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# Development of a Biological Signal-based Evaluator for Robot-assisted Upper-limb Rehabilitation: a Pilot Study

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**Abstract** Bio-signal based assessment for upper-limb functions is an attractive technology for rehabilitation. In this work, an upper-limb function evaluator is developed based on biological signals, which could be used for selecting different robotic training protocols. Interaction force (IF) and participation level (PL, processed surface electromyography (sEMG) signals) are used as the key bio-signal inputs for the evaluator. Accordingly, a robot-based standardized performance testing (SPT) is developed to measure these key bio-signal data. Moreover, fuzzy logic is used to regulate biological signals, and a rules-based selector is then developed to select different training protocols. To the authors' knowledge, studies focused on biological signal-based evaluator for selecting robotic training protocols, especially for robot-based bilateral rehabilitation, has not yet been reported in literature. The implementation of SPT and fuzzy logic to measure and process key bio-signal data with a rehabilitation robot system is the first of its kind. Five healthy participants were then recruited to test the performance of the SPT, fuzzy logic and evaluator in three different conditions (tasks). The results show: 1) the developed SPT has an ability to measure precise bio-signal data from participants; 2) the utilized fuzzy logic has an ability to process the measured data with the accuracy of 86.7% and 100% for the IF and PL respectively; and 3) the proposed evaluator has an ability to distinguish the intensity of biological signals and thus to select different robotic training protocols. The results from the proposed evaluator, and biological signals measured from healthy people could also be used to standardize the criteria to assess the results of stroke patients later.

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## 1 Introduction

Over the past decade, robots have been developed or revised for rehabilitation exercise, which can provide safe and effective labor-intensive physical training for stroke patients as compared to traditional manual therapy [1,2]. Up to now, widely accepted assessment tools for selecting suitable robotic training protocols are human-administered clinical scales, such as Fugl-Meyer Assessment (FMA) [3] and Modified Ashworth Scale (MAS) [4]. However, these assessment tools are subjective and time-consuming [5,6]. Meanwhile, due to a large number of patients and expensive medical costs, therapists can only offer a limited amount of time to quantify the severity of patients [7]. Therefore, automatic assessment tools with have been developed to eliminate these shortcomings [8,9]. These tools can provide fast and objective assessment outcomes which can be used for selecting suitable robotic training protocols [5,10].

To date, several robotic or robot-based assessment tools have been reported in the literature. Krebs et al [11] presented a MIT-MANUS robot-assisted assessment approach by using kinematic data. Based on this idea, Bosecker et al [5] proposed linear regression models to estimate clinical scores by using 20 kinematic and kinetic metrics from movement data recorded with the InMotion2 robot (the commercial version of MIT-MANUS). Total 111 chronic stroke patients were recruited in his experiment. The results showed that the models were accurate for Motor Status Score and FMA, which could be used for fast outcome evaluation. Furthermore, Park et al [12] reported a haptic elbow spasticity simulator by using quantitative data (position, velocity and torque) for improving the accuracy and reliability of clinical assessment of spasticity. The experimental results showed that the assessment results of 4 patients were 100% the same as MAS scores through 3 clinicians performed both in-person and haptic assessments. The commonly used metrics in the above mentioned assessment tools come from kinematic and kinetic data such as position, velocity and torque, which, however, cannot reflect muscle condition (e.g. muscle strength, muscle activity) or intentions of patients with neurological disorders [13]. In recent years, sEMG (surface electromyography) has been developed to detect the electric potential generated by muscle cells and thus to evaluate any medical abnormalities and the activation level of muscles [14-16]. By comparison, sEMG signals have two main advantages: 1) the low electromechanical delay (30-100ms), meaning the intentions of users can be shown in real time [17], and 2) for stroke survivors, sEMG signals can still be measured if their muscles can be stimulated by the activated motor units, no matter whether they can move their arms or not [18,19]. However, sEMG signal based (or included) assessment tools for selecting robotic training protocols, especially for robot-based bilateral rehabilitation, have rarely been reported.

Therefore, the main purpose of this work is to develop an upper-limb function evaluator based on biological signals of different participants, which is used for selecting robotic training protocols, especially for robot-based bilateral rehabilitation. IF (interaction force) and sEMG signals are used as the key bio-signal data, which can reflect patients' intentions and muscle conditions. Meanwhile, a robot-based SPT (standardized performance testing) is developed for measuring the required bio-signal data. Fuzzy logic is then used to regulate the measured data, which has been widely used for processing biological signals [20,21]. Compared to traditional data-driving based classification algorithms such as support vector machine (SVM), fuzzy logic would not be affected seriously by the small number of participants, and it have been proved to be useful to solve such problems [22,23]. The novelty of this work can be then concluded as three points: 1) to propose a biological signal-based evaluator, which is supposed to select robotic training protocols according to different conditions of participants with high accuracy; 2) to develop a robot-based SPT for measuring required biological signals, which is supposed to collect accurate bio-signal data; and 3) to use fuzzy logic to process the measured data, which is supposed to provide classification results with high accuracy. The rest of the paper is organized as follows: Section 2 details the methods of the evaluator; Section 3 describes an experimental validation; Section 4 presents the discussion on the experimental results, followed by the conclusive remarks in Section 5.

