A Novel Approach of Prosthetic Arm Control using Computer Vision, Biosignals, and Motion Capture

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***Abstract*— Modern day prosthetics are traditionally controlled using EMG readings, which allow the user to control a limited number of degrees of freedom at one time. This creates a serious disadvantage compared to a biological arm because it constrains the fluid motion and dynamic functionality of the device. We present a novel architecture for controlling a transhumeral prosthetic device through the combination of several techniques, namely computer vision algorithms operating on "eye gaze" data, traditional prosthetic control methods, and the operator's motion capture data. This sensor fusion allows the prosthetic device to locate itself in a 3D environment as well as the locations of objects of interest. Moreover, this architecture enables a more seamless motion and intuitive control of the prosthetic device. In this paper, we demonstrate the feasibility of this architecture and its implementation with a prototype.**

Keywords—Computer Vision; Biosignal Motion Capture; Prosthetic Arm Control; EMG; Transhumeral Prosthetics

I. INTRODUCTION

Prosthetics are artificial devices that replace injured or diseased body parts, and are externally worn or surgically implanted on the body. The main types of prosthetic arms are transradial (prosthesis attached below the elbow) and transhumeral (prosthesis attached to the upper arm when the elbow joint is missing). Two primary ways for operating a prosthetic arm are body-powered (attached to the body with a harness and cables) and myoelectric (controlled by electric signals from the residual muscle); the latter being the preferred control method and therefore the one used in this paper. In a myoelectric controlled prosthesis, the electric signals measured from the residual muscles are processed into commands that tell the prosthesis to open or close the hand, twist the wrist, or bend the elbow [1]. Traditional upper extremity prosthesis have at least 3 DOF (degrees of freedom), which cannot be simultaneously operated with ease [2]. Such devices have a disadvantage compared to anthropomorphic arms that have 22 DOF [2].

On the other hand, computer vision is being widely used in robotics to determine the location of the robotic system and the positioning of the objects around it in space. Examples include famous robotics systems like Honda's ASIMO and Boston Dynamics ATLAS. Also, recently released wearable technologies such as the Google Glass have given us a powerful interface to the user, as well as easily accessible real time data, in the form of a video stream.

In this paper, we propose to create a computer vision based algorithm using "eye gaze" data from the user, which, along with EMG signal processing, will achieve semi-autonomous, simultaneous, multi-joint operation of the prosthesis. Our solution, unlike the ones described in [1], [3], and [4], provides the amputee with a more intuitive and user-friendly human-machine interface.

II. STATE OF THE ART

Several new approaches have been proposed for overcoming the limitation of traditional prosthesis control.

Toledo et al. [2] discussed the different types of upper limb prosthesis as well as several state of the art advances in modern prosthetics. According to their paper, there is still a large gap for improvement because prosthesis on the market as of 2009 had only 3 DOF, quite far from the 22 DOF of a biological arm, and these had to be independently operated using residual muscles. This means that fluid anthropomorphic motion of the arm is not achievable with the current control methods.

Shinde et al. [5] proposed a prosthesis design that would be strong and reliable while still offering control over the exerted forces. The design had to account for mechanical and electrical design reliability and compactness. It concluded that the use of EMG signals for control of prosthetic arms has been historically plagued by the unreliability of the surface EMG sensor due to artifacts, wire breakage, inconvenience from the electrodes' doffing and donning procedures, maintenance of the skin's condition, and repeatability of the electrodes' placement. The control of powered upper limb prosthesis has not seen any revolutionary developments since its inception, but rather, incremental evolution. They showed progress towards more natural and effective means of myoelectric control by providing high accuracy, low response time and an intuitive control interface to the user.

Using computer vision to control robotic arms is not a new concept and extensive research has been done in the area, including object recognition, arm positioning, grasping estimation, and vision feedback control. However, not much research has merged this approach with EMG sensing to semi-autonomously control an anthropomorphic prosthetic arm.

