International Journal of Innovative Computing, Information and Control
Volume **16**, Number **2**, April **2020**

ICIC International ©2020 ISSN 1349-4198
pp. 597–608

A NEW FALL DETECTION METHOD BASED ON FUZZY REASONING FOR AN OMNI-DIRECTIONAL WALKING TRAINING ROBOT

Yina Wang[1], Wenqiu Xiong[1], Junyou Yang[1] and Shuoyu Wang[2]

[1]School of Electrical Engineering
Shenyang University of Technology
No. 111, Shenliao East Road, Shenyang 110870, P. R. China
wangyina0402@126.com; xiongvenco@163.com; junyouyang@sut.edu.cn

[2]School of Systems Engineering
Kochi University of Technology
185 Miyanokuchi, Tosayamada, Kami City, Kochi 782-8502, Japan
wang.shuoyu@kochi-tech.ac.jp

Received August 2019; revised December 2019

Abstract. *To regain and then improve the walking ability for the people with lower limb disabled, the authors have been developing a new type of omnidirectional walking training robot (WTR). This WTR can help physical therapist to conduct the walking training for lower limb disabled by performing specific training course designed by the physical therapist. To ensure the training effect, a path tracking controller was proposed to enable the WTR to precisely track the designed path. However, there is the risk of the fall while carrying out walking training by the WTR, which lead the second damage to users. In order to improve the functionality and reliability of the WTR, a fall detection method is proposed based on the fuzzy reasoning method. In detail, a posture sensor and a two-dimensional (2D) laser sensor are used to detect the body's posture and positions of two legs for user in the WTR. Then, a fuzzy knowledge base differentiating the normal walking state and one kind of falling state is set up based on the fusion information of the two sensors. Furthermore, a fall detection strategy based on the combination of upper body posture and gait information is proposed, while the user's fall state is analyzed by a novel fuzzy reasoning mechanism. Finally, the effectiveness of the proposed method is verified by a series of experiments.*

Keywords: Fall detection method, Walking training robot, Fuzzy reasoning, Degree of membership

1. **Introduction.** In recent years, population aging is a significant demographic characteristic of modern society [1]. Illness and traffic accidents have also led to an increase in the number of disabled people [2]. The weakening of the walking ability of the elderly and the disabled not only affects their lives, but also puts a burden on their families and society [3]. Therefore, it is necessary to improve their walking ability through training. At present, lower limb rehabilitation training robots have crutches, walking aids, exoskeleton walking booster and the wearable gait rehabilitation robot system coordinated with treadmill [4]. Some researchers have done a lot of research on the control of robots, which can help the elderly and the disabled to have better rehabilitation training. The authors of [5] proposed a semi-active fault tolerant control scheme, which can solve the problems of trajectory tracking, center of gravity (COG) deviation and actuator failure of omni-

DOI: 10.24507/ijicic.16.02.597

directional rehabilitation training robots. The authors of [6] proposed an intelligent walking robot sharing control algorithm based on reinforcement learning, which can improve the user's comfort when using equipment and automatically adapt to the user's behavior. However, due to the weakness of lower limb's muscles, people are prone to fall down and cause secondary injuries during walking training. Each year, an estimated 646,000 individuals die from falls globally, of which over 80% are in low- and middle-income countries [7]. Falling is undoubtedly the main cause of fatal injuries to the elderly and the disabled, so it is necessary to improve the ability of walkers to detect falls and prevent falls.

In recent years, many researches for detecting falls have been studied. Specifically, the authors of [8,9] developed an approach for fall detection based on multi-sensor fusion based on the back propagation (BP) neural network. It is inconvenient for the elderly to wear many sensors, and data fusion is also time consuming. The authors of [10] proposed to use torque sensor and laser sensor to identify the motion intentions of upper and lower limbs respectively, and then to detect falls by support vector machine algorithm. Due to the proportional relationship between human-machine interface based on force sensor and interactive force. It is difficult to adjust the appropriate scaling factor to increase the compliance of the walker. When people and robots fall down, the speed of the walker may be accelerated, which is dangerous for users. The shortcomings of [8-10] are that multi-sensor makes data fusion more time consuming and reduces the comfort and safety of users. To solve this problem, the authors of [11,12] proposed to use image recognition to recognize the falling state of people. Because the acquisition of visual information is easily affected by environment, the recognition rate is low. The authors of [1,13] proposed a zero-moment point (ZMP) algorithm to detect falling. However, the ZMP in human walking will not be fixed under the supporting feet. The authors of [14] proposed a COG algorithm to detect falling. When the user's COG exceeds the safety threshold, the user is detected to fall down. Up to now, compared with the above research, the data fusion of this research is faster and the recognition rate is also improved. However, there is still the problem that the COG has errors due to different walking speeds of users. The shortcomings of [1,11-14] are that the recognition rate is low and all the fall states of users cannot be detected quickly. To solve the problems of time-consuming data fusion, low comfort and safety of users, and low recognition rate in the existing research, this paper proposes a research on fall detection of walking training robot (WTR) based on fuzzy reasoning, which mainly uses a high precision posture sensor and a two-dimensional (2D) laser sensor. Using only one wearable sensor not only avoids the problem of low user comfort, but also ensures the recognition effect. Since the walking habits of users are not necessarily the same each time, the use of a sensor may easily lead to misjudgment of the walker. For example, the user's pace suddenly increases but is still in a normal walking state, but the robot will make corresponding protection measures when it detects the increase of the user's pace. To avoid misjudgment, this study proposes to measure the tilt angle of the user's upper body when walking normally with posture sensors and to measure the user's gait information with laser sensors. After data preprocessing, membership functions are respectively established through data rules, and then fuzzy rules of inclination angle and gait information are established. The membership degree of the user's safe walking state is obtained by the weighted average method so as to judge the user's walking state. By using the fuzzy reasoning method to analyze the upper body state and the lower limb state together, the walker can more accurately and comprehensively identify the forward falling state of the user, and the problem of low recognition rate is solved. Experimental results verify the effectiveness of the method.

