A Deep Neural Network for Gait Classification based on Inertial Sensors in Post-Stroke Patients

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Abstract

Background: Stroke survivors usually experience partial disability, due to abnormal gaits, which vary widely and require tailored rehabilitation programs. However, most gait classifications are based mainly on clinical assessments, which can be influenced by the therapist's experience. Inertial measurement units (IMUs) are devices that combine accelerometers and gyroscopes to detect movement. IMUs have been successfully used for assessing gait characteristics. Here, we aimed to develop a Deep Neural Network (DNN) model that incorporated information from a motion capture system and multi-labeling IMUs information. This DNN was developed to recognize individual gait patterns in patients affected by stroke to facilitate the design of suitable rehabilitation strategies and promote functional recovery.

Methods: We recruited ten patients, aged 20–75 years, with a first-ever, unilateral, ischemic stroke, which caused mild to moderate leg paresis 4 weeks after stroke and ten neurologically normal healthy controls. We applied a motion capture system integrated with multi-label IMUs to acquire the gait information. The motion capture system measured gait information by detecting movement of LED markers attached to each participant. In addition, the IMUs were attached to each participant's lower limbs to measure kinematic data. These measurements were then applied to the development of a DNN model that could recognize gait characteristics in patients after a stroke and in normal controls.

Results: The DNN model achieved an average accuracy of 98.28% in differentiating the stroke gait from the normal gait. Among patients with stroke, the DNN model had an average accuracy of 96.86% in classifying the gait abnormality as either a drop-foot gait or a circumduction gait. We also applied a publicly available dataset, the Physical Activity Monitoring Data Set, which contained IMU information from another independent set of participants to validate our DNN model. We found an average accuracy of 98.60%.

Conclusions: We developed a DNN model based on integrated information from a motion capture system and multi-label IMU inputs. This model might assist clinicians and therapists in identifying abnormal gaits more accurately and in applying suitable training programs within the “golden time window” of rehabilitation, after the onset of stroke.

Introduction

Stroke is a common medical emergency with a high mortality rate; it has ranked second as the leading cause of death in the last 15 years [1]. Patients who survive strokes commonly experience partial disability and inconveniences in their daily lives. Therefore, post-stroke patients usually require health care services and long-term rehabilitation. In the USA, the annual costs associated with managing stroke are about 34 billion US dollars [2]. On average, each stroke patient costs about 60,000 US dollars per year, and 30% of those costs are expended on rehabilitation and medical care [3].

Stroke survivors often have abnormal gaits due to neurological sequelae. These abnormalities include longer swing phases and reduced stance phases on the paretic side of the body. Abnormal post-stroke gaits vary widely and require personalized rehabilitation with therapists. The two most prevalent gait abnormalities observed post-stroke are known as the drop-foot [4,**Error! Reference source not found.**] and the circumduction gait [5,7]. The drop-foot gait develops when weakness or paralysis in the leg limits the ability to raise the front part of the foot. In the swing phase, the foot plate is unable to perform dorsi-flexion movements, and consequently, the toes are dragged when walking. Several rehabilitation strategies are applied for patients with drop-foot [**Error! Reference source not found.**]: first, a prosthesis, like braces or splints, is applied to help the patient hold the foot in the normal position; second, physical therapy is applied to strengthen the leg muscles and help the patient maintain adequate range of motion in the knee and ankle. The circumduction gait is also known as a hemiplegic gait and it is caused by weakness in the muscles, including the knee flexors, hip flexors, and dorsiflexors. The rehabilitation programs for patients with a circumduction gait usually require two therapists at the same time: one therapist needs to manually adjust the patient's pelvic motion and weight shifting, and the other therapist concomitantly assists the patient in stepping and controlling the lower limb during the stance and swing phases [8].

Inertial measurement units (IMUs), which include combinations of accelerometers and gyroscopes, can be used to measure the quality and quantity of physical activity in both healthy and pathological populations [10]. They have been successfully used for assessing gait characteristics (i.e., gait spatio-temporal parameters and gait variability). A few previous studies have attempted to design a computer program that could recognize abnormal gaits, based on IMU data, but classification systems for characterizing individual gait patterns are limited. One previous study found significant differences in the durations of gait phases between 10 healthy children and 10 children with hemiplegia, based on IMU data [11].

Due to the variability in gait problems encountered in survivors of stroke, it is important to determine each individual gait abnormality early after a stroke to ensure the timely design of an appropriate training strategy. Therapies applied within a 'golden time window of rehabilitation' improve the functional outcome. However, most current gait training programs are based mainly on clinical assessments, which might be influenced by the therapist's experience.