# 2 Methods

## 2.1 Bilateral Rehabilitation System

A bilateral upper-limb rehabilitation system developed in our previous work [24] will be used as the testbed for the biological signal-based evaluator. The bilateral rehabilitation system mainly contains two Universal Robot (UR) robots (master and slave sides) and two 6-axis load cells. A series of novel and interesting training protocols are designed based on the "Patient-cooperative" concept, muscle strength grading [25] and the suggestion of a physical therapist. Accordingly, an admittance controller is developed to control the proposed rehabilitation system and realize the proposed training protocols. The main training purpose of the proposed training protocols is to improve muscle activities of participants' affected arms, and further enhance the ability of muscle control and motor control. Therefore, two biological signals: IF (interaction force) and PL (participation level, processed sEMG signals) are then determined as the key bio-signal inputs for the evaluator. Note that the mentioned training protocols in this work are robot-based and designed for upper-limb bilateral rehabilitation.

## 2.2 System Overview

The overview of the proposed biological signal-based evaluator (BSE) is shown in Fig. 1. The inputs of the BSE are IF and PL, and the output of the BSE is a recommended training protocol. The BSE contains two fuzzy logic algorithms, two magnitude definers and one rules-based selector. Fuzzy logic is used to manage biological signals. Some numerical sets can be defined to classify the intensity of biological signals, which has been proved to be useful in biomedical signal processing [22,26]. Meanwhile, magnitude definer is developed to process the crisp output of fuzzy logic to obtain raw degrees (Big, Medium or Small). Then, the percentages of these raw degrees would be calculated to get the final status of biological signals. Furthermore, a rules-based selector is developed to select training protocols based on the final status of biological signals coming from the magnitude definer, which would be sent to the robot to perform. Take IF in Fig. 1 for example, the crisp inputs of fuzzy logic 1 are IF and the change of IF, and the crisp outputs ($\pm 10$) of fuzzy logic 1 would be sent to magnitude definer 1 to calculate the raw degrees of IF (Big, Medium and Small). After obtaining all raw degrees of IF, the magnitude definer 1 will calculate the percentages of these raw degrees. If Big gets the largest percentage, the final status of IF is defined as Big and so on. Finally, the final status of IF would be sent to the rules-based selector, which is used as key information to select an appropriate training protocol.

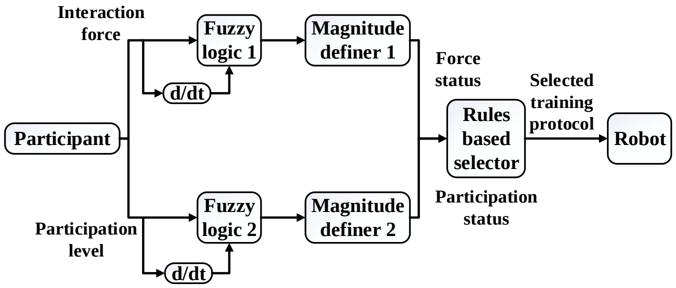


**Fig. 1** The block diagram of the BSE

### 2.2.1 Fuzzy Logic

Fuzzy logic is used to regulate biological signals before being fed into the proposed magnitude definer. Meanwhile, different membership functions (MFs) are utilized according to the reference [27] and authors' experience. Due to the simplicity and sensitivity [28,29], triangular MFs are chosen in this work rather than Gaussian MFs. It should be noted that all sets of two fuzzy logic algorithms can be revised according to participants, therapists, training stages or other experimental objectives at all times.

#### Fuzzy logic 1

Fuzzy logic 1 is utilized to manage IF for magnitude definer 1, and IF and change of IF are the crisp inputs. As discussed above, a series of training protocols have been proposed, which include bilateral-passive training (BPT), bilateral-cooperative training (BCT), bilateral-cooperative Plus trainings (BCPT) and bilateral active trainings (BAT). Thus, based on the muscle strength grading [25] (Table 1) and the suggestion of a physical therapist, grades 0 to 3 of muscle strength are regarded as Small, which should be suitable for BPT. Grade 4 of muscle strength is regarded as Medium, which should be qualified for BCT. Grade 5 of muscle strength is regarded as Big, which should be eligible for both BCPT and BAT. Therefore, the subsets of MFs (Fig. 2) are named as Positive Large (PL), Positive Medium (PM), Positive Small (PS), Zero (Z), Negative Small (NS), Negative Medium (NM) and Negative Large (NL), respectively.

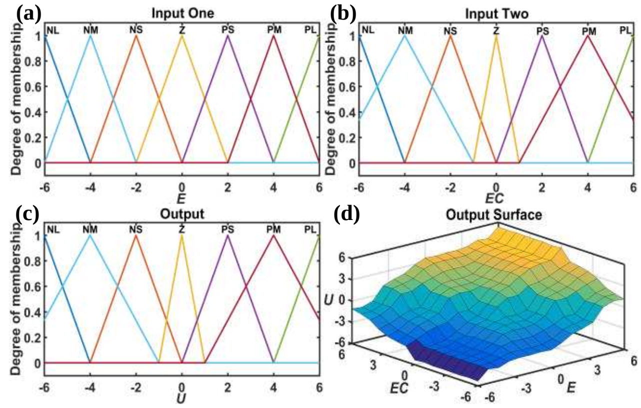


**Fig. 2** The membership functions of IF: **a** IF; **b** change of IF; **c** output; **d** the output surface of fuzzy rules