The remainder of the paper is organized as follows. In Section 2, we introduce the structure of WTR and the types of sensors, as well as the normal walking state and

forward falling state of users when using WTR. In Section 3, a fall detection strategy based on the combination of upper body posture and gait information is proposed, while the user's fall state is analyzed by a novel fuzzy reasoning mechanism. In Section 4, the effectiveness of the proposed method is verified by a series of trials and compared with another method. In Section 5, we conclude this paper and state the future research.

2. **Walking Training Robot, Posture Sensor and 2D Laser Sensor.** In previous research, we developed an omni-directional WTR which can help the physical therapist to conduct the walking training for lower limb disabled [15]. As shown in Figure 1, the transmission mechanism of WTR is composed by 4 omni wheels, and each wheel can be independently driven by a motor controlled by a servo controller. Users can adjust the speed and direction of each wheel by controlling panel to realize all-round movement. And, the training course can be uploaded in the panel to execute the walking training. However, the WTR has not the function of fall detection which is essential for the users. In order to improve the functionality and reliability of the WTR, a fall detection method is proposed in this paper.

The 2D laser sensor installed at the bottom of the walker is used to detect the left foot displacement (L_l) and the right foot displacement (L_r) as shown in Figure 1. The laser sensor has 682 laser spots with a scanning range of 240 degrees and a scanning distance of 4 meters as shown in Figure 2. In addition, the scanning period of the laser sensor is 100 ms. The posture sensor is a Wireless Standalone Sensing System (WSSS) wireless networking three-dimensional motion posture measurement system. The position of the posture sensor placed on the human body during the experiment and the directions of earth coordinate systems X, Y, Z and sensor coordinate systems X_s, Y_s, Z_s as shown in Figure 3. According to many experiments, the angle change of Roll rotating around the earth coordinate system X is the most obvious when the user falls down. Therefore, the rotation angle of Roll around the earth coordinate system X is selected as the target variable, expressed as θ_x in the position shown in Figure 3. In addition, the scanning period of the posture sensor is 50 ms.