Many studies have attempted to identify post-stroke walking patterns by taking objective measures in patients [12,13]. However, to date, no studies have been conducted on the classification of stroke gaits. Therefore, the present study aimed to develop a deep learning-based model based on integrated information from a motion capture system and multiple IMUs to determine accurate individual gait patterns in patients that survived a stroke. This information will be useful for designing suitable rehabilitation strategies and improving functional recovery.

Methods

Participants

We recruited ten patients aged 20–75 years with a first-ever, unilateral, ischemic stroke that exhibited mild to moderate leg paresis 4 weeks after the stroke. Inclusion criteria were: age> 20 years; stable medical and neurological conditions; Brunnstrom Stages 3-5 [**Error! Reference source not found.**], assessed on the lower extremity;

Functional Ambulation Category [14] stages 3-5; a Mini-Mental State Examination [16] score >24; sufficient cognitive ability to follow the instructions and report any discomfort; the ability to walk 10 m indoors with or without aid devices; the ability to stand up on their own, with a handrail and aids; and physical condition sufficient to complete 3 min of supported walking. Patients were excluded when they had other orthopedic or neurological disorders or cardiac conditions that could be affected by a physical load.

We also recruited ten healthy participants without neurological disorders as the normal reference group. All participants provided signed informed consent. This study was approved by the institutional ethics board committee of the National Taiwan University Hospital.

Development of a Deep Neural Network (DNN) Model

Data Collection and Processing

We collected gait information from each participant to develop a Deep Neural Network (DNN) model [17] that could recognize individual stroke gaits. A motion capture system [17] and IMUs [19] were applied to participants to acquire gait characteristics. The motion capture system detected LED markers that were attached to test subjects. Gait information was measured at a sampling rate of 100 Hz and a resolution of 0.015 mm, as the subject walked a distance of 1.2 m. We attached the

LED markers to the subject's lower limbs, according to the Helen Hayes Marker Set [20]: four on the waist, two on the thighs, two on the knees, two on the calves, two on the ankles, two on the toes, and two on the heels (Figure 1a). The IMUs consisted of a 3-axis accelerometer, a 3-axis gyroscope, and a 3-axis magnetometer. The IMU devices detected kinematic data at a maximum sampling rate of 128 Hz. We attached IMUs to the subjects' calves, to record gait information (Figure 1b). We recorded 3-axis accelerations and 3-axis angular velocities for both legs as the subject walked. All participants were required to complete two 10-min treadmill walking tests, where they walked at their most comfortable pace. Between the two tests, participants rested for 10 to 15 min to ensure that the second test would not be affected by fatigue.

To develop the DNN model, we recorded the angular velocity of the calf on the sagittal plane [21] (i.e., the y-axis in Figure 1b). For example, we recorded the angular velocities ω_y of patient P9's right (paretic) leg (Figure 2a), and the angular velocities ω_y of a healthy control's (H5) right leg (Figure 2b). Note that each gait cycle contained the following three important gait events [22]: the mid-swing: when the angular velocity achieved a maximum in the gait cycle; the heel-strike: when the heel touched the ground; and the toe-off: when the toes left the ground. We marked the mid-swing points of each gait. The set of measured data was divided into individual gait cycles; then, we normalized the gait data by dividing it into one hundred points for each gait cycle (Figure 2c, d). This normalization made it possible to compare subjects with different walking speeds and different gait-cycle lengths.

Gait data collected from patients with strokes are referred to as the “stroke gait” and data from healthy controls are referred to as the “normal gait”. Figure 2 shows a patient with abnormal trembles and vibrations in the paretic leg during walking. This characteristic was used in the model to distinguish stoke gaits from normal gaits. The stroke gaits were further classified as a stroke gait with a drop-foot (SGwDF) and a stroke gait with circumduction (SGwC), based on clinical diagnoses from therapists. Because patients showed variability in abnormal gaits, we created four designations to build a multi-label classification model (Table 1). For example, patient P2 exhibited both a drop-foot and circumduction in the right leg, but patient P1 exhibited only a drop-foot in the left leg. Conversely, patient P10 exhibited neither an obvious circumduction nor a drop-foot, although his gait had been affected by the stroke. We applied the gait data shown in Table 1 to establish a gait dataset with 22,650 gait cycles, including 12,553 stroke gait cycles and 10,097 normal gait cycles (Appendix A).

Model Architecture

We used the normalized gait data to build a multi-output gait recognition model. The model architecture included a detection part and a classification part (Figure 3).

