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REVIEW OF PHYSICAL ACTIVITIES RECOGNITION FOR PATIENTS WITH SPINAL CORD INJURIES

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ABSTRACT

Rehabilitation through physical activities is required to provide disabled individuals with the ability to perform activities of daily life. It redevelops motor skills which promote quality of life and increase level of self-care. To evaluate therapy programs, a therapist is involved in the process to identify whether the patient exercised the required activities through questionnaires and interviews with the patient. However, such involvement is not only time consuming and subjective in nature, but also might lead to inaccurate assessment due to human error. To overcome such limitations and enhance the rehabilitation process, these activities might be detected using activity recognition systems. The objective of this study is to review the literature on upper-limb activity recognition using wearable sensors for able-bodied and disabled populations with more emphasize on the latter. A total of 17 studies were included in the review. The type of recognized activities, approach used to build the model, and the number and health status of the participants were varied across the studies. Although several researches recognize part of the activities used to rehabilitate patients with spinal cord injuries, no one has completely covered these activities.
Keywords: *Rehabilitation, Activity Recognition, Machine Learning, Spinal Cord Injuries, Wearable Sensors*

1. INTRODUCTION

Disabled populations, especially patients with Spinal Cord Injuries (SCI), mostly experience associated symptoms such as obesity, low muscular strength. This could lead to secondary complications including cardiovascular diseases and diabetes. Physical Activities play a significant role in the overall health and minimizing risks of such symptoms [1]. In addition, rehabilitation through physical activities is required. It provides them with the ability to perform activities of daily life and redevelop motor skills which promote quality of life and increase functional independences (i.e. level of self-care and mobility) [2]. Different approaches are applied to support the rehabilitation process including in-home strengthening exercises [3, 4]. To ensure the complete application of these activities, occupational therapists mainly rely on patients' self-report measures and surveys. However, studies proved the wide variability between self-reported and realistically measured physical activities which can severely affect the right progress in their rehabilitation [5]. Moreover, there is a low commitment in applying in-home therapy program due to the effort required to use the upper limb, lack of motivation and musculoskeletal problems [3, 6]. As a result, an appropriate method with more sensitive and reliable detecting of this kind of activities is needed. Considering the growth in research and the potential applications in this field, this research aims to present a review of the literature regarding upper-limb activity recognition for SCI patients. To the best of our knowledge, this is the first review considering the activities used during the rehabilitation process of SCI patients. Through the review of systems investigated in this paper, the researchers will be informed of possible improvement and any gaps available in evaluation the rehabilitation process of SCI patients, specially 1) What are the approaches available to recognize activities of upper limb? 2) Which of the activities used to rehabilitate SCI patients has been recognized?

The reminder of the paper is organized as follows. Section 2 provides a background on the physical activities required to rehabilitate SCI patients. Section 3 presents the state of the art. In section 4, the research methodology is discussed. The results and finding are illustrated in Section 5. A summary of existing physical and daily living activity recognition systems will be demonstrated and discussed in section 6, followed by conclusions and future work in section 7.

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2. BACKGROUND

This section demonstrates relevant background information required to provide a general foundation of knowledge. It introduces the spinal cord with its parts and injuries. Moreover, it discusses a variety of physical activities required during the rehabilitation process and their significance in strengthening the related muscles of upper limb segments that are important and needed in performing activities of daily life and enhancing motor skills.

2.1 Spinal Cord

The spinal cord is about 18 inches long and protected by vertebrae bones through neck, chest and back. It expands from the bottom of the brain to approximately the waist.

It consists of bundles of nerve fibers that contain upper motor neurons (UMNs) and branches of spinal nerves in the neck and back which contain lower motor neurons (LMSs). The spinal cord is divided into four part: cervical, thoracic, lumbar and sacral vertebrate.

The significant of the spinal cord lies in being the communication center between brain and body segments through performing three major functions. First, it passes motion signals from brain to body parts such as muscles in order to perform an action. Second, it carries sensory signals from all over body parts to brain. Third, it performs reflexive actions (i.e. quick responses to external stimuli) [7].

2.2 Spinal Cord Injury

A spinal cord injury (SCI) is a term referring to a damage on any part of the spinal cord or cauda equine (i.e. nerve at the end of the spinal canal) due to fractured or dislocated vertebrate as shown in Figure 1.

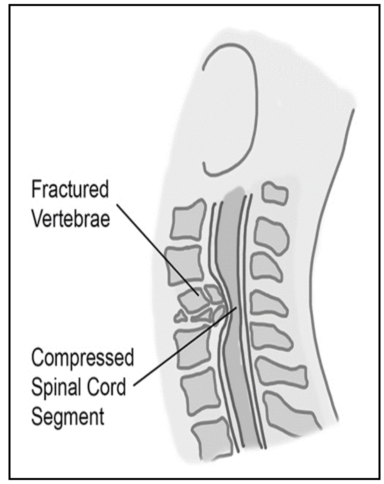

Figure 1: Spinal Cord Injury

According to the World Health Organization (WHO), yearly between 250,000 and 500,000 individuals suffer from a spinal cord injury around the world. The leading cause of injury currently is car crashes, followed by falls. Other common causes include acts of violence which is mostly gunshot wounds, sports accidents and medical/surgical errors [8]. This type of injury usually causes changes in strength, sensation level and other body functions below the position of the injury permanently [4, 7].