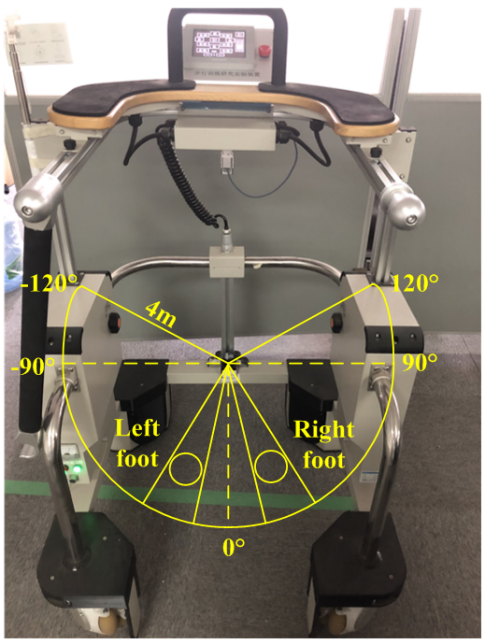


Figure 1. The WTR

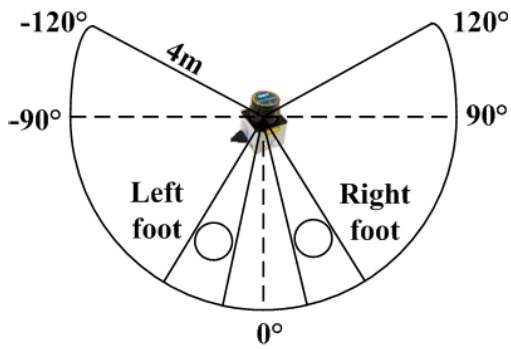


Figure 2. 2D laser sensor

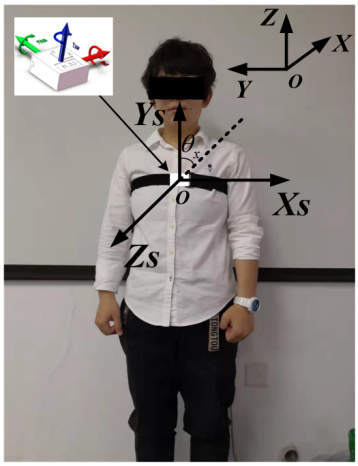
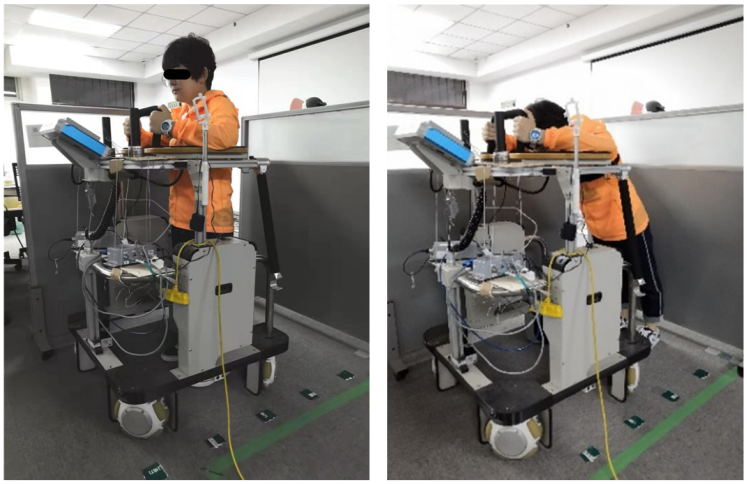


FIGURE 3. Wearing position of posture sensor



(a) Safety state (b) One danger state

FIGURE 4. Walking state

The user from the normal walking state to the forward falling state with the help of WTR is shown in Figure 4. During walking, the laser sensor will detect the user's gait information, and the posture sensor will detect the user's θ_x. And then, a fall detection method is proposed based on the fuzzy reasoning method using fusion information of the two sensors.

3. Fall Detection Method.

3.1. Establishing model. In practical walking assistant, the user walks inside the robot as shown in Figure 4(a) and the walking region as shown in Figure 5. The effective data that the laser sensor can scan is from -60 to 60 degrees.

In order to ensure the reliability of the experiment, we require the subjects to have a certain time interval for each walking training. After many experiments, we take the midpoint of the scanned leg as the characteristic point. The observation of the characteristic points shows that the data of θ_x, L_l and L_r of the user during normal walking conform to normal distribution.

$$X_i' = \frac{X_i - \mu}{\sigma} \tag{1}$$

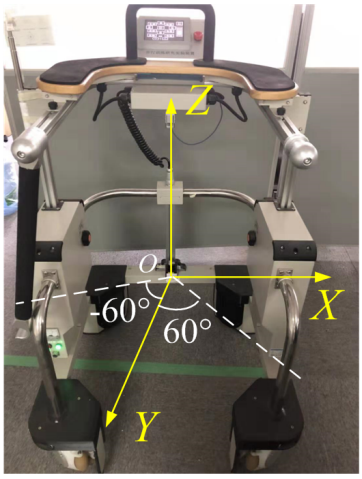


FIGURE 5. Walking zone within WTR

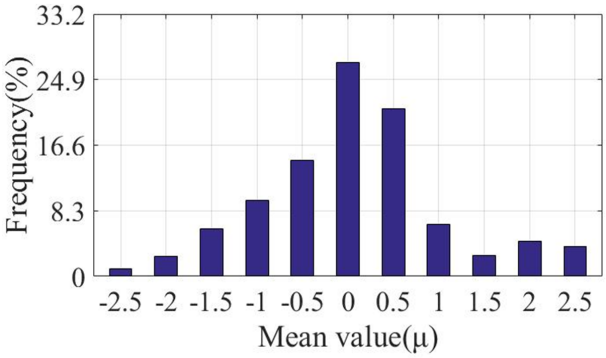


FIGURE 6. Standardized θ_x

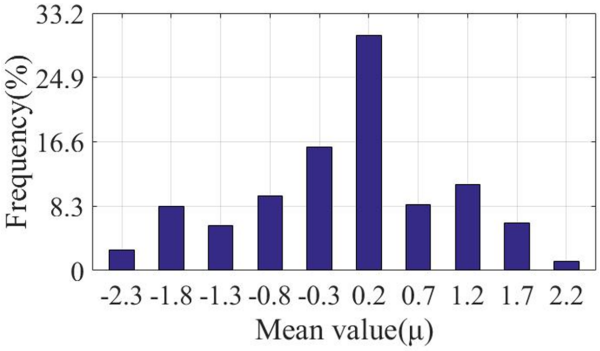


FIGURE 7. Standardized L_l

Therefore, the experimental data X_i are subjected to z-score standardization processing to obtain data X_i' as shown in Formula (1), μ is the mean value, and σ is the standard deviation.

The standardized data of θ_x, L_l and L_r conform to normal distribution. The data are gathered around 0 with a variance of 1 shown in Figures 6, 7 and 8. According to probability theory, the probability that the data conforming to normal distribution falls on $[\mu-3\sigma, \mu+3\sigma]$ is the largest. Considering the actual situation, the standardized ranges of θ_x, L_l and L_r are taken as the safety range for users to walk normally. Calculated by