**Table 1** Muscle strength grading [25]

| Grade | Ability to move |
|---|---|
| 5 | The muscle can move the joint it crosses through a full range of motion, against gravity, and against full resistance applied by the examiner. |
| 4 | The muscle can move the joint it crosses through a full range of motion against moderate resistance. |
| 3 | The muscle can move the joint it crosses through a full range of motion against gravity but without any resistance. |
| 2 | The muscle can move the joint it crosses through a full range of motion only if the part is properly positioned so that the force of gravity is eliminated. |
| 1 | Muscle contraction is seen or identified with palpation, but it is insufficient to produce joint motion even with elimination of gravity. |
| 0 | No muscle contraction is seen or identified with palpation; paralysis. |

**Table 2** The fuzzy rules for the interaction force

| E \ EC | NL | NM | NS | Z | PS | PM | PL |
|---|---|---|---|---|---|---|---|
| **NL** | NL | NL | NL | NL | NM | NS | Z |
| **NM** | NL | NM | NM | NM | NS | Z | Z |
| **NS** | NM | NS | NS | NS | Z | Z | PS |
| **Z** | NM | NS | Z | Z | Z | PS | PM |
| **PS** | NS | Z | Z | PS | PS | PS | PM |
| **PM** | Z | Z | PS | PM | PM | PM | PL |
| **PL** | Z | PS | PM | PL | PL | PL | PL |

Table 2 contains 49 (7*7) different fuzzy rules to turn different IF. These rules are employed by the Mamdani-type inference method, which is based on the if-then-else structure [30]. Meanwhile, the centre of area method is utilized to defuzzify the fuzzy output U. In this work, the universal set of IF is [-50N, +50N], the universal set of change of IF is [-40N/S, +40N/S], and the universal set of crisp output is [-10, +10]. In addition, all raw forces would be normalized by the universal set of IF to eliminate the individual difference by the following equation:

$$F_n = \frac{F_{u-max/min}}{F_{a-max/min}} * F_r \tag{1}$$

where $F_n$ means the normalized force, $F_r$ means the raw force, $F_{u\text{-}max/min}$ means the max/min of universal set of IF (in this work, the universal set of IF is ±50N), and $F_{a\text{-}max/min}$ means the max/min of actual set of raw force.

**Fuzzy logic 2**

Fuzzy logic 2 is used to manage PL for magnitude definer 2, and PL and change of PL are the crisp inputs. Meanwhile, different MFs and fuzzy rules are used to process PL. For the MFs, the subsets of E (fuzzy input) and U (fuzzy output) are named as Large (L), Small (S) and Zero (Z), and the subsets of EC (fuzzy input) are named as Positive Large (PL), Positive Small (PS), Zero (Z), Negative Small (NS) and Negative Large (NL). In this work, the universal set of PL is [0, +1], the universal set of change of PL is [-1, +1], and the universal set of crisp output is [0, +10]. It can be seen from Fig. 3(a) that the fuzzy set of Big in E is (1, 6] which is decided based on the finding of sEMG activation patterns in our previous work [24] ([0, 1] for Small). That is for anterior deltoids muscle, the average PL is round 0.2 to 0.4 during a robotic bilateral training with active force, and is round 0.1 to 0.2 during a robotic bilateral training with passive force. Accordingly, the fuzzy set of Positive Large in EC is [1, 6] (Fig. 3(b)). The fuzzy rules (Table 3) are also adjusted based on the same finding. That is the fuzzy output is Large if E or EC is Large. It should be noted that the PL used here is the processed sEMG signals which is normalized by dividing peaks with a maximum voluntary contraction (MVC) and thus the universal set of PL is [0, +1] with the unit of %MVC.

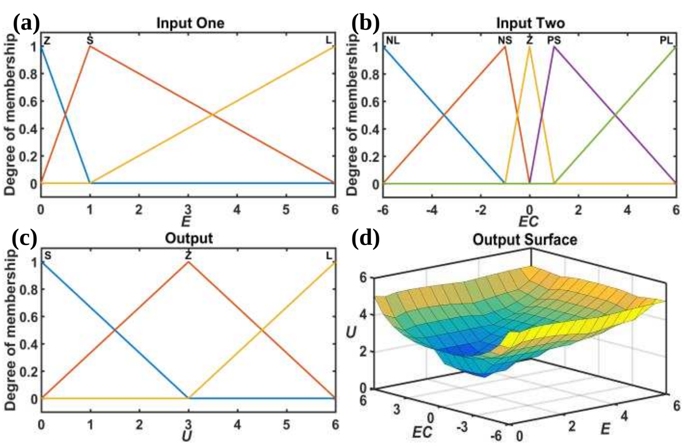


**Fig. 3** The membership functions of PL: **a** PL; **b** change of PL; **c** output; **d** the output surface of fuzzy rules

**Table 3** The fuzzy rules for the participation level

| E \ EC | NL | NS | Z | PS | PL |
|---|---|---|---|---|---|
| **L** | L | L | L | L | L |
| **S** | L | S | S | S | L |
| **Z** | L | Z | Z | Z | L |

### 2.2.2 Magnitude Definer

The magnitude definer is developed to process the crisp outputs (±10) of fuzzy logic before being fed into the rules-based selector. To be specific, the absolute values of crisp outputs would be calculated first and then the absolute values (0 to 10) would be classified by the magnitude definer to get raw degrees (Big, Medium and Small). For the IF (fuzzy logic 1), the set of [0, 10] would be evenly divided into three groups as Big, Medium and Small. Similarly, for the PL (fuzzy logic 2), the set of [0, 10] would be evenly divided into two groups as Big and Small. Once all raw degrees of biological signals (IF and PL) are obtained, the magnitude definer will calculate the percentages of these raw degrees. If Big gets the largest percentage, the final status is defined as Big and so on. Then the final status of biological signals (IF and PL) would be sent to the rules-based selector to select an appropriate training protocol.