After the injury, the ability to control upper and lower limbs depends on two factors: injury position along the spinal cord and the severity of injury to the spinal cord. The former means injuries may result from damage to the spinal cord itself or to other parts of spinal column including the vertebrae, ligaments or disks. The higher the injury to the vertebral column, the more effect it has on movement (motor function) and feeling (sensory function), while injury at lower level results in more movement and feeling. The latter called the completeness of the injury and classified into the following:

- Complete: produces total loss of sensory and motor function below the place of injury.
- Incomplete: partial loss of sensory and motor function below the affected area [9, 10].

2.3 Physical Activity of Upper Limb

Comparing to able-bodied population, researches have shown that individuals with physical disabilities who rely on wheelchair as their primary way of mobility such as the case in SCI patients, are less likely to be physically active. Accordingly, low muscular strength, aerobic capacity, and flexibility become associated symptoms. All the previous can restrict their functional independence and increase the risk for chronic and cardiovascular diseases, diabetes and secondary complications such as obesity, pain and depression [1].

During the hospitalization period of SCI patient after the injury, rehabilitation is required to prevent long term complications and resolve muscle atrophy and pain. After discharge, an additional rehabilitation is required by the occupational therapists. The aim of this rehabilitation is to be able to perform activities of daily life and redevelop motor skills which promote quality of life and

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increase level of independence (e.g. self-eating, drinking and replacement from wheelchair to another chair) [2]. To support the rehabilitation process, occupational therapists employ a variety of techniques including therapy sessions and in-home home strengthening exercises where the latter will be discussed in more detailed below [3, 4].

As the intention of this work is to review systems which monitor upper-limb physical activity of patients with SCI, the elbow and shoulder are the limb segments of focus. This is due to the necessity of their movements in strengthening major muscles required to obtain a satisfied level of independence in performing activities of daily living and develop motor skills.

2.3.2 Elbow movement

Two major muscles are related to elbow. These muscles are the biceps and triceps. Figure 2 below shows the anatomy of these muscles.

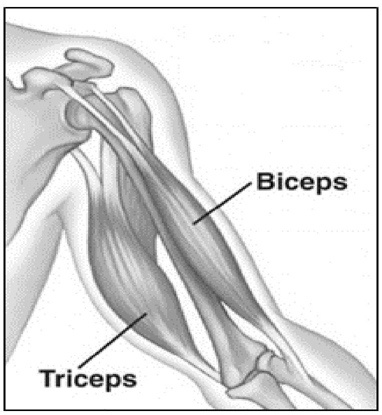

Figure 2: Major Muscles Related to Elbow

The main elbow activities to strengthen these major muscles are flexion and extension. In general, flexion is the process of bending the elbow joint which results in decreasing the angle between the forearm and upper arm. On the other hand, the opposite process happens during extension of the elbow where the angle between the forearm and upper arm increases while stretching.

a) Elbow flexor

The purpose of this activity is to strengthen biceps. It’s done by position the patient himself lying on the back. Start with the arm down beside the body and finish with hand up (i.e. near shoulder) ensuring that the elbow is held beside body as shown in figure 3.

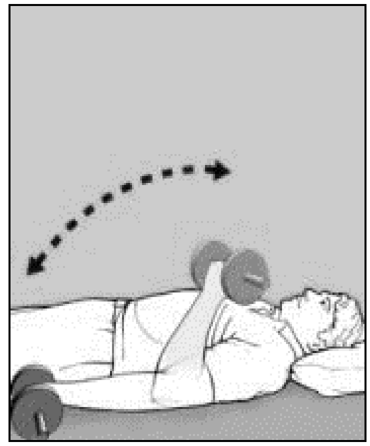

Figure 3: Elbow Flexor

b) Elbow extensor

The aim of this activity is to strengthen the triceps. The patient in this activity is directed to position himself lying on the back. Start with the shoulder held vertically and the elbow bent. Finish with the elbow straight as represented in figure 4 [11].

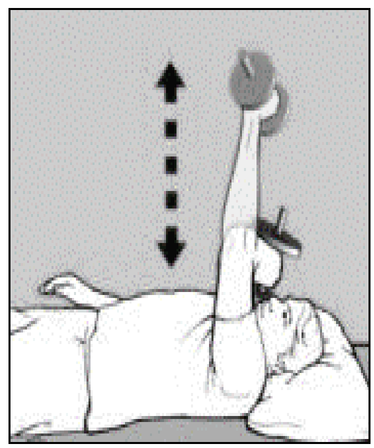

Figure 4: Elbow Extensor

2.3.2 Shoulder movement

The shoulder joint has the highest range of motion of any other joint in the body. This unique characteristic gives hands the ability to be placed in multiple positions needed for accomplishing upper limb activities.