The detection part first judged whether the input gait was a normal gait or a stroke gait. It contained an input layer, six hidden layers, and the detection output. Each fully connected layer included 100 neurons. The detection output included two neurons, which labeled the gait as a normal gait [1, 0] or stroke gait [0, 1]. Data sets for the stroke gaits were then classified. This part of the model contained ten hidden layers, with 100 neurons each, and the classification output. Note that we performed iterative tests to determine the numbers of hidden layers and neurons, because using more layers and neurons might give similar accuracy, but it would greatly increase the computing load. The classification output had three neurons for classifying stroke gaits as follows: [1, 0, 0] for stroke gaits without drop-foot and circumduction, [1, 1, 0] for SGwDF, [1, 0, 1] for SGwC, or [1, 1, 1] with both drop-foot and circumduction characteristics.

To develop the DNN model, we included three neuron-based functions: the activation function, the loss of function, and the optimizer.

1. The Activation Function: A neural network includes several nonlinear activation functions derived from neurons. In the present study, for activation of the hidden layers, we selected the Rectified Linear Unit (ReLU) [22] (Figure 4a), as follows:

$$\mathrm{ReLU}(z) = \max(0, z) \tag{1}$$

where z was the neuron input and ReLU(z) was the neuron output. This function could effectively overcome the vanishing gradient problem [24]; i.e., the neural network would not continue training, when the gradient value was small. Moreover, the computing load was reduced, because this function judged whether the input was greater than 0. When the input was ≤0, then ReLU(z)=0, and this neuron was directly deleted. Thus, the total number of neurons was reduced, and rapid convergence ensued.

On the other hand, to activate the output layers, we selected the following sigmoid function [25]:

$$\sigma(z) = \frac{1}{1+e^{-z}} \tag{2}$$

where z was the neuron input and $\sigma(z)$ was the neuron output. This sigmoid function converted a scalar number to a binary number [0, 1] (Figure 4b). When $\sigma(z)$ was above a threshold of 0.5, it was considered to belong to the 1. Because the probability of each neuron was independent, the sigmoid function was mostly used to activate the output layer for multi-label classifications.

2. The Loss Function: This function was applied to evaluate how well the algorithms interpreted the given data. It evaluated the loss (error) of the model and updated the weights to reduce the loss on the next evaluation. We applied the following cross-entropy equation [26] as the loss function:

$$C\ \ y,\hat{y}\ \ = -\frac{1}{n}\sum_{i=1}^{n}\hat{y}_i \cdot \log(y_i) + (1-\hat{y}_i)\cdot\log(1-y_i) \tag{3}$$

where y_i was the distribution of the true output, and $\hat{y}_i$ was the distribution of the predicted output. The cross entropy measured and quantified the similarity between y_i and $\hat{y}_i$. In addition, by simultaneously applying the cross-entropy as the loss function and the sigmoid function as the activation function to the output layer, the model could avoid learning-rate declines in the gradient descent [27].

3. The Optimizer: We selected Adam [28] as the optimizer of the DNN model. Adam is an adaptive learning rate optimization algorithm designed specifically for training DNNs. It combines the advantages of Adagrad [29] and RMSprop [30] by calculating the gradients and updating the weights [27].

Model Training and Validation

We applied the k-fold cross-validation test [31] to evaluate model performance. We set k=5 by dividing all classes of gait data into five parts (Fold 1, Fold 2, …, Fold 5), and we arranged them randomly for training and validating. Each training run used four of the five folds as a training dataset, and the remaining fold was used for validation. Figure 5 shows the training and validating flow chart. The 5-fold cross-validation was repeated five times. In the training process, 500 samples were selected for each model training run (batch size=500) to update the weights. This training process was repeated 60 times (Epochs = 60). The phenomena of overfitting and excessive time in the training process were avoided by adding a Dropout [32], with a dropout rate of 0.2, to each fully connected layer in the classification part of the model. Consequently, each neuron had a 20% probability of being deleted.

We applied the Confusion matrix [33] for quantitative fine-tuning and correcting the model (Table 2). Based on the data in Table 2, the following indicators were frequently applied to evaluate the quality of model training [33]:

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{9}$$

$$Precision = \frac{TP}{TP + FP} \tag{10}$$

$$Recall = \frac{TP}{TP + FN} \tag{11}$$

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{12}$$

where *Accuracy* was the most intuitive indicator, but it might be invalid in some cases [33]. In this study, we applied *Accuracy* and the *F1-score* to demonstrate the quality of the developed DNN model. Furthermore, to validate our developed DNN model, we applied data from a public dataset, known as the Physical Activity Monitoring Data Set (PAMAP2) [34], which stored information from IMUs recorded in an independent group of participants. These data were available from the University of California Irvine machine learning repository [35].

