

AUTOMATED MODIFIED ASHWORTH SCALE
ADAPTIVE IMPEDANCE ROBOTIC ASSISTED
TRAINING PLATFORM FOR UPPER EXTREMITY
MUSCLE SPASTICITY OF NEUROLOGIC DISORDER
PATIENTS

BY

ASMARANI AHMAD PUZI

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ABSTRACT

Robotic assisted training platforms have become a significant alternative to conventional training platforms as clinical therapeutic assistance to accommodate the increasing demand for neurological disorder physical treatments. Patients with neurological disorders usually experience conditions where their muscles are stiff, tight and prone to resist upon stretching, which in essence define muscle spasticity. The current method of muscle spasticity assessment is based on subjective assessment by therapists who heavily rely on their inner intuition, experience and skills. Based on the assessment, proper rehabilitation training tasks are prescribed as part of the training regimen. This, however, could be proven ineffective over the long run if the assessment is not done accurately. More so, in the case of robotic-assisted training systems used in training tasks, the deficiency in accurate information on muscle spasticity could largely affect any control strategy adopted to govern the robotic system. In order to address this problem, the research proposed to leverage on a synergetic combination of Modified Ashworth Scale (MAS) spasticity assessment tool and adaptive-impedance controller framed under a hybrid automata (HA) model applied on a patented upper limb rehabilitation platform, namely the Automated Muscle Spasticity Assessment System (A-MSAS). This required a dedicated spasticity characteristics model with control strategy during the assessment of muscle spasticity and an adaptive control based on impedance dynamics for the execution of the training tasks by A-MSAS. Spasticity characteristics model was developed using classification method and position-based impedance controller was adopted in strategizing the control of the A-MSAS. The latter was achieved through a dynamic mapping of the patient's recovery parameters to the control parameters. The research involved clinical measurements of muscle spasticity from 39 subjects diagnosed with neurological disorders to classify the MAS scores quantitatively. From the research of assessment regimen it was found that by using spasticity characteristics model, the rate in predicting the MAS score of the subjects was 92.86% accurate. Meanwhile for training regimen, the adopted control strategy has resulted in an average angular velocity reduction, by 28.75% for pre-catch phase while average angular velocity increase which there were observable boosts by 46.46% for post-catch phases. The controller objective has been proven by allowing a degree of compliance even as A-MSAS platform dynamically deviated from the desired trajectory; proportional to the feedback received. Based on the findings, it was conclusively justified that an objective spasticity assessment prior to the training task would enhance the adaptability of the control strategy. This leads to a minimized muscle strain instigated from the feedback of spasticity characteristics pattern, hence warranting a more effective rehabilitation training.