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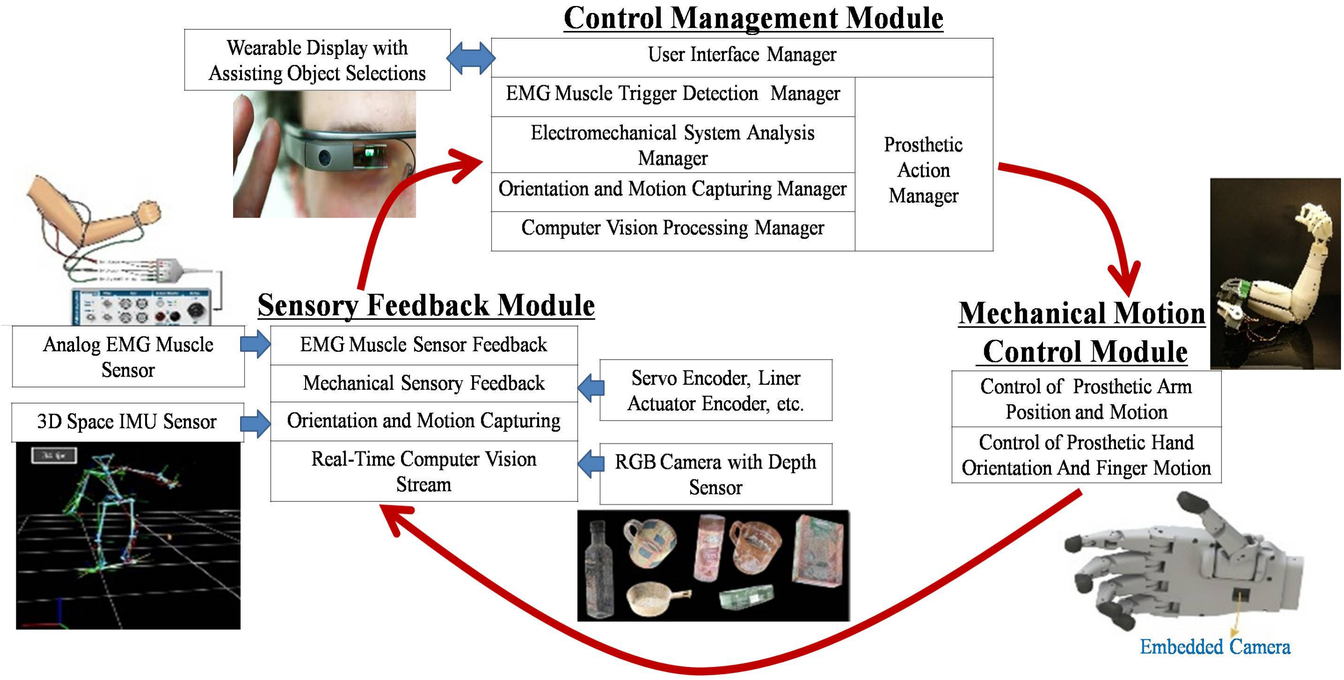

Figure 1. System Architecture Overview

Ashutosh et al. [6] proposes a four part algorithm that uses computer vision to control a robotic arm by inferring grasping points, perceiving the environment and obstacles, planning a path to the target object, and moving the arm to the desired position to perform the grasping task. Unlike previous algorithms, which assume detailed 3-dimensional models of the environment, the proposed algorithm focuses on robustness while dealing with uncertain and missing data, which most real world applications present.

The research presented by Puheim and Bundzel expands upon a Tracking-Learning-Detection (TLD) algorithm, which is able to detect and track an object in a continuous series of video frames [7]. The algorithm gives an idea about the position of the object in respect to the frame, but no other information about the location of the object in the environment is given. This is due to the fact that TLD algorithms only process 2-dimensional pictures. By using a stereoscopic vision camera system, they were able to determine the positions of objects in a three-dimensional space quite accurately. Using these vision-processing algorithms we can adapt this process to aid in the semi-autonomous control of a prosthetic arm and give feedback to the user about the real-time objects' location in the 3-dimensional space.

Our proposed system architecture will fill in the gaps left by previously discussed papers. The systems that were proposed in those papers have limited control features, and the controls are difficult to learn and operate, having control of only one degree of freedom at a time. We will merge a computer vision algorithm with EMG muscle readings and motion capturing to provide the operator a wider range of simultaneous multi-joint control.

III. SYSTEM ARCHITECTURE

Our control system architecture consists of three major components, Sensor Feedback Module (SFM), Mechanical Motion Control Module (MMCM), Control Management Module (CMM) as depicted at Figure 1.

SFM collects all sensory feedbacks and forwards them to CMM. MMCM controls mechanical prosthetic arms/hands based on control messages from CMM. CMM has six independent managers that all intercommunicate to achieve accurate control of the prosthetic arm.

- User Interface Manager (UIM)
- Electromechanical System Analysis Manager (ESAM)
- Computer Vision Processing Manager (CVPM)
- EMG Muscle Trigger Detection Manager (EMTDM)
- Orientation and Motion Capturing Manager (OMCM)
- Prosthetic Action Manager (PAM)

The User Interface Manager (UIM) is responsible for displaying all interactive data to the interface screen on the wearable glass technology. The displayed data includes video feed, tracked objects, and user interaction messages. The manager receives data from the Computer Vision Processing Manager as well as the occasional status message from the Electromechanical System Analysis Manager (ESAM).