The main activities required for strengthening the muscles related to shoulder are flexor, abductor, rotator and extensor.

c) Shoulder flexor

The objective of this activity is to strengthen the shoulder’s front muscles. The patient is instructed to Position himself sitting in a chair. Start with the arm down beside the body. Finish with arm above the

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head and ensure to keep the elbow straight. Figure 5 demonstrates this activity.

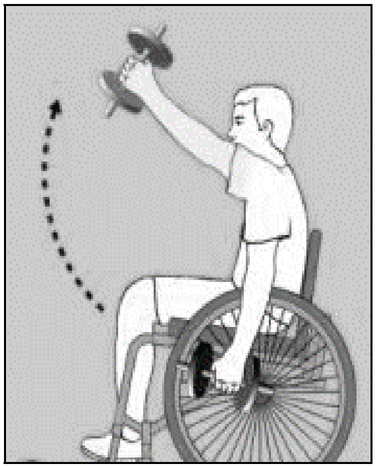

Figure 5: Shoulder Flexor

d) Shoulder abductor

The purpose of shoulder abductor is to strengthen the shoulder's top and side muscles. During this activity, the patient sits in a chair, start with the arm down beside the body, and finish with arm above the head while keeping the elbow straight as shown in figure 6.

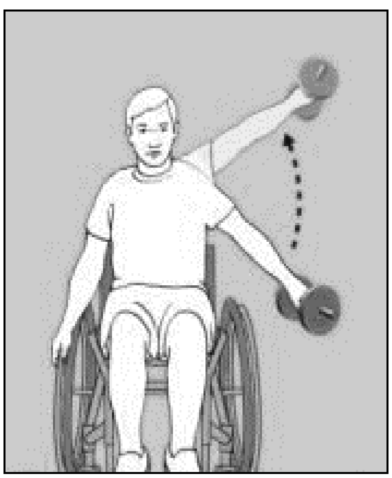

Figure 6. Shoulder Abductor

e) Shoulder external rotator

The therapist's aim of this activity is to strengthen shoulder muscles. In shoulder external rotator, the patient Position himself sitting with arm out to the side and the elbow bent. Start with hand pointing down and finish with hand pointing up. Figure 7 below describes the activity.

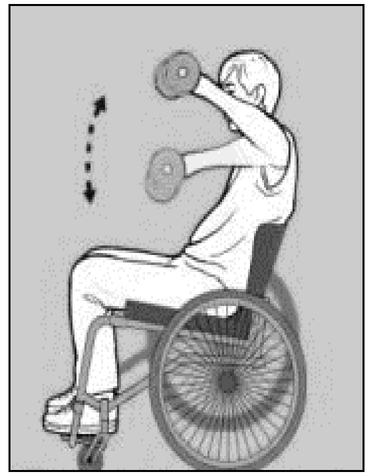

Figure 7: Shoulder External Rotator

f) Shoulder internal rotator

For the internal rotator, the objective is also to strengthen shoulders muscles. The patient is instructed to Position himself sitting in a chair. Start with hand away from the chest, Finish with hand across body as illustrated in figure 8.

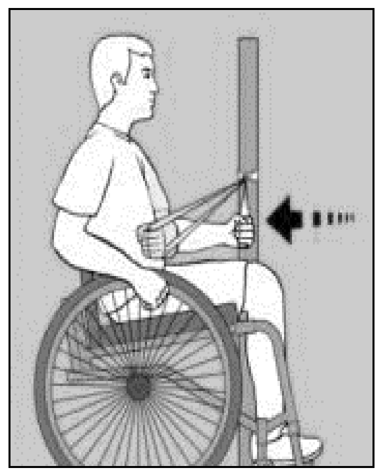

Figure 8: Shoulder Internal Rotator

g) Shoulder extensor

The importance of this activity is to strengthen the shoulder's back muscles. The therapist instructs the patient to position himself lying on the back. Start with the arm above the head and elbow straight. Finish with arm beside the body. Keep elbow straight during the process as shown below in figure 9.

