gait cycle were the beginning assistance timing and ending assistance timing, respectively. **(c)** Establishment of the database. The red point indicated the new normalized assistance timings. The abscissa indicated the normalized starting assistance timing and the ordinate indicated the normalized ending assistance timing.

function of a nerve cell, which receives excitation from an adjacent neuron and transmits it to the next adjacent neuron if the total received excitation exceeds a certain threshold (Fig. 3 (a)). The single neuron can be expressed with the following formula:

$$y = f\left(\sum_{i=1}^n w_i x_i - \theta\right)$$

where i is the serial number of the neurons; x_i is the output of the i neuron; w_i is the weight of the x_i ; θ is the threshold; and f is the activation function. The capability of a single artificial neuron is limited, but multilayer neural networks can fit any function in theory [24]. The structure and compositions of multilayer neural networks are shown in Fig. 3 (b). The parameters of the input layer are the static and dynamic parameters, and the parameters of the output layer are assistance timings. A multilayer neural network is trained to minimize the difference between the output value and the real value, which usually means the loss function is optimized as follows:

$$E = \frac{1}{2} \sum_{j=1}^k (\hat{y}_l - y_l)^2$$

where l is the l th group in a data set; k is the total group number in the training sample; \hat{y}_l is the l th group predicted assistance timings; y_l is the true values corresponding to \hat{y}_l in the training sample; and E is the value of the loss

function.

Validation process

Cross-validation is often used to evaluate the accuracy of a model[25]. According to the number of samples, we used ten-fold cross-validation. We randomly divided the samples into ten equal groups. Nine groups were used to train the multilayer neural networks, and the remaining group was used to test the multilayer neural networks. Then, training and testing were conducted in turn with new training data and testing data. The determination coefficient and root mean square error of the predicted and true values of each group of test data were calculated in each fold validation. The calculation formula of the determination coefficient and the root mean square error were as follows:

$$DC = \frac{\sum_{q=1}^m (\hat{y}_q - \bar{y})^2}{\sum_{q=1}^m (y_q - \bar{y})^2}$$

$$RMSE = \sqrt{\frac{\sum_{q=1}^m (\hat{y}_q - y_q)^2}{m}}$$

where DC is the determination coefficient; q is the q th group in a data set; $RMSE$ is the root mean square error; m is the total group number in testing sample; \hat{y}_q is the q th group predicted assistance timings; y_q is the true value corresponding to \hat{y}_q in the testing sample; \bar{y} is the mean of the true value in the testing sample.

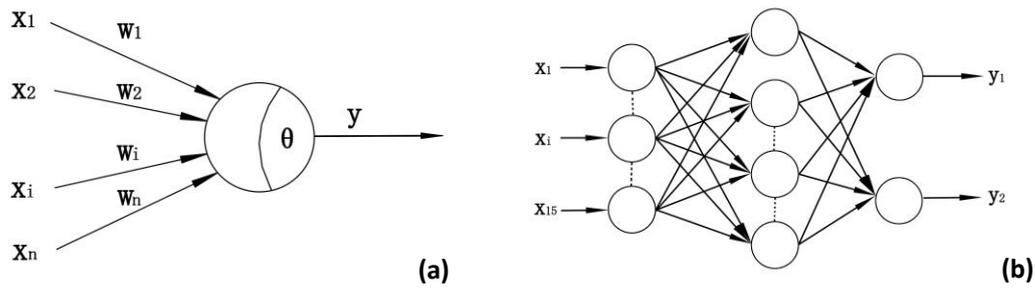


Fig. 3 (a) The structure and compositions of a single neuron model. **(b)** Structure and compositions of a multilayer neurons networks model.

Evaluation process

The average assistance timings of the data samples were consistent with the results of experimental methods in theory. Therefore, we compared the accuracy when using the individualized predicted value with that of the average value to evaluate our work. The accuracy contained data accuracy and practical accuracy. We evaluated the data accuracy by comparing the standard deviation of the sample and the root error mean square error between the predicted assistance timings and the true assistance timings. The standard deviation was regarded as the root mean error between the

mean assistance timings of sample and the true assistance timings of each subject. The practical accuracy was defined as the proportion of people who used the given assistance timings but still had an optimal reduced metabolic cost. we set $\pm 2\%$ assistance timing error as the boundary of practical accuracy, which meant the given assistance did not exceed 2% of the theoretical optimal assistance timing. The boundary setting was subjective but reasonable and strict because there is still no accurate experimental data to support this boundary directly, and we referred to the general results of some of studies where 6%

