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Review Studying of the Latest Development of Prosthetic Limbs Technologies

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ABSTRACT

The loss of one limb (Arm, Hand, or leg) can affect human life performance of the daily activity. Thus, amputation became a global problem. The current prosthetic solutions have poor contribution in solving these problems regarding to low interface solutions to control the prostheses. the ultimate goal for researchers is to provide design inputs in the field of prosthetics and increase the satisfaction level of the user. In this paper, a simple introduction to biomechanics and Kinematics of the human arm, and the latest technology used for controlling the prosthetic arm is presented by EMG and EEG signals. The ultimate goal of this work is to summarize the knowledge of the Prosthetic upper limb and how to control it to prepare our next work on controlling a prosthetic arm by Brainwaves. The EEG technology is considered an effective method of controlling the prosthesis, and over the last decades, several types of research have been done regarding it.

Keywords: **:**EEG, EMG, Prosthetic Limb, Biomechanics, Kinematics

1. INTRODUCTION

A Limb is a jointed bodily appendage that humans and many animals use for locomotion such as Walking, Running, Swimming, Prehensile grasping and climbing or any daily life activity. The Human limbs are classified into upper and lower Limbs [1][2]. The upper Limb is presented by the arm and hand, while the legs are considered as lower Limbs. The arms are connected at the shoulders to the Torso and the legs attached to the hip girdles, as shown in figures 1 and 2.

