LETTER

Development of Artificial Neural Network Based Automatic Stride Length Estimation Method Using IMU: Validation Test with Healthy Subjects

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SUMMARY  Rehabilitation and evaluation of motor function are important for motor disabled patients. In stride length estimation using an IMU attached to the foot, it is necessary to detect the time of the movement state, in which acceleration should be integrated. In our previous study, acceleration thresholds were used to determine the integration section, so it was necessary to adjust the threshold values for each subject. The purpose of this study was to develop a method for estimating stride length automatically using an artificial neural network (ANN). In this paper, a 4-layer ANN with feature extraction layers trained by autoencoder was tested. In addition, the methods of searching for the local minimum of acceleration or ANN output after detecting the movement state section by ANN were examined. The proposed method estimated the stride length for healthy subjects with error of \(-1.88 \pm 2.36\%\), which was almost the same as the previous threshold based method \((-0.97 \pm 2.68\%)\). The correlation coefficients between the estimated stride length and the reference value were 0.981 and 0.976 for the proposed and previous methods, respectively. The error ranges excluding outliers were between \(-7.03\%\) and \(-3.23\%\), between \(-7.13\%\) and \(-5.09\%\) for the proposed and previous methods, respectively. The proposed method would be effective because the error range was smaller than the conventional method and no threshold adjustment was required.

key words: inertial sensor, stride-length, neural-network, gait, rehabilitation

1. Introduction

Lower limb motor dysfunction due to paralysis or weakness causes a decline in activities in daily life. Therefore, rehabilitation training to improve motor function is necessary for elderly people with weakness and paralyzed patients. Measurement using inertial measurement unit (IMU) is useful for evaluating lower motor function in rehabilitation at a hospital or at home. In our previous studies, methods of estimating stride length \([1, 2]\), foot inclination angle \([3]\), and gait event timing \([4]\) using an IMU attached to the foot were developed.

Stride length is often used clinically as an indicator of mobility because of easiness of measurement. Variation of stride length during walking is also useful for evaluating walking stability and risk of falling \([5]\). In order to estimate the stride length with high accuracy by integrating the IMU signal, it is important to reduce the drift error. Many studies often use a method of detecting the timing when the foot velocity is zero to correct the velocity obtained by integrating the acceleration \([6, 7]\). In our previous study \([1]\), threshold values were set for the acceleration and angular velocity of the foot to detect the movement state, and stride lengths of healthy subjects and some hemiplegic patients were estimated with good accuracy. However, appropriate threshold values varied depending on the healthy subject and the patient, on measurement trial and on stride. Therefore, it was necessary to adjust the values for each measurement or for each stride.

Recent studies have reported that the effectiveness of gait analysis by artificial neural network (ANN) using IMU. Xing et al. estimated the stride length using an acceleration sensor and ANN for pedestrian dead reckoning \([9]\). However, this method estimated the average stride length during walking from features such as the stride frequency and the maximum value of acceleration, and did not analyze a single stride length or its variation. Hannink et al. estimated the stride length by regressing the data segmented for each stride with a convolutional neural network \([10]\). This method has the advantage that it is not subject to methodological restrictions because it does not perform double integration of the acceleration signal. However, because stride segmentation was performed by dynamic time-warping and peak detection, it may be difficult to automatically analyze abnormal gait such as gait in patients with motor paralysis.

In order to solve these problems, our group has developed a method to automatically classify movement or stationary state using the ANN \([2]\). The method could detect appropriately the movement state of 7 healthy subjects and a hemiplegic subject. However, stride length estimation with the automatic detection method was required to be improved. This study aimed at development of the automatic method of stride length estimation using the movement state detection by ANN. The estimation accuracy of stride lengths of healthy subjects using the previous threshold based method \([1]\) and the methods using ANN were compared.
2. Stride Length Estimation Method

2.1 Outline of Stride Length Estimation

The stride length is estimated by calculating the integral of motion acceleration of the foot as shown in Fig. 1 (a), in which the acceleration is measured by an IMU sensor attached to the dorsum of the foot [1]. In order to integrate the motion acceleration, the integration section is determined for each stride based on the walking state (movement state and stationary state) detected by ANN as shown in Fig. 1(b).

