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FALL PREDICTION IN WALKING REHABILITATION TRAINING USING DEEP LEARNING APPROACH

Yingdong Gu, Di Zhang and Hongbin Chang*

School of Artificial Intelligence
Shenyang University of Technology
No. 111, Shenliao West Road, Eco. and Tech. Development Zone, Shenyang 110870, P. R. China
guyd@smail.sut.edu.cn; zhangdi5427@163.com; *Corresponding author: chang.hongbin@sut.edu.cn

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Abstract. *Fall prediction and protection measures are crucial for improving the safety of walking rehabilitation training for elderly, who may experience falls during the training process due to intrinsic lower limb muscle functional impairments or extrinsic factors. Accurately predicting and timely taking protective measures for fall events can significantly reduce risks associated with walking rehabilitation training. In this paper, we utilize an Inertial Measurement Unit (IMU) to obtain the user's motion information and design a fall prediction model for the elderly based on a two-layer Long Short-Term Memory (LSTM) network and attention mechanism. LSTM models excel in capturing and processing the temporal features of data, while attention mechanisms can filter out the most relevant features. This model can effectively improve the lead-time for fall prediction and increase the accuracy of classification. On the collected dataset, the proposed model achieved a classification accuracy of 90.9% for distinguishing between normal walking and falls, with an average lead-time of 1.82 seconds. This model demonstrates the effectiveness in improving the accuracy of fall prediction and prolonging the lead-time of fall prediction, which can provide elderly individuals with increased opportunities to receive assistance prior before falling.*

Keywords: Fall prediction, Walking rehabilitation training, Two-layer long short-term memory network, Attention mechanism

1. **Introduction.**

With the development of industrialization and modern technology, human life expectancy has been continuously increasing, leading to an aging population trend in many countries. Population aging is a significant issue that the 21st century human society must face, with the number of elderly people over 60 years old having grown to 10.5 billion, accounting for 13.5% of the total global population [1]. The changes in population structure and human lifestyle have accelerated the unprecedented rise in societal healthcare demands. As aging continues to become prevalent, it poses a significant challenge on the public health resources. It is reported that approximately 28%-35% of the elderly who are over the age of 65 fall each year. The risk of falling will rise as the age increases. It is reported that the percentage of adults over the age of 70 who fall each year is expected to increase to 32%-42% [2]. As the incidence of sudden accidents caused by falls among the elderly has greatly increased the pressure on social medical resources, it has become increasingly important to predict and prevent fall accidents for the elderly, thus reducing the harm caused by falls.

In addition to age, multiple risk factors can contribute to elderly falls. For example, sedentary behavior and fracture are independent risk factors for falls in older adults [3]. The intrinsic factors contributing to falls in older adults include decreased gait stability and impaired balance function. Changes in step height, step length, continuity, linearity, and smoothness can all lead to falls. In the daily life of the elderly, a multidisciplinary

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approach is employed to enhance their awareness of fall prevention, including providing early warning of potential fall accidents and implementing protective measures which can effectively reduce the fear of falling and physical injuries among the elderly.

In recent years, the studies on fall prediction mainly include wearable fall prediction systems and non-wearable fall prediction systems. The non-wearable fall prediction systems are primarily composed of the devices that can be placed in the proximity of the users, such as cameras [4], photovoltaic sensors, and radars. However, non-wearable fall prediction systems have the disadvantage of limited coverage area and may pose a risk of violating privacy, as in the case of cameras [5]. In addition, due to limitations in computing power of the devices, researchers and practical applications tend to prefer wearable sensors. Wearable devices offer advantages such as ease of use, better privacy, and wider range of options, such as inertial sensors [6], pressure sensors [7,8], and surface electromyography sensors [9].

Inertial sensors are popular due to their low cost, small size, light weight, and versatility in various application scenarios. The majority of IMU units consist of accelerometers, gyroscopes, and magnetometers. They can provide 2 to 6 degrees of freedom, involving the motion of different objects in three-dimensional space, and can be easily attached to any part of the body, such as the head, the hip, and the legs. Noh et al. utilized inertial sensors to obtain gait information of human walking, by selecting 14 different feature quantities, and used XGBoost to predict the possibility of falling in elderly individuals [10]. The results showed that the stride length during slow walking and the walking speed during fast walking can also accurately predict falls, with an accuracy of around 70%. Lockhart et al. utilized inertial sensors to collect human gait information and assessed the risk of falls using Random Forest (RF), achieving an accuracy of 81.6% [11]. Additionally, inertial sensors were also utilized for fall prediction in the works of [12-14].

