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Design And Development Of Bio-Prosthetic Arm With Use Of Artificial Intelligent

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Abstract

The incorporation of artificial intelligence (AI) into the field of prosthetics has resulted in a paradigm change, accelerating the development of advanced and intelligent bio-prostheses. This study investigates the design and development of an AI-enhanced bio-prosthetic arm with the goal of not only recovering lost limb functions but also increasing human potential through the seamless integration of human-machine interactions. The suggested bio-prosthetic arm combines cutting-edge technologies, such as advanced robotics, AI algorithms, and biofeedback mechanisms, to build a smart and adaptive prosthetic system.The fundamental goal of this research is to improve the user experience by offering a bio-prosthetic arm that closely resembles the complicated movements and sensory feedback of a genuine limb. The artificial intelligence component of the prosthetic arm is meant to analyse neural signals from the user's brain, enabling .

The development of bio prosthetic arms enhanced by artificial intelligence (AI) represents a significant leap in the field of prosthetics, aiming to restore functional capability and improve the quality of life for individuals with upper limb loss. This review paper explores the evolution, current state-of-the-art, and future prospects of AI-driven prosthetic limbs.

The integration of AI technologies such as machine learning, neural networks, and computer vision has revolutionized prosthetic design by enabling advanced functionalities previously thought unattainable. AI algorithms facilitate real-time processing of sensory feedback from various sensors embedded within the prosthetic limb, allowing for natural and intuitive control. These sensors include electromyography (EMG), which detects muscle signals, and tactile sensors that provide sensory information crucial for grip strength and object manipulation.

Moreover, AI enables adaptive learning capabilities, where the prosthetic arm learns and adjusts its movements based on the user's intentions and environmental cues. This adaptive feature not only enhances usability but also promotes user acceptance and satisfaction.

Technological advancements in materials science have further complemented AI-driven prosthetic development, with the use of lightweight and durable materials improving comfort and reducing the burden on users. Additionally, developments in 3D printing have facilitated personalized prosthetic designs that optimize fit and functionality for individual users.

Ethical considerations surrounding AI in prosthetics, including data privacy, autonomy, and equitable access, are also critical areas of discussion. As AI technologies continue to evolve, addressing these ethical concerns becomes paramount to ensure safe and inclusive deployment.

In conclusion, AI-driven bio prosthetic arms represent a promising frontier in medical technology, offering unprecedented capabilities to enhance limb functionality and integrate seamlessly into users' lives. This review paper aims to provide a comprehensive overview of the design principles, technological innovations, challenges, and future directions in AI-enhanced prosthetic arms, highlighting their transformative potential in rehabilitation and prosthetic care.

Introduction

Human is the most intelligent creature in the planet for their brain power and neural network. The human brain is extremely complex with more than 80 billion neurons and trillion of connections [1]. Simulation scales can array from molecular and genetic expressions to compartment models of subcellular volumes and individual neurons to local networks and system models [2]. Deep Neural Network nodes are an over simplification of how brain synapses work. Signal transmission in the brain is dominated by chemical synapses, which release chemical substances and neurotransmitters to convert electrical signals via voltage-gated ion channels at the presynaptic cleft into post-synaptic activity. The type of neurotransmitter characterizes whether a synapse facilitates signal transmission (excitatory role) or prevents it (inhibitory role). Currently, there are tenths of known neurotransmitters, whereas new ones continuously emerge with varying functional roles. Furthermore, dynamic synaptic adaptations, which affect the strength of a synapse, occur in response to the frequency and magnitude of the presynaptic signal and reflect complex learning/memory functions, (Spike time dependent plasticity) [3, 4]. Recently, evidence has found that surrounding cells, such as glia cells that are primarily involved in ‘feeding’ the neurons, can also affect their function via the release of neurotransmitters. This new vision of “tripartite synapses,” composed of perisynaptic glia in addition to pre- and postsynaptic terminals certainly makes this one of the most exciting discoveries in current neurobiology.

