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Can Trunk Acceleration Differentiate Stroke Patient Gait Patterns Using Time- and Frequency-Domain Features?

Wei-Chun Hsu ^{1,2,3,†}, Tommy Sugiarto ^{1,2,4,†}, Ying-Yi Liao ⁵, Yi-Jia Lin ¹, Fu-Chi Yang ⁶, Dueng-Yuan Hueng ⁷, Chi-Tien Sun ⁴ and Kuan-Nien Chou ^{7,*}

- ¹ Graduate Institute of Biomedical Engineering, National Taiwan University of Science and Technology, Taipei 10607, Taiwan; wchsu@mail.ntust.edu.tw (W.-C.H.); d10622817@mail.ntust.edu.tw (T.S.); jiajia527@gmail.com (Y.-J.L.)
- ² Graduate Institute of Applied Science and Technology, National Taiwan University of Science and Technology, Taipei 10607, Taiwan
- ³ National Defense Medical Center, Taipei 11490, Taiwan
- ⁴ System Integration and Application Department, Information and Communication Research Laboratory, Industrial Technology Research Institute, Hsinchu 31057, Taiwan; ctsun@itri.org.tw
- ⁵ Department of Gerontological Health Care, National Taipei University of Nursing and Health Sciences, Taipei 112, Taiwan; ianliao1209@gmail.com
- ⁶ Department of Neurology, Tri-Service General Hospital, National Defense Medical Center, Taipei 11490, Taiwan; fuji-yang@yahoo.com.tw
- ⁷ Department of Neurological Surgery, Tri-Service General Hospital, National Defense Medical Center, Taipei 11490, Taiwan; hondy2195@yahoo.com.tw
- * Correspondence: imchou1207@gmail.com; Tel.: +886-28792-3311
- + These authors contributed equally to this work.

Abstract: This study classified the gait patterns of normal and stroke participants by using time- and frequency-domain features obtained from data provided by an inertial measurement unit sensor placed on the subject's lower back (L5). Twenty-three participants were included and divided into two groups: healthy group (young and older adults) and stroke group. Time- and frequency-domain features from an accelerometer were extracted, and a feature selection method comprising statistical analysis and signal-to-noise ratio (*SNR*) calculation was used to reduce the number of features. The features were then used to train four Support Vector Machine (SVM) kernels, and the results were subsequently compared. The quadratic SVM kernel had the highest accuracy (93.46%), as evaluated through cross-validation. Moreover, when different datasets were used on model testing, both the quadratic and cubic kernels showed the highest accuracy (96.55%). These results demonstrated the effectiveness of this study's classification method in distinguishing between normal and stroke gait patterns, with only using a single sensor placed on the L5.

Keywords: clinical gait analysis; gait classification; feature selection; Support Vector Machine; stroke gait; wearable sensor

1. Introductions

Wearable devices, especially ones equipped with accelerometers and inertial measurement unit (IMU) sensors, have been widely used in gait analysis or physical activity monitoring [1–4]. Wearable devices can be used not only for calculating important gait parameters, such as spatiotemporal parameters [1–3], or for investigating the gait stability and variability between normal and pathological gait [4–7], but also for classifying different types of gait patterns, for example, Complex Regional Pain Syndrome (CPRS) gait pattern [5] or Parkinson's disease gait pattern [6]. Wearable devices can open up the possibility of collecting huge amounts of data during daily life conditions. Then, the bigger amount of data collected, combined with specific feature extraction process, will lead to possible application in clinical gait analysis, such as early detection of gait movement disorder.



Citation: Hsu, W.-C.; Sugiarto, T.; Liao, Y.-Y.; Lin, Y.-J.; Yang, F.-C.; Hueng, D.-Y.; Sun, C.-T.; Chou, K.-N. Can Trunk Acceleration Differentiate Stroke Patient Gait Patterns Using Time- and Frequency-Domain Features? *Appl. Sci.* **2021**, *11*, 1541. https://doi.org/10.3390/app11041541

Academic Editor: José Ignacio Serrano Received: 7 January 2021 Accepted: 5 February 2021 Published: 8 February 2021

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Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). Compared to the conventional method, gait classification with a wearable device would increase the mobility of gait assessment, while still minimizing the subject's discomfort, and it finally would provide the long-term goal of gait assessment in everyday life, in order to be able to do early detection of gait alteration. The gait parameters calculated and analyzed with wearable devices are not only limited to parameters related to clinical-gait performance, such as spatiotemporal parameters (stride time, step time, step length, etc.), but also features extracted from wearable signals, such as an accelerometer or gyroscope. In fact, a gait spatiotemporal characteristic can also be represented based on features extraction from a set of spatiotemporal local descriptors from gait video sequences [7].

