Adopting a Single Inertial Sensor and Designed Motion to Classify Brunnstrom Stages for Lower Extremities on Post-stroke Patients

Shao-Li Han¹, ³, Hsin-Ta Li², Hsien-Po Chang³, and Min-Chun Pan¹, ²*

¹Dept of Mechanical Engg, National Central University (NCU), Zhongli Dist., Taoyuan City 320, Taiwan
²Dept of Biomedical Sciences and Engineering, NCU, Zhongli Dist., Taoyuan 320, Taiwan
³Dept of Rehabilitation, Cathay General Hospital, Taipei 106, Taiwan
Email: pan_minc@cc.ncu.edu.tw

Abstract. The use of inertial measurement units associated with various algorithms has been proposed and developed to evaluate functional abilities and kinematics for stroke patients. In previous research, complex mathematical models were adopted successfully to clarify and to validate the functional results from different sensors. However, only a few algorithms stemmed from the process of motor recovery after a stroke or the way to administer clinical assessment scales. Based on the recovery process or how to conduct the assessment scales, the algorithm-sensor based module is supposed to accurately classify clinical motor recovery status and to provide additional kinematics in stroke survivors. In this study, only one sensor is affixed on the dorsum of the affected foot to reduce the burden on a weak extremity. A special movement while in seated, extend their knee and then dorsiflex their feet, based on the motor recovery process after stroke is proposed and tested to classify Brunnstrom stages for lower extremities. After analyzing 24 participants and adopting suitable threshold values for different Brunnstrom stages, the overall accuracy is 86.8%. The ability to distinguish Brunnstrom stage II from others can even reach a 100% accuracy. The accuracies for distinguishing Brunnstrom stage III, stage IV, and stage V are 86.6%, 94%, and 92.8%, respectively. We also analyze these misclassified data and investigate why the errors occurred. The results reveal the feasibility of the kinematics-based algorithm even using a single sensor.

1. Introduction
The most common cause of disabilities worldwide in adults is the stroke. Before establishing rationale rehabilitation, doctors or therapists often use clinical assessment scales to test and to record the neuromotor recovery after strokes. The most well-known assessment scale after stroke is the Brunnstrom recovery stage system, a six-stage system, ranging from totally flaccid (Stage I) to voluntary control of individual joint well (Stage VI) after stroke [1]. Stroke patients regain their muscle control in a sequencing movement pattern. Also, the appearance of spasticity, synergy, and individualized joint movements are the critical components for Brunnstrom stage systems. Clinical experts can sort Brunnstrom stages by these unique movement features [1] [2].

The rule to sort the Brunnstrom stages for lower extremity is to observe how stroke patients control their affected hip, knee, and ankle joints. Aside from flaccid status, extensor synergy and flexor synergy movements are the common coupled movement patterns during their recovery process. Patients with stage VI are viewed as normal movement as healthy adults. Extensor synergy and flexor synergy movement are the prominent milestone in patients with Brunnstrom stage III. Patients with
stage IV mean they can break the synergy [1]. To sum up, the sorting rules for low extremities are all based on the movements along the sagittal planes of the body.

To conduct clinical assessments is always time-consuming and expert-dependent. To overcome these disadvantages, researchers have proposed several methods to set up classifying clinical scales automatically. The basic structure for automatic assessments comprises sensors and sophisticated algorithms that stem from individual mathematical models [3].

Many sensors have been used to get motion data. With suitable algorithms, these sensors have been proven as valid and reliable to monitor daily activities or neuro-motor recovery [4][5]. Inertial measurement units (IMUs) own the advantage of low prices, durability, and feasibility. They are also easy to fasten on the body to get kinematic information and add clinically useful information to clinical assessment scales [2][3][6][7].

2. Literature review

Medical experts carry out the assessments by asking patients to do required movements or to complete specific tasks. Somewhat inevitably subjective errors and the inability to detect small changes do exist [1][8]. Therefore, many endeavors have been paid to obtain assessment results automatically [9][10]. Most of the research adopted complicated mathematical methods and many sensors to analyze the kinematics from several sensors or different types of sensors. The inconvenience to wear on and increasing other weights to weak muscles should be taken into consideration when considering the clinical application.