Functional loss from amputation, spinal cord damage, brachial plexus injury, or traumatic brain injury causes a loss of brain-to-extremity link, resulting in weakened extremities that cannot function as well as the healthy limb.

Prosthetics, orthotic devices, and rehabilitation aids were used to replace lost structure and function in the extremities. Conventional prostheses are mechanical devices that only perform basic functions. Orthosis supports weaker portions without fully replicating the deleted area. Biomechatronics is a sub-discipline within mechatronics. The development of mechatronic systems to aid or repair the human body has taken the concept of prosthetics and orthotics to a new level. The biomechatronic system comprises four units:

Biosensors sense human intents through biological reactions in the neurological and muscle systems. The controller works as a translator between biological and electrical structures,

monitors the operations of the biomechatronic device. Mechanical sensors collect data about the biomechatronic device and send it to the biosensor or controller. The actuator is a robot mechanism that generates force or movement to support or replace human bodily functions. Biomechatronics applications include orthotics, prostheses, exoskeletons, rehabilitation robots, and neuroprostheses. Robots are intelligent gadgets that can perform cyclic movements in rehabilitation, control introduced forces, duplicate required forces in repeating exercises, and provide more precision in various conditions.

Basic concept of AI and machine learning (ML)

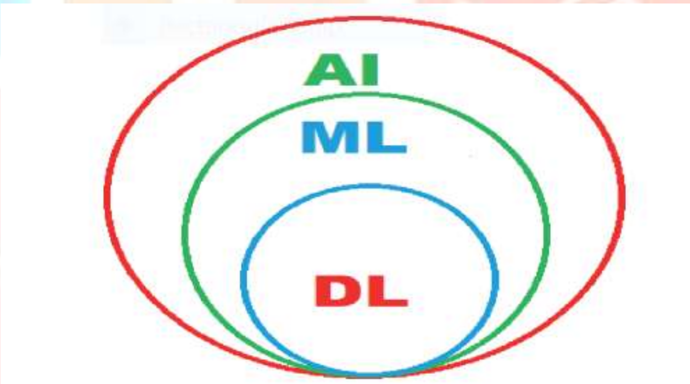
A. Machine learning

Machine learning, which combines mathematics, statistics, and computer science, is advancing the field of artificial intelligence. It is the study of computer algorithms that grow and develop via experience. This is a subset of AI, as illustrated in Figure 1. ML algorithm methods Generally classified into two types: supervised and uncontrolled learning.

B. Supervised instruction

The process of forecasting a model using a learning function to map the known output onto a trained range of inputs and identify patterns in fresh data sets.
Example 1: To forecast the trained model for the microprocessor knee joint Using multiple input or labelled data of the knee angle change in various subphases of the gait cycle and applying the phase-dependent pattern recognition approach to fresh amputees to forecast new data.

Pattern recognition is an automatically recognition of pattern applied in data analysis, signal processing etc. when the pattern of algorithm trained from labeled data that is supervised learning. When the model of algorithm is fruitfully trained, the model can be used for the prediction of a new data. The ultimate goal of this ML is to develop a successful predictor function. The models of discrete or categorical categories of dependent variables are known as classification algorithm and with continuous value known as regression algorithm. Three basic steps followed to finalize a model are training, validating and application of algorithm to new data. Algorithm used for supervised learning are support vector machines, linear regression, linear discriminant analysis (LDA)etc.Thisiserrorbaslearning.

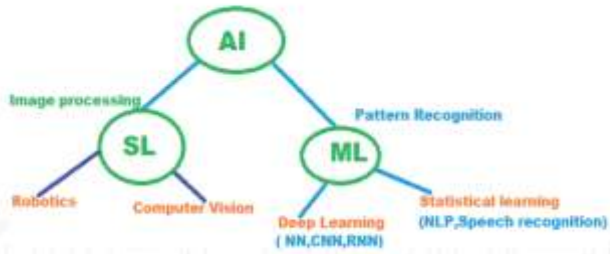


- Relationship between artificial intelligence (AI), machine learning (ML) and deep learning (DL).