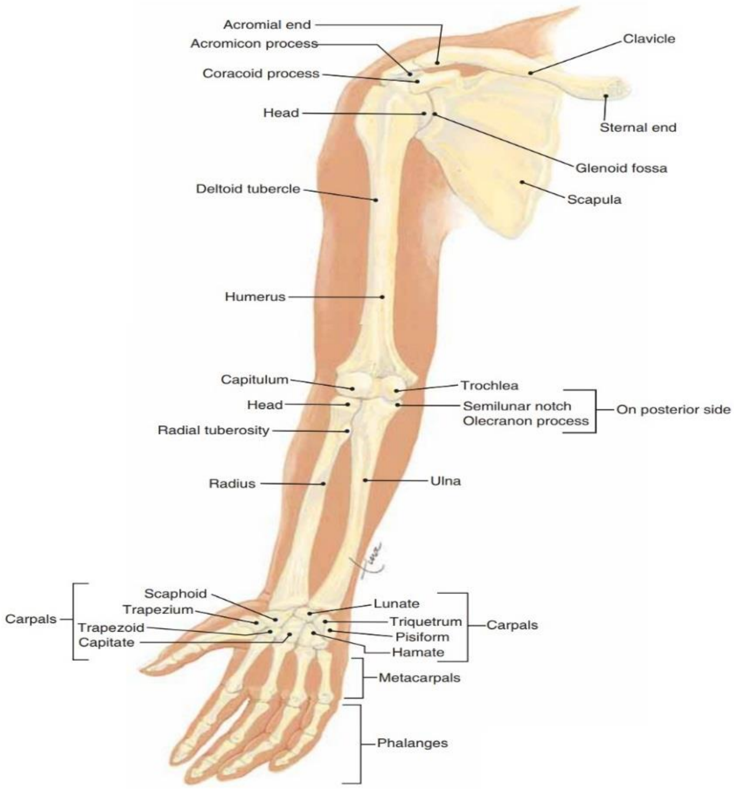

Figure 1 Upper Limb

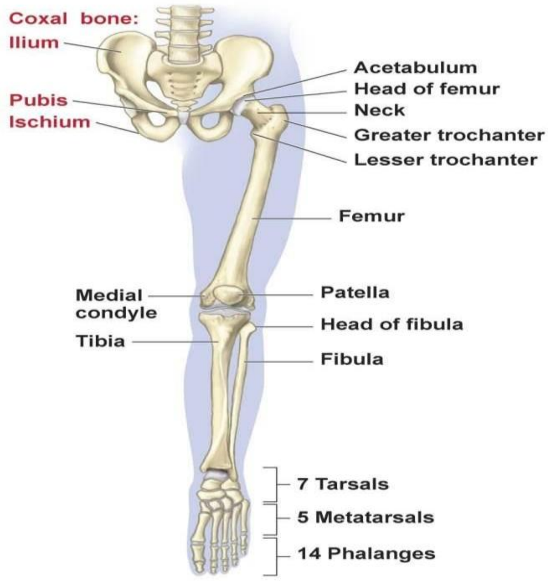

Figure 2 Lower Limb

1.1. Statistics

Latest statistics [3] indicate that around fifty eight million people live with limb mutilation due to traumatic causes worldwide, according to that: 36% falls, 15.7% road injuries, 11.2% transportation injuries, and 10.4% Mechanical forces, as shown in figure 3.

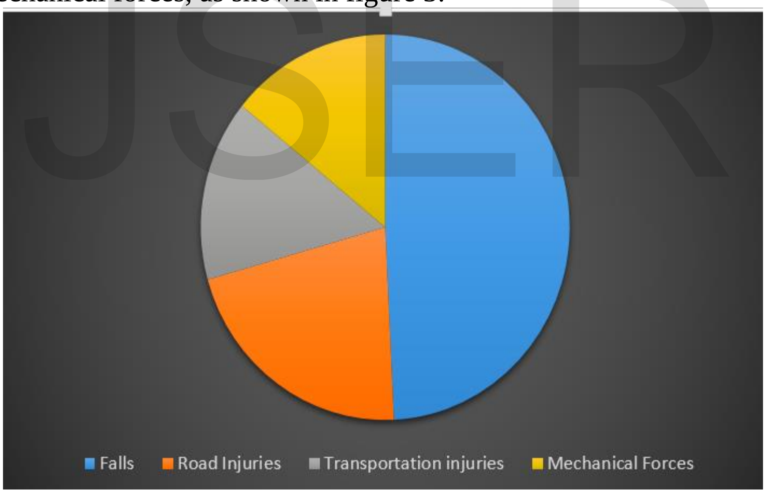

Figure 3 Limb amputation statistics.

The Highest No. of coomon amputations was in South and East Asia, the Western Europe, North Africa, the Middle East, Eastern Europe and North America. In the United States of America, Statistics from the National center of Health statistics [4] estimate that:

- 50,000 new amputation every year.
- Amputation Ratio of upper limb to lower limb is 1:4.
- Most widespread is lost of partial hand or fingers 60,000
- Next prevalent lost is one arm amputation with 25,000.
- 60% of amputation are between ages of 21 and 64, 10 % are under 21 years of age.

Table 1 shows the most common causes of amputations.

Table 1 Amputation causes

Amputation causes	Percent
Congenital	8.9%

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Tumor	8.2%
Disease	8.8%
Trauma	77%

1.2. Biomechanics of Human Arm

The Shoulder Girdle, Elbow, and Wrist are three interconnected processes that make up the upper limb (Human Arm) [5]. These processes allow for a large range of combined motion, and the human arm will have the most mobility of any part of the body. When bones are considered in pairs, seven joints can be identified: the stemclavicular joint, which articulates the clavicle's proximal end onto the sternum; the sternoclavicular joint, which articulates the clavicle's distal end onto the sternum; the sternoclavicular joint, which articulates the clavicle. The scapula glides on the thorax thanks to the acromioclavicular joint, which articulates the scapula by its acromion onto the distal end of the clavicle, scapulothoracic joint.

The ulno-humeral joint is a scapula joint that permits the humeral head to rotate in the glenoid fossa. The ulno-humeral and the humero-radial joints, which articulate both ulna and radius on the distal end of the humerus. Finally, the ulno-radial joint where both distal ends of ulna and radius join together. All of the above joints except the scapulothoracic joint are considered a ball and socket joints assuming the translation is negligible.