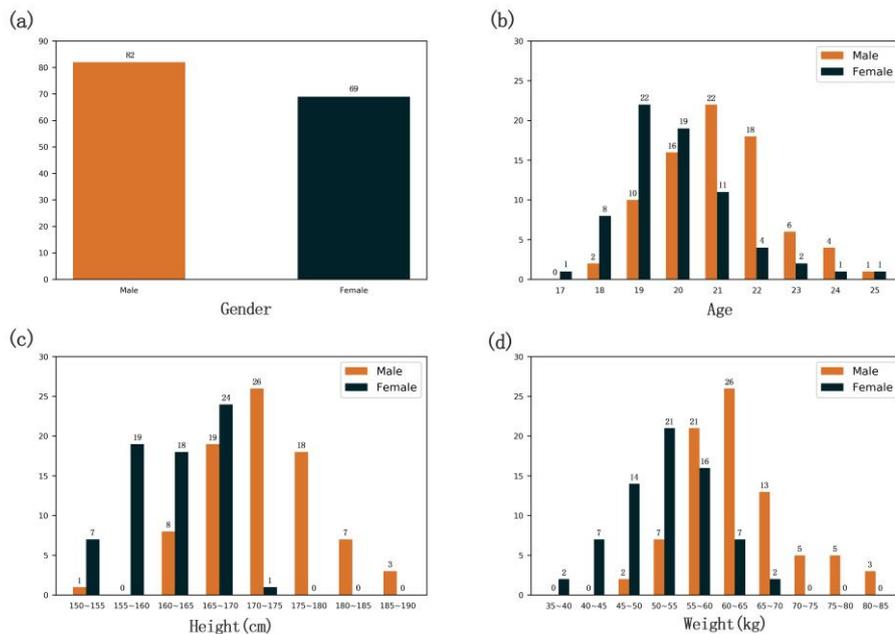


Fig. 4 A total 151 subjects participated in the data collection experiment. **(a)** Gender distribution. **(b)** Age distribution. **(c)** Height distribution. **(d)** Weight distribution.

errors of the optimal assistance timings caused a 21% increase in metabolism [12]. We compared the proportion of people who used the mean value that did not deviate from the true value by 2% with the proportion of people who used the predicted value that did not deviate from the true value by 2% to test the practical accuracy.

Result

The distributions of some of the main physiological parameters are shown in Fig. 4. A comparable number of males and females were recruited for the experiment. For both gender, age, height, and weight showed a normal distribution. The results were consistent with expectations for the method of inviting subjects.

Table 1: the ten-fold cross-validation results

Test number	Starting assistance timing		Ending assistance timing	
	RMSE	DC	RMSE	DC
1	0.0123	0.7302	0.0061	0.8536
2	0.0145	0.7355	0.0151	0.2781
3	0.0159	0.6276	0.0057	0.8721
4	0.0144	0.7370	0.00069	0.8558
5	0.0142	0.7062	0.0076	0.8414
6	0.0156	0.6911	0.0076	0.8002
7	0.0172	0.5856	0.0058	0.8536
8	0.0145	0.7122	0.0094	0.7203
9	0.0142	0.6950	0.0072	0.7536
10	0.0134	0.8039	0.0072	0.8755
Mean	0.0146	0.7024	0.0079	0.770
SEM	0.000429	0.019119	0.000875	0.057117

Table 1 shows the result of the ten-fold cross-validation. The RMSEs of the predicted starting and ending assistance timings were 0.014 ± 0.000429 and 0.0079 ± 0.000875 , respectively (Fig. 5 (a)). The DEs of the starting and ending assistance timings were 0.7024 ± 0.019119 and 0.770 ± 0.057117 , respectively. The standard deviations of the starting and ending assistance timings were 0.0265 and 0.0172, respectively (Fig. 5 (a)). Compared to generally using average assistance timings as the assistance timing for each user, using our method can reduce the error of the starting and ending assistance timing by 46.8% and 54.1%, respectively.