Schematic diagram of flow of information with bento arm

The artificial intelligence is rewarded or penalised based on the actions that the agent takes. The environment instantly returns to evaluate the previous action as the reward. An agent's objective is to maximise the reward given the collection of acts. The agent uses the exploration and exploitation principle to determine the best course of action and potential rewards. Exploitation makes use of previously discovered information to obtain rewards, whereas exploration seeks for and gathers additional information from the environment.

This type of machine learning combines AI and supervised and unsupervised learning techniques. It makes use of representation learning in conjunction with artificial neural networks (ANNs). Inspired by the neural network of the human brain, ANN system of networks whether the ANN is static and symbolic while the human brain network is dynamic (Plastic) and analogue. It is capable of learning, remembering, extrapolating, and modelling the biological nervous system on cue. When it comes to solving issues with pattern recognition, matching, clustering, and classification, ANNs work better. The input layer of an ANN can serve as the input layer for a subsequent output of a simple network of neural systems. The ANN is composed of three conventional layers: input, output, and hidden.



The methods or techniques used for the AI are classifier and prediction. Classifier is an algorithm that implements classification; the classifiers are Perceptron, Naïve Bayes, Decision trees, Logistic regression, K nearest Neighbor, AANN/DL and support vector machine [24]. Perceptron is the basic building block of the neural network it breakdown the complex network to smaller and simpler pieces. The classifier used in the myoelectric prosthetic hand is LDA classifier, Quadratic discriminant classifier and Multilayer perceptron neural network with linear activation functions etc. LDA (linear discriminant classifier) is a simple one that helps to reduce the dimension of the algorithm for application of neuralnetwork model. Prediction is a method to predict a pattern an output noise free data with a model from input data in hidden layer. Examples: EMG CNN based prosthetic hand, EGG based Mind controlled prosthesis with sensory feedback, robotic arm, exoskeleton Orthosis.

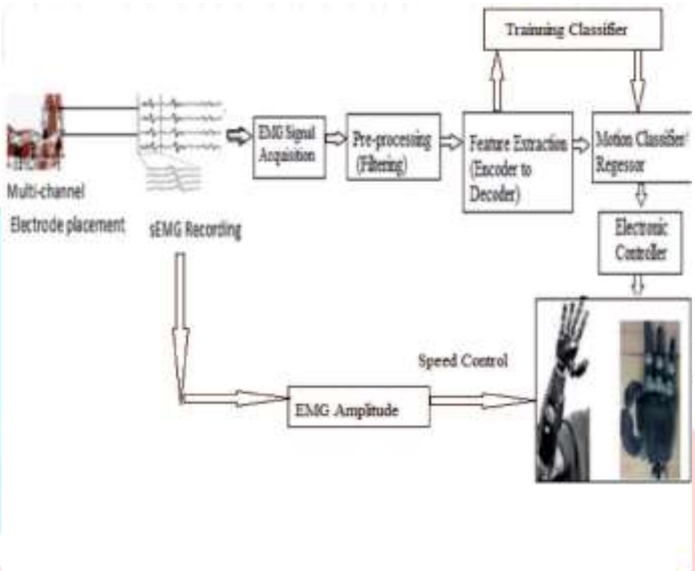
The use of artificial intelligence in prosthesis control has grown significantly, allowing amputees to use their devices in more convenient ways.
A system could operate more in line with the intended output with the help of adaptive controlling.

by using a feedback mechanism to modify the input. The most recent development in the artificial intelligence-assisted control system was the introduction of a mind-controlled limb, which is a form of myoelectric controlling. A prosthetic limb that is modular in nature and can be fully controlled by brain implants has been developed through a collaborative effort between the Pentagon and Johns Hopkins Applied Physics Laboratory (APL). The prosthetic would even allow for the restoration of tactile sensation by returning electrical impulses from the limb to the sensory cortex.