Furthermore, Sejdic et al. examined gait patterns, using time, frequency, and timefrequency domain features, from an accelerometer signal, which was placed on the lower back of the subject [8]. The statistical analysis revealed that some of the extracted features could differentiate between the healthy and clinical population, which, in that case, included Parkinson's disease and Peripherals Neuropathy [8]. Moreover, some studies have used different machine learning techniques to discriminate neurodegenerative diseases, such as Parkinson's disease and Huntington's disease [9,10]. In 2017, Papavasileiou et al. proposed a method for successfully distinguishing patients with post-stroke and Parkinson's disease from healthy participants, by using a pair of smart shoes that can measure the ground contact force on both feet [11]. Besides gait pattern, gait stability was also being monitored by wearable devices. In 2012, Iosa et al. examined gait stability and harmony in children with Cerebral Palsy (CP) [9]. The gait stability itself can be quantified by measuring the upper-body acceleration's dispersion and smoothness. Meanwhile, the gait harmony is defined as the capacity of our body to transfer the symmetry and rhythmic movement of intra-limb. The gait harmony itself can be calculated by the ratio between the even and odd harmonics from the acceleration signal; it can also be calculated by the ratio between gait parameters from one leg to the opposite leg [9]. Their study found a general reduction of gait stability, which showed by higher root mean square (RMS) acceleration, peak-to-peak angular velocity, and minimal value of acceleration in children with CP [9].

In terms of gait-pattern classification with wearable devices, previous studies from Hsu et al. [10] and Caramia et al. [11] compared several combinations of IMU sensors placed on the lower limb and trunk. In addition, their studies achieved 89.1% accuracy and 96% accuracy, respectively [10,11]. However, compared to our study, which used only a single IMU sensor, those studies used several IMU sensors placed on the lower limb and trunks. Furthermore, the other two studies from Mannini et al. [12] and L. Wang et al. [13] utilized less sensors: three IMUs on both shank and lumbar spine, and two shank-mounted accelerometers, respectively. Those studies classified multi-class gait patterns from healthy, post-stroke, Huntington's disease, and Parkinson's disease with accuracy of 90.5% and 93.9%, respectively [12,13].

Therefore, to the best of our knowledge, there is no study which used data only from a single IMU sensor placed on the lower back, for differentiating normal and stroke gait patterns. Accordingly, in this study, we classified normal and stroke gait patterns by using time and frequency features of data obtained from only a single IMU sensor placed on a subject's lower back (L5). We hypothesized that, the time- and frequency- domain features from acceleration of lower back is able to classify normal and stroke gait pattern with the help of feature selection and machine learning classifier.

2. Materials and Methods

2.1. Participants

Twenty-three participants participated in this study, which comprised 7 healthy young adults (age: 23.5 ± 1.9 years), 4 healthy older adults (age: 70.5 ± 5.3 years), and 12 patients with stroke (age: 63.4 ± 6.9 years), and all of them were divided into two groups (healthy group and stroke group).

2.2. Equipment

signed written consent before experiment.

A TrignoTM wireless IMU sensor (Delsys Inc., Boston, MA, USA) was used in this study. The IMU sensor comprises a triaxial accelerometer (sampling rate 148 Hz; range ± 16 g), a gyroscope (sampling rate 148 Hz; range $\pm 2000^{\circ}$ /s), and a magnetometer gyroscope (sampling rate 74 Hz). All the three sensors were coupled with a 16-bit analogue-to-digital converter. However, in this study, we used only the data from the accelerometer and gyroscope.