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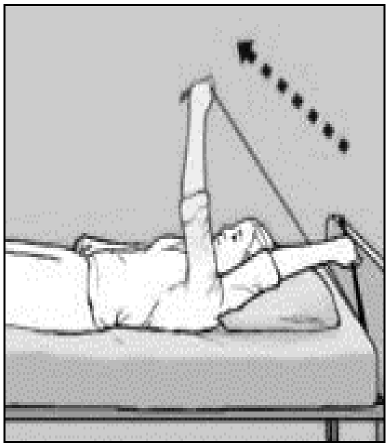

Figure 9: Shoulder Extensor [11]

3. LITERATURE REVIEW

Recently, wearable systems for monitoring activities of daily life and physical activities are attracting more interest both in research and clinics due to increasing advancement in technology and the miniaturization of devices. The provision of reliable feedback has become a key component in the operation of such systems as it allows the gaining of insight into the patient status and respond accordingly. In addition, it provides the ability to assess movements of patients outside the clinic settings [12]. Monitoring systems with this aim mostly involve a variety type of components. These components include sensors, wearable materials and/or smart textile for sensing process, while actuators, wireless communication modules and links, system control and processing units for actuating and processing purposes. Additionally, for user interaction and feedback, user interface software, advanced algorithms for data extraction and decision making, and/or interactive games have been used [13].

Monitoring process can be done on able-bodied as well as on disabled populations. Moreover, it may consider gait, upper or lower limb activities or other patterns of body movement or behavior. In addition, in order to measure physical activity, different variables might be used including activity count, active minutes, activity bouts, step count and energy expenditure [14].

3.1 Monitoring Activities of Able-Bodied Population

Monitoring systems using wearable sensors can be applied on able-bodied population for variant objectives. In the area of physical activities and sport, these systems have become popular solutions for sport activity recognition applications. Fitness devices and products with embedded sensors that track and analyze physical or other movements and activity are currently the most mature market [15]. Using embedded, wearable sensors, a long-term analysis of athlete performance has been developed and tested [16]. Margarito et al. [17] proposed a system for recognizing common sport activities using a triaxial accelerometer placed on the users' wrist. Inanc et al. [18] employed sport activities dataset to recognize 11 different activities, and the gender of subjects. Jun Qi et al. [19] built a two layer framework for gym physical activity recognition, which classifies 19 gym physical activities including free weights, aerobics and sedentary activities. Using a single wrist-worn accelerometer, Margarito et al. [20] designed a template matching-based framework to recognize a set of eight sports activities of high relevance for healthcare and lifestyle applications.

Monitoring systems which aim to recognize people's activities of daily living may be used by healthy and able-bodied individuals as a proactive solution. For instance, an early disease detection or health improving using daily progress as feedback which could be accomplished through a long-term analysis of activities [21]. Moreover, this process might be considered an important component in the treatment of a health condition such as obesity [22]. In order to stimulate the maintenance of activity, Inanc et al. presented a model that recognizes eight activities, using five different sensor units that were located on torso, right and left arms, and right and left legs. Each unit of these sensors consists of a 3-D accelerometer, 3-D gyroscopes, and 3-D magnetometers. Ronao et al. [23] proposed a two-stage classifier using acceleration and gyroscopic sensors embedded in a smartphone to recognize six daily activities. Furthermore, the necessity to extract more efficient feature to capture sensor behavior differences in a precise manner has been demonstrated. Attal et al. [24] compared different supervised and unsupervised classification approaches in terms of the recognition of twelve daily activities which can be categorized into static, dynamic and transition activities using three internal measurement units placed on the chest, the right thigh and the left ankle. Based on this comparison, it has been shown that supervised approaches are more accurate compared to unsupervised approaches when using raw data or extracted features however, the latter does not require any labeling. Bayat et al. [25] designed a recognition system for six various everyday activities using accelerometer data from a smartphone placed in hand and pocket. Garcia-Ceja et al. [26] presented a

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model to recognize long-term activities including shopping, showering, dinner, working, commuting, brushing teeth from accelerometer data collected with a wristwatch. Moncada-Torres et al. [27] classified 16 daily activities based on data from only two wrist modules of six healthy subjects. Gupta et al. [28] used data collected from a sensor which is positioned on the waist to recognize seven basic daily activities. Gao et al. [29] designed a wearable system using multiple sensors placed on different body locations to recognize activities including side standing, sitting, lying, walking and transition. Almuslukh et al. [21] proposed monitoring system based on deep learning algorithms to recognize activities such as jumping, lying, standing, sitting, jogging and walking. Data were collected from smartphones (Samsung Galaxy S4) and a smart-watch (LG G Watch R) located at seven different body positions.

With regard to elderly people, they mostly require immediate medical intervention in case of significant issue, or otherwise it could lead to fatal consequences. One of these issues is falling which lead to several major health problems. Monitoring the activities of the elderly in a continuous fashion may help to avoid these situations or at least reduce the risk of their complications [16, 30]. Within this context, Huynh et al. implemented a system to detect four different types of fall using fall data form accelerometer and gyroscope sensors placed on the chest [31]. Pierleoni et al. [32] proposed a fall detection system consisting of an IMU positioned on the waist of subject and includes triaxial accelerometer to detect the following types of falls: backward fall, forward fall, side left fall, side right fall and fainting fall. Dias et al. [33] presented a monitoring system to detect elderly falls in indoor environments using data from the embedded accelerometer placed in sideways at the waist.