خلاصة البحث

أصبح التدريب والتأهيل بمساعدة الروبوت بديلاً هاماً عن التأهيل التقليدي كمساعدة علاجية سريرية لاستيعاب الطلب المتزايد على العلاجات البدنية للاضطرابات العصبية. يعاني مرضى الاضطرابات العصبية عادة من حالات تكون فيها عضلاتهم متصلبة ومشدودة مما يجعلها عرضة لمقاومة حركات التمديد، وهي تدل على تشنج العضلات. الأسلوب الحالي لتقييم تشنج العضلات يعتمد على التقييم الذاتي من قبل المعالجين النفسانيين والذين يعتمدون بشكل كبير على الحدس والخبرة والمهارات. يتم تحديد واجبات التدريب المناسبة بناء على التقييم كجزء من نظام التأهيل. ومع ذلك، وعلى المدى الطويل قد يثبت عدم فاعلية واجبات التدريب إذا لم يتم التقييم بدقة. في حالة التدريب والتأهيل بمساعدة الروبوت المستخدمة في واجبات التدريب، نقص دقة المعلومات عن تشنج العضلات قد يؤثر إلى حد كبير على نوعية استراتيجية التحكم المتبنية لنظام الروبوت. ولأجل معالجة هذه الإشكالية، اقترح البحث الاستفادة من المزيج المتأزر لمقياس آشورث المعدل لتقييم التشنج ووحدة تحكم تكيف المقاومة المؤطرة في إطار نموذج أوتوماتا الهجين والذي تم تطبيقه لإعادة تأهيل الطرف العلوي، والحاصل على براءة اختراع، والمسماة بنظام تقييم تشنج العضلات الأوتوماتيكي. وهذا يتطلب نموذجاً خاصاً بخصائص التشنج مع إستراتيجية التحكم أثناء تقييم تشنج العضلات والتحكم التكيفي المعتمد على ديناميكيات المقاومة لتنفيذ واجبات التدريب بواسطة مقياس آشورث المعدل لتقييم التشنج. تم تطوير نموذج خصائص التشنج باستخدام طريقة التصنيف واعتماد جهاز تحكم المقاومة القائم على الموضع في وضع استراتيجية التحكم لمقياس آشورث المعدل لتقييم التشنج. تم تحقيق هذا الأخير من خلال رسم خريطة ديناميكية لمعامل استشفاء المريض إلى معامل التحكم. تضمن هذا البحث قياسات سريرية للتشنج العضلي من 39 شخصاً تم تشخيصهم باضطرابات عصبية لتصنيف درجات مقياس آشورث المعدل كمّاً. من خلال البحث في نظام التقييم، وجد أنه باستخدام نموذج خصائص التشنج، كان المعدل في التنبؤ بنتيجة مقياس آشورث المعدل للمواد 92.86%. وفي الوقت نفسه بالنسبة لنظام التدريب، أسفرت استراتيجية التحكم المعتمدة عن انخفاض متوسط السرعة الزاوية، بمقدار 28.75% لمرحلة ما قبل الالتقاط بينما متوسط زيادة السرعة الزاوية وحيث كانت هنالك تعزيزات ملحوظة بنسبة 46.46% لمراحل ما بعد الالتقاط. تم إثبات هدف التحكم من خلال السماح بدرجة من الامتثال حتى مع الانحراف الديناميكي لمنصة مقياس آشورث المعدل عن المسار المطلوب؛ متناسباً مع ردود الفعل الواردة. بناءً على النتائج، كان هناك ما يبرر بشكل قاطع بأن تقييم التشنج الموضوعي قبل واجبات التدريب سيعزز القدرة على التكيف مع استراتيجية التحكم. وهذا يؤدي إلى تقليل شد العضلات المستحث من ردود الفعل من نمط خصائص التشنج، مما يستدعي مزيداً من تدريبات إعادة التأهيل أكثر فعالية.

APPROVAL PAGE

The thesis of Asmarani Ahmad Puzi has been approved by the following:

Shahrul Na'im Sidek
Supervisor

Hazlina Md. Yusof
Co-supervisor

Muhammad Mahbubur Rashid
Co-supervisor

Narimah Daud
Co-supervisor

Md Raisuddin Khan
Internal Examiner

Lee Yoot Khuan
External Examiner

Siti Anom Ahmad
External Examiner

Akram Zeki Khedher
Chairman

DECLARATION

I hereby declare that this thesis is the result of my own investigations, except where otherwise stated. I also declare that it has not been previously or concurrently submitted as a whole for any other degrees at IIUM or other institutions.

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Signature:.....

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LIST OF SYMBOLS

B_s	Damping of robot ($\text{kg } s^{-1}$)
$C(q, \dot{q})$	Robotic dynamic Coriolis
K_s	Stiffness of robot
K_{preC}	Stiffness of pre-catch phase
K_{postC}	Stiffness of post-catch phase
L	Langrangian
M_s	Inertia of robot
MAV_1	Mean average value
WDR	Work done of region
P_c	Catch angular position
$PROM$	Passive ROM
(t)	Arm angular position ($^\circ$)
max	Maximum ROM ($^\circ$)
q_d	Desired angular position
\dot{q}	Angular velocity
\ddot{q}	Angular acceleration
r_i	Control symbol f HA
RMS	Root Mean Square
s_i	State symbol of HA
T_c	Catch Moment (Nm)
x_i	Condition guard of HA