Figure 1 (b) shows the flow of movement state estimation by ANN. The ANN was designed to classify the walking state into the movement state or the stationary state from sensor signals at each time. Accelerations $a$ and angular velocities $\omega$ for 32 samples from the current time to past 31 samples at a sampling rate of 100 Hz were used as input signals to ANN. In addition, ACC which was the L1 norm of the acceleration vector expressed by Eq. (1) was also used as the input vector because it was used to detect the movement state of the foot in the previous study [1].

\[
\text{ACC}(n) = |a_x(n)| + |a_y(n)| + |a_z(n)|
\]  

(1)

Here, $n$ is a time index, and $a_x$, $a_y$ and $a_z$ are x-, y-, and z-axis components of acceleration.

The number of samples used for ANN input was determined by preliminary experiments. ANNs with the different number of samples for the input were trained, and the rate of movement detection for a total of 1609 strides of seven healthy subjects including the training data was calculated.

As shown in Table 1, it was found that the highest detection rate was obtained when the number of samples was 32. Based on this result, the number of samples of the input to ANN was determined to be 32 in this study.

The average value of each IMU signal for 100 samples in the stationary state immediately after the start of measurement was subtracted from each measured signal as its offset value. Thereafter, each signal was normalized by its maximum value for each measurement trial. The input signals were given to the ANN by using the sliding window with the window size of 32 samples. The output of ANN represents the probability of the movement state at current time. The output of the ANN was processed by a fourth-order zero-phase Butterworth low-pass filter with a cutoff frequency of 4 Hz and then binarized by a threshold function with hysteresis characteristics (0.5 when detecting “High” from “Low”, and 0.3 when detecting “Low” from “High”). After that, movement state was determined from the output signal.

In this study, the binarized values of the ANN output were not used directly as walking state because teacher signals to train the ANN were adjusted as shown in Fig. 1(c). The teacher data (“1” was for the movement state and “0” was for the stationary state).
was for the stationary state) was obtained from measured IMU data by using the threshold method. Therefore, it was not necessary to measurement using other devices to label the data. However, the rising edge of the movement state of the teacher signal was shifted by 32 samples equal to the input window width as shown in Fig. 1 (c), and then the rising edge of the binarized value of the ANN output was shifted 32 samples as shown in Fig. 1(d). This was to prevent inadequate training near the boundary where the movement state changed, because IMU signals for the movement state near the boundary were similar to those for the stationary state. In Fig. 1(d), if the movement start timing of the current stride overlaps with the movement section of the previous stride, one sample before the current stride movement start timing was set to the stationary state and the end of the movement state of the previous stride was shifted.

2.2 Architecture of Neural Network

The ANN used in this study was a four layer feedforward network with two feature extraction layers by autoencoder [2]. Encoder1 has 40 neurons and encoder 2 has 15 neurons. The transfer function of the encoder is expressed as follows.

\[ f(x) = \frac{1}{1 + \exp(-x)} \]  

(2)

The transfer function of the output layer was the softmax function. The loss function was the cross-entropy expressed by the following equation.

\[ E = -\sum_k t_k \log y_k \]  

(3)

Here \( k \) is a data index, \( t \) is a teacher signal, and \( y \) is an ANN output. Training of the ANN was performed by following steps.

**step1** The input dataset were used as input and teacher data. A three-layer network with 40 neurons in the hidden layer was trained by backpropagation. The hidden layer from the input layer of this model was used as encoder1.

**step2** The encoder2 with 15 neurons was obtained in the same way as step1. The dataset converted by encoder1 were used as input and teacher data.

**step3** The model shown in Fig. 2 was constructed using encoder1 and encoder2. The output layer was a softmax layer that classifies movement state or stationary state. The teacher data was generated as described in Sect. 2.1 using IMU data detected by the threshold method. The weights of the output layer were trained by the back propagation.

3. Experimental Method

3.1 ANN Training

Teacher signals for ANN training was obtained from previously measured gait data. The gait data were measured with 2 healthy subjects with wireless inertial sensors (WAA-006, CRESCO Wireless, Inc.). The sensor signals were sampled at 100 Hz and recorded by a personal computer. Subjects walked at least 10m at three speeds (slow, moderate, and fast). The gait data of two trials for each walking speed were used for training. The teacher signal of the timing of the movement state were obtained by the previous threshold-based method [1]. The threshold value was determined so as not to cause false detection of stride.