Institutional Human Research Ethics Committee. All the participants were informed and

The wireless IMU sensor was synchronized with a three-dimensional (3D) motioncapture system comprising seven cameras (sampling rate 200 Hz) (Qualisys AB, Göteborg, Sweden) and three force platform devices, namely two AMTI (Advanced Mechanical Technology, Inc., Watertown, MA, USA) force platforms (sampling rate 2000 Hz) (Advanced Mechanical Technology, Inc., Watertown, MA, USA) and one Kitsler force platform (sampling rate 2000 Hz) (Kitsler Instruments, Winterthur, Switzerland). All the equipment, including the camera, force plates, and IMU sensors, were synchronized via a trigger line and controlled with *Qualisys Track Manager QTM* (Vers. 2.12; Qualisys AB, Göteborg, Sweden). However, because of the different sampling rates of the motion-capture system and wireless wearable devices, the IMU sensor sampling rate was up-sampled to 2000 Hz, matching that of the force platform.

2.3. Experimental Protocol

Retroreflective markers were placed on the subject's lower extremity and secured with medical-grade tape. In total, there were 30 markers placed on the bilateral hip, knee, and ankle segments of the subject. Subject static calibration was performed before a level walking trial, with the subject standing in the neutral position on one of the force platforms.

The IMU sensor was placed on the subject's lower back (L5), according to previous studies using wearable IMUs for gait analysis [8,14,15], and secured with medical-grade tape. After the static calibration process was completed, the participants were asked to perform level walking for approximately 12 m. The three force platforms were placed at the same floor level in the middle of the walking route, so that the participants could step on the three force platforms consecutively. Figure 1 shows the illustration of synchronized sensor and motion-capture-system equipment. Each subject performed six repetitions of the level-walking trial at his/her self-preferred speed.

The trajectory of each marker and the ground reaction force (GRF), acceleration, and angular velocity data were recorded and exported to .c3d files, for further processing.



Figure 1. Illustration of synchronized sensor and equipment (motion-capture system). IMU, inertial measurement unit; AMTI, Advanced Mechanical Technology, Inc. (Watertown, MA, USA).

2.4. Data Processing and Feature Extraction

The 3D trajectory data from the motion-capture system were labeled, using QTM 2.12 software. After the labeling process, the data were exported in .c3d format, for further analysis with Visual 3D Professional (C-Motion Inc., Germantown, MD, USA) software.

In Visual 3D software, the trajectory data were combined with the GRF data, to define the heel-strike (HS) and toe-off (TO) gait events. The defined HS and TO events were used for data segmentation. The 3D acceleration data were filtered by using a fourthorder Butterworth low-pass filter with a cutoff frequency of 2 Hz [16,17]. Then, the events defined using Visual 3D were applied to segment the acceleration data into one stride (HS to another HS on the same foot). The filtered and segmented data could only be used with the time-domain features. The time- and frequency-domain features were extracted for each of the three axes respectively. In this study, we decided to used data from a 3D-motion-capture system, to define the gait events, since we included stroke patients as our subject, and according to our best knowledge, there is no validated algorithm to define gait cycle for stroke patient population from an accelerometer placed on lower-back.

The problem of automatic gait-event detection with a wearable device was that the algorithm was developed specifically for particular sensor placement. For example, Perez-Ibara, in 2020 [18], compared some algorithms that used a heel-placed sensor to identify gait event, and Gadaleta et al., in 2019, used 3 sensors placed on the ankle and L5, with a deep learning method, to identify gait event [19]. Moreover, even if we could find an algorithm that used the same sensor placement, it may not validate abnormal gaits, like hemiparesis, myelopathic, or other neurological disease gait. Perez Ibara et al. proved that none of the available algorithms in the literature could maintain high accuracy when being used to identify gait event on hemiparesis or myelopathic subjects, even though they had good results on normal subjects [18]. Nevertheless, Del Din et al. successfully validated gait-event detection with an accelerometer on a Parkinson's disease patient, but still not on hemiparesis or stroke patients [15]. Therefore, in our study, we preferred to used data from a 3D-motion-capture system for gait-event detection.

The time-domain features extracted in this study were standard deviation, skewness, and kurtosis of the acceleration in the vertical, anteroposterior, and mediolateral directions. The root mean square (RMS) of the acceleration data and peak-to-peak value of the gyroscope in the vertical, anteroposterior, and mediolateral directions were also extracted

to examine gait stability, according to previous studies in which gait stability have been examined by using wearable devices [9,20–22].

The frequency-domain features extracted in this study were peak frequency [8,23], bandwidth, lower bound frequency, upper bound frequency, power at 99% occupied bandwidth, and power at half-power bandwidth. All the accelerometer and gyroscope signal processing and feature extraction procedures were performed by using MATLAB (The MathWorks Inc., Natick, MA, USA). Table 1 presents the list of features and their descriptions.