Then above studies utilized various sensors to achieve falling prediction. Considering the actual walking training, visual and other sensors would be impacted by external environment. In this study, we hope to utilize the minimum number of wearable inertial sensors. The sensor will be worn on the chest while ensuring minimal interference to the normal activities of the participant. The participant is able to walk freely within the room to simulate the process of falling and collect posture information. We will use a deep learning model to classify between normal walking and potential falls.

Typically, posture characteristics change during several steps before falling. For this sequential problem, we adopt the deep learning model of LSTM. At the same time, attention mechanism is employed to enable the model to focus more on the features that can more relevant to falling. Compared with previous research, our study achieves a higher accuracy and a significant improvement in lead-time compared to state-of-the-art methods. The deep learning model based on the LSTM and the attention mechanism is employed to classify the falling and the normal walking. The recognition accuracy is 90.9%, the F1-score is 65.6%, and the mean lead-time is 1.82 seconds, which shows the effectiveness of the proposed model.

This paper is divided into five sections. The second section introduces the data collection process and explains the differences between falling and normal gait. The third part focuses on the LSTM and attention mechanism, as well as the main parameters of the LSTM-attention deep learning model. In the fourth part, the analysis process and the results of the experiment are presented. Finally, the summary of the experiment is presented.

2. **Data Processing.** The Alubi B2 wireless posture sensor was utilized in this paper, as shown in Figure 1.

The participant wore the device on the chest and moved freely within a 4 m $\times$ 5 m space. The sensor collected information regarding the acceleration and angular velocity of the chest. The collected data consists of six types of anterior chest posture information,

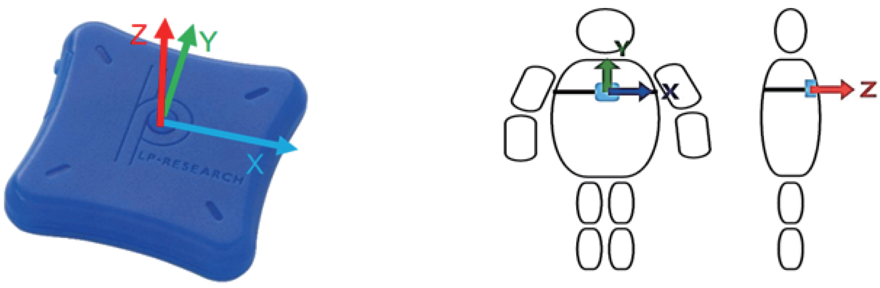

FIGURE 1. The wireless sensor

including acceleration along the x, y, and z axes, as well as angular velocity around the x, y, and z axes, as shown in Figure 1. The dataset comprises 1000 sets of data, which are categorized into walking and falling postures. Each set consists of 10 seconds of anterior chest posture information collected at a frequency of 400 Hz.

During the process of falling, a loss of balance results in the acceleration of the body towards the ground due to gravity. This generally irreversible process occurs within a duration of 1-3 seconds. Theoretically, the falling event can be divided into four phases: pre-fall phase, critical phase, post-fall phase, and recovery phase. In this study, the fall prediction research mainly focuses on the critical phase. The figures below illustrate the frontal acceleration and angular velocity signals of the chest during normal walking and falling events.

Walking: As shown in Figure 2, it can be observed that the variation on both acceleration and angular velocity is small during straight walking, while angular velocity exhibits a significant change during turns. Acceleration maintains a stable trend throughout. A total of 500 sets of chest posture information during normal walking were collected in the experiment.