Early in our attempts at using a single IMU attached on an ankle-foot orthosis to judge knee movements were promising [5]. This hybrid module takes advantage of embedding into a rigid and oriented orthosis to overcome several challenges when adopting IMUs to compute kinematics. The algorithm for classification is intuitive and straightforward. Although exploring the possibility of using a single IMU to reduce the labor of patients, not all stroke patients need additional walking devices to prevent further clinical application.

A recent excellent study pointed out the feasibility of evaluating daily activities by obtaining different planes of motion in healthy participants [6]. Unfortunately, little research focused on the algorithms originated from kinematics and neuro-motor recovery process [10]. In theory, these specific movement sequences, direction, and magnitudes obtained from motion sensors can be easily integrated to classify Brunnstrom stages. Motion sensors can easily detect small changes of motion even without visible differences. In theory, the classification algorithm stemming from the motor recovery process is reasonable and workable.

3. Research question

Given the movements to assess Brunnstrom stages for lower extremities are along the sagittal plane of the human body, can it be possible to use a single IMU with physiology-based feature extraction to classify Brunnstrom stages? This study aims to provide a useful and straightforward method to classify the clinical assessment.

4. Methods

4.1. Experimental setup and designed movements

One self-made IMU module is used in this study. A nine-degrees-of-freedom IMU chip (SparkFun Electronics, Niwot, CO, USA) with a Li-ion battery is embedded into a small box. The nine degrees of freedom features an accelerometer, gyroscope and magnetometer. They can obtain motional and magnetic changes along the three dimensions. The dimensions of each sensor unit were 5.8 × 4 × 2.5 cm. The sampling rate is set to 25 Hz. The full-scale ranges of the accelerometer and the gyroscope were ±4 G and ±2000 dps, respectively. This IMU is affixed on the dorsum of foot and the orientation of the IMU is illustrated below as Figure 1(a). Two sequential movements are administered in this study to assess the Brunnstrom stage [1]. Participants sit on the edge of the bed, high enough to allow
their legs to move freely without touching the floor. They are asked to extend their affected knees first and then to dorsiflex the affected ankle while knee joints are extended. The sequence of movements is shown in Figure 1(b). This IMU is affixed on the lateral and dorsal foot, above the third, fourth, and fifth metatarsal bones. Researchers, caregivers, and even patients themselves can easily fasten an IMU firmly on this inclined plane. The maximal amount of motion changes can be observed directly along the Y-axis during participants performing knee (flexion/extension) and ankle (dorsiflexion/plantarflexion) movements. The magnitudes of movement along the sagittal plane (Y-axis) and rotation along the sagittal plane (Z-X plane) are the crucial factors in this study. The system is based on a laptop. A graphical user interface (GUI) based on LabVIEW was used to acquire and analyze all motion data.

Participants are asked to perform the task at a comfortable speed. They practice this task several times before motion data are acquired. The number of repetitions, 20, was chosen from our previous study [5]. In the previous study ten repetitions for each motion of lower extremity was collected, and thus, we could obtain at least 100 pieces of motion from one subject for analysis. Nevertheless, in this study, we acquire motion data from one plane. Therefore, we increase the repetitions without inducing subjects’ fatigue by setting the number of repetitions as at least twenty. This is an empiric value.