Table 1. Features number, name, and abbreviation.

Feature No.	Name	Abbreviation	
1–3	Acceleration SD on 1 stride gait cycle	SD ACC V/AP/ML	
4–6	Acceleration Skewness on 1 stride gait cycle	Skew ACC V/AP/ML	
7–9	Acceleration Kurtosis on 1 stride gait cycle	Kurt ACC V/AP/ML	
10-12	Acceleration RMS on 1 stride gait cycle	RMS ACC V/AP/ML	
13–15	Peak-to-peak angular velocity on 1 stride gait cycle	P2P Gyro V/AP/ML	
16-18	Acceleration first dominant frequency	FD Freq V/AP/ML	
19–21	Acceleration band power on 3 dB bandwidth	Power 3dB V/AP/ML	
22-24	Acceleration bandwidth frequency on 3 dB bandwidth	BW 3dB V/AP/ML	
25-27	Acceleration lower bounds frequency on 3 dB bandwidth	Flo 3dB V/AP/ML	
28-30	Acceleration upper bounds frequency on 3 dB bandwidth	Fhi 3dB V/AP/ML	
31–33	Acceleration band power on 99% occupied bandwidth	Power all V/AP/ML	
34–36	Acceleration bandwidth frequency on 99% occupied bandwidth	BW all V/AP/ML	
37–39	Acceleration lower bounds frequency on 99% occupied bandwidth	Flo all V/AP/ML	
40-42	Acceleration upper bounds frequency on 99% occupied bandwidth	Fhi all V/AP/ML	

2.5. Statistical Analysis and Feature Selection

One-way ANOVA was performed to statistically determine the difference between the groups for all extracted features. A Tukey post hoc test was also performed for multiple comparisons between groups for each extracted feature. Statistical significance (α) was set at 0.05. All statistical analysis procedures were performed by using SPSS Version 24.0 (IBM Corp, Armonk, NY, USA). A post hoc power analysis was performed on statistically different features determined from one-way ANOVA [24]. The power analysis was performed with G*Power software (ver. 3.1.9.2; Heinrich-Heine-Universität Düsseldorf) [24].

Two stages of feature selection were performed in this study. After obtaining the statistically different features from the post hoc test results, the second stage of feature selection was then performed by calculating the signal-to-noise ratio (*SNR*) [25]. The *SNR* is used to rank features and define how well the feature can discriminate between two classes. The *SNR* can be calculated by using the following formula:

$$SNR = \frac{(\mu_{class 1} - \mu_{class 2})}{(\sigma_{class 1} + \sigma_{class 2})}$$
(1)

where $\mu_{class 1}$ and $\mu_{class 2}$ are the mean value of features of classes 1 and 2, respectively; $\sigma_{class 1}$ and $\sigma_{class 2}$ are the standard deviation of the features of classes 1 and 2, respectively. After the calculation of the *SNR* and ranking of all the features, four features with the highest *SNR* score were selected to be used as features for the classification model.

2.6. Classification

The Support Vector Machine (SVM) classification method, a powerful method that has been widely used in many areas, including human-motion and gait-pattern classification, was used in this study [12,26–31]. This geometry-based classifier produces the largest margin between two classes by constructing boundaries that separate all data points of one class from the other class. In this study, the aim of the SVM classification was to find Optimal Separation Hyperplane (OSH) between healthy and stroke patients groups. SVM finds the OSH margin by maximizing the distance between class. That can happen by transforming the input data into a higher dimensional space by calculating the means of a kernel function. Then, the separation hyperplane can be constructed between the 2 classes in the transformed space [32].

Training datasets from selected features were used to train four SVM kernels (linear, Gaussian, quadratic, and cubic), by employing the Classification Learner toolbox in MATLAB [33]. From all 23 subjects, 18 subjects (9 from healthy group and 9 from stroke group) were used for training and validation purpose; meanwhile, the others 5 subjects (2 from healthy group and 3 from stroke group) served as the unseen testing dataset. Since each of subjects completed 6 trials of the level walking task, there was a total of 30 testing datasets (12 datasets from normal group and 18 datasets from stroke group). Tenfold cross-validation was performed to validate the models [12]; then, the final trained model was tested on the unseen 30 testing dataset, as explained before.