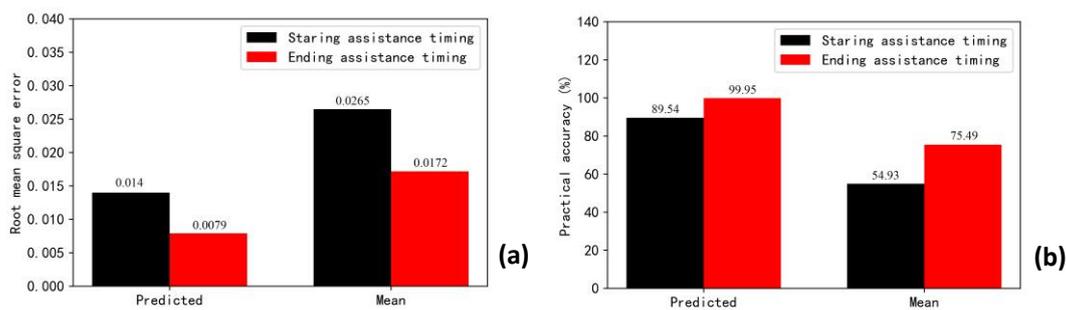


Fig. 5 Accuracy when using the predicted value with that of the average value. (a) Data accuracy. (b) practical accuracy.

Fig. 6 shows the predicted assistance timings and corresponding true assistance timings. Intuitively, the distance between the predicted value and the corresponding true value was smaller than that between the average value and the real value for most of the subjects. We set $\pm 2\%$

as an acceptable practical error. The statistical results showed that within the error range, the practical accuracies of our method were 89.54% and 99.95% while those of the method using the average starting and ending assistance timings were 54.93% and 75.49%, respectively (Fig.5 (b)).

We improved the practical accuracy to a degree that our method could generate theoretical

optimal assistance timings for almost all the users.

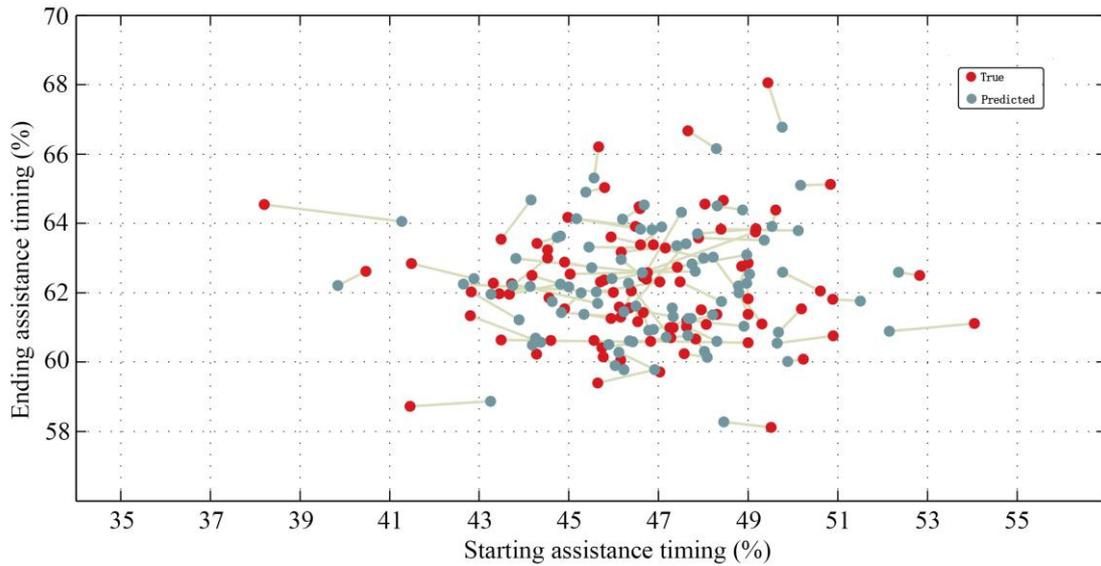


Fig. 6 Predicted assistance timings and corresponding true assistance timings. Red points are the true assistance timings, and blue points are the predicted assistance timings. Black lines indicated the corresponding relationship between the predicted value and the true value.

5. Discussion

The main contribution of this paper is that for the first, the contradiction between the sensitivity of the assistance effect to assistance timings in practical application and the accuracy and availability of the existing methods is addressed, making the selected assistance timings can effectively adapt to different subjects walking at different speeds. We propose a machine learning methodology to generate appropriate assistance timings for the users. Compared to methods that used general assistance timings for ALLAR users, the presented method can generate more accurate and individualized assistance timings. The accuracy of the results meets the practical application requirements for most of the users.

Validation and evaluation

The determination coefficient is often used to verify the fit of the regression model. The determination coefficient refers to the proportion of variation of the dependent variable explained by the regression relationship in its total variation[26]. The larger the coefficient of determination, the better the fit of the model.

There is no uniform standard, and we believe that the determination coefficient in our results were relatively high based on our experience. This supported that the selection of the static physiological parameters and the hyper-parameters were appropriate.