If all joints are considered are independent, the number of the degree of freedom DOF for the Upper Limb (Arm) is 22, however as they are organized as closed chains, The Number of Degree of freedom of the Upper Arm is reduced to 12, as shown in figure 4.

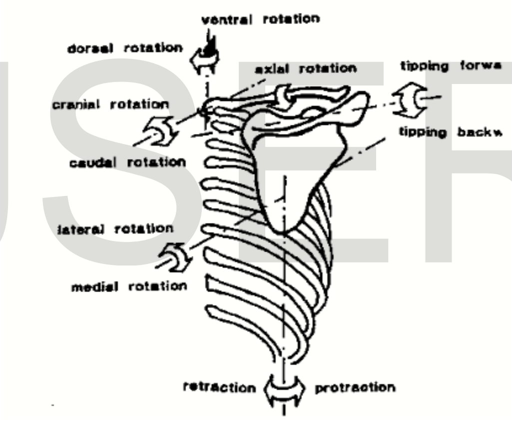

Figure 4 Shoulder Rotation

Twenty-two muscles equipped the upper LimbTo to perform the movement. Some of the muscles are divided into different bundles, which are attached to other bones. They can divide into many groups depending on the bone they move and the degree of freedom they control.

1.3. EEG Sensors

Electroencephalography or EEG (Figure 5) [6-12], is an electrophysiological process that record the brain's electrical activity. EEG measures the electrical activity changes that the brain produces.

Figure (5) EEG

Billions of the brain cells produce a minimal electrical signal that performs a non-linear pattern named as Brain Waves. An EEG machine measures the cerebral cortex`s electrical activity, the outer layer of the brain, through out the EEG test. The EEG sensors measure four types (depending on the frequency) of brain waves; Beta (14-30) Hz, Alpha (7-13)Hz, Theta (4-7)Hz and Delta(up to 4 Hz). Both Limb and Brain Make a closed-Loop that is responsible of motor control and sensory feedback.

Depending on the basis of their functionality, Upper Limb Prostheses are classified into two main categories: Passive and active prostheses. Passive divided into Cosmetic and Functional. On the other side, the active includes (body-powered and externally powered). The difference between the Cosmetic and Functional is that the Cosmetic only substitutes the missing part while the functional can perform several daily activities.
Cables fastened to the limb of the amputee control the body-powered active prostheses. It requires high energy, which is considered as one of the disadvantages. The externally powered active prostheses exploit an external; power source to raise energy needed for the movement—this type is classified into Myoelectric controlled by EMG (Electromyographic) signal and Electric.
This paper will present the previous studies of Different Technologies used to control the Upper Limb Prosthetic. The motion analysis of arm movement from one point to another. In the Discussion section, we will introduce a report about requirements to be satisfied by prosthetic.

2. Previous Studies.

This paper intends to carry out the latest technologies used for controlling a prosthetic arm. This will help the researchers summarize the current knowledge in the field, plan the user priorities and point the main requirement for the prosthetic arm. This section will focus on two main technologies of controlling the Prosthetic limb, The EMG and EEG.

2.1. EMG Technology

EMG is the abbreviation for electromyography.The electromyography signal captured from the amputees' residual limb muscle is an important source of control input for body-powered upper limb prosthesis that are designed to restore lost limb function.This is because the EMG signal provides motor / neural information that may be used to determine the intention of limb movement.
Furthermore, most amputees can still create these signals with their residual limb muscles [13-14]. In 2012 S. Sudarsan et al. [15] worked with EMG sensors to extract the signals from the muscles to control the motors equipped with a prosthetic arm. The signal extraction was in two phases: the relaxation phase and the contraction phase. In this case, the extraction phase is more important for extracting the signals as it can control more DOF for Prosthetic arm movement. The EMG pattern can be analysed using Neural Network as Akira et al. [16] did. They used a backpropagation neural network to recognise the FFT analysed pattern for 1-channel surface EMG of flexor digitorium superficial. After 1000 training cycles for the network, the N.N recognised 20 out of 30 patterns. Ashik et al. [17] present their work with a design and development of EMG based prostheses for upper arm prosthetics that overcome myoelectric movement limitation. The system designed was affordable by apple. The system was 5 DoF am with two fingers. The work of Bushra et al. [18] aimed at techniques used to analyse EMG signals to improve hand movement pattern recognition. In their research, they compare the interpretation of ANN and LDA to