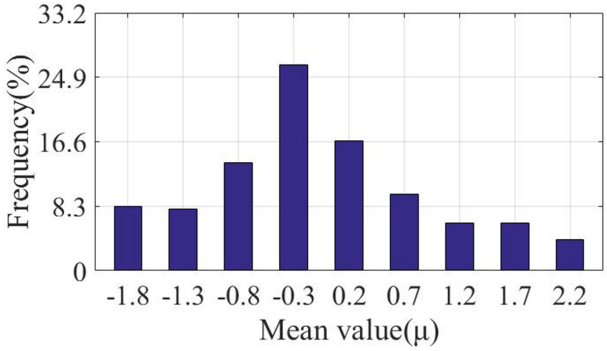
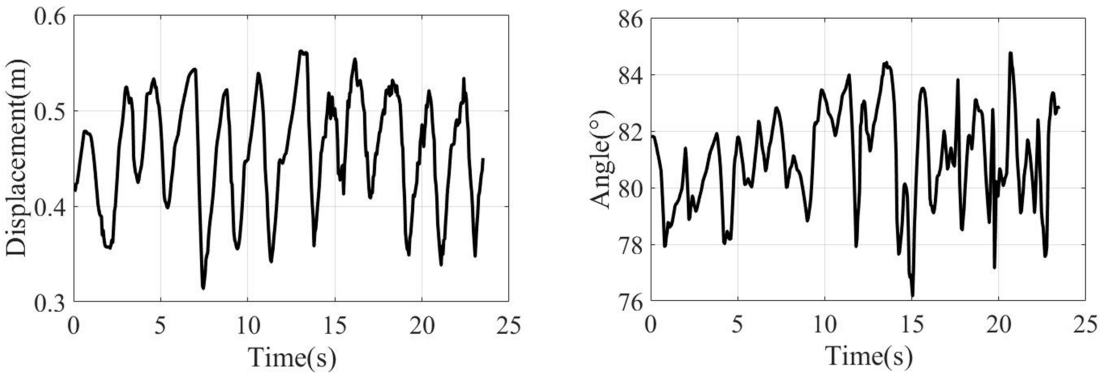


FIGURE 8. Standardized L_r

Formula (1), the safety range of θ_x is $[70.4°, 91°]$, the safety range of L_l is $[316.9, 594.4]$ mm, and the safety range of L_r is $[322.3, 595.8]$ mm.

3.2. **Data processing of 2D laser sensor and posture sensor.** The scanning range of the 2D laser sensor is 240 degrees and the scanning distance is 4 meters. During walking, the user's maximum foot movement range is 60 cm and the movement area is 120 degrees. To eliminate the interference of WTR external motion, it is very important to extract the user's effective gait information. Therefore, we only acquire laser scanning data in the area shown in Figure 5. As the user walks, the extracted data is processed as shown in Figure 9(a). The posture sensor can feed back the Yaw, Pitch, Roll in real time. As the user moves forward, selecting a characteristic θ_x for preprocessing, the extracted data is processed as shown in Figure 9(b).



(a) Gait information (b) θ_x information

FIGURE 9. Eigenvalue curve of walking forward

3.3. **Fuzzy reasoning method.** Fuzzy reasoning system is a system based on fuzzy set theory and fuzzy reasoning method, which is used to process fuzzy information and make decisions. Fuzzy reasoning is a reasoning method used to solve fuzzy phenomena and is a bionic reasoning process based on behaviors [16]. Fuzzy reasoning is considered as an effective method to deal with the problem of uncertain rules [17]. For the process from normal walking to falling, due to the sudden and uncertain nature of the process, the safety thresholds of θ_x, L_l and L_r obtained through limited experiments are not representative and cannot represent the walking situation each time. Therefore, we adopt the fuzzy reasoning method to judge the current state of θ_x, L_l and L_r to establish reasonable fuzzy

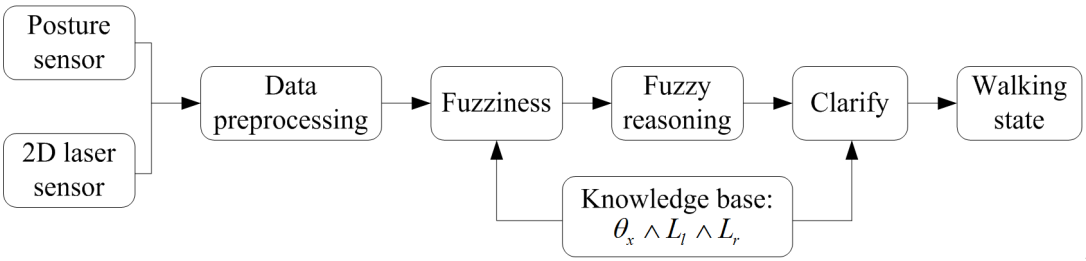


FIGURE 10. Fuzzy reasoning flow chart

rules to judge the walking state of the person more accurately and effectively to avoid falling. The fuzzy reasoning flow chart is shown in Figure 10.

3.4. **Determining membership function.** Membership degree belongs to the concept of fuzzy evaluation function: fuzzy comprehensive evaluation is a very effective multi-factor decision-making method to make a comprehensive evaluation of things affected by various factors. The value of $[0, 1]$ indicates the degree to which the accurate value belongs to the fuzzy value. Its characteristic is that the evaluation result is expressed by a fuzzy set instead of absolutely affirming or negating. In Section 3, it has been found that θ_x, L_l and L_r satisfy the normal distribution rule after many trials. Considering the actual situation of falling forward, observe the probability distribution of standardized θ_x, L_l and L_r in Figures 7, 8 and 9, and find that the absolute safe range of θ_x is between $[-2.7, 1]$, and $[1, 2.7]$ including both safe and dangerous states. The absolute safe range for L_l is between $[-2.5, 1]$ and $[1, 2.5]$ including both safe and dangerous states. The absolute safe range for L_r is between $[-2, 1]$, and $[1, 2.5]$ including both safe and dangerous states. The range of each state is calculated by Formula (1), and membership function is obtained shown in Tables 1, 2 and 3.