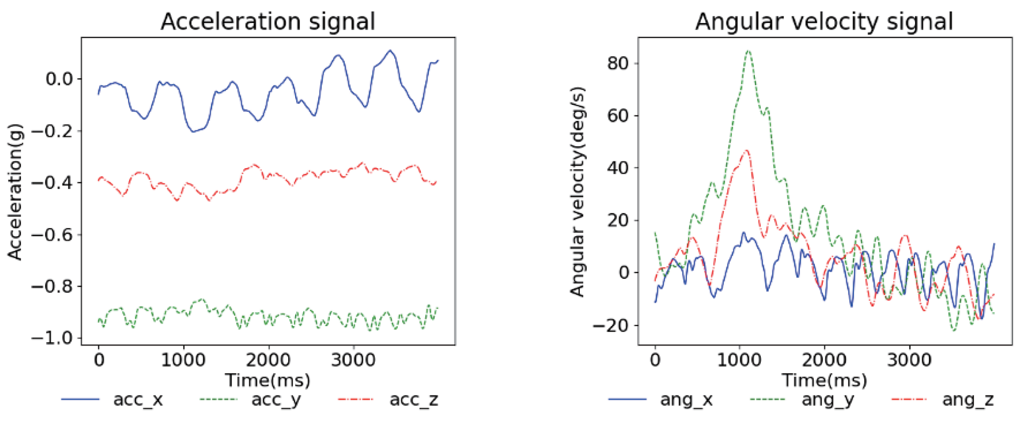

FIGURE 2. Walking posture

Falling: Figure 3 reveals that significant changes in both acceleration and angular velocity values can be observed during the critical phase of falls. Prior to falling, the three-dimensional acceleration of the chest area of the human body undergoes a rapid increase, while it gradually decreases upon bodily impact with the ground. A total of 500 sets of chest posture information were collected in the experiment, in which falls occurred after walking.

3. **Network Model.** This section introduces the structure of the LSTM and the attention mechanism. Subsequently, we will describe the basic theory, structure, and main parameters of the LSTM-attention model utilized in this study.

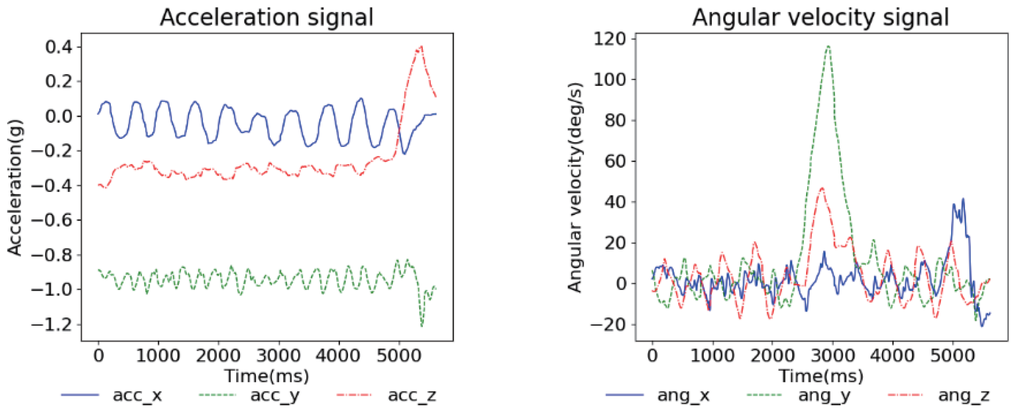

FIGURE 3. Falling posture

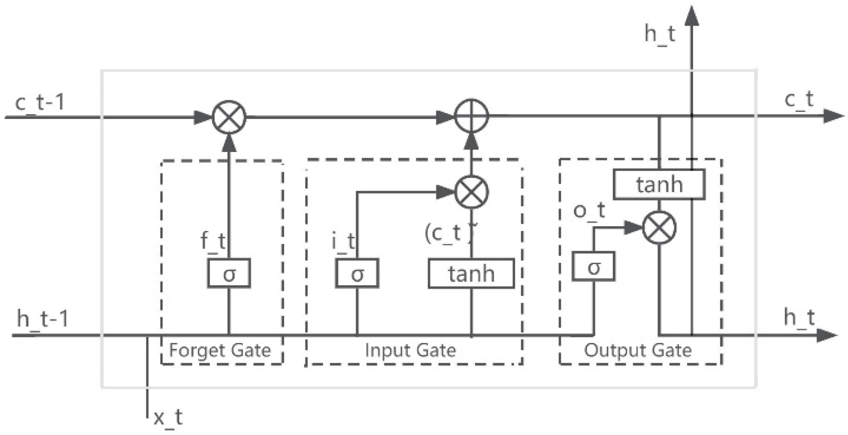

FIGURE 4. LSTM model

3.1. **LSTM (Long Short-Term Memory).** LSTM is a distinct type of Recurrent Neural Network (RNN) that is capable of learning long-term dependencies and addressing the issue of vanishing or exploding gradients in traditional RNN [15]. The structure of LSTM is more intricate than RNN, consisting of four core components: forget gate, input gate, cell state, and output gate. These four components work in unison to provide the LSTM with strong memory capabilities. The forget gate is responsible for determining the amount of cell state from the previous time step that should be retained for the current time step. To make this determination, the forget gate takes the input h_{t-1} from the previous cell and the input x_t from the current cell, to produce an output vector f_t between 0 and 1. The value of 0 in the output vector corresponds to discarding the corresponding information completely, while the value of 1 corresponds to retaining all of the information. The aforementioned process can be expressed using the following equation:

$$f_t = \sigma\left(w_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{1}$$

where σ represents the sigmoid function, w_f represents the weight matrix of the forget gate, and b_f represents the bias term.