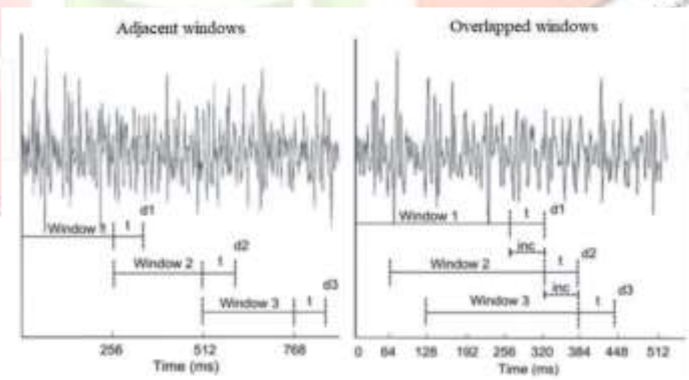
A multilayer artificial neural network (ANN)-based model was suggested by Chang et al. (2009) to determine the critical association between the intrinsic impaired neuromuscular activities and extrinsic gait behaviours of individuals with spina bifida (SB) [26]. The application of AI in orthotics and prosthetics is broken down into different subparts based on the affected region, such as upper and lower extremity orthoses and prostheses, rehabilitation aids such motorised mobility devices, and lower extremity prostheses and orthoses.

Artificial intelligence is employed in upper limb prosthetics through a variety of signals, sensors, controllers, and algorithms to provide both direct and indirect control from a neural network. The two forms of humans are the source of the control signals.

to perform electromyography (EMG) and electroencephalograms (EEG) in order to operate the upper extremity prosthesis. Previous attempts to control prosthetic elements voluntarily have centred around the use of electromyography (EMG) signals from voluntary muscle groups. The majority of this work has been focused on upper extremity prosthetic control systems. The USSR unveiled the first powered hand myoelectric prosthesis for sale in 1960 [27]. By using an EMG pattern recognition based control technique, myoelectric prosthesis with EMG control has advanced. This approach allows the user to control the prosthesis with multiple degrees of freedom. The most advanced and developed neural machine interface technology was TMR or targeted muscle reinnervation. To obtain sufficient myoelectric pattern information for pattern recognition control in a multifunctional prosthesis, multi-channel myoelectric recordings are required. The quantity and arrangement of electrodes in a multifunctional prosthesis would mostly depend on the number of movement classes required and the number of An amputee's remaining muscles can be used for myoelectric control. In the case of myoelectric transradial prostheses, the EMG signals are obtained from the residual muscles using a set of bipolar electrodes (8–16). Eight of the electrodes are evenly distributed around the proximal part of the forearm, while the remaining four electrodes are positioned on the distal end. The severed arm's elbow was fitted with a sizable round electrode as a ground. For acquisition of EMG signal 50 Hz-60 Hz can be used to remove or reduce more low-frequency to increase the control stability of a multifunctional myoelectric prosthesis [32]. EMG feature extraction is performed on windowed EMG data, all EMG recordings channels are segmented into a series of analysis windows either with or without time overlap (WL (window length) is 100-250 ms)



Process of EMG pattern recognition control.

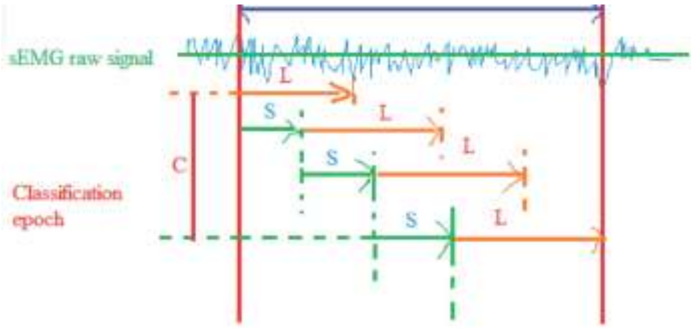


(Windowing techniques, time to process each window analysis is ‘t’ and decisions (d1, d2, d3). In adjacent windows the processing time is less and the classifier is idle most of the time but in overlapping windows increase frequency of class decision because the analysis window slides with small increment (inc), the amount of overlap is equal to processing time which help the controller to process next class decision before the previous decission has been completed)