The performance of the SVM classifier was validated by using the following three metrics [26,34]:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \times 100\%$$
(2)

$$Sensitivity = \frac{TP}{TP + FN} \times 100\%$$
(3)

$$Specificity = \frac{TN}{FP + TN} \times 100\%$$
(4)

where *TP* and *TN* are the number of true positives and true negatives, respectively. *FP* and *FN* are the number of false positives and number of false negatives, respectively. In this study, *TP* was defined as the classifier correctly identifying a stroke gait, and *TN* was defined as the classifier correctly identifying a normal gait.

The classifier accuracy indicates the overall detection accuracy. *Sensitivity* refers to the accuracy of the classifier in recognizing the stroke gait condition. *Specificity* is defined as the ability of the classifier to avoid false detection of normal gaits [26]. The summary of the methodology is shown in Figure 2.



Figure 2. Diagram of classification method from data pre-processing, feature extraction and gait classification with Support Vector Machine (SVM) classifier.

3. Results

Feature Extraction and Selection

Forty-two features were extracted from the time- and frequency-domain accelerometer and gyroscope data. Specifically, from time-domain acceleration data (12 features), time-domain angular velocity data (3 features), and frequency-domain acceleration data (27 features). Additionally, among the 42 features, only 15 showed a significant difference between the young–elderly and stroke participants, whereas only one feature showed a significant difference between all groups. The 15 features that showed a significant difference between the young–elderly and stroke participants exhibited no significant difference between the young and elderly participants (*p*-value < 0.05). These are outlined as follows: the acceleration standard deviation in the vertical and anteroposterior directions, acceleration skewness in the vertical direction, acceleration RMS in the vertical and anteroposterior directions, first dominant frequency in the anteroposterior direction, power at 3 dB bandwidth in the vertical and anteroposterior directions, lower and upper bound frequency at 3 dB bandwidth in the anteroposterior and mediolateral directions, bandwidth, and upper bound frequency at 99% occupied bandwidth in the mediolateral direction.

The result of frequency characteristic of acceleration on three different axes was calculated by Fast Fourier Transform (FFT), and the result is show in Figure 3. Among these 15 features, the mean value of features from the young and elderly groups was always higher than that of features from the stroke participants.

This study classified normal and stroke gait patterns, using data obtained from the IMU sensor placed on the subject's lower back (L5); therefore, we only selected 15 features with significant difference between the young–stroke and elderly–stroke groups. The post hoc test revealed the achievement of statistical power, and the *SNR* value was calculated for those 15 features; the results are listed in Table 2. The result from the statistical power calculation revealed that all the significantly different features had a statistical power of more than or equal to 0.8. This statistical power analysis indicated that there was lower probability of making Type II error (false negative). In other word, with our current sample size, we had a higher probability of detecting an effect when there was an effect.

Feature Number	Feature Name (Abbreviation)	<i>p-</i> Value (ANOVA)	Achieved Statistical Power	SNR Value
1	SD ACC V	0.000	0.99816	0.42581
2	SD ACC AP	0.000	0.99999	0.37793
4	Skew ACC V	0.050	0.79921	0.17291
10	RMS ACC V	0.000	0.99810	0.42377
11	RMS ACC AP	0.000	0.99999	0.37786
17	FD Freq AP	0.002	0.99990	0.35230
19	Power 3dB V	0.001	0.90132	0.40920
20	Power 3dB AP	0.004	0.82464	0.39399
26	Flo 3dB AP	0.001	0.99994	0.35812
29	Fhi 3dB AP	0.002	0.99981	0.33804
31	Power all V	0.000	0.98057	0.41361
32	Power all AP	0.000	0.99999	0.53191
33	Power all ML	0.038	0.80151	0.15502
36	BW all ML	0.002	0.91135	0.33509
42	Fhi all ML	0.002	0.91121	0.32780

Table 2. List of statistically significant features and signal-to-noise ratio (SNR) value.

The second stage of feature extraction was performed for the 15 features. The *SNR* was calculated for each feature, and the features were ranked according to the calculated *SNR* values. The four features that had the highest *SNR* values were selected for SVM training, and their description is explained below:

- Root mean square of acceleration on vertical direction (RMS ACC V): calculated from root mean square of vertical acceleration data on one stride gait cycle [9,20–22].
- Standard deviation of acceleration on vertical direction (SD ACC V): calculated from standard deviation of vertical acceleration data on one stride gait cycle [9,20–22].
- Band power on 99% occupied bandwidth on anteroposterior acceleration (Power all AP): calculated from 99% occupied bandwidth of the result from Fast Fourier Transform on anteroposterior acceleration data during whole duration of level walking [8,23].