The use of the mean assistance timings as a control group has practical and statistical significance. Regarding the practical significance, the experimental results that explore the optimal assistance timings should be close to the mean, so the mean is representative of general assistance timings. Regarding the statistical significance, the assistance timings in the samples approximately adhered to a normal distribution based on the observation of the sample distribution. When the average assisting timings were used for different users, the minimum root mean square error was achieved. The root mean square error was equal to the standard deviation. Therefore, we compared the mean RMSE of assistance timings of ten-fold cross-validation with the standard deviation of the assistance timings in the samples. The improvement of the data accuracy of the starting and ending assistance timings by 46.8% and 54.1%

confirmed that the individualized generation of assistance timings for each subject was better than the use of the general value of the assistance timings.

Furthermore, we evaluated the practical accuracy of our method. Aiming to obtain the appropriate assistance timings for ankle active robots, some previous experimental studies have come to a similar conclusion[12]. If the experimental results were used as the assistance timings for each subject, the 6% assistance timings error would cause about a 21% decrease in the assistance effect. However, the conclusions of these studies were not suitable for the practical application of other robots, because the number of samples in these experiments was too small to obtain a result of statistical significance, and the results ignored the effect of speed variation and the response of ankle robots to the assistance timings. The inappropriate use of these results will result in a greater decline in the effect of assistance since a 6% difference in the assistance timing can cause a maximum of a 50% decrease of assistance effect[12]. Therefore, we subjectively set a more stringent assistance timings error range of $\pm 2\%$ as an acceptable boundary. Our results showed that the individualized method improved the accuracy probability of starting and ending assistance timings from 89.54% and 99.95% to 54.93% and 75.49%, respectively. These results met practical application requirement.

Parameter selection

Assistance timings are relative to gait, so the factors affecting the gait can affect the appropriate assistance timings. A large number of studies have found that these factors included age, gender, height, weight, muscle strength, speed, and habit of exerting force[15-17, 27]. Not all factors were selected because some factors were difficult to measure, and too many parameters would increase the model dimension and model training difficulty. Therefore, we selected 10 static physiological parameters and 3 dynamic parameters that significantly affect or relate to the

gait. Both static physiological parameters and dynamic parameters are quick and easy to obtain. The static physiological parameters have often been acquired in advance in most ALLARs to make initial adjustments, such as prestretching and size adjustment. The dynamic parameters can be measured by the footswitches or the devices with similar functions of most of ALLARs.

Regression algorithm

At present, there are many powerful regression methods such as multilayer neural networks regression[23], support vector regression[28], and Gaussian process regression[29]. We chose to use multilayer neural networks because of their excellent nonlinear mapping capability. It has been confirmed that neural networks with three layers can fit any continuous nonlinear function perfectly[24]. Since the complexity of the relationship between the assistance timings and the 13 parameters was unknown, the model with the strongest mapping capability was preferred.

Conclusion

In summary, this paper proposed a statistical methodology to solve problems with the generation of appropriate assistance timings for ALLAR users. This method can generate individualized assistance timings that can be adapted to different subjects walking at different speeds. The results show that the proposed method greatly improves the accuracy and breaks through limitations of assistance timings on the practical application of ALLARs.

Moreover, a new reference for ending assistance timing is proposed. The dynamic parameters and a database of static physiological parameters, dynamic parameters, and assistance timings provide a reference for later research.

Future work

In this paper, we only analyzed the error between the assistance timings generated by our method and the real assistance timings, and the accuracy rate within the error boundary of practical application. The error boundary for practical

accuracy was assumed based on the results of previous studies. Future work will be performed to experimentally apply the proposed method to active robots and test the assistance effect. The results obtained from using the experimental method will be compared with current results to verify the effectiveness of the proposed method in the experiment.

Abbreviations

ALLAR: Active lower limb assistant robot; PLLAR: Passive lower limb assistant robot; DC: determination coefficient; RMSE: root mean square error; SD: standard deviation.

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Authors' contributions

GH conceived the study design, designed the experiment, analyzed the data, discussed the result, and drafted the manuscript. ZZ collected the gait data and trained the multilayer neural networks. BL and JN measured the static physiological parameters of males and females, respectively. LX and YL were involved in the study design. All authors read and approved the final manuscript.

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Practicability of data and material

The datasets analyzed during the current study are available from the corresponding author on reasonable request.

Ethics approval and consent to participate

Informed consent was obtained from all participants to complete the protocol approved by the Guangzhou First People's Hospital Department of Ethics Committee.

Consent for publication

The authors received consent for the publication of

the photographs used within the manuscript.

Competing interests

The authors declare that they have no competing interests.

Author details

Shien-Ming Wu School of Intelligent Engineering, South China University of Technology, Guangzhou 510640, China.