The prosthetic arm has many different actuators and sensors. Mechanical sensory feedback from these devices is essential to a robust and seamless control of the arm. Multiple servos return functioning data such as angular position, temperature, and angular acceleration. Other sensors that provide control feedback range from potentiometers, current sensors, force/pressure sensors, and battery life indicators. All of this data is forwarded to the Electromechanical System Analysis Manager (ESAM). This manager controls most of the error checking and keeps track of the status of all of the electromechanical devices in the system. It also forwards status data to the user interface upon request. It keeps track of servo positions, to prevent the occurrence of joint over extension, and to forward these positions to the Prosthetic Action Manager (PAM) and Orientation and Motion Capture Manager (OMCM).

The Computer Vision Processing Manager (CVPM) receives the real time depth and RGB video stream from the vision system. Using a depth and RGB camera mounted on wearable glasses technology near the user's eyes, a real-time video stream and pixel depth information can be forwarded to the CVPM, representing "eye-gaze" data that is actually contained in the user's field of view. Its first task is to process this data into a 3D point cloud so that targetable objects can be detected and tracked more easily. The video feed and tracked objects are then forwarded to the user interface, which displays them to the user. Triggers processed by the EMG Muscle Trigger Detection Manager (EMTDM) are forwarded into this manager allowing selections to be controlled by the user. The selections are also displayed in the user interface. The CVPM also calculates the distances and shapes from the selected and tracked objects, and forwards this data to the Prosthetic Action Manager (PAM).

EMG muscle sensory feedback includes the physical sensors (electrodes), EMG amplifier, and a microcontroller to forward the data to the computer for further analysis. The electrodes are placed on the operator's muscles and connected to the EMG amplifier. The EMG amplifier then gets the voltage on the user's skin from the surface electrodes and amplifies it so that it can be used to determine the muscle flex force. The amplifier intensifies the analog signal voltage from the muscle flex to be later interpreted by the corresponding EMG Muscle Trigger Detection Manager (EMTDM). The EMG amplifier board will be connected to a microcontroller in order to feed the information to a computer. EMG Muscle Trigger Detection Manager (EMTDM) then retrieves this data and it is used to determine which muscle is being activated. Depending on the muscle or combination of muscles being activated, triggers are generated to allow the user to select which object the arm and hand should adjust itself to grab.

The Orientation and Motion Capturing Manager (OMCM) gathers information about the users head (eye gaze direction), body, and limb position. The user orientation and motion capture data will be used to determine if the object is out of reach for the prosthetic arm/hand. Using sensors known as Inertial Measurement Units (IMUs), the angles and skeleton information allow us to have position and orientation data about any full or partial limb including the users head. With the data, the direction in which the user's arm must move in order to assist the prosthetic arm in grabbing an object from a table can be determined. It will update the status on whether the user must move his/her arm in order to grasp a triggered object.

The Prosthetic Action Manager (PAM) is the largest manager in the system, as it controls several key operations. Along with maintaining working status of all other managers, the PAM controls how the data from each manager interacts with one another. The PAM also combines the input from other managers to determine final commands, and send them out to the physical prosthesis.

IV. IMPLEMENTATION AND EVALUATION

In this implementation, we excluded the use of Inertial Measurement Units (IMUs) because they are not required for the proof of concept that computer vision can be combined with traditional prosthesis control. Our prosthetic arm is composed of several subsystems. They individually realize a task and communicate with one another to achieve a common goal. Thus, we used simplified control architecture for this implementation as depicted at Figure 2.

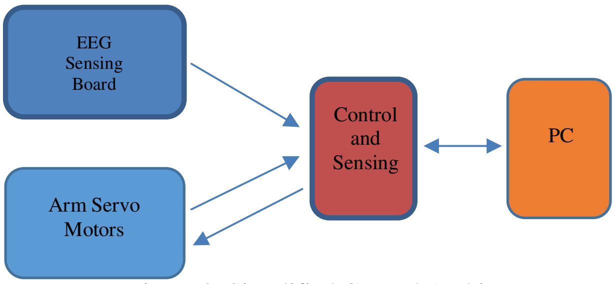

Figure 2. Simplified Control Architecture

- The EMG Sensing board reads the electrical signals from the muscles and transmits them to the Control and Sensing module through SPI communication to be further processed by software on the PC.
- The arm's servomotors not only act as actuators but also as sensors. They provide information such as their current angle, torque, and temperature. Torque and position information are used to calculate the relative position of the arm to the body or the objects trying to be picked up.
- The control and sensing module acts as an intermediary and translator between the PC and the Sensors and actuators. It communicates with the PC using RS-232 communication and the use of a package frame to prevent data misalignment or corruption.