Furthermore, senior people have a greater risk to be affected by one of common age-related nerve degenerating disease such as Parkinson and Alzheimer which better to be detected at early stages. To accomplish this, Varatharajan et al. [34] provided an approach to monitor human motion in a continuous manner. By using IoT devices, the walking patterns of Alzheimer patients were collected first, then analyzed using dynamic time warping algorithm. Automatic early detection techniques for Parkinson's disease are appreciated by patients, clinicians and neuroscientists. Rastegari et al. [35] developed an automated gait analysis system through the application of pattern recognition algorithms on data extracted from accelerometers attached to the ankle of the subjects to distinguish between three groups of people: healthy elderly, geriatrics, and patients with Parkinson disease.

3.2 Monitoring Activities of Disabled Population

Nowadays, inactivity has been contributing significantly in the exacerbation of physical diseases. Additionally, the World Health Organization identified it as the fourth risk factor that leads to mortality, which follows high blood pressure, smoking and diabetes. As a result, many actions to motivate activity have been made recently. For instance, a variety of pedometers were made to help individuals accomplish different activity goals, including number of minutes or steps per day. Furthermore, many smartphone applications have been developed for activity self-tracking and motivation. However, there is a little equivalent work in the literature for individuals with physical disabilities, although current commercial physical activity measurement devices are not appropriate for them. Consequently, more research is needed for the development of tracking and motivational systems to support wheelchair users especially for people with spinal cord injuries since they mostly adopt sedentary habits leading to higher rates of secondary complications such as obesity, diabetes and cardiovascular diseases. In addition, these systems can be utilized by healthcare providers to monitor the behavior of their patient and recognize different types of activity, including activities of daily life and physical activities [36].

3.2.1 Activities of daily life

To provide more active and healthier lifestyle for people with disabilities, and to assist them in tracking their regular daily activities, a variety of monitoring systems have been developed to recognize level, duration and types of daily life activities such as wheelchair propulsion, lying, housework, eating and cooking. In this context, Hiremath et al. [37] proposed an activity monitoring system that consists of a gyroscope-based wheel rotation monitor and an accelerometer device worn on the upper arm or on the wrist to recognize a list of activities with different intensity as a representative of everyday activities. The system evaluated various classification algorithms, including naïve Bayes (NB), decision trees (DT) and support vector machines (SVM).

Masso et al. [38] presented a classification model based on linear discriminant analysis (LDA), quadratic discriminant analysis (QDA) and support vector machines (SVM) algorithms. The accuracy of the classifier was (55-72%) for individual daily activities, while it reached (83.2 - 93.6%) to correctly recognize five categories of grouped activities performed by manual wheelchair users when using a greater number of accelerometers. The study concluded that grouping activities by their aim can provide promising results and using more accelerometer can higher classification accuracy.

Lemmens et al. [39] developed a monitoring system for identifying specific arm-hand related activities including drinking, eating and brushing hair. The system long term objective is to evaluate arm-hand therapies for neurological patients with the use ambulatory sensor that consists of tri-axial accelerometer, a tri-axial gyroscope and a tri-axial magnetometer which are placed on the hand, wrist, upper arm and chest. The study demonstrated the promising results regarding the applicability of these systems for activity recognition among able-bodied as well as disabled populations.

Zambrana et al. [40] proposed a hierarchal approach to monitor stroke survivors in order to receive feedback to maintain correct posture. The first level of this approach aimed to differentiate between arm movement and non-movement. The second level recognizes the movement as non-purposeful (e.g. walking) or purposeful (e.g. eating, drinking, pouring water and teeth brushing).

3.2.2 Physical activities

Physical activity is typically defined by WHO as "Voluntary bodily movement using skeletal muscle that requires energy beyond resting levels" [14]. Rehabilitation through physical activities is required for Patients with limited capacity in limbs and mobility impairment resulting from conditions such as spinal cord injuries [41]. In-home therapy is necessary for these patients for many reasons. To support the rehabilitation process due to the limited time regarding in-clinic therapy sessions. Additionally, it is a convenient option since many patients might travel to and from the clinic to receive professional care. Furthermore, outpatient physical therapy can be crowded and noisy, which can be avoided through in-home physical activities.

However, this process has several drawbacks, including lack of commitment and motivation [6]. Also, physical therapists can mainly rely on self-report measures and surveys to detect the complete application of these activities while studies proved the wide variation in both self-reported and objectively measured physical activity. To overcome these issues, physical activity monitors with sensor technology have been used for more sensitive and reliable detecting of this kind of activities [5]. Moreover, these systems play a significant role in improving quality of physical activity during rehabilitation process [12].

Activity recognition systems found in the literature are divided based on the approach they follow. The approaches are machine learning approach and biomechanical approach which will be explained in more detailed in section 4.

Using this approach, Pernek et al. [42] designed a monitoring system that consists of a Wireless Body Area Network (WBN) and a smartphone to recognize the type and intensity of physical activities such as strength exercises. The system utilizes the two layers of support vector machine to first recognize the type of activity being performed then recognize its intensity. The study showed that this hierarchical algorithm achieved high accuracy in activity type recognition of a set of six upper body strength training exercises with around 85%.