References

- [1] W. Huo, S. Mohammed, J. C. Moreno, and Y. Amirat, "Lower Limb Wearable Robots for Assistance and Rehabilitation: A State of the Art," *IEEE Systems Journal*, vol. 10, pp. 1068-1081, 2017.
- [2] A. J. Young and D. P. Ferris, "State of the Art and Future Directions for Lower Limb Robotic Exoskeletons," *IEEE Transactions on Neural Systems & Rehabilitation Engineering*, vol. 25, pp. 171-182, 2017.
- [3] L. M. Mooney, E. J. Rouse, and H. M. Herr, "Autonomous exoskeleton reduces metabolic cost of human walking during load carriage," *Journal of neuroengineering and rehabilitation*, vol. 11, p. 80, 2014.
- [4] A. B. Zoss, H. Kazerooni, and A. Chu, "Biomechanical design of the Berkeley lower extremity exoskeleton (BLEEX)," *IEEE/ASME Transactions on mechatronics*, vol. 11, pp. 128-138, 2006.
- [5] F. A. Panizzolo, I. Galiana, A. T. Asbeck, C. Sivi, K. Schmidt, K. G. Holt, *et al.*, "A biologically-inspired multi-joint soft exosuit that can reduce the energy cost of loaded walking," *J Neuroeng Rehabil*, vol. 13, p. 43, May 12 2016.
- [6] S. H. Collins, M. B. Wiggin, and G. S. Sawicki, "Reducing the energy cost of human walking using an unpowered exoskeleton," *Nature*, vol. 522, pp. 212-215, 2015.
- [7] F. A. Panizzolo, C. Bolgiani, L. Di Liddo, E. Annese, and G. Marcolin, "Reducing the energy cost of walking in older adults using a passive hip flexion device," *Journal of*

- NeuroEngineering and Rehabilitation*, vol. 16, 2019.
- [8] W. Meng, Q. Liu, Z. Zhou, Q. Ai, B. Sheng, and S. S. Xie, "Recent development of mechanisms and control strategies for robot-assisted lower limb rehabilitation," *Mechatronics*, vol. 31, p. S0957415815000501, 2015.
- [9] L. M. Mooney and H. M. Herr, "Biomechanical walking mechanisms underlying the metabolic reduction caused by an autonomous exoskeleton," *J Neuroeng Rehabil*, vol. 13, p. 4, Jan 28 2016.
- [10] A. T. Asbeck, S. M. M. D. Rossi, K. G. Holt, and C. J. Walsh, "A biologically inspired soft exosuit for walking assistance," *International Journal of Robotics Research*, vol. 34, pp. 744-762, 2014.
- [11] P. Malcolm, W. Derave, S. Galle, and D. De Clercq, "A simple exoskeleton that assists plantarflexion can reduce the metabolic cost of human walking," *PloS one*, vol. 8, p. e56137, 2013.
- [12] S. Galle, P. Malcolm, S. H. Collins, and D. De Clercq, "Reducing the metabolic cost of walking with an ankle exoskeleton: interaction between actuation timing and power," *Journal of neuroengineering and rehabilitation*, vol. 14, p. 35, 2017.
- [13] Y. Ding, F. A. Panizzolo, C. Siviyy, P. Malcolm, I. Galiana, K. G. Holt, *et al.*, "Effect of timing of hip extension assistance during loaded walking with a soft exosuit," *Journal of Neuroengineering & Rehabilitation*, vol. 13, p. 87, 2016.
- [14] B. Quinlivan, S. Lee, P. Malcolm, D. Rossi, M. Grimmer, C. Siviyy, *et al.*, "Assistance magnitude versus metabolic cost reductions for a tethered multiarticular soft exosuit," *Sci. Robot*, vol. 2, pp. 1-10, 2017.
- [15] G. Cappellini, Y. P. Ivanenko, R. E. Poppele, and F. Lacquaniti, "Motor patterns in human walking and running," *J Neurophysiol*, vol. 95, pp. 3426-37, Jun 2006.
- [16] D. C. Kerrigan, M. K. Todd, and U. D. Croce, "GENDER DIFFERENCES IN JOINT BIOMECHANICS DURING WALKING Normative Study in Young Adults," *American Journal of Physical Medicine & Rehabilitation*, vol. 77, pp. 2-7, 1998.
- [17] M. M. Samson, A. Crowe, P. L. d. Vreede, J. A. G. Dessens, S. A. Duursma, and H. J. J. Verhaar, "Differences in gait parameters at a preferred walking speed in healthy subjects due to age, height and body weight," *Aging Clinical & Experimental Research*, vol. 13, pp. 16-21, 2001.
- [18] Y. Yun, H. C. Kim, S. Y. Shin, J. Lee, A. D. Deshpande, and C. Kim, "Statistical method for prediction of gait kinematics with Gaussian process regression," *J Biomech*, vol. 47, pp. 186-92, Jan 3 2014.
- [19] C. C. Jisoo Hong , Seung-Jong Kim, and Frank C. Park, "Gaussian Process Trajectory Learning and Synthesis of Individualized Gait Motions," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, pp. PP(99):1-1, 2019.
- [20] Y. Ding, I. Galiana, C. Siviyy, F. A. Panizzolo, and C. Walsh, "IMU-based iterative control for hip extension assistance with a soft exosuit," in *2016 IEEE International Conference on Robotics and Automation (ICRA)*, 2016, pp. 3501-3508.
- [21] M. P. Kadaba, H. K. Ramakrishnan, and M. E. Wootten, "Measurement of lower extremity kinematics during level walking," *Journal of Orthopaedic Research*, vol. 8, pp. 383-92, 1990.
- [22] J. Perry, K. Slac, and J. R. Davids, "Gait Analysis," *Journal of Pediatric Orthopaedics*, vol. 12, p. 815, 1992.
- [23] C. M. Bishop, *Neural Networks for Pattern Recognition*: Oxford University Press, Inc., 1995.
- [24] K. Hornik, "Approximation capabilities of