3.2 Validation Test of Stride Length Estimation

The ANN was tested on gait data measured with 9 healthy subjects, different from the subjects used for training the ANN. The data were measured with wireless inertial sensors (custom-made IMU using MPU-9150, InvenSense, Inc.). The sensor signals were sampled at 100 Hz and recorded by a personal computer. The reference stride length was measured using a 2.4 m portable walkway device with a pressure sensor (MW-1000, ANIMA Corp.) embedded in the middle of the walking distance. Subjects performed 40 trials each at 16 m walking at three speeds (slow, moderate, and fast).

In order to estimate stride length, the following methods of determining the integration section were examined.

- Method A: Using the section of estimated movement state as the integral section.
- Method B: Using the section determined by the local minimum of ACC. The local minimum of ACC is searched near the timings of movement start and end detected by ANN after filtering the ACC signal by zero phase second order Butterworth LPF with the cutoff frequency of 6 Hz as in [1].
- Method C: Using the section determined by the local minimum of ANN output. The local minimum of ANN output is searched near the timings of movement start and end detected by ANN after LPF processing as the same as method B.

These process was performed offline because pre-processing was required. The ANN was implemented and trained using MATLAB and Deep Learning Toolbox (The MathWorks, Inc.).
4. Result

The value of the loss function $E$ of the ANN converged to 0.063. Figure 3 shows an example of ACC and movement state estimated by ANN. A total of 1677 strides were used to verify the accuracy of stride length estimation. The average and standard deviation of the error of stride length estimated by the threshold method, method A, method B, method C were $-0.97 \pm 2.68\%$, $-2.33 \pm 2.38\%$, $-1.85 \pm 2.55\%$ and $-1.88 \pm 2.36\%$, respectively. Figure 4 shows the error of the stride length estimated by the threshold method [1] and proposed methods using ANN. For slow and moderate speeds, although the mean absolute errors were larger for the proposed method A, B and C than for the threshold method, the range of the error bar in method B and C was almost within the range of the threshold method, so the variation of the error became small. For fast speed, it was about the same for all methods. The variation of error was small with slow and moderate speeds, but increased with fast speed in any method. The error ranges for all strides estimated by the threshold method, method A, method B and method C were between $-7.13\%$ and $5.09\%$, between $-7.75\%$ and $3.04\%$, between $-8.08\%$ and $4.04\%$ and between $-7.03\%$ and $3.23\%$, respectively, excluding outliers. The range of each error bars in method C was $-6.46\%$ to $2.92\%$ for slow, $-6.44\%$ to $2.82\%$ for moderate, $-8.11\%$ to $4.19\%$ for fast, all of which were narrower than the threshold method.

The correlation coefficient between the reference stride length and the estimated value were $0.976$, $0.982$, $0.980$ and $0.981$ for the threshold method, method A, method B and method C, respectively. Figure 5 shows the relationship between the reference value of the stride length and the estimated value by method C.

5. Discussion

Method B and C were able to estimate the stride length with almost the same accuracy as the threshold method. Since manual threshold adjustment is unnecessary, the proposed methods that can automatically estimate the stride length from the measurement results are highly practical. In the estimation of the movement section by ANN, the state after the movement could be detected automatically. However, it was difficult to capture small changes at the beginning of movement. Therefore, method B and C that include the process of searching for the local minimum of the signal showed good stride length estimation results. Although there is room for improvement in the variation in error at the walking speed of fast, most paralyzed or elderly subjects do not walk fast, so it is considered that proposed method can be applied sufficiently.

In the generation of teacher data for ANN training, only IMU signals were used and no other devices were required. In addition, the correlation coefficient between the estimated stride length and the reference was higher with the proposed ANN methods than with the threshold method. In the threshold method, it is assumed that the error variation has increased because of determination of the threshold.
value by trial and error. When estimating the stride length of paralyzed patients, the determination of the threshold may be more complicated. Therefore, the present method, which can reduce error variation and automatically estimate stride length, is expected to be clinically effective. However, in order to reduce the number of input dimensions of the ANN and to improve to the performance, it is a future task to study suitable features of input to the ANN. Although only healthy subjects were tested in this paper, this method should be tested in paralyzed patients in the future work.

6. Conclusion

Automatic stride length estimating methods from IMU signals using ANN were developed. Only IMU signals were used to generate teacher data without using other devices. These methods were able to estimate stride length with less variation than the previous threshold method for healthy subjects. The proposed methods might be useful in clinical measurements because it didn’t require threshold adjustment for each subject and could be measured automatically. In the next step, it is necessary to verify that ANN method is also effective for abnormal walking, such as paralyzed patients.

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