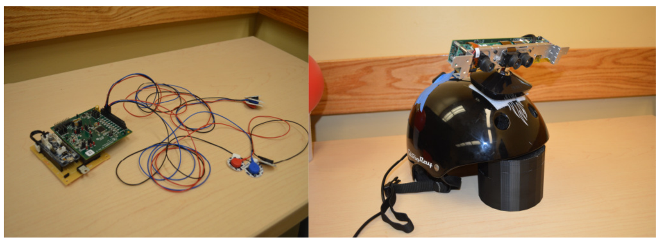

Figure 3: EMG Sensor Board (left) and helmet mounted Kinect (right)

Figure 4: Elbow connection joint (left) and prototype prosthesis (right)

Our prototype consists of several hardware components and sensors. The EMG Signal Board (Texas Instruments ADS1299EEG-FE), along with the OpenCM (Figure 3 left), controls the forwarding of the muscle signal data to the PC, as well as the physical control of the arms' servomotors. We are using 2 of the Robotis Dynamixel MX-106 Servo Actuators. Our prototype also uses the Microsoft Kinect sensor (Figure 3 right) to acquire RGB camera feed and depth information that is fed into our computer vision algorithm. We designed and assembled a prototype prosthetic arm for testing purposes. Figure 4 shows our custom designed and printed bracket that allows control of 2 degrees of freedom in the elbow joint. From the elbow joint, we attached a temporary forearm, wrist rotation servo, and simple gripper attachment. Figure 4 also shows an overview of our prototype.

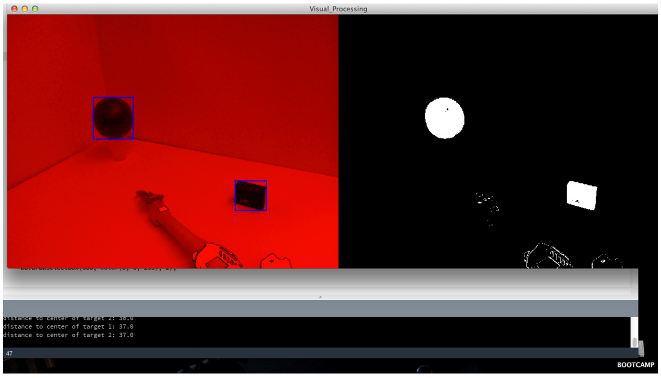

Figure 5: Blob detection algorithm for our prototype

Using the Processing language integrated development environment (IDE), we were able to implement a simple color based blob tracking algorithm to detect and track target objects, the prosthetic arm, and return all of these selectable options to the user. Our future implementation uses a more complicated 3D point cloud approach, where the entire environment is mapped as a set of 3D points. This provides several key advantages over our prototype blob-detection algorithm. Using a 3D point cloud, information about the shape of the object can be easily determined for assisting with grasping motions for the prosthetic hand. Also, it is an inherently more stable algorithm in such a dynamic real-world environment. We implemented two separate modes: manual and semi-autonomous. The prototype allows for the users to see all valid objects displayed on screen, switch between valid objects, and access distance information to these objects in the manual mode. In the semi-autonomous mode, the algorithm calculates the distance to the desired object(s) and sends commands to the servos, autonomously moving the arm within grasping distance of the desired object.

Figure 5 shows a screenshot of the results of our prototype blob detection algorithm. Using a color threshold against a uniform white background, we are able to detect which pixels are similar in color intensity, and declare them as blob objects. We were able to track and label objects in a given seen, allowing the user to toggle between possible selectable targets. The user is then able to trigger that he/she wants to grasp the selected object and our system then finds the location of the object in a 3D space and calculates all needed movements for the arm to reach its destination.

When comparing the results of our control method with other well proven myoelectric control methods, there are two key qualities we concentrated on, speed and ease of operation. With traditional control methods, EMG signals can be used as triggers to incrementally control the position of the arm as it approaches the object. Our system uses these exact signals, but not to directly control the actuators. The EMG signals are instead used to make selections of available objects in the field of view, which the arm can then autonomously interact with the object. We expect our system to perform some of these simple object manipulation tasks at 10% the time a traditional prosthetic would offer, while also presenting an easier to use interface for the client.