Results

The basic clinical characteristics of the 10 patients with strokes and the 10 healthy controls are shown in Table 3. We applied the gait data from individual participants to establish a gait dataset with 22,650 gait cycles, including 12,553 stroke gait cycles and 10,097 normal gait cycles (Appendix A). We applied a 5-fold cross-validation test [31] by dividing all classes of gait data into five parts (Fold 1, Fold 2, …, Fold 5) and randomly arranging them for training and validating. The results in Tables 4–6 show the results of training each model with four of the five folds and verifying with the remaining fold. The process (Figure 5) was repeated five times to develop the DNN model.

The confusion matrix of the detection layer (Table 4) shows model *I*, where all gait data were applied, except Fold *I*, for training; then, the gait data of Fold *I* were applied for validation. The results show that the model could successfully identify the stroke gaits with only a few false-positive and false-negative rates on the off-diagonal terms (Table 4). Figure 2 shows that the stoke gaits could be easily distinguished from the normal gaits, because they included abnormal trembles, and they were less reproducible. However, stroke could cause different gait patterns in different patients, which can cause difficulties in identifying individual stroke gaits. For example, Figure

6 shows the angular velocities ω_y of patient P10's right (paretic) leg and of subject H6's right (healthy) leg. A comparison of Figure 2d and Figure 6d indicated that healthy subjects tended to have similar gait patterns. In contrast, a comparison of Figure 2c and Figure 6c indicated that patients with stroke could develop very different gait patterns. Nevertheless, the DNN model could automatically learn the different patterns between various stroke gaits without human supervision, and it successfully distinguished stroke gaits from normal gaits.

Among the data coded as stroke gaits, we also differentiated between drop-foot and circumduction gaits with the classification part of the DNN model. The confusion matrix of the classification layer is shown in Table 5. There, we listed the independent output neurons to observe the errors that occurred in classifying the drop-foot and circumduction gaits. The results showed that the model could effectively distinguish between drop-foot gaits and circumduction gaits. The false positive and false negative rates on the off-diagonal terms in the classification layer (Table 5) were slightly higher than those in the detection layer (Table 4), for differentiating between the normal and stroke gaits.

The validation of the DNN model for detecting and classifying stroke gaits are shown in Table 6. The detection layer achieved an average of accuracy of 98.28% and an F1-score of 0.9846 in differentiating between normal gaits and stroke gaits. The classification layer achieved an accuracy of 96.86% and an F1-score of 0.9716 in differentiating between the SGwDF and the SGwC abnormal stroke gaits. That is, the proposed DNN model could effectively detect stroke gaits and classify the two common gait abnormalities.

With this established DNN model, we further applied the public PAMAP2 dataset, which included nine healthy subjects (1 female and 8 males) that wore IMU devices. Those subjects performed 12 different activity tests, including standing, sitting, and walking. We applied the angular velocity of the calf in the PAMAP2 walking activities as input data for the five DNN models. The testing results are shown in Table 7. The average accuracy was 98.60% and the average F1-score was 0.9929. These results suggested that the DNN model we developed could effectively differentiate between stroke gaits and normal gaits, based on the angular velocity data recorded with the IMUs attached to the calves of subjects in the public database.

Discussion

This study developed a DNN model that could detect stroke gaits and classify two common abnormal gaits: the drop-foot gait and the circumduction gait, based on the angular velocity of the calves. Our DNN model achieved 98.28% accuracy in detecting stroke gaits and 96.86% accuracy in classifying the gait abnormality. During validation, the model achieved an average accuracy of 98.60% and an average F1-score of 0.9929, which demonstrated that the model could effectively detect stroke gaits.