### 4.2. Algorithm design

The algorithm is set up based on the recovery process after stroke and how smoothly stroke patients extend their knees. As mention above, the sagittal plane, including the accelerations and directions of leg rotations, are the key factors. Lacking active knee movement among patients with Brunnstrom stage II, an acceleration threshold value, Rule (a), is intuitively set as the classifier. In the same way, the Rule(b) and Rule(d), the magnitude of acceleration when extending subjects’ affected knees and dorsiflexing their affected ankles can be used to classify Brunnstrom stage III, IV, and IV. The Brunnstrom’s rules to classify stage III and IV are the appearance synergic movements [1]. Unfortunately, Brunnstrom stage III is hard to be distinguished from other stages well [5]. The discrepancy of rotational directions during knee extension and ankle dorsiflexion is intended to overcome the difficulty. Synergic movements mean the affected hip, knee, and ankle joints move in a linked method. Extensor synergy among stage III patients induces unavoidably foot inversion and plantar flexion when they try to extend their affected knees. Thus, the additional criteria, rotation directions along the X-axis and the Z-axis, can be set as the Rule(c). After integrating all these rules, the decision-making algorithm is illustrated as Figure 2.
Figure 2. Scheme of Brunnstrom stage classifying rules. Rule (a) adopts the absolute value of acceleration changes along the Y-axis, $|\delta A_Y|$, less than the threshold value (TH1); Rule (b) and Rule (d) apply the same concept for threshold value 2 (TH2) and threshold value 3 (TH3).

Rule (c), $\phi(G_X) = \phi(G_Z)$, means the spin directions of Gyro along X axis and Z axis remain the same when patients try to extend the knee and dorsiflex their ankles.

4.3. Statistical methods
Descriptive statistics is the method to describe the general data of all participants. The receiver operating characteristic curve (ROC curve) is then used to determine the best threshold values [11]. After adopting the best threshold values, we apply sensitivity, specificity, positive predictive value, negative predictive value, accuracy, and F1 score to test the efficacy of the algorithm.

4.4. Inclusion criteria
Patients after stroke over six months are recruited in this study. They are asked to complete the designed movements for at least 20 repetitions at a comfortable speed after wearing an IMU on their dorsum of the affected foot. We exclude patients with unstable neuromotor status, poor mental conditions, and history of surgical intervention for affected limb, prominent deformities. Besides, those cannot sit well, and reduced endurance to perform at least 20 repetitions of designed movements are also excluded. A senior qualified rehabilitation doctor administers all Brunnstrom stage assessments.

4.5. Ethic issue
This study was approved by the IRB of Cathay General Hospital (CGH-P104014). All data were collected after obtaining participants’ informed consent. All participants did not report any discomfort during and after these tests.
5. Results

5.1. Recruited participants
Twenty-four participants took part in this clinical study, including seventeen male and seven female stroke patients, aging from 29 to 78 years (mean age ± standard deviation: 60.6 ± 12.4 years). Nine of them have left limb weakness, and fifteen have right limb weakness after stroke. Table 1 lists their Brunnstrom stages obtained from the physicians’ clinical assessments. A total of 484 motion data were analyzed here.

Table 1. Clinical assessment results for twenty-four recruited participants.

|       | Stage II | Stage III | Stage IV | Stage V | Total |
|-------|----------|-----------|----------|---------|-------|
| Male  | 1        | 6         | 4        | 6       | 17    |
| Female| 1        | 3         | 1        | 2       | 7     |
| Total | 2        | 9         | 5        | 8       | 24    |

Some of the IMU results are illustrated below in Figure 3. In these figures, the white, red, and green lines represent for the data coming from the X-, Y-and Z-axis in order. The (a) depicts the Brunnstrom stage II. The Gyro signals come from trunk compensated movements when patients try to move their weak legs. The Gyros in a patient with stage III, (c), reveal the same direction of rotation along the X-axis and the Z-axis when patients try to do ankle dorsiflexion. These results explain well the clinical rules to administer Brunnstrom stages, including the appearance of synergetic movements and the magnitudes of accelerations along sagittal plane.

Figure 3. Illustrating four patients with Brunnstrom stage II, III, IV, and V. The upper part of each picture contains the original data of linear accelerations and angular velocity during knee extension. The motion data in the lower parts of each picture come from ankle dorsiflexion.
5.2. Determination of threshold values

After obtaining all motion data, several threshold values are tested, and the best threshold values were then specified to achieve the best classifying results. The receiver operating characteristic (ROC) curve is adopted to find the best cut-off point, and all the ROC curves are shown in Figure 4. The result, when the threshold value is set as 0.225 G for TH1, has an excellent ability to classify Brunnstrom stage II from others. The other two threshold values, TH2 and TH3, are 0.6 G and 1.15 G, respectively. The area under the curve (AUC) for threshold value 2 is 0.8462, and the AUC for threshold value 1 and value 3 are 1 and 0.999. All these three threshold values own excellent ability to discriminate neighboring Brunnstrom stages.

