Classification of Gait Data from Daily Walking Using Long Short-Term Memory

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1. Introduction

Walking is a natural means of movement in our lives, and it is one of the easiest exercises for human beings. If a person cannot perform stable walking, it may be difficult for him/her to lead an ordinary life and the risk of various illness rises [1]. Falls are very common and yet dangerous among the elderly population and are a major health concern. With the increase of elderly population all over the world, objective fall risks evaluations from various walking gaits for the geriatrics can be very attractive and useful. Gait analysis using a lightweight body-worn sensor is a convenient and inexpensive method that potentially allows for easy and quantitative assessment of fall risks of the geriatric population.

In this study, older adults who each worn a gait belt on the lower back were evaluated using data obtained from lightweight sensors including a triaxial accelerometer and a triaxial gyroscope. Algorithms such as support vector machine (SVM) [2]-[3], artificial neural network (ANN) [3] and Long Short-Term Memory (LSTM) [4] were used to classify fallers vs. non-fallers.

2. Method

In the dataset we used for this work, 71 community-living elderly people (mean age = 78.3 ± 4.71 years, range = 65 87 years, mean height = 1.62 ± 0.07m, mean weight: 71.98 ± 12.88 kg) were tested. Subjects are divided into faller or non-faller based on self-reporting of past fall experience. If the subject falls more than twice in the past year, that person is classified as a faller, otherwise they were considered non-fallers. Subjects attached the gait belt on lower part of waist as shown in Fig. 1 and took various tests while walking. Among them, the data from the following two experiments were used for this work:

1) 1-minute walk in lab: Walk in the lab at a personal selected comfortable speed with the gait belt on lower back.
2) 3-day long term recording: After a 1-minute walk test in the lab, subjects were required to spend 3-days wearing the gait belt, except for taking shower, etc. but the reason for the removal must be reported.)

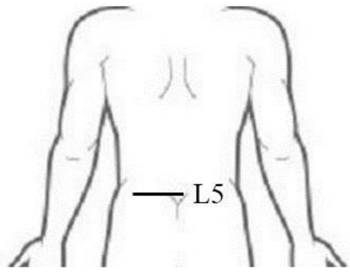

Fig. 1 Indicating where the gait belt was attached to subjects (at L5; lower back).

LSTM is one of the models for sequential data analysis that appeared as an extension of Recurrent Neural Network (RNN). LSTM is realized by replacing the unit in the middle layer of RNN with a memory, and a block with three gates that are called LSTM block as shown in Fig. 2. In RNN, in order to maintain the storage of input data, the middle layer has a loop. This allowed RNN to include the previous data in the judgment. However, the basic RNN had various issues such as the gradient loss problem, and its learning is not very effective. The

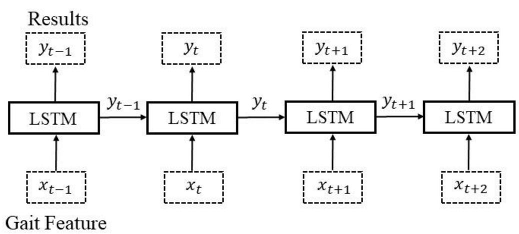

Fig. 2 Learning structure of LSTM

LSTM block includes a forget layer, a retention layer, and so on. The feature of LSTM is that it can learn long-term dependencies that were difficult to learn in the RNN and can solve the gradient loss problem. In other words, it can be divided into necessary information and unnecessary information, then proceed with learning using only the necessary information. Thus, LSTM has attracted the attention of its learning superiority on long-term sequential data that was difficult to predict in RNN.