TABLE 1. Membership function $\mu(x)$ of θ_x (°)

State \ Angle	$[70.4, 84.5)$	$[84.5, 91)$	$[91, +\infty)$
Safety	1	$e^{-\frac{1}{6.5}(\theta-84.5)^2}$	0
Danger	0	$1 - e^{-\frac{1}{6.5}(\theta-84.5)^2}$	1

TABLE 2. Membership function $\mu(x)$ of L_l (mm)

State \ Displacement	$[316.9, 511.1)$	$[511.1, 594.4)$	$[594.4, +\infty)$
Safety	1	$e^{-\frac{1}{83.3}(L-511.1)^2}$	0
Danger	0	$1 - e^{-\frac{1}{83.3}(L-511.1)^2}$	1

According to Tables 1, 2 and 3, draw the membership function of θ_x, L_l and L_r shown in Figure 11.

The first figure of Figure 11 shows that when the $\theta_x \in [70.4, 87.8)$, $\mu(x)_s > \mu(x)_d$. When the $\theta_x \in [87.8, +\infty)$, $\mu(x)_s < \mu(x)_d$. Therefore, it can be known by the principle of maximum membership when the $\theta_x \in [70.4, 87.8)$ is safer, when the $\theta_x \in [87.8, +\infty)$ is more dangerous. By the same token, when the $L_l \in [316.9, 552.8)$ is safer, when

TABLE 3. Membership function $\mu(x)$ of L_r (mm)

State \ Displacement	$[322.3, 513.7)$	$[513.7, 595.8)$	$[595.8, +\infty)$
Safety	1	$e^{-\frac{1}{82.1}(L-513.7)^2}$	0
Danger	0	$1 - e^{-\frac{1}{82.1}(L-513.7)^2}$	1

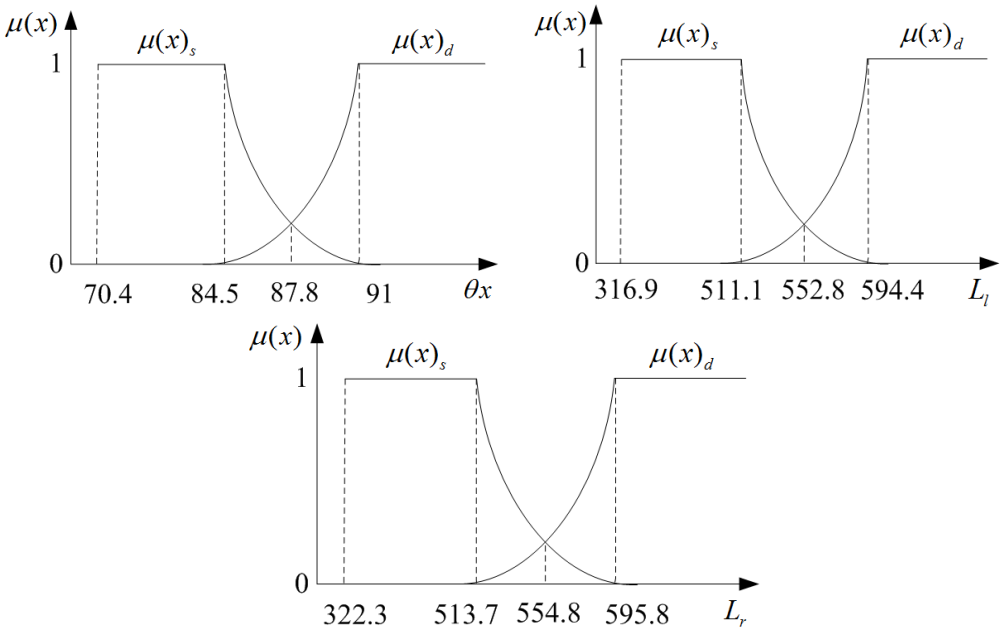


FIGURE 11. Membership function diagram of θ_x, L_l and L_r

$L_l \in [552.8, +\infty)$ is more dangerous; when the $L_r \in [322.3, 554.8)$ is safer, when the $L_r \in [554.8, +\infty)$ is more dangerous.

3.5. **Establishing fuzzy rule.** According to the membership function to establish fuzzy rules, in order to better describe the rules, it is stipulated that: $\theta_s \in [70.4, 87.8]$, $\theta_d \in [87.8, +\infty]$; $L_s \in [316.9, 552.8]$, $L_d \in [552.8, +\infty]$; $R_s \in [322.3, 554.8]$, $R_d \in [554.8, +\infty]$. Therefore, 8 kinds of fuzzy rules can be established as shown in Table 4. Through a large number of experiments, the membership degree of safety state under each rule is as follows.