- multilayer feedforward networks," *Neural Networks*, vol. 4, pp. 251-257, 1991.
- [25] K. RON, "A study of cross-validation and bootstrap for accuracy estimation and model selection," in *Proceedings of the Fourteenth International Joint Conference on Artificial Intelligence, 1995*, 1995.
- [26] J. A. Cornell, "Factors that influence the value of the coefficient of determination in simple linear and nonlinear regression models," *Phytopathology*, vol. 77, pp. 63-70, 1987.
- [27] J. Lexell and U. B. Flansbjer, "Muscle strength training, gait performance and physiotherapy after stroke," *Minerva Medica*, vol. 99, pp. 353-368, 2008.
- [28] A. J. SMOLA and B. SCHOELKOPF, "A tutorial on support vector regression," *Stats and computing*, vol. 14, pp. p.199-222, 2004.
- [29] MATTHIAS and SEEGER, "GAUSSIAN PROCESSES FOR MACHINE LEARNING," *International Journal of Neural Systems*, 2004.

Figures

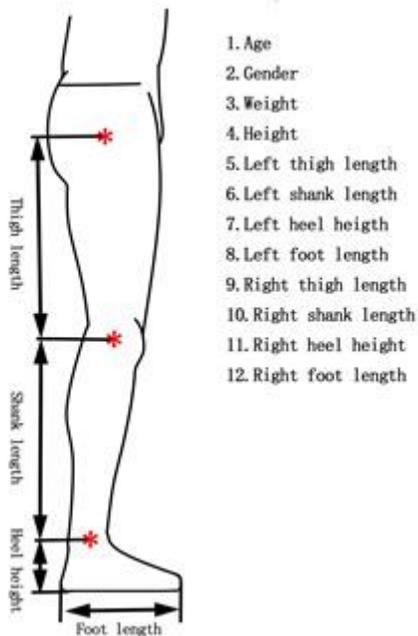


Figure 1

A total of 12 physiological parameters significantly affected the individualized gait. Age and gender were recorded by a questionnaire. The weight and height were obtained via a weight and height measurement instrument. The thigh length was defined as the distance from the center of rotation of the hip joint to that of the knee joint. The shank length was defined as the distance from the center of rotation of the knee joint to that of the ankle joint. The heel height was defined as the distance from the center of rotation of the ankle joint to the ground. The foot length was defined as the length of the sole. These lengths were measured by a tape, and the measurements were conducted by a specific operator for a stable measurement errors.