• Band power on 99% occupied bandwidth on vertical acceleration (Power all V): calculated from 99% occupied bandwidth of the result from Fast Fourier Transform on vertical acceleration data during whole duration of level walking [8,23].

Figure 3. Frequency domain characteristic of acceleration from young (**a**), elderly (**b**), and stroke (**c**) subjects on three different directions.

SVM training, coupled with 10-fold cross-validation, was performed with four kernels (linear, Gaussian, quadratic, and cubic). Thereafter, a set of test data was used to train the models. The results derived for the models and performance assessment are shown in Table 3. The performance index table obtained from the cross-validation of the models showed that the SVM classifier with the quadratic kernel had the highest accuracy (93.46%), whereas the SVM classifier with the cubic kernels had the lowest accuracy (90.65%). However, testing the trained models by using different test datasets revealed that both the quadratic kernel and cubic kernel had the highest accuracy (96.55%), whereas the linear and Gaussian kernels had the lowest accuracy (89.29%). Additionally, the model with the linear SVM kernel had the highest sensitivity (92.16%) on train/validation dataset; meanwhile, the quadratic and cubic kernels had the highest sensitivity (94.4%) on the testing dataset. The specificity assessment results revealed that all SVM kernels achieved

Performance Index	SVM Linear	SVM Gaussian	SVM Quadratics	SVM Cubic
Train/Validation				
Accuracy (%)	91.59	92.52	93.46	90.65
Sensitivity (%)	92.16	90.20	90.20	88.24
Specificity (%)	91.07	94.64	96.43	92.86
Testing				
Accuracy (%)	89.29	89.29	96.55	96.55
Sensitivity (%)	82.35	82.35	94.44	94.44
Specificity (%)	100.00	100.00	100.00	100.00

100% specificity, indicating that the four models can avoid misclassification of normal and gait data.

Table 3. Classifier performance assessment result of four different SVM kernel classification

4. Discussion

We classified normal and stroke gait patterns by using data from an IMU sensor placed on the subject's lower back (L5). First, the accelerometer and gyroscope data were segmented based on gait event, which was defined by a 3D-motion-capture system. Then, the time- and frequency-domain features were extracted from the segmented data, and the features which showed statistically significant differences between groups were selected for next-stage feature-selection process. The second stage of the feature-selection process calculated the SNR values of the features and ranked them accordingly. The results from the second-stage features selection were used to train four SVM kernels, and the trained models were used to test a different test dataset. To the best of our knowledge, this study is the first to classify normal and stroke gait patterns by using features obtained from an IMU sensor placed on the subject's lower back. A previous study from Mannini et al., in 2016, used two sensors placed on the shank and waist, and then classified three different gait patterns by using features from the Hidden Markov Model (HMM) [12]. Meanwhile, our study used only one sensor placed on subject's lower back and extracted features from the time- and frequency-domain features of the sensor. Moreover, both time- and frequency-domain features were selected, instead of selecting only time-domain features, because previous studies have shown that frequency-domain features have unique characteristics that can discriminate between normal and pathological gait patterns or activities [8,12,33,35,36]. A study performed frequency-domain analysis of gait by using an accelerometer, demonstrating the acceleration frequency characteristics of human gait [23,37].

Feature selection through statistical analysis and *SNR* calculation was performed to obtain minimum redundancy, implying that the selected features should be maximally different from each other and have maximum relevance, as well have the strongest correlation with the target variable [29]. The statistical analysis acted as the first stage of feature selection, by indicating which feature has significant differences between groups. Furthermore, the second level of feature selection was done by the *SNR* calculation, which ranked the selected features and demonstrated how well the features could discriminate between two classes.

One of the selected features was the acceleration RMS in the vertical direction, which was related to gait stability. RMS of acceleration is commonly used in gait analysis study due to its easy calculation and has clear physical value [38]. Mizuike et al., in 2009, examined the RMS of acceleration data from normal and stroke subjects, while doing level walking with self-preferred speed. The result showed that the raw RMS of acceleration in three different axes was significantly lower in the stroke group, as compared to the elderly group [38].