### 2.2.3 Rules-based Selector

The goal of the rules-based selector is to select different training protocols for participants according to their IF and PL. Based on the muscle strength grading [25] and the training purpose of each recovery stage of Brunnstrom approach [31], the proposed training protocols can be allocated as follows: BPT and BCT can be used for stage 4 of Brunnstrom approach since weak muscle strength and low muscle activity (muscle control) occurred in these two trainings; BCPT can be suitable for stage 5 of Brunnstrom approach due to the requirement of medium muscle strength and good muscle activity (muscle control) for participating in BCPT; and BAT can be eligible for stage 6 of Brunnstrom approach due to the necessity of good muscle strength and muscle activity (muscle control) for taking part in BAT. The details of Brunnstrom approach can be found in Table 4. General rules for selecting training protocols are summarized as follows (Table 5):

**Table 4** The Brunnstrom stages of stroke recovery [31,32]

| Stage | Characteristics |
|---|---|
| **4** | • Some movement combinations outside the path of basic limb synergy patterns are mastered.<br>• Spasticity begins to decline. |
| **5** | • More difficult combinations are mastered.<br>• Spasticity continues to decline. |
| **6** | • Individual joint movement becomes possible.<br>• Coordination approaches normalcy.<br>• Spasticity disappears: individual is more capable of full movement patterns. |
| **7** | • Normal motor functions are restored. |

**Table 5** The rules for selector

| IF \ PL | Small | Big |
|---|---|---|
| **Small** | BPT | BCT |
| **Medium** | BCT | BCPT |
| **Big** | BCPT | BAT |

BPT=Bilateral-Passive Training, BCT=Bilateral-Cooperative Training, BCPT=Bilateral-Cooperative Plus Training, BAT=Bilateral Active Training

1) If IF is **Small** and PL is **Small**, participants would be asked to try SPT again to collect 'updated' biological signals since there could be two situations. The first situation is that the muscles of participants are weak. Biological signals indicate that participants have a limited ability to move normally, which should be classified as stage 4 of Brunnstrom approach. The purpose of this stage is to improve muscle strength and muscle activity (muscle control). Therefore, BPT is selected, in which the affected arms of participants would be moved carefully by the slave robot, and therapists can adjust the trajectory through the master robot according to the actual performance of participants in real-time. The second situation is that participants do not try their best during SPT, and thus negative results are measured. Note that if participants receive this selection 3 times, BPT would be chosen for safety purpose.
2) If IF is **Small** and PL is **Big**, BCT would be chosen. Biological signals show that participants' muscles are anomalous and they might have muscle rigidity, spasms or other diseases due to the abnormal high PL in comparison with the small IF. Meanwhile, due to the small IF, participants should still be classified as stage 4 of Brunnstrom approach. Therefore, for safety purpose, BCT is recommended, in which the affected arms of participants would still be moved by the salve robot carefully, and therapists can adjust the trajectory through the master robot as well. At the same time, due to the adaptive admittance controller, the trajectory of the slave robot can be adjusted by the force caused by the anomalous muscles of participants and thus the affected arms can be protected from injury [33].
3) If IF is **Medium** and PL is **Small**, BCT would be chosen. Biological signals indicate that the muscles of participants have recovered to grade 4 in terms of muscle strength (Table 1). However, muscle activity is still weak due to the low PL, and thus a bad motor control is caused [34-36]. This means that the movement of the affected arm might still be out of sync with muscle synergies, and participants should still be classified as stage 4 of Brunnstrom approach. Therefore, BCT is selected, in which participants can follow or adjust the trajectory of slave robot through their own efforts.
4) If IF is **Medium** and PL is **Big**, BCPT would be chosen. Biological signals indicate that the muscle strength of participants has recovered to grade 4, and muscle activity has been improved a lot. So participants can be considered as stage 5 of Brunnstrom approach, in which voluntary movements are purposeful and goal oriented. Therefore, BCPT is recommended, in which participants need to apply more efforts to adjust the trajectory of the slave robot, and improve the muscle strength, muscle activity and motor control continually.
5) If IF is **Big** and PL is **Small**, BCPT would be chosen. Biological signals indicate that the muscle strength of participants has recovered to grade 5, however, muscle activity (muscle control) is still weak. So participants would be regarded as stage 5 of Brunnstrom approach, in which the status of the muscle activity (muscle control) would still be focused on. Therefore, BCPT is recommended with the same reason of the fourth situation.
6) If IF is **Big** and PL is **Big**, BAT would be chosen. Biological signals indicate that the muscle strength of participants has recovered to grade 5 and muscle activity is almost fully restored, thus having a good motor control. This means that participants could be classified as stage 6 of Brunnstrom approach, and more challenging movements should be performed. Therefore, BAT is recommended, in which the trajectory is totally created by participants. According to [37,38], active training is more effective on motor functional improvement than passive training, and muscle strength and motor control can benefit more from active training before the full recovery.

It should be noted that this work focuses on the recovery stages of later sub-acute phase (5 weeks to 6 months) and chronic phase ($\geq$ 6 months) after stroke onset [39], in which spasticity is decreased a lot [31], and muscle strength, muscle activity and motor control can be improved significantly through continuous passive or active training [25,37,40].