evaluate the result for improved EMG control. Nili et al. [19] reported another study on a unique controller for a motorized prosthetic arm. The desired endpoint for a complete arm prosthesis, which could drive the forward motion of individual joints, can be predicted using a combination of EMG and visual data.

The goal of this project is to better understand how Gaze, EMG, and arm motion interact during reaching and placement tasks, as well as to design a control system to help people with high-level upper-limb amputations use a full-arm, multi-DoF prosthesis..

Surface Electromyography sEMG is advice that measures the amount of electrical activity the muscle release during contraction. Neelum et al. [20] present work on the control of prosthetic arm using sEMG signals acquired from triceps and biceps. Fifteen healthy and four amputees volunteers were involved. In this study, four-arm motions included: elbow extension, elbow flexion, wrist pronation and wrist supination. In addition, the classification of ten domain features was considered to recognise the 4-arm motion. Can utilise The research for rehabilitation and training of transhumeral amputated subjects. The results show that using appropriate features and classifiers improve classification accuracies for controlling prosthetic arm using EMG.

Multiple DoF electromyogram pattern recognition performance based prostheses control systems have been observed to be reduced by MOS or Mobility of Subjects and MCFV muscle contraction force variation.To address this issue, Mojisola et al. [21] conducted a study to systematically investigate the impact of MOS-MCFV on the performance of a PR-based movement intent classifier, using EMG signals recorded from eight participants who performed various arm motions in static and dynamic scenarios with three different muscle contraction force levels. Then, in the presence of both components, an invTDD (invariant time-domain descriptor) was proposed to characterize the Multi-class EMG signal patterns. The results demonstrated that MCFV-MOS had a negative impact on amputee and non-amputee subjects' limb movement intent on decoding accuracy. However, one of the study's findings isn't just relevant to the upper limb; it could also pave the way for wheelchair development. Cengiz et al. [22] propose a model by EMG signal processing fingers in a prosthetic hand that can move independently. The process was in several steps: Recording the Data set, filtering the data, Preprocessing feature extraction and finally EMG signal classification. The results were high, with accuracy achieved up to 93.86 %.

2.2. EEG sensors.

An electroencephalography sensor, aka EEG is able to record thousands of snapshots of the brain`s electrical activity within a single second. Then the recorded signal is sent to the amplifier then to a computer or the cloud to process the data [23-26]. There are many types of research regarding EEG signals to use to control several applications such as; prosthetic limbs, robot arms, drones, wheelchairs etc. J Utama et al. [27] Present a research to discuss the system of brainwave that can move the prosthetic arm using brainwave activity. First, detection of brainwaves was established using LabView software. The research methods had two modes: the 1st mode is selecting the movement with the eye blink. The 2nd mode of attention is to move the false arm. A prosthetic arm can make the movement designed for extension, flexion, supination or pronation and increase or depression. The speed of response for the system was 9.54 sec., which is considered acceptable but still a little bit slow. Catuer et al. [28] proposed a feature extraction for the EEG signal in eight-different channels using DWT or the discrete wavelet coefficient. The wavelet coefficient was then transformed to the frequency domain using Fourier transform DFT. The next step is that the average power spectrum calculates the classification of three classes: first the imagination of right body movement, second the left movement, and theird the random word. Using multiclass SVM or the support vector machine shows promising results of sensitivity of (96.8%), (86.12 %) and (52.7%) from three different subjects.