TABLE 4. Membership degree of fuzzy rules in safety state

Rule	$\theta_s L_s R_s$	$\theta_s L_s R_d$	$\theta_s L_d R_s$	$\theta_s L_d R_d$	$\theta_d L_s R_s$	$\theta_d L_s R_d$	$\theta_d L_d R_s$	$\theta_d L_d R_d$
$\mu(x)$	1	0.7	0.7	0.3	0.7	0.3	0.3	0

The fuzzy matrix $\boldsymbol{R}$ of safe walking is obtained through Table 4:

$$\boldsymbol{R} = \begin{bmatrix} 1 & 0.7 & 0.7 & 0.3 & 0.7 & 0.3 & 0.3 & 0 \end{bmatrix} \tag{2}$$

The fuzzy subset $\boldsymbol{U}$ of the output in the safety state is calculated through the comprehensive rules [18]. After calculation, the output $\boldsymbol{U}$ is:

$$\boldsymbol{U} = \begin{bmatrix} 1 & 0.7 & 0.7 & 0.3 & 0.7 & 0.3 & 0.3 & 0 \end{bmatrix} \tag{3}$$

Through (2) and (3), the membership degree of the safety state can be obtained by the weighted average method:

$$\mu(x)_s = \frac{\boldsymbol{R} \cdot \boldsymbol{U}^{\mathrm{T}}}{\sum_{j=1}^{8} \boldsymbol{U}_{1j}} = 0.7 \tag{4}$$

Therefore, when $\mu(x) \geq 0.7$, it is judged to be in a safety state.

In order to avoid falling down, the future work content is to control the speed of the walker according to the user's state. Therefore, it is planned to divide the safety status into several levels, namely 'extremely' safe, 'very' safe and 'slightly' safe. As can be seen from the previous membership function, $\mu(x) = 0.7$ is the critical point between safety and danger.

As shown in Figure 12, when a user's walking state is detected by fuzzy reasoning method, the corresponding measures are taken by judging the degree of safety level. When $\mu(x) = 1$, a user is in an 'extremely' safety state, the motor maintains its current speed; when $\mu(x) = 0.7$, a user is in a 'very' safety state, the motor starts to decelerate. When $\mu(x) < 0.7$, a user is in a 'slightly' safety state, and the motor starts to slow down. If the speed reduction cannot make people reach the normal state, the motor should stop rotating to ensure the safety of users.

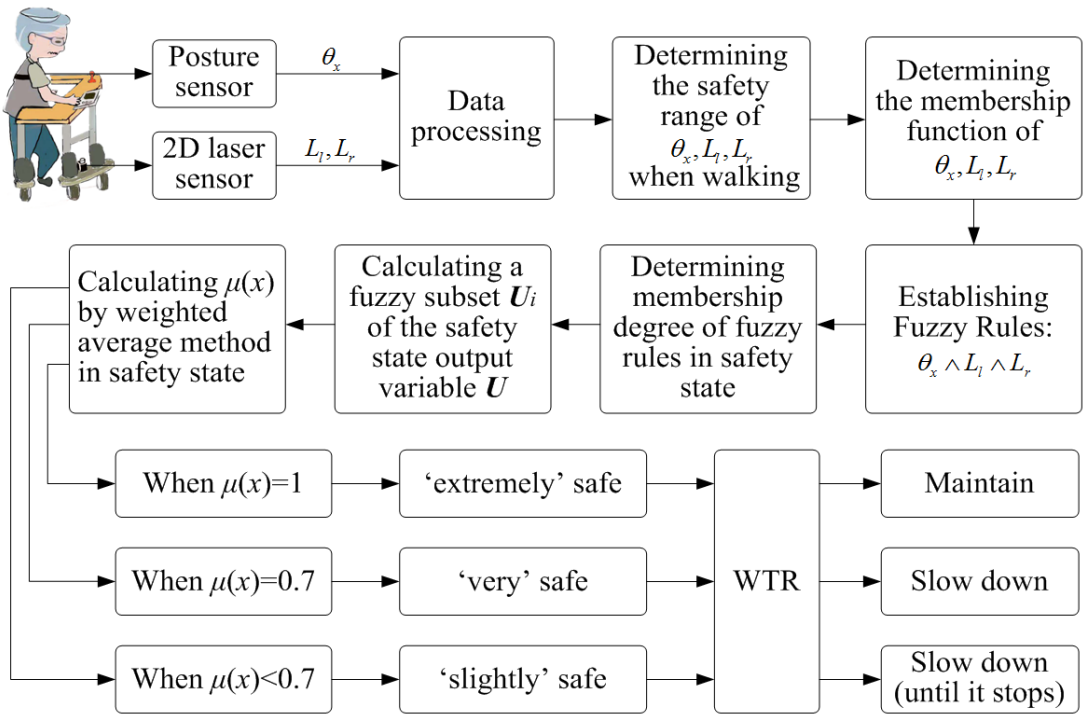


FIGURE 12. Control block diagram of the fall detection

4. **Experiments Results and Discussion.** To verify the effectiveness of the proposed method, we conduct the validation tests. 15 subjects were introduced in the experiment. It has obtained the consent of all subjects and conforms to the ethical rules. The average age of the subjects was 24, the average height was 170 cm, and the average weight was 63 kg. To show the superiority, a fall detection method proposed in [14] was also valid under the same experiment setting.