3. Results and discussion

In this study, we classified fallers vs. non-fallers using SVM, ANN and LSTM as algorithms. However, since SVM and ANN are not directly suitable for classification of sequential data, the data obtained as input data was modified and used. Range, standard deviation (STDEV) and Range + standard deviation (STDEV) were used as input data when we classify using SVM and ANN. Range is the maximum value minus the minimum value of the signal obtained on each axis. The reason for using the STDEV is that the fallers' movement in their daily living is likely to be unstable, and the variation in data might become large, and it is thus reasonable that larger STDEV could differentiate themselves from the non-fallers. Table 1 shows the results when we use SVM and ANN as classifying algorithms; 70% was used as training data and 30% as test data. As can see from the Table 1, not all features have achieved very high accuracy. In particular, when only STDEV was used in the input data, it showed the same or lower accuracy than when using Range alone. This indicates that the variability of the data may not be significantly different between fallers and non-fallers. In the case of Range + STDEV, a high accuracy of 71.67% was obtained when 1-min lab walk was classified using ANN, but this did not improve accuracy for other cases. For the 1-min walk, ANN had higher accuracy than SVM in all features by 2% to 16%. For the 3-day recording, ANN has higher accuracy than SVM in two features by 5%-6%, but in the case of STDEV it has 4% lower accuracy. Although the overall accuracy is not so high as shown in Table 1, it is suspected that the cause is at least partially due to that classification was performed by ignoring the time factor despite of the time series sequential gait data we are given. In the case of Range, in particular, it uses the maximum and minimum values in tests that can be for a very long time, so it may not be very suitable for accurate classification.

Table.1 Overall classification accuracy of fallers vs. non-fallers using ANN and SVM for both tests.

Feature	Overall Classification Accuracy			
	1-min Walk		3-day Recording	
	ANN	SVM	ANN	SVM
Range	67.27%	56.52%	67.27%	61.10%
STDEV	60.76%	58.79%	57.14%	61.91%
Range + STDEV	71.67%	55.91%	57.14%	52.38%

Next, analysis was performed using LSTM. Note in the case of the above ANN and SVM, the obtained gait data was transformed (features extracted) to make it easier to classify, but in the case of LSTM, it was classified using the obtained raw gait data (all six axes data were used as input data) without deformation. This is done to preserve the continuous time series component of the recorded data by not transforming it into range, etc. The final classification accuracy was 72.72% for the 1-min lab walking, and a very high 81.81% for the 3 days of recording, as shown in Table 2. Compared to ANN and SVM, LSTM gave that by using LSTM, it can help to predict future results from past data. From the above analysis and results, it is clear that we can classify fallers vs. non fallers with high accuracy by classifying using LSTM rather than using ANN or SVM. The final accuracy after learning is summarized in Table 2.

Table.2 Final accuracy with LSTM.

Classifier	1-min Walk	3-day Recording
LSTM	72.72%	81.81%

However, LSTM is not full of good points only. Of course, when forecasting using LSTM, the more data we have, the longer it will take to calculate. Accuracy is important for fall risks prediction, but the speed of calculation may also be important for performing a fall risks assessment. Even if high accuracy is obtained, real-time analysis is not feasible if classification takes more than a few minutes. Therefore, it is necessary to compare the calculation speed of each classifier. Fast calculation speeds lead to quick feedback from the doctor to the patient. Table 3 summarizes the calculation speed of each classifier. SVM takes only about 1 second to calculate on a typical PC (Windows 10 Pro, Intel core i5-7300U, 2.60GHz, 2.71GHz, 8.00GB, 64 bit, 64-bit operating system), and ANN takes about 7 seconds. In the case of LSTM, the 1-min lab walk classification takes 27249 seconds and the 3-day recording classification takes 39815 seconds. As a result, although LSTM has higher accuracy than SVM and ANN, it has the disadvantage that it takes much more calculation time, even though with higher accuracy. It turned out that SVM with a simple structure is very fast and suitable for real-time gait analysis. Which classifier is best for fall risks evaluation is likely to vary depending on the specific application. If we do not need immediate feedback and can use a fast server to calculate, we should choose to spend more time making predictions with LSTM as it is considerably more accurate.

Table.3 Summary of each classifier's speed when different input features are used.

Classifier	Overall Classifier Speed (s)	
	1-min Walk	3-day Recording
ANN	7.681	7.379
SVM	1.079	1.128
LSTM	27249	39815

4. Conclusion

The results presented in this study using ANN, SVM, and LSTM suggest that we can classify fallers vs. non-fallers with considerably higher accuracy using LSTM than ANN or SVM. In this study, we used data collected from the 1-min walking and the 3-day daily living activities for 71 subjects and achieved a classification accuracy of 72.72% and 81.81%, respectively. These results suggest that long-term monitoring and the analysis on the temporal changes in gait behaviors can be a rather powerful and novel technique for quantitatively evaluating fall risks on the geriatric patients performing their average daily living activities.

References

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