5.3. Adopting thresholds

After adopting threshold values, 484 pieces of data were analyzed, and 64 pieces of data were misclassified. The accurate rate for this algorithm is 86.8%. The other results are listed in Table 2. The misclassified results are also listed in Table 3. The results reveal that motion data from Brunnstrom stage III can be misclassified as stage IV or stage V, but motion data from stage IV or V can only be misclassified as stage III. Only one participant with Brunnstrom stage IV is classified as Brunnstrom stage III, and all his motion data are all classified as Brunnstrom stage III. Two participants with Brunnstrom stage V are misclassified as being Brunnstrom stage III at first, but their following motion data are later classified correctly.

| Stage     | Sensitivity | Specificity | PPV   | NPV   | F1-score | Accuracy |
|-----------|-------------|-------------|-------|-------|----------|----------|
| Stage II  | 100.0%      | 100.0%      | 1.00  |       |          | 100.0%   |
| Stage III | 87.3%       | 86.5%       | 6.451 | 0.15  | 0.83     | 86.8%    |
| Stage IV  | 80.0%       | 97.7%       | 34.1  | 0.20  | 0.85     | 94.0%    |
| Stage V   | 87.1%       | 95.6%       | 19.97 | 0.13  | 0.89     | 92.8%    |

Table 2. The statistical analysis of established algorithm to classify Brunnstrom stage for lower extremity. Stage III is the most difficult stage to be distinguished (PPV: positive predictive value; NPV: negative predictive value).

| True Brunnstrom stage | Stage III | Stage IV | Stage V |
|-----------------------|-----------|----------|---------|
| Misclassified as       |           |          |         |
| Stage III              | 20(1)     |          | 21(2)   |
| Stage IV               | 8(4)      |          | 0       |
| Stage V                | 15(1)     |          | 0       |

Table 3. The misclassification results. The number in parentheses represents the number of participants.
6. Discussion
The results after adopting a suitable threshold value, Rule (a), revealed an excellent result of sensitivity (100%) and specificity (100%) to distinguish patients with Brunnstrom stage II from others. Clinically, the apparent discrepancy between Brunnstrom stage II and other stages is the lack of visible knee extension; therefore, the excellent results are reasonable.

Rules (b) and (c) still cannot reach an as satisfactory result as others. Eight pieces of motion data, misclassified as being Brunnstrom stage IV, are obtained from four participants with Brunnstrom stage III in lower extremities. After inspecting their motion again, these four participants exerted to dorsiflex their weak ankles, but extensor synergy prevented further ankle movements. They adopted hip flexion to compensate that, and then they raised their legs. Leg raising by excessive hip flexion when patients intended to dorsiflex their weak ankle may be the source of different rotational directions along the Z-axis in Gyro. Acceleration along the Y-axis is more prominent and causes errors.

There are fifteen pieces of misclassified motion data from one participant, stage III, as stage V. After observing his motion again, generalized tremor after stroke in his affected limbs was noted. He could not hold his knee still when knee extended, and tremor induced acceleration along the Y-axis, which misled this algorithm.

While extending the knee, the magnitude of acceleration along the Y-axis is set as a rule (d) to classify the stage IV, and stage V. The results support this hypothesis well, but one participant with Brunnstrom stage IV was misclassified as stage III. After inspecting how he moved his leg again, he had very weak ankle dorsiflexion when sitting with the knee flexed. Undoubtedly, he was clinically classified as Brunnstrom stage IV. The reason is that this required task is not the standard method to evaluate the Brunnstrom neuromotor recovery stage. Participants must overcome weak knee extensor first and then dorsiflex their ankles. If their knee extensors are too weak to overcome extensor synergy well, their motion data are classified as Brunnstrom stage III.