The study in [43] presented a methodology for detecting three basic movements of the upper limb (extension, flexion and rotation). This methodology applied pattern recognition on data gathered from a single wrist-worn, inertial sensor consists of a wrist-worn, wireless tri-axial accelerometer and tri-axial rate gyroscope. With the same objective, in order to recognize three fundamental activities of the human forearm, Panwar et al. [44] designed a generalized model based on a single wrist worn accelerometer sensor. The study demonstrated that Convolution Neural Network (CNN) produces high accuracy in term of activity recognition. In addition, Cai et al. [45] developed an upper-limb robotic device to rehabilitate stroke patients. It works by first recognize the motion of the healthy side such as elbow flexor and shoulder abductor, then it provides mirror therapy to the effected side.

In the context of frozen shoulder rehabilitation, Lin et al. [41] proposed a model for recognizing physical activities prescribed for treating such condition. The model is based on wireless sensor network (WSN) that consists of a tri-axial accelerometer as well as bi-axial and uni-axial gyroscope and applied in six exercises designed to rehabilitate patients with frozen shoulder with accuracy between (85% - 95%). The study showed the applicability of these types of models to recognize rehabilitation exercises in ubiquitous healthcare self-management.

Physical activity recognition systems can be developed also through the use biomechanical

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models of the human body. Using this approach, Algohari et al. [46], combined several models designed to control a robotic arm, in order to estimate human joint angles using wearable inertial sensors. The results of this study demonstrated the potentiality of wearable internal sensors in recognizing normal and pathological human movement.

In [47], Brice et al provided a comparative assessment of the sensor-to-segment calibrations of the Magnetic and Inertial Measurement Units (MIMU) through the estimation of wrist, elbow, and shoulder joint angles. The participants in the experiment were directed to perform wrist flexion-extension, wrist abduction-adduction, right elbow flexion-extension, shoulder flexion and abductions movement.

Peppoloni et al. [48] proposed a wearable system to assist work-related musculoskeletal disorder risks. To achieve this objective, the system calculates angles related to shoulder flexion, elbow flexion and extension.

Alvarez et al. presented a method in [49] which mainly aims to measure joint angles. This method was able to estimate a variety of activities including elbow flexion, shoulder flexion, shoulder abduction and shoulder internal rotation.

To evaluate the effect of task complexity and duration on technological error of IMUs, Robert-Lachine et al. [50] developed a method where several joint angles were measured. These measurements were obtained through different activities such as wrist flexion, elbow flexion, shoulder flexion and abduction.

4. METHODOLOGY

4.1 Search Strategy

A literature search was undertaken using combination of key words with AND/OR phrases. The search was targeting recent studies from January 2015 to March 2020. In addition, inclusion and exclusion criteria provided in table 1 were applied. Only papers that fellfield the inclusion criteria were selected for further investigation and content assessment.

Table 1: Study Inclusion and Exclusion criteria

Decision	Criteria
Inclusion	Original peer reviewed published manuscripts
	Available as full text
	Written in English
	Used wearable sensors for data collection
	Defined clear data processing and model development
	Related to the research questions
	Recognized at least one activity of upper limb
Exclusion	Had full text not available
	Had non-English manuscript
	Data collection conducted within a laboratory setting
	Review studies
	Duplicated Studies

4.2 Data Extraction

The relevant information was extracted and collated from the full manuscripts selected for final review. A total of 4 parameters were extracted from the 17 research studies, including the type of physical activities (if any), type of daily life activities, approach used to build the model ,and the number and health status of subjects who participated in the experiment. The justification of choosing these parameters is shown in table 2.

5 RESULTS AND ANALYSIS

Overall, there are two main approaches used to build models for recognizing upper-limb physical activities of spinal cord injury patients: Machine learning approach and biomechanical approach. While the former attempt to identify the patients' activities using classification techniques, the models of the latter approach are built based on biomechanical models of the human body. More details on these two approaches are illustrated in the next subsections.

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Table 2: Parameters Used for Information Extraction

Parameter	Justification
Physical Activity Activity of Daily Life	To check which of the seven activities used to rehabilitate SCI patient is covered
Approach	To detect and identify all the approaches available for recognizing upper limb activities
No. of Subjects	To recommend the suitable number of subjects might be considered when conducting the experiment

5.1 Machine Learning Approach

As the name suggests, models based on this approach use machine learning algorithms as their classification techniques. The overall process of recognizing the activity using machine learning approach includes the following steps:

Data collection: In this step the sequence of movements of the subjects is recorded using devices such as wearable sensors.

Data Preprocessing: Preprocessing the raw data is essential to obtain the most representative of each activity since motion signals are noisy due to the nature of motion artifacts and sensor errors.