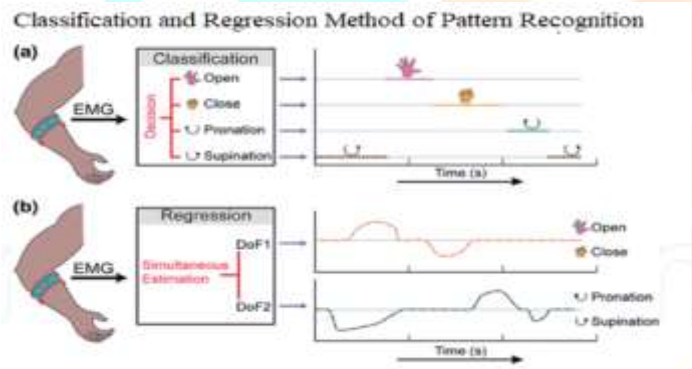
feature matrix (L × C × W, where L, C, and W are the number of features, the number of channels, and the number of analysis windows, respectively) from the training set is provided to a classifier for training shown in Figure 7. Example: The features extracted from four channels of surface EMG in each window is 44 and the data analyzed for the three windowed length, the EMG feature matrix for this situation (L × C × W = 44 × 4 × 3 i.e. L = 44, C = 4, W = 3).
The aim of pattern recognition based classifier is to discriminate the intended movements from the EMG recordings as accurately as possible. Many classification techniques have been investigated, including linear

discriminate analysis, Bayesian statistical methods, artificial neural networks, and fuzzy logic [34, 35]. The LDA classifier is much simpler to implement and much faster to train without compromising the accuracy (>93%). Then the performance of a trained classifier in identifying a movement is evaluated using the testing data set and measured by the classification accuracy, which is defined as:

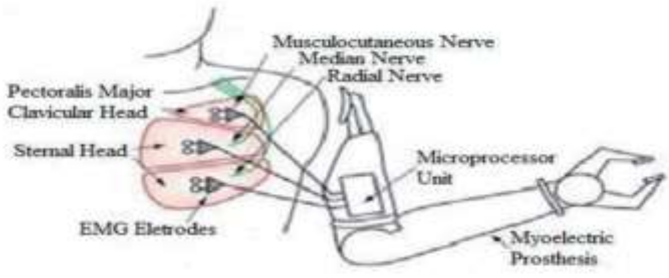
Number correctly classified samples x100%
Total number of testing samples ×



EMG windowing in continuous feature extraction. Size of successive window for analysis is L, the sEMG data for classification is divided into C segments for every L that is the length of integrated samples as a feature extraction and the start point is shifted every S.

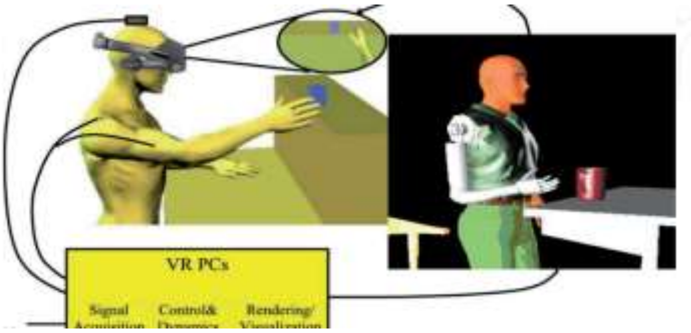


a. Pattern recognition is able to classify different movement patterns, but only in sequence, which limits multifunctional control. b. Regression control is able to identify different movements at the same time, leading to more intuitive prosthetic control