LIST OF ABBREVIATIONS

<i>A – MSAS</i>	Automatic Muscle Spasticity Assessment System
<i>ADL</i>	Activity Daily Living
<i>ANFIS</i>	Adaptive Neuro-Fuzzy Inference System
<i>ANOVA</i>	Analysis of Variance
<i>BLDC</i>	Brushless DC Motor
<i>CNS</i>	Central Nervous System
<i>CP</i>	Cerebral Palsy
<i>DAQ</i>	Data Acquisition
<i>DOF</i>	Degree of Freedom
<i>EMG</i>	Electromyography
<i>FL</i>	Fuzzy Logic
<i>GBD</i>	Global Burden Disease
<i>HA</i>	Hybrid Automata
<i>IREC</i>	IIUM Research Ethics Committee
<i>KNN</i>	K-Nearest Neighbors
<i>LABVIEW</i>	Laboratory Virtual Instrument Engineering Workbench
<i>LOOCV</i>	Leave-One-Out Cross Validation
<i>MAS</i>	Modified Ashworth Scale
<i>MATLAB</i>	Matrix Laboratory
<i>MTS</i>	Modified Tardieu Scale
<i>NMSD</i>	Normative Mean Signed Deviation
<i>PID</i>	Proportional-Integration-Derivatives
<i>ROM</i>	Range of Motion
<i>TBI</i>	Traumatic Brain Injury
<i>UMNS</i>	upper motor neuron syndrome

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

Neurological disorders contribute to the burden of healthcare globally. Neurological disorders are diseases associated with the brain and spine as well as the nerves that connect them. Stroke, cerebral palsy and traumatic brain injury are among the significant contributors of neurological disorders. Often, patients are unable to manage themselves and consequently become dependent on others for assistance. Therefore, they face difficulties in carrying out Activities of Daily Living (ADL) such as eating, walking, and driving among others. The symptoms that may affect the quality of ADL is fundamentally the increase in spasticity of unimpaired limbs of which intended motion for said limbs may become limited and experience jerks during movement.

Spasticity is a type of motor disorder characterized by a velocity-dependent increase in tonic stretch reflexes (muscle tone) with exaggerated tendon jerks, resulting from hyperexcitability of the stretch reflex, as one component of the upper motor neuron syndrome (Lance, 1981). Muscle tone is described as the resistance perceived by examiners to affected limb movement about joints. Essentially, patients who suffer from spasticity experience abnormal stiffness or tightness in the muscle that amplify resistance during passive movement of the affected limb.

Patients must undergo training and exercise to reduce the stiffness of the muscles and improve their motor controls. The recovery process necessitates an efficient training strategy to reinstate their motor control to the closest normal state before the

occurrence of the impairment. The spasticity severity of affected muscle must be assessed by the therapist before undergoing training or exercise. This is performed to allow the therapist to monitor the recovery process of the muscle as well as to plan the best rehabilitation training regimen for the patient.

Hitherto, spasticity assessment is carried out on a subjective basis. Even though there are standard tools to measure the levels of muscle spasticity as reported in earlier studies such as Modified Ashworth Scale Ashworth (1964), Modified Tardieu Scale Tardieu et al. (1957) and Fugl-Meyer Assessment Fugl-Meyer et al. (1975); J. Wu et al. (2010), these assessments rely heavily on the therapists' intuition, knowledge and experience (Blackburn et al., 2002; Priebe et al., 1996). Thus, the appraisal is susceptible to variations and possibly poses a challenge to screen the progress and plan the most suitable training for the patient effectively, especially if the training sessions are carried out by different therapists. In the long run, the problem could lead to an increase in overall expenditures pertaining to cost, time, and effort to undergo the training at rehabilitation centres.

Findings from the Global Burden of Disease Study Injuries and Risk Factors Study (GBD) have shown that the number of patients with neurological disorders has kept increasing despite neurological support and services provided by relevant agencies (Feigin & Vos, 2019). According to a similar report, neurological disorder patient population has reached an estimation of up to 1 billion out of 7.7 billion world population and one third suffers from permanent disability, commonly involving deficits in motor function (Feigin & Vos, 2019). If left untreated, neurological disorders could instigate severe depression or even death after several years. It is a common clinical practice that one-to-one rehabilitation session with a therapist must be conducted to

restore the flaccidity of the affected limb. Muscle flaccidity is a neurological condition where the muscle tone is lacking in the affected muscles in which tendon reflexes are either decreased or absent. As stated in The Conference Board, the labour shortage index (demand-supply) estimation is 98.9 from the year 2014 to 2024 (Gad Levenon, 2019). Labour shortage index pertains to the difference between labour demand and labour supply and is expressed as a percentile rank across all occupations. The index value ranks from 0 to 100 for least amount of risk to most amount of risk. Thus, the imbalance between physiotherapists and patients poses a challenge in maintaining the rehabilitation process efficacy, mainly due to the physical limitations of the therapists themselves such as effort and time consumption. Hence, the use of robotic assisted technology might be the immediate response to accommodate the increasing demand from the affected segment of society for better rehabilitation services.