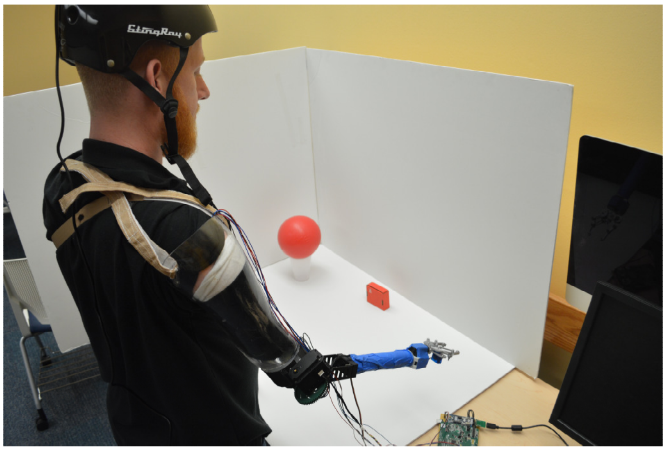

Figure 6: Setup and initialization of object tracking

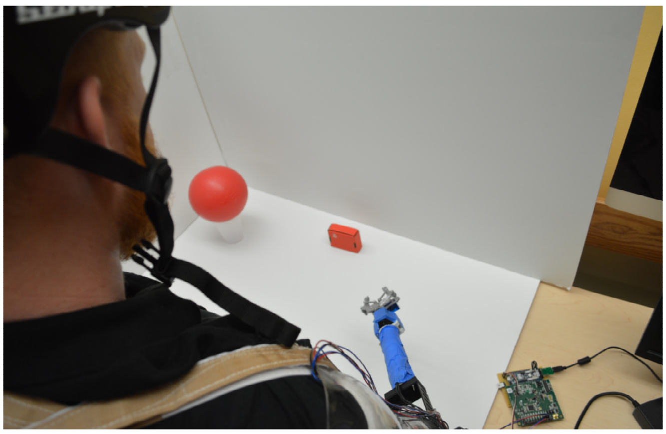

Figure 7: Object detection and target selection

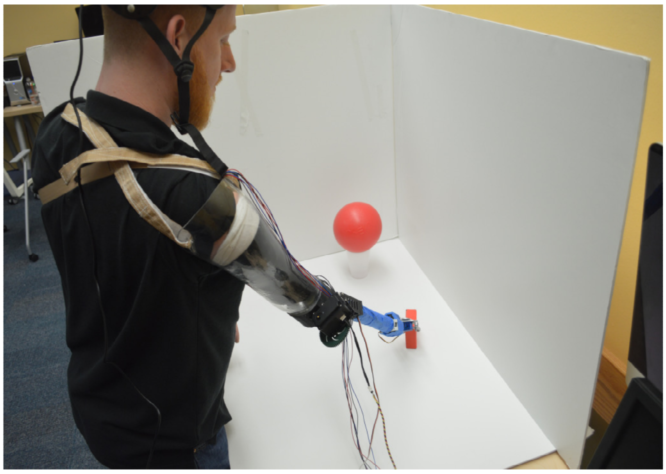
Figure 8: Autonomous motion towards target location


Figure 9: Object grasping through manual control.

In figure 6, an operator is wearing our prosthetic prototype and it has begun its initialization process. Figure 7 demonstrates how the prototype behaves once the target object has been designated. Figure 8 shows how the forearm straightens as it approaches the target object, finally getting within grasping distance. Figure 9 shows how the operator is finally able to retrieve the desired object.

V. Conclusion

Through the implementation of our proposed system, we proved that the combination of a computer vision algorithm along with EMG muscle readings to create a more seamless control structure can be achieved. Our proposed architecture allows the user of the transhumeral prosthetic device to easily control the toggling between selectable objects for a more intuitive human-machine interface. The semi-autonomous operation mode achieved by the computer vision algorithm provides the user with a less complex control method while allowing simultaneous multi-joint control of the prosthesis.

Our implementation is a proof of concept prototype, and many refinements of our algorithms and control approach will result in an even better device. Inertial Measurement Units (IMUs) should be used to provide a more accurate localization of the prosthesis in the camera's field of view and the user's physical environment. Also a more developed and robust computer vision algorithm, based on 3D point cloud object recognition techniques will allow an even more enhanced control of the prosthesis. Future works also include implementing gesture and action recognition in the control algorithm. This addition could recognize anything from handshakes, to helping the patient interact with everyday tasks like shopping, running errands, or even driving.

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