## 3 Results

In order to test the proposed BSE, five healthy participants were recruited to perform SPT in three different conditions (tasks). The IF and raw sEMG signals were measured during the experiment at all times.

### 3.1 Participants

Five healthy male participants, between 27 and 29 years old, with no known nervous system diseases or upper-limb disorders, participated in this work. Demographic information of these participants is listed in Table 6. All experimental procedures were approved by the University of Auckland Human Participants Ethics Committee (reference 015256). Furthermore, all participants received a participant consent form and a participant information sheet, and verbal information about the robot and the EMG device. The emergency button of the robot would be kept close to researchers and participants all the time for safety purpose.

**Table 6** The demographics of participants

| Participants | Gender | Age | Height (cm) | Weight (kg) |
|---|---|---|---|---|
| 1 | Male | 28 | 187 | 81 |
| 2 | Male | 29 | 172 | 60 |
| 3 | Male | 27 | 180 | 85 |
| 4 | Male | 29 | 175 | 70 |
| 5 | Male | 28 | 171 | 72 |
| Mean | | 28.2 | 177 | 73.6 |
| Standard Deviation | | 0.75 | 5.90 | 8.78 |

## 3.2 Testing Protocol

SPT was completed through the revised bilateral rehabilitation system (half) which contained one UR robot (UR10, Universal Robots A/S, Denmark), one 6-axis load cell (SRI M3713C, Sunrise Instruments LLC, China) and one customized handle (Fig. 4(b)). Before testing, disposable Ag-AgCI electrodes (3M Red Dot, 3M Health Care, Germany) were placed in pairs over skin with an inter-electrode spacing of 0.02m [41]. Prior to sEMG electrode placement, each participant's skin was shaved of any hair if necessary, and vigorously cleansed with alcohol wipes until erythema was attained. sEMG electrodes were then placed along the main direction of the muscle fibre based on suggestions by SENIAM (the European project on sEMG) [41]. According to the previous experimental results, the right anterior deltoid (RAD) muscle was selected as it is one primary contributor for shoulder movements. After fully instrumented, each participant was asked to do a MVC. Subsequently, they were invited to sit on an adjustable chair and grab onto the handle attached to the robot to do SPT (Fig. 4(b)).

The movement in SPT was designed based on the muscle strength testing [42] of anterior deltoid muscle. That is the robot will move the right arms of participants passively along a predefined trajectory: shoulder flexion with the range of [-60$^o$, 0$^o$] at the speed of 10$^o$/s (Fig. 4(a), 0$^o$ means horizontal position) [43]. Furthermore, three different tasks were performed based on SPT with randomized orders: RPT, RNAT and RMAT. 'RPT' referred to a robot-based passive task, 'RNAT' referred to a robot-based normal active task, and 'RMAT' referred to a robot-based max active task. The difference between these three tasks was that there was no force applied by the participants in RPT, but normal force and max force would be performed to impede the movements of the robot in RNAT and RMAT respectively. The participants were asked to perform 3 rounds for each task, so a total training time was around 15 minutes including one acclimation stage, three different tasks, six short breaks (one-minute break after each round) and two long breaks (two-minute break after each task). Note that breaks were used to avoid muscle fatigue, and participants were only be asked to apply force during the movement from 0$^o$ to -60$^o$ rather than the movement from -60$^o$ to 0$^o$. A flow chart by using the BSE is shown in Fig. 5, which is used as a guideline for experiment. In addition, in a normal SPT, only RMAT with 3 rounds is needed.

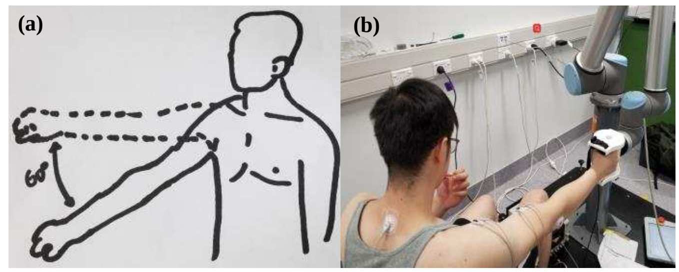


**Fig. 4** Testing protocol and experiment setup: **a** shoulder flexion exercise; **b** a healthy participant during SPT