Segmentation: Partitioning the collected data into multiple segments is essential in order to map each segment with a particular activity.

Feature extraction: Extracting different kinds of features from the raw data.

Classification: Assigning objects to one of several predefined categories.

This approach relies heavily on the data and it is the most obvious limitation. If the model is fed poorly, then it will give poor results. This can manifest itself in two ways: lack of data, and lack of good data. Additionally, classification is a supervised learning technique that imposes manual annotation for a massive amount of data. Collecting and annotating the data are not only time consuming, but also require a huge amount of human effort [51].

Also, the machine learning models can be rendered powerless unless they can be interpreted, and the process of human interpretation follows rules that go well beyond technical prowess. For this reason, interpretability is a paramount quality that machine learning methods should aim to achieve if they are to be applied in practice [52].

5.2 Biomechanical Approach

Systems within this approach are built based on biomechanical models of the human body. This model as illustrated in the figure below consists of segments with variable lengths and connecting joints (represented by gray circles in figure 10). In this approach, MIMU are used to capture human motion. The relative motion between two consecutive segments (i.e. joint angles) can be calculated by placing a MIMU sensor on each related body segment (indicated by cubes in figure 10). However, this motion measurement has no significant meaning and cannot be converted into interpretable data such as joint angles (i.e. physical activity) unless an appropriate calibration is performed [47, 53].

The calibration for the placement of MIMU sensors with human body segments plays an important role in the sensing of the motion capture systems and computing the joint angles. Manually measuring segments length based on anatomical landmarks (i.e. bony prominences) are used to help calibrate MIMU sensors [54]. This method likely leads to errors up to several centimeters, which increases the difficulty in precisely locating the joint centers [53].

One of the main limitations of this approach is the calibration procedure conducted by the experts. This procedure should be repeated for each user, as each has a different anatomy and relationships between anatomical landmarks. Also, it requires an expert, which may not be available, because any small or abnormal movements of body segments will affect the process. Furthermore, Some equipment might be needed in the calibration process which increases the overall costs [53].

5. SUMMARAY AND DISCUSSION

A summary of existing physical and daily living activity recognition systems is shown in table 3. As mentioned earlier, these systems were compared

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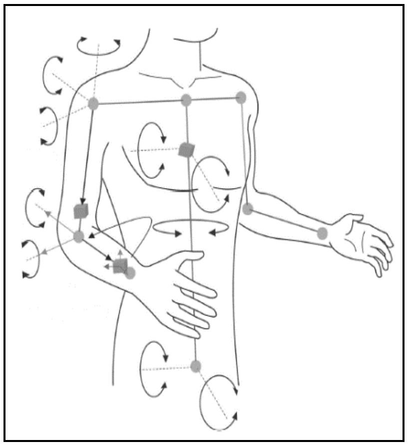

Figurer 10: Biomechanical Model of Human Body

using different factors. The first factor is which of the seven physical activities mentioned earlier were covered (if any). The second factor is which activities of daily life were recognized (if any). Third, the approach that the system was developed based on. Finally, the number and health status of the subjects who participated in the experiment are presented.

In Table 3, it is obvious that machine learning approach used heavily to recognize the daily activities, while the biomechanical approach focuses on recognizing the physical activities. Also, the comparison shows that fewer numbers of subjects were used with the biomechanical approach compared to the machine learning approach. This is perhaps due to the need of human involvement in the biomechanical approach (i.e. experts for calibration) which may not be available. Although several researches have applied the biomechanical approach to recognize the seven activities highlighted in Section 2.3, no one has completely covered these activities. On the other hand, only three activities have been considered by machine learning approach in [44] and [55]; elbow flexor, shoulder abductor and shoulder extensor.

Regarding the machine learning approach, once the model is developed, it can be applied on anyone without the need for further unique settings for each user. Moreover, there is no need for expert intervention. Concerning the overall cost, due to the inexpensive wearable sensors used, it is considered low. On the other hand, most models built using this approach require supervised learning. This type of learning involves training massive of data for real activity recognition where a major limitation in performing automatic labeling.

In the biomechanical approach, systems have sufficient recognition rate in the optimal case. However, the calibration process which is a significant step in this approach has some limitations. Since different people means different anatomy, this step must be repeated for each user. Also, it should be done by an expert due the sensitivity of the measurement where any small or abnormal movements of body segments will affect the process. Nevertheless, the expert might not be available. Moreover, the overall cost might be increased for the additional equipment required in the process.

An analysis of the literature revealed a potential research and a necessity for developing additional upper limb monitoring systems. This is due to the gap appears in recognizing some of the physical activities applied during the rehabilitation process of SCI patients. However, there are some general challenges must be considered when developing such systems. One of these challenges is intra-class variability where the same physical activity might be performed differently by different people. It also can occur when the performance of the activity is vulnerable to be affected by any factor, including stress or fatigue. Another challenge is the interclass similarity which refers to different classes (i.e. activities) showing similar characteristics which make them hard to be recognized correctly. There are also experimental challenges associated with data collection specially there is no general-purpose datasets of human physical activity in contrast to other research fields such as speech recognition [56]. Dealing with real life experiments instead of laboratory environment is also considered a challenge, especially regarding the placement of sensors used to monitor individuals. Since orientation plays an important role in recognizing human activities, misplacing wearable sensors of its standard orientation causes rotation of axes which disorientate the data analysis eventually [55].