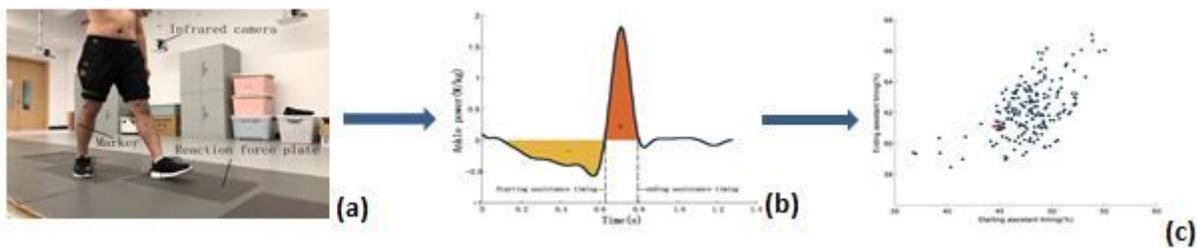


Figure 2

(a) Raw data collection from the motion capture system (Vicon, Oxford Metrics, UK; 250 Hz) and reaction force plates (Bertec, portable force plate, FP4060-05-PT, USA; 1000HZ). The markers were stuck to the lower limbs and two Velcro strips were used to tie the shorts to the thigh to reduce the shaking of the markers. (b) Acquisition of assistance timings. The orange refers to the positive power and the yellow

refers to the negative power. The starting timing and the ending timing of the positive work in a gait cycle were the beginning assistance timing and ending assistance timing, respectively. (c) Establishment of the database. The red point indicated the new normalized assistance timings. The abscissa indicated the normalized starting assistance timing and the ordinate indicated the normalized ending assistance timing.

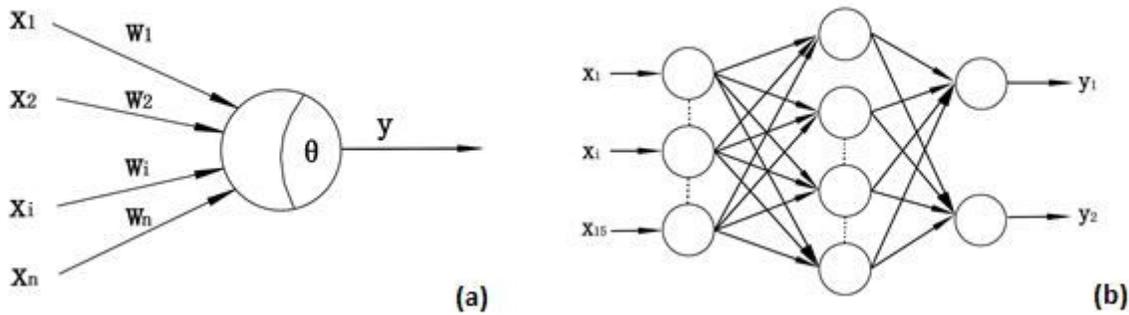


Figure 3

(a) The structure and compositions of a single neuron model. (b) Structure and compositions of a multilayer neurons networks model.

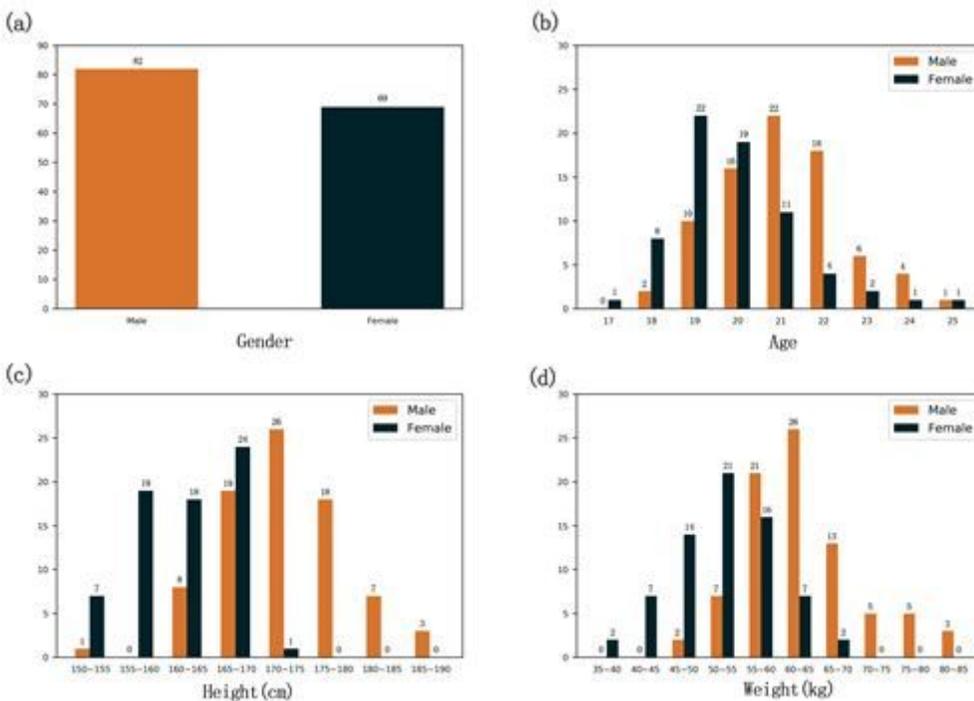


Figure 4

A total 151 subjects participated in the data collection experiment. (a) Gender distribution. (b) Age distribution. (c) Height distribution. (d) Weight distribution.