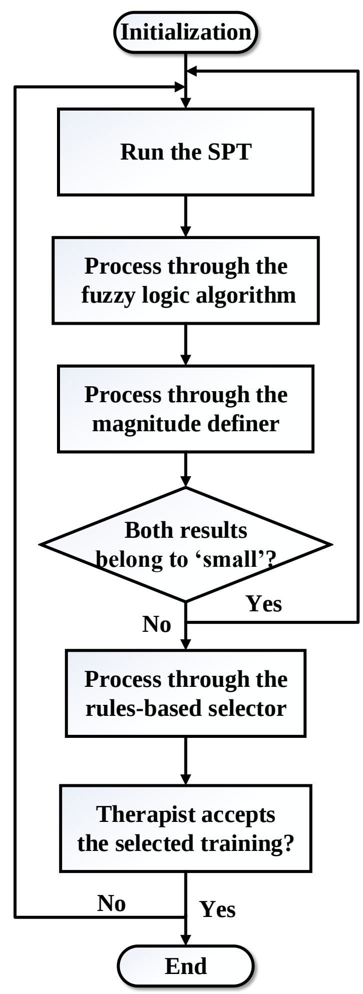


**Fig. 5** The flow chart of experiment with the BSE

### 3.3 Data Preprocessing and Evaluation Criteria

In SPT, IF was recorded by a 6-axis load cell at 600 Hz. A notch filter at 50 Hz was used to eliminate the electrical network noise, this filter is internal hardware filter in the Interface Box (M8128, Sunrise Instruments LLC, China). The force data was then filtered by a fourth-order low-pass Butterworth filter with a cutoff frequency at 10 Hz. The raw sEMG signals were collected with a g.USBamp at 1200 Hz (24 Bit biosignal amplification unit, g.tec Medical Engineering GmbH, Austria). A notch filter at 50 Hz was used to eliminate the electrical network noise. Meanwhile, a bandpass filter from 5 Hz to 500 Hz was applied to remove the artefacts and the DC offset. Both filters are internal hardware filters in the g.USBamp device. Subsequently, the linear envelope of sEMG signals was obtained by: 1) a second-order high-pass Butterworth filter with a cutoff frequency at 20 Hz; 2) a full-wave rectification; 3) a fourth-order low-pass Butterworth filter with a cutoff frequency at 4 Hz; and 4) normalized by dividing peaks with MVC [41,44]. Furthermore, in order to calculate the ensemble-averaged IF and PL waveforms, the processed IF and sEMG linear envelopes were divided by each round and then averaged.

Two aspects were evaluated in this work: 1) the performance of the proposed BSE, and 2) the performance of fuzzy logic. Specifically, the ensemble-averaged IF and PL waveforms of five participants in different tasks (Fig. 6) were used as the inputs. Meanwhile, the mean values of IF and PL (Table 7) were used to evaluate the performance of fuzzy logic. In addition, the performance of the BSE was also evaluated by comparing with the existing works.

### 3.4 Experimental Results

For the performance of the proposed BSE, the results are presented in Table 8, and the analytical results of the BSE are shown in Table 9. In general, there are two messages can be derived from the results. First, the BSE has the ability to distinguish the intensity of IF and PL of each participant and thus to select different training protocols. It can be seen from Table 8 that the BSE can select different training protocols through IF and PL, and in-depth information can be explored through the analytical results of the BSE (Table 9): BPT is selected for tasks in which participants do not apply force (RPT); BCT is recommended for tasks in which participants apply medium force (RNAT); and BAT is chosen for tasks in which participants apply max force (RMAT). Second, the BSE can provide more detailed information about recovery stages through the percentages of IF and PL even though a same training protocol is recommended for different participants. To be specific, in RNAT, participants are only asked to perform medium force, which means that the actual IF and the related analytical results can be different due to individual difference. Accordingly, as shown in Table 9, the Medium percentage of each participant in RNAT are different, and participant 3 even got a certain percentage of Big for the IF. Therefore, it is acceptable that the related PL of participant 3 is treated as Big due to the percentages of Big and Small are 65.213% and 34.787% respectively. The same situation is found in RMAT, in which the IF of participants 1 and 5 is treated as Medium even though they tried best. The evidence can be found in Table 9, in which the percentages of Big of participants 1 and 5 for the PL are 86.071% and 99.883%, respectively.

The performance of fuzzy logic can also be observed from the results, which can provide objective outcomes. To be specific, in Table 8, for RMAT, the BCPT is recommended to participants 1 and 5 rather than the BAT recommended by the mean values. Accordingly, it can be seen from Fig. 6, participants 1 and 5 apply big force first which, however, cannot be maintained. Therefore, the negative change of IF occurs even though the force is still belonged to the set of Big and the big mean value. However, the negative change of IF means that the force is reduced and the participant cannot keep a stable force for a while, so it might be something wrong with his muscle strength or muscle control, and the IF is not belonged to the set of Big. Thus, it is acceptable that the percentages of Big and Medium are 15.385% and 69.231% for the IF of participants 1 and 5 (Table 9), respectively. More experimental results have been attached as the Online Resource 1, in which more interesting outcomes are observed.

In addition, the performance of the proposed BSE was compared with the existing works in terms of classification accuracy. It can be seen from Table 10, hidden markov model used by Chan et al [45] receives the highest accuracy of 94.6%, followed by the heuristic fuzzy logic used by Ajiboye et al [46] with the accuracy of 94%. The proposed BSE receives the accuracy of 86.7% which is an acceptable result. It should be noted that the accuracy of the BSE was based on the results of mean values. It can be seem from Table 8, only two different results are found between the BSE and mean values (P1 and P5 in RMAT), thus getting the result of 86.7% (13/15).

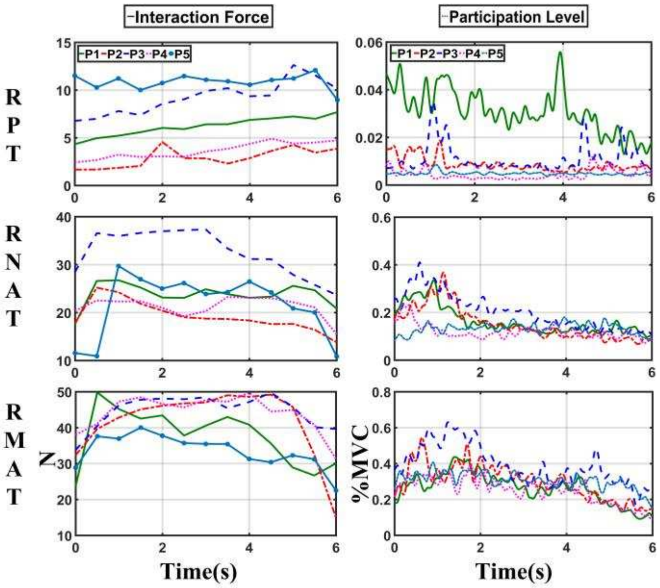


**Fig. 6** The averaged interaction forces and related averaged participation levels of right anterior deltoids muscles of five participants (P1 to P5) during different tasks