Patients with neurological disorder often experience limb motion with spasticity characteristics pattern resulting from partial or complete loss of proprioceptive sense, reduced cognitive abilities and velocity-dependent resistance (spasticity) (Ali-biglou et al., 2008; Yom et al., 2015). Spasticity characteristics pattern in impaired limbs consists of three forms of patterns accountable for spasticity assessment, which are pre-catch, catch point and release point. The spasticity characteristics pattern is distinctively detectable during fast passive flexion and extension (Zakaria et al., 2015). This irregular increase in spasticity characteristics pattern is associated with the increase in resistance to passive movement, thus reflecting the severity of the spasticity levels (Bohannon & Smith, 1987). Recently, Duret et al. (2019) reported that passive training based on the affected limb movement behaviour results in having a significant beneficial impact on the neurologically disordered population Duret et al. (2019).

Moreover, therapeutic assistance from robotic systems has gained recognition in clinical applications. In the case of robotic systems, this may suggest the need to have more effective control regimes to adapt and embrace the dynamic response from appropriate autonomous training plan. In the context of the research, the model of an affected limb is assumed by a second-order inertia-spring damper system. The downside to this is that there will be an increase in biomechanical stiffness, which may be accounted for spastic resistance. There are many published studies describing the significant changes in impedance properties, mainly viscoelasticity/damping, stiffness and effective mass through muscle contraction. These changes also vary according to posture and dynamics of the affected limb (Mizrahi, 2015; Tanaka & Tsuji, 2004; Tanaka et al., 2014). Thus, neuromuscular properties like mass, damping and stiffness factors could be quantified as the patients counteract the undesired effects of load and disturbances from the therapists' hand as well as the force exerted during passive movement (Perreault et al., 2014; Piovesan et al., 2013; Tanaka et al., 2014). Thus, the integration of quantitative evaluation of spasticity with dynamic adaptive control framework is a significant step towards the advancement of robotic assisted training platform with adequate confidence level in providing the rehabilitation services. The proposed research employed the Modified Ashworth Scale (MAS) assessment tool due to its high inter-rater reliability and simple criterion categorisation (Akpinar et al., 2017; Bohannon & Smith, 1987; Puzi et al., 2018).

The proposed work focuses on the development of an objective MAS assessor system and position-based impedance controller framed using hybrid automata (HA) modeling technique, representing a discrete system mode of operation (criteria of HA); based on prior MAS assessment in determining the severity level of an

unimpaired limb. A single degree of freedom (DOF), patented robotic platform; i.e. Automatic Muscle Spasticity Assessment System (A-MSAS), was developed to integrate the muscle spasticity level assessment based on MAS tool and training regimen by employing adaptive control strategies into a single platform targeting the upper extremity. Figure 1.1 depicts the A-MSAS robotic device used for the research work. The system features a single-turn potentiometer to measure the flexion angle at the elbow joint. A custom-designed torque sensor is used to measure the feedback moment around the elbow joint. The remaining part of the system is composed of an arm plate, a lever to orient the arm plate, and a laptop with Labview software connected to a data acquisition card (NI DAQ card USB-6211).