The input gate determines how much of the current input is allowed to be stored into the cell state and can be expressed using the following equation, where w_i represents the weight matrix of the forget gate, and b_i represents the bias term:

$$i_t = \sigma\left(w_i \cdot [h_{t-1}, x_t] + b_i\right) \tag{2}$$

The current cell state c_t is calculated as the product of the output of the forget gate f_t and the previous cell state c_{t-1}, and added to the product of the output of the input gate i_t and the candidate cell state $\tilde{c}_t$, expressed as follows:

$$c_t = c_{t-1} * f_t + \tilde{c}_t * i_t \tag{3}$$

The candidate cell state $\tilde{c}_t$ is computed using the following equation, where w_c represents the weight matrix of the forget gate, b_c represents the bias term, and $\tanh(\cdot)$ represents the activation function:

$$\tilde{c}_t = \tanh\left(w_c \cdot [h_{t-1}, x_t] + b_c\right) \tag{4}$$

The cell unit integrates the current candidate cell state $\tilde{c}_t$ with the long-term memory c_{t-1} to form a new cell state.

The output gate regulates how much of the current cell state should be outputted to the cell unit as the current output value, while the final output of the cell unit h_t is determined by the output gate and the cell state, as specified by the following equation, where w_o represents the weight matrix of the forget gate, and b_o represents the bias term:

$$o_t = \sigma\left(w_o \cdot [h_{t-1}, x_t] + b_o\right) \tag{5}$$

$$h_t = o_t * \tanh(c_t) \tag{6}$$

By controlling the switch states of the three gate structures, the processing method of information can be determined. The forget gate is responsible for preserving information from a distant past, whereas the input gate selectively allows content relevant to the current state to enter into memory. The long-term memory is governed by the output gate, which regulates the current output to allow both long-term and short-term data to perform their respective functions.

3.2. **Attention mechanism.** Similar to the human brain, the attention mechanism can selectively focus on important information at a given moment while ignoring other irrelevant information. This process can be described as a mapping from a variable to a series of key-value pairs. The computation process can be broken down into three steps: first, the similarities between the query and each key are calculated to generate weights; secondly, apply a softmax function to standardizing these weights; lastly, the weights are multiplied by their corresponding values and summed up to yield the final output. This process can be mathematically expressed as follows:

$$Attention(Query, Source) = \sum_{l=1}^{l_x} Similarity(Query, Key_i) = Value_i \tag{7}$$

3.3. **LSTM-attention model.** The traditional LSTM model consists of a single hidden LSTM layer and a standard feedforward output layer. The stacked LSTM is an extension of this model, which integrates multiple LSTM layers, each consisting of multiple memory cells. The addition of stacked hidden layers empowers the model to more accurately capture the features of the data. The input features of the data consist of six classes, namely the acceleration and angular velocity along the x, y, and z axes. After the data is inputted, it first goes through the initial LSTM layer. The subsequent LSTM layer then recombines the information outputted from the previous layer, enabling the model to learn more effective features from the data. The output from the LSTM layer is subsequently fed into the attention mechanism module. The attention mechanism assigns different weights to different features and connects them to the fully connected layer. Finally, we use Softmax function to sort the normal walking and the falling. The model architecture is depicted in Figure 5, and Table 1 shows the primary parameters of the model.

4. **Experimental Method and Results Analysis.** The first part of this section presented the experimental procedure and parameter settings. The second part presents the classification results of the model.

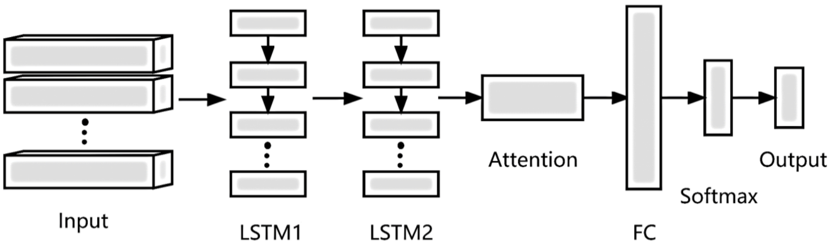

FIGURE 5. Schematic diagram of the model structure

TABLE 1. Some parameters of the model

Layer name	Paramater
LSTM Layer 1	312
LSTM Layer 2	312
Attention Layer	58896
FC	0
Softmax Layer	39266

4.1. **Experimental method.** The training process involves using an LSTM-attention model. Prior to training, the collected data is shuffled. The training set is then composed of 80% of the entire dataset, with the remaining 20% being allocated as the test set. The model parameters are adjusted to achieve optimal accuracy, followed by three rounds of testing using these parameters and the calculation of the mean accuracy. The LSTM-attention model is configured with the following parameter values based on the debugging results: batch size of 5, 30 epochs, initial learning rate of 0.0005, weight decay coefficient of 0.00001, cross-entropy as the loss function, and Adam as the optimization algorithm.