Brain-computer interface (BCI) technology can design a robotic-arm whose decision is based on brain signals. Talha et al. [29] proposed this system. In this research, the EEG signal was observed and used to classify the motions type. As a result, robotic arm movement (based on Alpha and Beta waves) was performed precisely. Humaira et al. [30] presented another work on prosthetic arm control. In this work, a facial expression is used as a control method for the arm. The Robotic arm consists of a 3D printed hand attached to the forearm and elbow made of craft wood. The arm is designed for four moves, each move controlled by one facial expression. Hence, 4 different EEG signals were used. The system worked adequately with an accuracy of 95%. However, it isn`t considered an ideal way to control the arm. It should be controlled using conscious and subconscious thoughts.

3. Kinematic analysis of Prosthetic Arm.

In this section, two things are going to be discussed: the human motion analysis in general, and the second section will discuss the upper arm kinematics presented by elbow joint kinematics.

3.1. Human motion analysis

Figure (6) below shows the human movement system. From the figure, we can notice that movement is the product of the articular system. The articular system represents the skeletal system joints connective tissue ligaments is the passive tissue that is non-excitable [31].

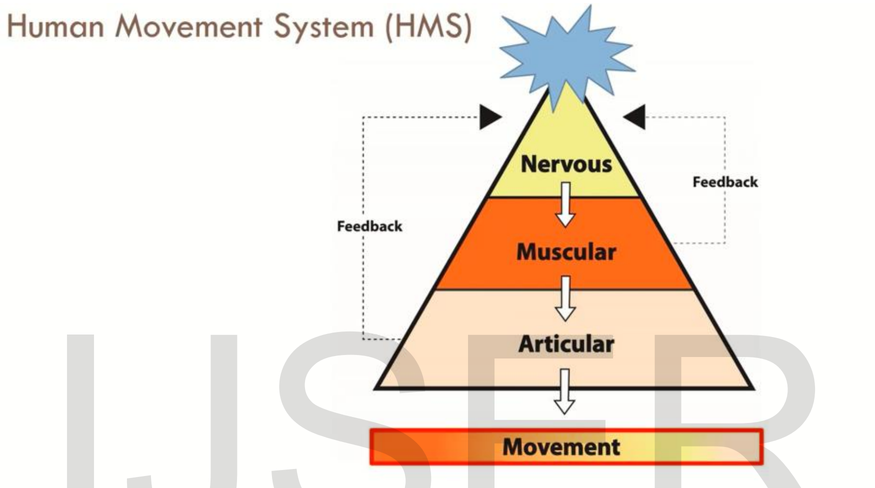

Figure (6) Human movement system

The articular system is 100 % dependent on the muscular input, and the latter is 100 % dependent upon the nervous system. The nervous system is dependent upon conciouse and subconscious thoughts. The human body can do an infinite amount of positions and movements. Movements occur at the joints. The joints are made from the interactions of the bones. The human body will be classified into segments to understand human motion, as shown in figure (7). Arms and legs are extensions of force generation coming from the spine [36-38]. The spine is the engine that drives human movements. The shoulder and the pelvic gride are the transition or relay stations that transfer the force from the spine to the upper and lower extremities.

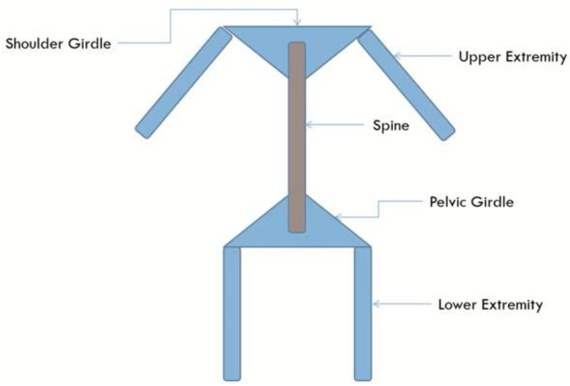

Figure (7) Human body segments.