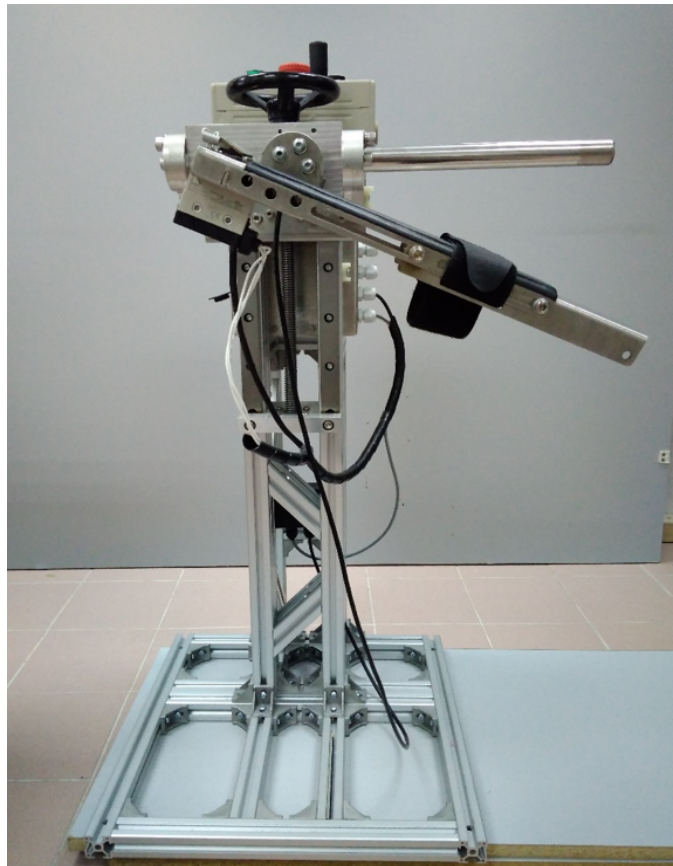


Figure 1.1: A-MSAS robotic assessment-training platform.

1.2 PROBLEM STATEMENT

The goal of the therapeutic training session is to provide adequate and effective rehabilitation to the affected limbs of patients diagnosed with neurological disorders. Continuous rehabilitation trainings are crucial in the recovery process. Several limitations have been identified in the current practice that considerably limit therapists in optimizing the efficacy of a rehabilitation training session.

The severity of muscle spasticity evaluated using MAS tool relies heavily on the therapists' experience, skills and intuition in scoring the spasticity level. Fair enough, the subjective procedure would lead to inconsistency in the assessment, primarily due to the factors mentioned above. Therefore, an objective assessment is proposed in the research to overcome the limitation of the existing method in assessing spasticity level. Previous research have offered an objective spasticity assessment by distinguishing two categories namely healthy and spasticity affected control groups (Seth et al., 2015). The problem with the current technique is the lack of description on spasticity severity conditions affecting the limb. This innovation would prove to circumvent the problem by characterizing the spasticity level based on the level prescribed in the MAS tool by using a classification technique. The accurate assessment of muscle spasticity is paramount to ensure the efficacy of the rehabilitation regimen deployed during a rehabilitation session. This study however, in assessing the spasticity level of affected limb quantitatively showed great margin for improvement.

Once a muscle assessment has been conducted, the current clinical practice would normally prescribe a suitable training regimen for the patient to undergo. The training process generally takes around an hour, which involves several repetitive rounds of rehabilitation training with the therapist until the next assessment is conducted; usu-

ally in the subsequent month. The subjective assessment may be administered by different therapists, whereupon it is likely in many cases to lead to different readings of muscle spasticity level. Applying such rehabilitation training regimen to different levels of muscle spasticity throughout the treatment would definitely be direful to patients over time as long as the spasticity characteristics pattern is concerned. Hence, a more flexible and adaptive system is necessary to provide better experience and efficiency in robotic based training management. An intelligent model-free based control technique is proposed to be employed for the rehabilitation training, which is based on the dynamic characteristics of muscle spasticity characteristics pattern and MAS evaluation of the affected limb. Dynamic adaptability position-based impedance control scheme gives beneficial impact to people with neurological disorder as this proposed treatment shall utilize the right position, velocity, and time based on the muscle spasticity characteristics pattern.

Ensuring patient safety and comfort while using a robotic assisted training system is crucial in choosing a suitable control scheme. The lack of systematic adaptation according to the extent of neurological disorder in the robotic assisted training model has indeed gained attention. Applying such control regimes to different levels of severity can be awful to patient in the long run. Thus, a more robust and dynamic system is required to offer better robotic training regimen in terms of experience and performance. Thus, utilizing control strategy to dynamically adapt to a MAS criterion could potentially improve the efficacy and efficiency of robotic assisted training regimen.