A previous study using upper-body acceleration investigated gait stability between stroke and normal participants and revealed that the acceleration RMS of stroke participants was slightly smaller than that of the healthy control group [39]. This finding is in agreement with our finding, which indicates that the acceleration RMS in the vertical direction was significantly smaller in the stroke participants than in the healthy participants (young and elderly). Therefore, this feature yielded a satisfactory *SNR* value, indicating adequate discrimination between the two classes.

Furthermore, the data segmentation into specified gait-event bases, like heel strike or toe-off, was important in our study, because the features that may be useful happened during that specified gait event. The level-walking trial performed by each subject included the phase where the subjects prepared to walk and stop their walk after finishing the trial, thus segmenting the data of the whole duration of the walk into each independent stride (from heel-strike to another heel-strike) was important to make clean data for the classification model. Since SVM relies on hand-crafted features, feeding the classifier model with clean data and highly correlated features is important to produce classifier with high accuracy. Moreover, the duration of each subject's stride or step time was different; thus, segmented data in a constant time frame will create less meaningful features, since the segmentation was created on different gait events. However, there is also a possibility to combine the features segmented based on gait-event with features extracted from whole duration data, such as being done by Rehman et al., in 2020, which used whole duration-based features extraction in forms of signal complexity, signal power-spectral-density, and signal magnitude [2].

Trained model validation showed that the SVM classifier with the quadratic kernel had the highest accuracy among the other three models. However, when the trained models were tested by using different testing datasets, both the quadratic and cubic kernels had the highest accuracy (96.55%). Among the 18 stroke datasets, these models misclassified only one subject as a normal subject. This result was anticipated, because the misclassified data came from the subject with mild impairment condition, which may not affect the subject's gait patterns significantly. According to a previous study classifying normal and pathological gait patterns, this result is also expected because this type of classification method focused on gait alteration caused by pathology, not on the pathology itself [12]. Testing model specificity revealed that all SVM kernels exhibited 100% specificity, indicating that no normal subject was misclassified with the stroke gait pattern. This result can be attributed to the mean value derived for the elderly and young participants, which was always greater than the stroke participants, when a significant difference existed between them.

Compared with state-of-the-art of the studies, our result achieved the best accuracy, with a testing result of 96.55%. In 2009, Kaczmarczyk et al. classified different gait patterns of post-stroke patients with only a 3D-motion-capture system and not using any wearable devices [40]. Their result showed accuracy of 100% and 86% with kinematics input from the lower limb. However, this study did not use any wearable sensor; thus, it was anticipated that the classification result will be good because it used the golden standard of the 3Dmotion-capture system [40]. Furthermore, if we compared with more recent published studies that used a wearable device to classify different gait patterns, we found that our result still outperformed the best result from Caramia et al., in 2018, which produced 96% accuracy [11]. However, they achieved their result by using eight IMU sensors attached to the lower limbs and trunk. In addition, another study from Mannini et al., in 2016, used only three IMU sensors placed on both the shank and lumbar spine and achieved 90.5% accuracy for classifying healthy elderly, post-stroke, and Huntington's disease groups [12]. The study from Mannini et al. [12] only achieved better results against a study from Hsu et al., in 2018, which compared several combinations of seven IMU placements and achieved 89.1% accuracy when using a shank-based sensor and decision-tree-based model [10]. Another study that used only two shank-mounted accelerometer achieved its best result with 93.9% accuracy of classifying multi-class gait patterns (healthy, peripheral neuropathy, post-stroke, and Parkinson's disease) [13]. To summarize, our study outperformed the other studies which used wearable devices to classify different types of gait patterns; even more important, our study achieved the result by using only a single IMU sensor placed on the lower back (Table 4).

However, there are still limitations in our study: first, the gait-event definition that still used data from a motion-capture system. Further investigation is required to replace the motion-analysis system to classify the walking cycle, using IMU sensor data, so that the amount of equipment required can be reduced and simplified. Second, the analysis and data processing was not being done in real-time manners. In the future, an additional mobile-computing device may be considered to be used, in order to create real-time application for clinical setup/hospital.