The joints are the pivot points for the bones interaction. Human movement is a rotation converted to translation; in other words, the linear output is due to rotational input occurring within a musculoskeletal neuromuscular system. To answer the big question of what causes the joint motion, it is the force. The force comes from different sources [39-42]. There are two types of force: external, which represents gravity, and internal force symbolises muscular contraction. Most of the muscles are connected to more than one bone. Therefore, all skeletal muscle crosses at least one joint, as shown in Figure (8).

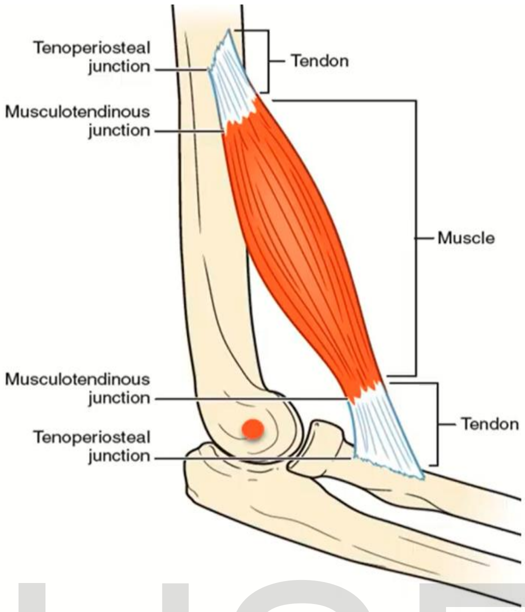

Figure (8) Muscle and joints

The red dot in the figure is the rotational axis; the muscle crosses at least that one joint. Bi-articulated muscles are the muscles that cross more than one joint, such as Biceps. For example, it crosses elbow joints and shoulder joints.

3.2. Elbow joint Kinematic

The Elbow joints consist of the Humero-ulnar joint and humero-radial joint. The humero-ulnar joint comprises the trochlea of the humerus and the concave trochlea notch of the ulna [43-44]. The joint is classified as a modified hinge joint: flexion and extension with 1 DoF flexion and extension. It is called by that name since the Ulna experience a slight amount of axial rotation and side to side motion, as shown in figure (9).

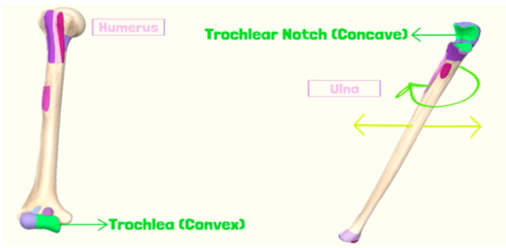

Figure (9) Modified Hinge joint

The humeral radial joint shown in figure (10) is an articulation between the cup-like Phobia of the radial head rounded capitulum of the humerus. The humeral radial joint is typically classified as a pivot joint with the radial head pivoting around the humeral capitulum.

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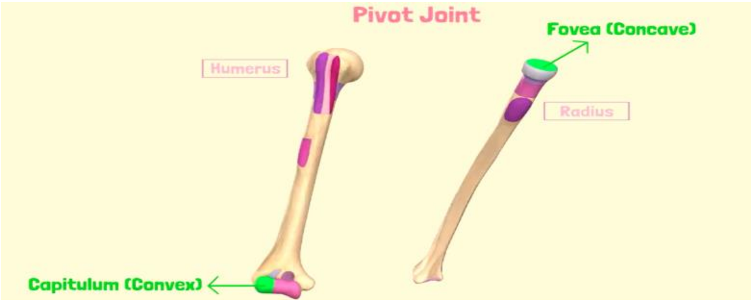
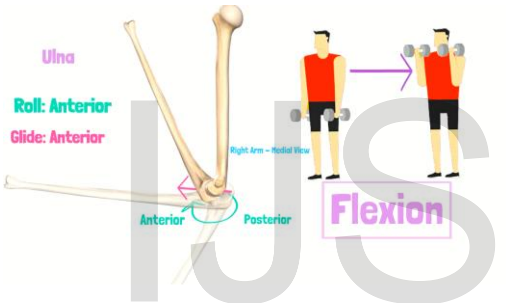


Figure (10) Pivot Joint

The move of these two joints can be observed from two distinct prospectives: open chain kinematics and close chain kinematics.