**Table 7** The mean interaction forces and participating levels of five participants in different tasks

| Tasks | Participant No. | Mean If (N)[a] | Mean PL (%MVC) |
|---|---|---|---|
| RPT | P1 | 6.204 | 0.031 |
| | P2 | 2.909 | 0.009 |
| | P3 | 9.209 | 0.011 |
| | P4 | 3.666 | 0.004 |
| | P5 | 10.851 | 0.005 |
| RNAT | P1 | 23.726 | 0.162 |
| | P2 | 19.203 | 0.152 |
| | P3 | 32.457 | 0.203 |
| | P4 | 21.239 | 0.120 |
| | P5 | 21.594 | 0.133 |
| RMAT | P1 | 37.530 | 0.264 |
| | P2 | 41.522 | 0.299 |
| | P3 | 44.667 | 0.393 |
| | P4 | 44.093 | 0.254 |
| | P5 | 33.486 | 0.308 |

[a]Absolute value of interaction force

**Table 8** The results of the BSE and the mean values of five participants in different tasks

| T | No | The BSE | | | The Mean Values | | |
|---|---|---|---|---|---|---|---|
| | | ST | IF | PL | ST | IF | PL |
| RPT | P1 | BPT | Small | Small | BPT | Small | Small |
| | P2 | BPT | Small | Small | BPT | Small | Small |
| | P3 | BPT | Small | Small | BPT | Small | Small |
| | P4 | BPT | Small | Small | BPT | Small | Small |
| | P5 | BPT | Small | Small | BPT | Small | Small |
| RNAT | P1 | BCT | Medium | Small | BCT | Medium | Small |
| | P2 | BCT | Medium | Small | BCT | Medium | Small |
| | P3 | BCPT | Medium | Big | BCPT | Medium | Big |
| | P4 | BCT | Medium | Small | BCT | Medium | Small |
| | P5 | BCT | Medium | Small | BCT | Medium | Small |
| RMAT | P1 | BCPT | Medium | Big | BAT | Big | Big |
| | P2 | BAT | Big | Big | BAT | Big | Big |
| | P3 | BAT | Big | Big | BAT | Big | Big |
| | P4 | BAT | Big | Big | BAT | Big | Big |
| | P5 | BCPT | Medium | Big | BAT | Big | Big |

T=Task, ST=Selected Training, IF=Interaction Force, PL=Participation Level, BPT=Bilateral-Passive Training, BCT=Bilateral-Cooperative Training, BCPT=Bilateral-Cooperative Plus Training, BAT=Bilateral Active Training

**Table 9** The analytical results of the BSE of five participants in different tasks

| T | No | Interaction Force | | | Participation level | |
|---|---|---|---|---|---|---|
| | | Big% | Medium % | Small% | Big% | Small% |
| RPT | P1 | 0 | 0 | 100 | 13.776 | 86.224 |
| | P2 | 0 | 0 | 100 | 0 | 100 |
| | P3 | 0 | 0 | 100 | 0.014 | 99.986 |
| | P4 | 0 | 0 | 100 | 0 | 100 |
| | P5 | 0 | 0 | 100 | 0 | 100 |
| RNAT | P1 | 0 | 84.615 | 15.385 | 36.009 | 63.991 |
| | P2 | 0 | 76.923 | 23.077 | 34.245 | 65.755 |
| | P3 | 38.462 | 46.154 | 15.385 | 65.213 | 34.787 |
| | P4 | 0 | 84.615 | 15.385 | 12.512 | 87.488 |
| | P5 | 0 | 69.231 | 30.769 | 20.803 | 79.197 |
| RMAT | P1 | 15.385 | 69.231 | 15.385 | 86.071 | 13.929 |
| | P2 | 61.538 | 23.077 | 15.385 | 91.432 | 8.568 |
| | P3 | 69.231 | 30.769 | 0 | 99.847 | 0.153 |
| | P4 | 53.846 | 38.462 | 7.692 | 88.016 | 11.984 |
| | P5 | 15.385 | 69.231 | 15.385 | 99.833 | 0.167 |

**Table 10** Comparison of accuracy between existing works and current work for processing biological signals

| Work | Algorithm | Accuracy |
|---|---|---|
| Current work | Fuzzy logic | 86.7% |
| Ajiboye et al [46] | Heuristic fuzzy logic | 94.0% |
| James et al [20] | Fuzzy logic + Artificial neural network | 82.0% |
| Si et al [21] | Fuzzy logic + Neural network | 91.0% |
| Huang et al [47] | Back-propagation neural network | 85.0% |
| Subasi et al [48] | Wavelet neural network | 90.7% |
| Bu et al [49] | LLGMN[a] | 85.1% |
| Sabeti et al [50] | Linear discriminant analysis | 84.6% |
| Yom-Tov et al [51] | SVM | 87.0% |
| Wei et al [52] | SVM | 93.0% |
| Chan et al [45] | Hidden Markov model | 94.6% |

[a]LLGMN: log-linearized Gaussian mixture network

## 4 Discussion

Up to now, the development of robot-based assessment tools is still stagnant for several reasons. First, robot-based assessment tools are difficult to evaluate in traditional ways due to their specificity [53], that is, many robot-based assessment tools are especially designed for specific systems or robots rather than universal devices. Second, also due to their specificity, the performance of existing robot-based assessment tools cannot be well confirmed and thus cannot be widely accepted and utilized in comparison with traditional clinical scales such as FMA and MAS [5,6]. However, as discussed in the introduction section, robot-based measures are objective and repeatable, and they can reduce assessment time drastically [5]. Therefore, it is still attractive to explore this new technology which might be a useful assistive tool for therapists, and can provide valuable information during stroke rehabilitation.