In terms of future application, this study opened up the possibility for building an in-home healthcare monitoring system, together with other wearable sensor algorithms for gait event detection, gait analysis, and physical activity classification. On those systems, wearable devices will take part in monitoring the user's gait pattern in home; thus, early detection of gait alteration could be known before the user gets a medical diagnosis from a hospital. Furthermore, for elderly people, the application will not be limited to monitoring the gait pattern but also to monitor their activity intensity and fall detection. All of those applications for in-home healthcare monitoring will become valuable data sources for clinicians in hospitals, in order to create more precise treatments for each patient.

Table 4. Comparison of method and results with other studies.

Authors/Year	Subjects	Sensor Placement	Features and Classifier	Results
Kaczmarczyk et al., 2009 [40]	74 hemiplegic patients	Only 3D motion capture and no wearable sensors	• Kinematics feature from 3D motion capture	100% and 86% accuracy from kinematic feature
Mannini et al., 2016 [12]	15 post-stroke, 17 Huntington's disease, 10 healthy elderly	3 IMU sensors placed on both shank and lumbar spine	 Group specific HMMs and time- and frequency-domain features SVM classifier 	90.5%
Hsu et al., 2018 [10]	20 subjects of post-stroke and other neurological disorder	Multiple placement: 7 IMU on lower back, both thigh, shank, and foot	 Time-domain feature and gait temporal parameter Various classifier: SVM, MLP, DT, RF 	89.13% testing accuracy from shank-based sensor and DT model
Caramia et al., 2018 [11]	27 healthy control and 27 PD with different stages	8 IMU placed on lower limbs and trunk	 Spatiotemporal gait and kinematic parameters Various classifier: NB, LDA, K-NN, DT, SVM 	96% when using all IMU and majority voting classifiers
L. Wang et al., 2020 [13]	8 peripheral neuropathy, 15 PD, 13 post-stroke, and 13 healthy control	2 IMU placed on shank	 8 gait parameters SVM Classifier	93.9%
Ours	11 healthy control and 12 post-stroke	1 IMU placed on lower back (L5)	 Time- and frequency- domain features SVM with 2 stages feature selection 	96.55%

HMM, Hidden Markov Model. PD, Parkinson's disease. MLP, Multi-Layer-Perceptron. DT, Decision Tree. RF, Random Forest. LDA, Linear-Discriminant Analysis. K-NN, K-Nearest Neighbor.

5. Conclusions

This study classified normal and stroke gait patterns by using time- and frequencydomain features obtained from acceleration data provided by an IMU sensor placed on the subject's lower back. Two stages of feature selection, which included statistical analysis and *SNR* calculation, were used to reduce the selected features until only four features remained. Among four SVM kernels, the quadratic kernel showed the highest accuracy when evaluated through cross-validation; this kernel and the cubic kernel both showed the highest accuracy (96.55%) when different test datasets were used. This study proved that a single placement of an accelerometer on a trunk was able to differentiate between normal and stroke gait patterns with the help of time- and frequency-domain features and an SVM classifier.

Author Contributions: Conceptualization, W.-C.H.; data curation, T.S., Y.-J.L., F.-C.Y. and K.-N.C.; formal analysis, T.S.; funding acquisition, W.-C.H., D.-Y.H. and K.-N.C.; investigation, Y.-J.L.; methodology, T.S.; project administration, W.-C.H.; resources, W.-C.H.; software, T.S. and C.-T.S.; supervision, Y.-Y.L., F.-C.Y., D.-Y.H., C.-T.S. and K.-N.C.; writing—original draft, T.S.; writing—review and editing, W.-C.H., Y.-Y.L. and Y.-J.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research supported and funded by Tri-Service General Hospital with project code: TSGH-D-109032; and Tri-Service-General Hospital & National Taiwan University of Science and Technology grant number: TSGH-NTUST-106-03.

Institutional Review Board Statement: The study was conducted according to the guidelines of the Declaration of Helsinki, and approved by the Institutional Review Board of Antai-Tian-Sheng Memorial Hospital (TSMH IRB 16-079-B1).

Informed Consent Statement: Written informed consent was obtained from all subjects involved in the study.

Acknowledgments: The authors would like to thank all subjects who participated on this study. The authors would like to thank the graduate student who helped during subject recruitment and data collection process. The authors would also like to thank for the funding No. TSGH-D-109032 and TSGH-NTUST-106-03.

Conflicts of Interest: The authors declare there is no conflict of interest on this study.

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