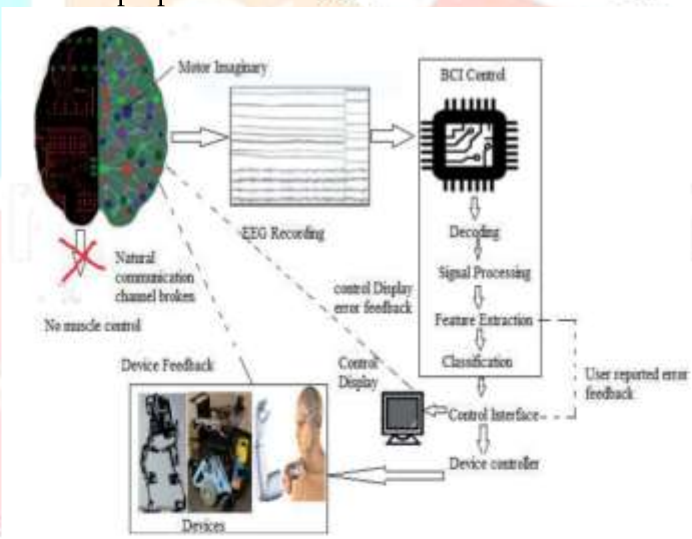


Targeted muscle reinnervation (TMR)

Another advanced technique to control the multifunctional limb is Virtual reality (VR) based platforms have been developed for the purposes of development and performance quantification of multifunctional myoelectric prosthesis control system These VR platforms are designed to create an efficient, flexible, and userfriendly environment for prosthetic control algorithm development in the laboratory, application in a clinical setting, and eventual use in an embedded system. The major function modules of this platform include multi-electrode EMG recording (up to 16 channels), classifier training and testing in offline, virtual and physical prosthesis control in real time to regulate performance Apart from EMG signal the Electroencephalography (EEG) is the widely used non-invasive method by placing the electrode on the scalp for picking brain signal that has been utilized in brain machine interface (BCI/BMI) applications. It has high temporal resolution (about 1 ms) in comparison with other brainwave measurements such as electrocorticograms (ECoGs), magneto encephalograms functional magnetic resonance imaging (fMRI) and near-infrared spectroscopy (fNIRS). The advanced prostheses may best control by EEG signal with BCI, connected by ANN. The neural signals associated with arm movements as control signals of artificial neuroprosthesis collected from either the cortex of brain directly or from residual nerves. The diagram of EEG based control and EMG pattern recognition based control in utilized in upper extremity prosthesis is shown in schematic.



Virtual reality system (VR), subjects can operate a simulated prosthetic arm to interact with virtual objects. Multiple input modalities such as motion tracking systems and EMG/EEG electrodes provide maximum flexibility when evaluating different control approaches. Figure shows a subject operating a prosthetic arm prototype in VR (right side). Subject controls the arm via real-time motion tracking (left side), and 3-D visual feedback is provided via stereoscopic goggles for closed loop operation

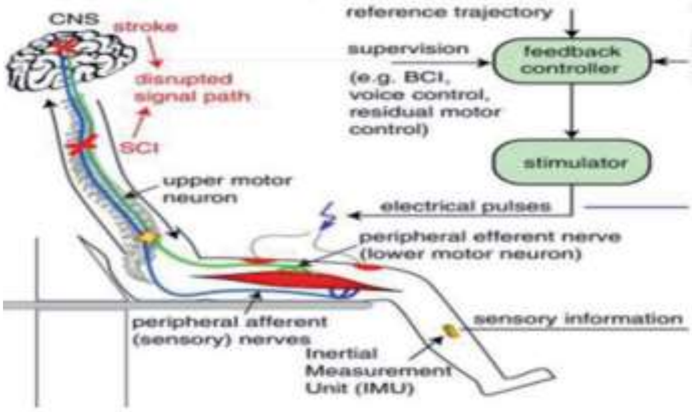


Brain computer Interface (BCI), controlling prosthetic and orthotics devices.

Applying electrical stimulation to a paralysed nerve or muscle in order to restore or achieve function is known as functional electrical stimulation, or FES. FES is most frequently used with task-specific practice in neuro rehabilitation.

One typical orthotic substitution example is the neuroprosthesis [45]. Adaptive control can be used to both feed forward and feed backward controllers. A control system can be open loop, also known as feed forward control, closed loop, or feed backward control. In closed-loop FES, joint or muscle position sensors are used to enable increased reactivity to muscle fatigue or to abnormalities in the surroundings. In open-loop controlled FES, the electrical stimulator regulates the output.