The same conditions occurred while analyzing those with the participants with Brunnstrom stage V but misclassified as Brunnstrom stage III. One had very weak foot dorsiflexion when his knee was extended lying on a bed, which was the standard position for lower extremity evaluation. The other had very severe spasticity that he could not dorsiflex his ankle when knee extended while in seated.

**Figure 4.** ROC curves of these three threshold values. Although TH2 owns less satisfactory results as the other two thresholds, the AUC of TH2 still proves good classification results.
However, their data were misjudged at the beginning and could be correctly classified after several repetitions of tests. It is noted all the misclassified data came from male. The obvious reason relates to the fact that most subjects are male. However, the locations of injured brains may also play an important role to worsen the misclassification. These possible causes warrant further studies but far beyond the scope of this study.

7. Summary
To sum up, we propose a single inertial sensor integrating with designed movements is a promising approach to sorting the Brunnstrom stages for stroke patients. A physiology-based algorithm is an intuitive and workable method. However, different neurological conditions need to determine the various thresholds. Further research is worthy of application to different neurological disorders.

8. Acknowledgments
The Ministry of Science and Technology in Taiwan, through the grant MOST 107-2221-E-008-095, partially funded this research. The authors gave thanks to all participants for their patience and cooperation to accomplish this study. The authors also thank Dr. Chien-Sheng Liu for his constructive advice and recommendation.

9. References
[1] S. Brunnstrom, Motor testing procedures in hemiplegia: based on sequential recovery stages, Phys. Ther. 46 (1966) 357-375.
[2] Z. Zhang, Q. Fang, X. Gu, Objective assessment of upper-limb mobility for poststroke rehabilitation IEEE Trans. Biomed. Eng. 63 (2016) 859-868.
[3] J. Lee, S. Park, H. Shin, Detection of hemiplegic walking using a wearable inertia sensing device, Sensors. 18(2018) 1736.
[4] L. Yu, D. Xiong, L. Guo, J. Wang J, A remote quantitative Fugl-Meyer assessment framework for stroke patients based on wearable sensor networks, Comput. Methods Programs Biomed. 128 (2016) 100-110.
[5] S.L. Han, M.J. Xie, C.C. Chien, Y.C. Cheng, C.W. Tsao, Using MEMS-based inertial sensor with ankle foot orthosis for telerehabilitation and its clinical evaluation in brain injuries and total knee replacement patients, Microsyst. Technol. 22 (2016) 625-634.
[6] M. Al-Amri, K. Nicholas, K. Button, V. Sparkes, L. Sheeran, J. Davies, Inertial measurement units for clinical movement analysis: reliability and concurrent Validity. Sensors 18 (2018) 719.
[7] V. Cimolin, N. Cau, G. Malchiodi Albedi, V. Aspesi, V. Merenda, M. Galli, P. Capodaglio, Do wearable sensors add meaningful information to the Timed Up and Go test? A study on obese women, J. Electromyogr. Kinesiol. 44 (2019) 78-85.
[8] K.J. Sullivan, J.K. Tilson, S.Y. Cen, D.K.Rose, J. Hershberg, A. Correa A, J. Gallichio, M. McLeod, C. Moore, S.S. Wu, P.W. Duncan, Fugl-meyer assessment of sensorimotor function after stroke: Standardized training procedure for clinical practice and clinical trials, Stroke. 42 (2011) 427-432.
[9] B.T. Nukala T. Nakano, A. Rodriguez, J. Tsay J. Lopez , T.Q. Nguyen, S. Zupancic, D.Y.C. Lie, Real-time classification of patients with balance disorders vs. normal subjects using a low-cost small wireless wearable gait sensor, Biosensors. 6 (2016) 58.
[10] G. Pacini Panebianco, M.C. Bisi, R. Stagni, S. Fantozzi, Analysis of the performance of 17 algorithms from a systematic review: Influence of sensor position, analysed variable and computational approach in gait timing estimation from IMU measurements, Gait Posture. 66 (2018) 76-82.
[11] K.H. Zou, J.O'Malley, L.Mauri, Receiver-operating characteristic analysis for evaluating diagnostic tests and predictive models, Circulation. 115(2007) 654-657.