To compare the two methods, excluding the interference of the external environment, each subject carried out 10 forward fall experiments with the help of WTR. The experimental process was that all participants walked for about 11 s every time. During normal

walking, subject was inside the robot. As their own speed could not keep up with the speed of the WTR, the subject's body gradually leaned forward and the lower body also moved to the outside of the WTR. The results of fuzzy reasoning and COG threshold method are shown in Table 5, the recognition rate of fuzzy reasoning method is 94.7%, and the recognition rate of COG threshold method is 44.7%. It is obvious that the fuzzy reasoning method is much better than the COG threshold method. As mentioned earlier, the method of [14] has the problem that walking speed affects COG error. COG error of the subject at different walking speeds is shown in Table 6. It can be seen that the error is about 5 cm each time. Because the step length of the elderly is short, the error of 5 cm actually has great potential safety hazard. In addition, when the walking speed and the walking direction of the user suddenly change, the COG error is large, which leads to the method not being able to accurately detect the fall of the person. Fuzzy reasoning method is effective in most cases, but the COG method is basically not useful. Thus, the effectiveness of fuzzy reasoning was verified. The experimental results are accurate and convincing.

Table 5. Fall detection results of fuzzy reasoning and COG threshold method

Key indicators / Method	Number of subjects	Number of trials	Number of successes	Recognition rate
Fuzzy reasoning	15	10	142	94.7%
COG threshold	15	10	67	44.7%

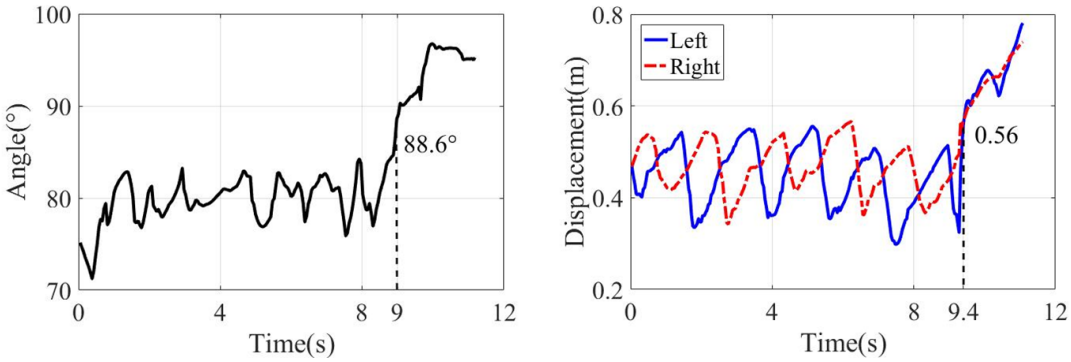
Table 6. COG error at different walking velocities

Trial	1	2	3	4	5
Walking velocity (m/s)	0.6	0.8	1.1	1.5	1.8
COG_{err} (cm)	5.71	5.33	5.82	4.98	5.72

In addition, we randomly selected the experiments of two subjects (coded A, B) for further discussion. As shown in Figure 13, before 9 s, the subject was in a safe state, the θ_x, L_l and L_r fluctuated smoothly within a safe range, query from table, $\mu(x) = 1$. At the 9 s, the θ_x was out of safety range, but the L_l and L_r were still within the safety range, the subject did not fall down, query from table, $\mu(x) = 0.7$. At the 9.4 s, the subject A fallen down was detected, at this time, the L_l and L_r were also beyond the safety range, query from table, $\mu(x) = 0$, it conformed to the established fuzzy rules.

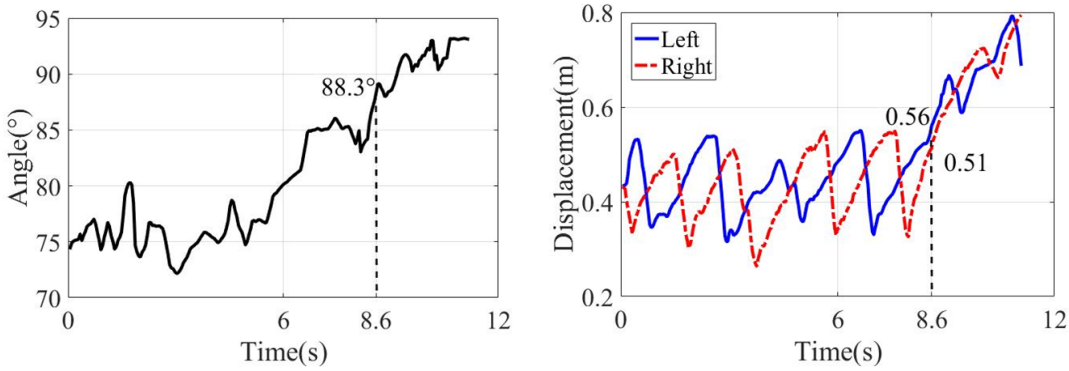
As shown in Figure 14, before 8.6 s, the subject was in a safety state, the θ_x, L_l and L_r fluctuated smoothly within a safe range query from table, $\mu(x) = 1$. At the 8.6 s, the subject B fallen down was detected at this time, the θ_x and L_l were out of safety range, L_r did not exceed the safety range, query from table, $\mu(x) = 0.3$, it conformed to the established fuzzy rules. From the above two groups of experiments, it can be concluded that under the premise of similar experimental environment, this research can accurately detect different forward falling postures of users, effectively avoiding secondary injuries of the elderly and the disabled.