Electrodes act as interfaces between the electrical stimulator and the nervous system. The FES utilizes electrical current to stimulate muscle contraction so that the paralyzed muscles can start functioning again. The desired purpose is to stimulate a motor response (muscle contraction) through activation of a specific group of nerve fibers, typically using fibers of peripheral nerves. This may be achieved by the activation of motor efferent nerve fibers showed



DESIGN OF EXTERNALLY POWEREDPROSTHETIC HANDS

Several factors delayed progress toward creatinga multi-DOF, EMG-controlled hand. One common requirement for the creation of a hand prosthesisis that it must be roughly the same size and weight as the human hand. Ideally, all components would be contained inside the palm. This type of intrinsic actuation leads to a severe reduction in the allow- able DOF of the prosthesis; the size of the motors, sensors, and additional electrical components wouldexceed size and weight restrictions if more than oneDOF were allowed.[9] Currently, there are prosthetic hands controlled with EMG capable of moving withup to 20 DOF and a thumb with four DOF. The tradeoff is a large increase in the number of motors required (in this case, 11) and, consequently, the weight of the prosthesis.[10] The most advanced, com-mercially available prosthesis operated by EMGis the i-LIMB Hand from Touch Bionics.[11] The i- LIMB uses implantable EMG electrodes and allows each finger to be actuated independently to performkey, power, and precision grips as well as the indexfinger pointing motion.

As design methods improved, researchers be- gan identifying the types of motion that would be most crucial for performing activities of daily living(ADL). Five grasp patterns were initially identified as the most important to the functional capabilities of a prosthetic hand: pinch grasp (used to hold smallobjects), lateral grasp (used to hold a key), hook grasp (used for carrying items such as books or briefcases), spherical grasp (thumb and fingers grasp a spherical object), and cylindrical grasp (thumb andfingers grasp a cylindrical object).[6] Three additionalimportant grasps were later identified: the flattened hand (for holding large surface objects), the central-ized grip (used to hold items such as eating utensils),and wrist flexion.[14–17] The eight most important grippatterns for performing ADL are shown in Figure.

- Mechanical Linkage Designs

A common method for enhancing DOF in a prosthesis is to decrease the number of required actuators (thereby reducing the required space for motors and the weight of the prosthesis) by actuating multiple hand components at the same time. It is recognised that the finger joints function through linked rotation rather than separate motion. Mechanical linkage designs are the most popular way to actuate many joints concurrently. Researchers who utilise this technology recognise that the finger bends in a natural curling action and use a linking system to mimic the finger's trajectory.18 Baek et al. (19) constructed a robotic finger. For use in prosthetic hand design, this device delivers flexion and extension for each of the three finger joints while using a single motor. A mechanical linkage system was employed to transmit the driving force. Although the created forces were tiny, the results demonstrated that they were adequate for retaining objects. The six-axis Southampton-Remedi hand employs a four-bar linkage system to reduce prosthesis weight while providing various degrees of freedom without increasing the user's physical or psychological strain.20 Mahmoud et al. proposed a novel design, the Osaka City University Hand.21 The five-fingered hand uses planar bar connection mechanisms and has 19 degrees of freedom (DOF). Each finger (except the middle finger) contains four DOF, and the thumb is designed with a maximum of 110 degrees of yaw, maximizing the thumb's ability to orient to an object's surface.

SMA Actuators:-

As an alternative to traditional motors, SMA ac- tuators have shown significant potential for use in upper extremity prostheses.[45,46] SMA actuators are light, thin, metallic wires that deform (during grasp-ing, in the case of a prosthesis) when cooled and return to their predetermined shape when heated.[47] Despite the advantage of reduced weight, SMA ac- tuators are less popular than traditional DC motors.