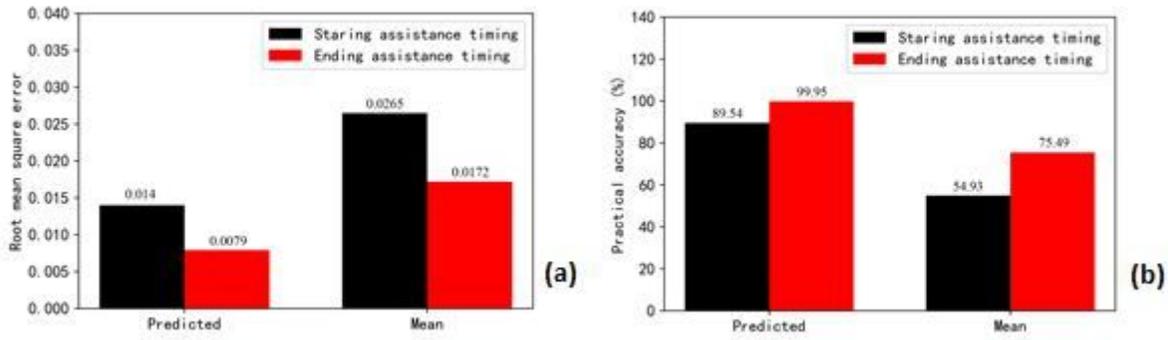


Figure 5

Accuracy when using the predicted value with that of the average value. (a) Data accuracy. (b) practical accuracy.

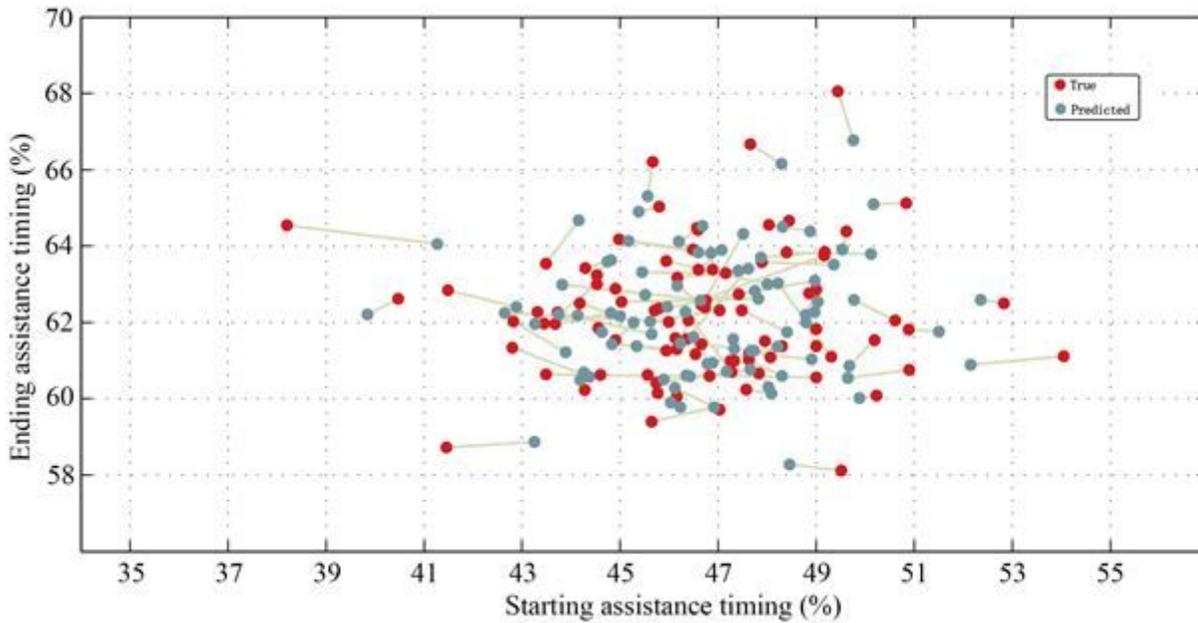


Figure 6

Predicted assistance timings and corresponding true assistance timings. Red points are the true assistance timings, and blue points are the predicted assistance timings. Black lines indicated the corresponding relationship between the predicted value and the true value.