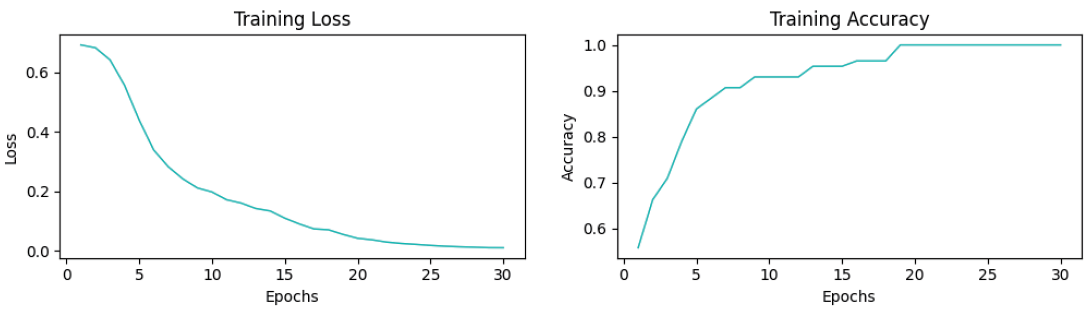

FIGURE 6. Train accuracy and loss results in the mode

4.2. **Results analysis.** To evaluate the effectiveness of the classification model, this study utilizes several evaluation standards, including Accuracy (A), Precision (P), Recall (R), and F1-score. True (T) and False (F) represent correct and incorrect results, respectively. Four categories are derived from these results. True Positive (TP) represents the truth is falling and the prediction is falling. True Negative (TN) represents the truth is falling and the prediction is walking. False Positive (FP) represents the truth is walking and the prediction is falling. False Negative (FN) represents the truth is walking and the prediction is walking. The computation of each category is as follows:

$$A = (TP + TN)/(TP + TN + FP + FN) \cdot 100\% \tag{8}$$

$$P = TP/(TP + FP) \cdot 100\% \tag{9}$$

$$R = TP/(TP + FN) \cdot 100\% \tag{10}$$

$$F1 = (2 \cdot P \cdot R)/(P + R) \cdot 100\% \tag{11}$$

The dataset used in this paper contains two states, the normal walking and the falling after walking, each with 500 samples. Each sample contains 10 seconds of chest posture information prior to walking. The experimental results are shown in Table 2, in which, the accuracy of the classification achieved by the model is 90.9%, the precision is 95.2%, the recall is 50%, and the F1-score is 65.6%. In addition, the mean lead-time for predicting falls is 1.82 seconds. Compared with previous studies on falling prediction, this study has achieved significant improvements in terms of lead-time.

Table 2. Experimental results

Accuracy	90.9%
Precision	95.2%
Recall	50%
F1-score	65.6%
Mean lead-time/s	1.82

In a state-of-the-art study [16], a recall of 81.4% and an accuracy of 79.4% were achieved with a lead-time of 0.287 seconds. Our approach, in comparison, demonstrates significant improvements in the precision, recall, and lead-time.

5. **Conclusions.** This paper utilizes the Alubi B2 series wireless posture sensor to obtain the physical information of the experimenter. We collected a total of 1000 sets of anterior thoracic posture data, including walking and falling after walking, without interfering with the participant's daily activities. A deep learning model based on the LSTM and the attention mechanism was employed to classify the falling and the normal walking in the elderly population. The recognition accuracy is 90.9%, the F1-score is 65.6%, and the mean lead-time is 1.82 seconds, which shows that the model is accurate and reliable, and demonstrates a good performance for fall prediction using the six features extracted from a single posture sensor. This provides the evidence for the efficacy of the approach proposed in this study. Our future research aims to improve the model's classification accuracy, prolong lead-time, and enhance its generalization capability. Building on this study, we also intend to integrate the model with rehabilitation robots to prevent and protect against falls during elderly rehabilitation training.

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