because of their small strain capacity. In addition, the relaxation phase of the SMA wires is deter- mined by the cooling rate of the wire and is often too slow for practical use. Andrianesis and Tzes[48] developed a five-fingered prosthetic hand with 16 joints and seven active DOF using SMA actuators. Results showed that the device was able to performsix of the canonical hand postures (cylindrical, tip, hook, palmar, spherical, and lateral grasps). O'Tooleet al.[45] designed a four-fingered artificial hand usingSMA actuators, attempting to optimize the strain re-sponse of the SMAs by maximizing the heat transfer to and from the actuator. The authors recognized the disadvantage of a required cooling system that mustbe inexpensive, portable, and safe. Using heat sinksas a cooling strategy, the cooling time was reduced to 1.9 seconds (compared to 3.4 seconds with natu-ral cooling) but must still be significantly reduced for practical use in an artificial limb. Price et al.[4] used SMA actuators to create an artificial muscle for use in anthropomorphic upper limb prostheses. To address the problem of limited strain capabilities, four strands of SMA ribbons were loosely braided together and twisted to ensure uniform tension, as shown in Figure 3. A maximum contractile strain of31.6% was achieved (compared to a maximum of 10% for previous uses of SMA actuators).

Materials use in bio- prosthetic arm :-

1. **Materials and Construction:**
    1. Lightweight and durable materials such as carbon fiber, titanium, and medical-grade plastics are used to minimize weight and maximize strength.
    2. Using a Soft silicone or composite materials are used for the outer skin layer to provide a natural appearance and texture.
    3. Internal components are designed to withstand everyday use and potential impacts while maintaining reliability and performance.
2. **Control and Power System:**
    1. The prosthetic arm is controlled through a combination of myoelectric sensors, electromyography (EMG), and/or neuromuscular control systems.
    2. Battery-powered actuators and motors drive the movement of the prosthetic joints, with sufficient battery life for a full day of typical use. Approx (4500MHZ)

In conclusion, the design and development of an AI-enhanced bio-prosthetic arm represent a groundbreaking frontier in assistive technology with the potential to elevate human potential. Through the convergence of artificial intelligence, neuroscience, and biomechanics, this innovative prosthetic arm aims to provide users with a level of control, adaptability, and sensory feedback that was once considered beyond reach.

The integration of AI brings forth a paradigm shift, enabling the prosthetic arm to transcend mere functionality and embrace a more intuitive and responsive interaction with its user. The marriage of advanced neural interfaces and machine learning algorithms allows for the decoding of intricate neural signals, translating intention into seamless, natural movements. This breakthrough not only restores lost motor abilities but also opens avenues for users to engage in a wide spectrum of daily activities with newfound independence.

The real-time adaptability of the AI-driven prosthetic arm is a testament to its continuous learning mechanisms. By dynamically adjusting to changes in the user's neural patterns and preferences, the prosthetic arm becomes a personalized extension of the individual, evolving over time to meet their evolving needs and capabilities.

Sensory feedback, a cornerstone of this design, further blurs the boundary between the artificial and the natural. Haptic sensations and proprioceptive cues provide users with a tactile connection to their surroundings, fostering an enhanced sense of spatial awareness and control. This not only improves the functionality of the prosthetic arm but also contributes to a more immersive and integrated user experience.

The ethical considerations woven into the fabric of this endeavor are paramount. From safeguarding user privacy to ensuring the responsible

development and deployment of AI technologies, a commitment to ethical principles underscores the entire process. As we strive to push the boundaries of technological innovation, it is crucial to remain vigilant in addressing ethical implications and societal impact.

As this AI-enhanced bio-prosthetic arm emerges as a beacon of progress, it signifies a collaborative effort between engineers, healthcare professionals, and users. The journey from concept to reality underscores the importance of iterative design, rigorous testing, and user feedback in refining a solution that genuinely meets the needs and aspirations of those it seeks to empower.

In essence, "Elevating Human Potential: The Design and Development of an AI-Enhanced Bio-Prosthetic Arm" is not merely a technological achievement; it is a testament to our collective commitment to enhancing the quality of life for individuals with limb differences. It exemplifies the fusion of cutting-edge technology with a human-centric approach, ultimately contributing to a future where assistive technologies redefine the boundaries of what is possible, one prosthetic arm at a time.

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