3.2.1. Open chain Kinematics.

The distal segments move on the proximal segment, for example, bending an elbow to lift a cup of tea or lifting a dumbbell. In these examples, the ulna and radius move on top of the humerus created by the concave on the convex movement. to examine the humera-ulna athrokinemantic, flexion is the movement that will be looked at [45]. Figures (11) and (12) show concave trochlear notch move around the convex choclia, the roll and the glide will occur in the same direction with flexion observe the ulna roll and glide in the interior direction [46]. In the extension, the roll and glide are in the posterior direction



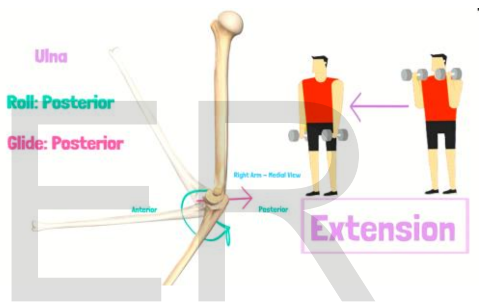


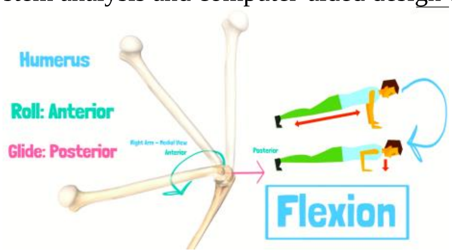
Figure (11) Flexion-open kinematic

Figure (12) Extension-open kinematic

3.2.2. Close kinematic Chain

In this movement, the proximal segment move on the distal segment. A real-life example for it would be the push up as shown in figure (13), where the radius and the ulna are fixed by bar end, and the only way to execute the movement is to move the humerus. In this example, the humerus moves on the top of the radius created by the convex on a concave movement. To examine the humera-ulna arthokinematics, we will also consider flexion and extension. In the flexion, the convex trochlea move on a concave trochlea notch, the roll and glide will appear in the opposite direction[47-50]. With the flexion the humerus roll interior and glide posterior, while in extension, the humerus roll posterior and glide anteriorly [51], as shown in Figure (14).

Both open and closed chain kinematics can be modelled based upon works of R. Szabolcsi supporting both time and frequency domain system analysis and computer-aided design of control systems [52]-[53].



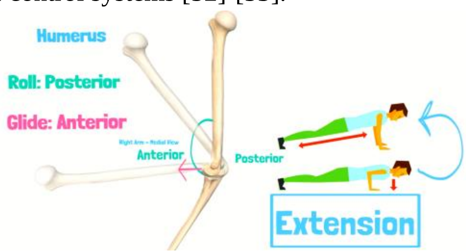


Figure (13) Flexion-closed kinematic

Figure (14) Extension-close kinematic

4. DISCUSSION

There is a significant amount of population suffering from limb loss, especially the upper parts (Arm, Hand), which affect their daily life activities as well as involved in the society again. Therefore, to bring them back to that Liveliness, several technologies were introduced to solve this problem. This paper focused on those technologies and discussed the methods and researches regarding them. Besides that, to understand this technology, we should understand the kinematics of the limbs. This paper focused on upper limb kinematic.

5. CONCLUSION

Amputation is a serious problem that the world has faced for decades. This work review the literature of upper limb prosthetic control to cope with the technological solution to move the Arm and perform simple and complex activities. The work dealt with statistics about amputees and two leading technologies used to control the prosthetic limb, the EEG and EMG signal extraction from the brain and muscles, respectively. The team will focus on brainwaves signal extraction for future work and use them to control the prosthetic limb faster. As a result, the user will execute the limb with more comfortability and a shorter time in response.

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