Gait is a symmetrical, rhythmic, periodic motion that can be disrupted by various neurological disorders, including stroke, which is the most common in our aging society. Abnormal stroke gaits can decrease the efficiency of walking. The early, accurate identification of gait abnormalities is crucial in designing appropriate training strategies for rehabilitation. Previous studies have used several objective measures to detect and differentiate stroke gait from normal gait. For example, Knutsson and Richards [12] used surface electromyogram signals to identify three types of abnormal muscle activation patterns in patients that experienced a stroke. Wong et al. [13] applied load sensors to analyze the foot contact pattern when evaluating walking ability in patients with hemiplegic stroke. In addition, several recent studies have applied machine learning techniques to develop gait classification models for patients with various neurological disorders. Li et al [35] used a dynamic time warping algorithm, a sample entropy method, and an empirical-mode decomposition-based stability index to analyze the symmetry, regularity, and stability of post-stroke hemiparetic gaits. They reported that their approach achieved an area-under-the-curve of 0.94 in differentiating normal gaits from stroke gaits. Similar to our study, Mannini et al applied IMUs to the calves to detect difference patterns between normal gaits and pathological gaits, including stroke and choreatic gaits. They applied the maximum class-specific likelihood evaluation and found an overall accuracy of 66.7% [37]. They improved the accuracy to 73.3% by performing further analyses with Hidden Markov Models that included time and frequency domains [37]. In comparison, our model provided higher accuracy (>98%) in detecting stroke gait and in differentiating between drop-foot and circumduction gait patterns (>96%). The major difference between our study and the Mannini study [37] might be explained by the objectivity of the DNN model. The Mannini study [37] partially relied on human knowledge when applying the supporting vector computation, which limited the performance of gait classification. In contrast, we applied multi-layer algorithms in the DNN model to process the large amount of gait information input from IMUs. Indeed, the main advantage of the DNN model, compared to its predecessors, was that it could automatically detect important features without human supervision. The DNN was also computationally efficient, due to its convolution and pooling operations and its use of parameter sharing [38]

However, our model showed lower accuracy for stroke gait classification than for abnormal gait detection (96% vs. 98%). One possible explanation for this discrepancy could be that the number of stroke gaits in the dataset was not sufficiently large enough to analyze all the inter- and intra-subject gait variabilities that characterized the stroke group. This heterogeneity might have reduced the efficacy of capturing a common signature that could describe the group as a whole. A future large-scale study that incorporates patients with different neurological disorders and different stroke types could improve the accuracy of the classification model in differentiating different gait abnormalities.

This study had several limitations. First, the numbers of subjects in the stroke and normal control groups were limited. Second, the mean age of the control group was younger than that of the stroke group. Future studies that include a larger number of patients with various stroke locations and age/gender-matched controls are needed to confirm our findings. Nevertheless, our model validation, based on the PAMP2 public database, successfully demonstrated the efficacy of our DNN model in differentiating normal gaits from pathological gaits.

In conclusion, we developed a DNN model, based on information from multi-IMU inputs, for assisting clinicians and therapists in identifying stroke gaits more accurately. This model might expedite the design of suitable training programs to provide therapy within the golden time window of rehabilitation after stroke onset. Our study could be expanded in the future to identify more types of abnormal gaits caused by various neurodegenerative disorders in our aging society.

List of abbreviations

DNN, Deep Neural Network; IMU, Inertial measurement units; SGwDF, stroke gait with a drop-foot pattern; SGwC, stroke gait with circumduction

Declarations

Ethics approval and consent to participate

All participants provided signed informed consent, and the study was approved by the Human Subject Research Ethics Committee of the Institutional Review Board.

Consent for publication

Not applicable

Availability of data and materials

The datasets used and analyzed during the current study are available from the corresponding author upon reasonable request.

Competing interests

All authors declare no competing interests.

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Figure legends:

Figure 1. Multi-IMU measurements. (a) A participant wears multiple sensors attached to the waist, thighs, knees, calves, ankles, and toes, according to the Helen Hayes Marker Set [20] for the motion capture system; (b) The IMUs detect 3-dimentional angular velocity.

Figure 2. The angular velocities and gait patterns of patient P9 and control individual H5. (a) angular velocity of patient P9's right (paretic) leg; (b) angular velocity of subject H5's right (healthy) leg; (c) gait cycles of patient P9's right (paretic) leg; (d) gait cycles of subject H5's right (healthy) leg.

Figure 3. Architecture of the DNN model developed in the current study.

Figure 4. The nonlinear activation functions derived in neurons used to develop the neural network for the DNN model. (a) the ReLU function; (b) the Sigmoid function.

Figure 5. Flow chart shows the processes of model training and validation.

Figure 6. The angular velocities and gait patterns of patient P10 and healthy control H6. (a) Angular velocity of patient P10's right (paretic) leg; (b) angular velocity of control subject H6's right (healthy) leg; (c) gait cycles of patient P10's right (paretic) leg; (d) gait cycles of control subject H6's right (healthy) leg.

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Appendix A: Gait dataset used in this study.

The dataset of gaits applied in this study is available at:

http://140.112.14.7/~sic/PaperMaterial/dataset_of_gait.rar