Based on the eagerness of this new technology and the purpose to establish a baseline to assess the results performed by stroke patients later, an upper-limb function evaluator is designed for selecting robotic training protocols according to different biological signals of participants. In order to test the proposed evaluator, five healthy male participants were recruited to perform the customized SPT with three different tasks. The experimental results (Tables 7 to 9) show that the developed SPT has the ability to measure accurate bio-signal data. Meanwhile, fuzzy logic has the ability to process complex biological signals and provide objective results. Thus, the proposed BSE has the ability to distinguish the intensity of IF and PL, and to select training protocols accordingly. On the other hand, the performance of the BSE has been compared with the exiting works in terms of classification accuracy. It can be seen from Table 10, the proposed BSE shows a promising result with the accuracy of 86.7%. In fact, the performance of the BSE is related to the performance of fuzzy logic. In this work, the utilized fuzzy logic can provide the accuracy of 86.7% (13/15) and 100% (15/15) for the IF and PL respectively (Table 8). The classification accuracy of the PL is better than most existing works. However, the classification accuracy of the IF is low, which reduces the performance of the BSE. The possible reason for the low classification accuracy of the IF could be its small dataset caused by the low sampling rate of the load cell (600 Hz compared with 1200 Hz of sEMG signals), and a small number of participants. Although a comparison between the existing works and current work was made (Table 10), it should be noted that there is a lack of research comparing the performance of different algorithms/models based on the same dataset. Therefore, the performance differences between these algorithms/models are still largely unknown and future work is expected toward this end.

Furthermore, based on the percentages of biological signals, the BSE has the ability to distinguish IF and PL more precisely, that is, IF and PL can be evaluated more visualized and objective, thus improving the accuracy of recommendation. Take participant 3 in RNAT for example, it can be seen from Table 8, the PL of participant 3 in RNAT is classified as Big. Accordingly, the analytical results of the BSE in Table 9 show that the PL percentage of Big for participant 3 in RNAT is 65.213%. Meanwhile, it can be found that the percentages of the related IF are 38.462% and 46.154% for Big and Medium, respectively. In RNAT, the other participants get zero percentage of Big even though they have the same result as participant 3 in terms of IF. This means that the BSE can detect recovery stage more objective and thus to select practical training protocols.

The performance of fuzzy logic has been evaluated by comparing with the mean values. It can be concluded from the results (Tables 8 and 9), fuzzy logic can process complex biological signals and provide objective outcomes by comparing with the mean values of the IF and PL. The detailed example has been shown in the result section. Meanwhile, as discussed above, the utilized fuzzy logic can provide the acceptable accuracy of 86.7% and 100% for the IF and PL respectively. These results cause the proposed evaluator to be a promising tool for selecting training protocols, especially for robot-based bilateral rehabilitation.

However, this work has some limitations. Firstly, only healthy participants were recruited, which can test the reliability rather than the validity of the BSE. Secondly, only one muscle was used to measure the sEMG signals. There is no doubt that the accuracy of the BSE could be improved with additional biological signals such as other muscles, velocity and angle information of each joint. Thirdly, the proposed BSE might be only suitable for the rehabilitation system and training protocols proposed in our previous work.

Future work would be done in three aspects according to the experimental results and the limitations. Firstly, more muscles would be considered in the BSE, and the weight of each muscle would be obtained and optimized by the genetic algorithm, thus improving the accuracy of the BSE [54]. Secondly, stroke patients would be recruited through the collaboration with other medical groups and hospitals, and the muscle tone would be considered to reflect their degrees of spasticity. The results of the BSE can be then compared with those obtained from traditional clinical scales to further assess the BSE. Thirdly, some modules and selection rules would be adjusted for popularizing the proposed BSE for universal robot-involved rehabilitation systems.

## 5 Conclusion

In this work, a biological signal-based evaluator is developed for selecting robotic training protocols for upper-limb bilateral rehabilitation. The evaluator contains two fuzzy logic algorithms, two magnitude definers and one rules-based selector, and the IF and the PL are used as inputs. The experimental results show that the proposed SPT can measure accurate bio-signal data, fuzzy logic can then process the measured data and provide object results. Meanwhile, the proposed BSE has the ability to distinguish the intensity of inputs, and select robotic training protocols objectively. Furthermore, due to the percentages of "Big, Medium and Small", the information of muscles (strength and control) can be presented and thus the recovery stages of participants can be better understood. Last but not least, the experimental results of the BSE and the biological signals measured from 5 healthy participants can be used as a baseline to assess the results of stroke patients through the same BSE and testing protocols.

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## Compliance with Ethical Standards

**Conflict of Interest** The authors declare that they have no conflicts of interest.

**Ethical Approval** The ethical approval has been approved by the University of Auckland Human Participants Ethics Committee (reference 015256).

**Informed consent** Informed consent was obtained from all participants.

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