With regard to physical activity recognition of patients with SCI, since these activities are mainly performed by the upper limb, this might add extra challenges. The narrow space that these activities are taking place makes the sensing process and the correct recognition much difficult. Furthermore, the disability degree of the monitored individuals is also added to the list of factors that might affect the performance of activities.

Table 3: Summary of Existing Activities Recognition Models

No. of subjects		45 SCI patients	12 SCI	30 healthy	7 healthy	Not	16 healthy	9 healthy
Approach		ML	ML	ML	ML	ML	ML	ML
Activity of Daily Life		10 daily activities include: Lying, housework, eating and cooking.	7 daily activites include: Lying down, body transfers, moving items, mopping, working on a computer	Drinking Eating Brushing hair	Eating Brushing teeth Combing hair Writing on a computer Talk by phone Drinking	Desk work Browsing the computer Eating	Washing dishes Set up a table Using a laptop	Eating Drinking Pouring water Tooth brushing Towel folding
Physical Activity	**PA7**	X	X	X	X	X	X	X
	PA6	X	X	X	X	X	X	X
	PA5	X	X	X	X	X	X	X
	PA4	X	X	X	X	X	X	X
	PA3	X	X	X	X	X	X	X
	PA2	X	X	X	X	X	X	X
	PA1	X	X	X	X	X	X	X
Research		[37]	[38]	[39]	[57]	[36]	[58]	[40]

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Table 3: Summary of Existing Activities Recognition Models (Cont.)

No. of subjects		11 healthy	4 healthy 4 patients	Not provided	4 healthy	5 healthy	7 healthy	10 healthy	Not provided	Not provided	12 healthy
Approach		ML	ML	ML	ML	ML	Biomechanical	Biomechanical	Biomechanical	Biomechanical	Biomechanical
Activity of Daily Life		None	None	None	None	None	None	None	None	None	None
Physical Activity	**PA7**	✗	✗	✓	✗	✗	✓	✓	✗	✗	✗
	PA6	✗	✗	✗	✗	✗	✓	✓	✗	✓	✓
	PA5	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗
	PA4	✓	✗	✗	✗	✓	✗	✓	✗	✓	✓
	PA3	✗	✗	✗	✗	✗	✓	✓	✓	✓	✓
	PA2	✗	✗	✗	✗	✗	✓	✓	✓	✗	✗
	PA1	✓	✗	✗	✗	✓	✓	✓	✓	✓	✓
Research		[42]	[43]*	[41]	[44]*	[45]	[46]	[47]	[48]	[49]	[50]

(PA1): Elbow Flexor - (PA2): Elbow Extensor - (PA3): Shoulder Flexor -(PA4): Shoulder Abductor -(PA5): Shoulder External Rotator -(PA6): Shoulder Internal Rotator -(PA7): Shoulder Extensor - (ML): Machine Learning.

* Recognizes other types of physical activities

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6. CONCLUSION AND FUTURE WORK

This review reported the literature on upper-limb activity recognition for patients with SCI. In addressing the research questions, two approaches for model development were used to recognize upper limb activities across the reviewed studies. Machine learning approach, where models use machine learning algorithms as their classification techniques. This approach relies heavily on the data and mostly imposes manual annotation for a massive amount of data. However, once the model is developed, it can be applied on anyone. Systems within biomechanical approach are built based on biomechanical models of the human body. Typically, the calibration procedure in this approach should be repeated for each user and it requires an expert. From the exploration of models summarized in this paper, a gap appears in recognizing some of the physical activities for the rehabilitation of individuals with spinal cord injuries. Although several researches have applied the biomechanical approach to recognize the seven activities, no one has completely covered these activities. On the other hand, only three activities have been considered by machine learning approach; elbow flexor, shoulder abductor and shoulder extensor.

Through this review, it can be determined that majority of the works were directed to able-bodied population and there is a need for the development of an additional upper limb monitoring system for the purpose of recognizing physical activities required during in-home rehabilitation process of disabled population.

A number of possible directions are available for future research to develop an upper limb activity recognition model. One possible direction is to develop an upper limb activity recognition using machine learning approach. Also, a hybrid approach that combines the strength of machine learning and biomechanical approaches might be used to recognize the upper limb activities. One main application to apply these models is in-home physical activities designed by occupational and physiotherapists in [11] to rehabilitate disabled individuals with SCI. In doing so, the proposed models will have significant contribution in motivating patients and improving quality of physical activity during the rehabilitation process.

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