5. **Conclusion and Future Work.** The main contribution of this paper is proposal of a fuzzy reasoning method to detect the state of a person during walking. This research can accurately detect a user's falling. Experiments show that the recognition accuracy of the method used in this paper is 94.7%. The error is mainly caused by the detection error of the sensor. In order to better prevent people from falling down while using the



(a) θ_x (b) L_l and L_r

FIGURE 13. The trend of θ_x, L_l and L_r of subject A



(a) θ_x (b) L_l and L_r

FIGURE 14. The trend of θ_x, L_l and L_r of subject B

WTR, the future work is to control the speed of the motor by judging different states of people walking, thus avoiding the occurrence of secondary injuries.

Acknowledgment. This research was funded by Ph.D. Start-up Fund of Natural Science Foundation of Liaoning Province, Grant number 20170520449; the Science and Technology Bureau Project of Shenyang City, Grant number 18013020; and the Liaoning Provincial Natural Science Foundation, Grant number 20180550994.

This work is partially supported by Minxuan Li, Zechao Xu, Junjiu Zhang et al. The authors also gratefully acknowledge the helpful comments and suggestions of the reviewers, which have improved the presentation.

REFERENCES

[1] M. Li, G. H. Xu, B. He, X. L. Ma and J. Xie, Pre-impact fall detection based on a modified zero moment point criterion using data from Kinect sensors, *IEEE Sensors Journal*, vol.18, no.13, pp.5522-5531, 2018.

[2] K. Yamazaki, R. Ueda, S. Nozawa, M. Kojima and K. Okada, Home-assistant robot for an aging society, *Proc. of the IEEE*, vol.100, no.8, pp.2429-2441, 2012.

[3] L. Jonsson, *The Importance of the 4-Wheeled Walker for Elderly Women Living in Their Home Environment*, The Swedish Handicap Institute, 2001.

[4] J. Y. Ni, Lower limb rehabilitation training robot, *Lower Limb Rehabilitation Training Robot*, vol.19, no.1, pp.127-128, 2010.

[5] H. Chang, S. Wang and P. Sun, Semi-active redundant fault tolerant control for an omnidirectional rehabilitative training robot with center of gravity shift, *ICIC Express Letters*, vol.13, no.2, pp.141-150, 2019.

[6] W. X. Xu, J. Huang and Y. J. Wang, Reinforcement learning-based shared control for walking-aid robot and its experimental verification, *Advanced Robotics*, vol.29, no.22, pp.1463-1481, 2015.

[7] World Health Organization (WHO), *WHO Falls – Fact Sheet*, http://www.who.int/mediacentre/factsheets/fs344/en/, 2018.

[8] S. C. Wang and X. D. Zhang, An approach for fall detection of older population based on multi-sensor data fusion, *IEEE*, pp.320-323, 2015.

[9] Y. B. Wang, X. D. Zhang and X. Q. Mu, Research on the fall prediction method for elderly people used to assist their old companions in robots, *Journal of Electronic Measurement and Instrument*, vol.32, no.7, pp.1-7, 2018.

[10] W. X. Xu, J. Huang and L. Cheng, A novel coordinated motion fusion-based walking-aid robot system, *Sensors*, vol.18, no.9, pp.1-24, 2018.

[11] S. Taghvaei and K. Kosuge, Image-based fall detection and classification of a user with a walking support system, *Frontiers of Mechanical Engineering*, vol.13, no.3, pp.427-441, 2018.

[12] K. Myeongseob, K. Suneung, K. Mingi and K. Kwangtaek, A novel approach for outdoor fall detection using multidimensional features from a single camera, *Applied Sciences*, vol.8, no.6, pp.1-22, 2018.

[13] X. J. Tan, W. L. Jin and X. D. Geng, Human fall detection improvement based on artificial neural network and optimized zero moment point algorithms, *IEEE International Conference on Real-time Computing and Robotics (IEEE RCAR)*, pp.662-666, 2018.

[14] J. Huang, W. X. Xu, M. Samer and S. Zhen, Posture estimation and human support using wearable sensors and walking-aid robot, *Robotics and Autonomous Systems*, vol.73, pp.24-43, 2015.

[15] Y. Wang and S. Wang, A new directional-intent recognition method for walking training using an omni direction robot, *Journal of Intelligent & Robotic Systems*, pp.1-16, 2017.

[16] X. P. Qiu, R. X. Sun and D. Yu, Method of establishing membership functions of car-following behavior based on fuzzy clustering, *Application Research of Computers*, vol.33, no.7, pp.1952-1956, 2016.

[17] J. Cano and P. A. Nava, A fuzzy method for automatic generation of membership function using fuzzy-neural control, *Proc. of Annual Meeting of the North American Fuzzy Information Processing Society*, pp.158-162, 2002.

[18] G. Q. Zeng, J. A. Hu and D. Wang, Fuzzy control theory and engineering application, *Huazhong University of Science and Technology Press*, pp.83-84, 2012.