PHAM: PROSHETIC HAND ASSESSMENT MEASURE

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ABSTRACT

Current methods of assessing the functionality of prosthesis systems are often qualitative in nature. As such, there are issues with evaluation consistency and difficulty scaling these assessments across patient populations. Here, we describe an alternative outcome measure, the Prosthetic Hand Assessment Measure (PHAM) which quantifies the performance of manipulation tasks using body kinematics. Task performance scores are composites of individual deviation metrics and allow for standardized comparison across patient populations. It is our hope that the PHAM may aid both engineers in prosthetic systems development and clinicians in patient functionality assessment.

INTRODUCTION

Despite recent advances in upper limb prostheses over the last decade, device abandonment rates remain high at 35% with impaired functionality primarily driving rejection [1]. These statistics suggest a disconnect between the traditional outcome measures used to validate prosthetic system efficacy and the actual utility gained from these systems. Current outcome measures often evaluate performance in a small activity envelope with minimal degrees of freedom (DOF). For example, the popular Box and Block Test [2] evaluates the performance of a single DOF, open / close, throughout a $53.7 \times 25.4 \times 8.5$ cm^3 area directly in front of the subject's chest. Furthermore, the manipulated objects, cubes measuring 15.625 cm^3, are not representative of common objects amputees are likely to interact with. These limitations are addressed in part by more advanced assessments, such as the Southampton Hand Assessment Procedure (SHAP) [3] and the Clothespin Relocation Test (CRT) [4]; however, their respective areas of evaluation still remain limited. Exploring larger activation spaces has proven increasingly important as emerging control paradigms, such as pattern recognition, are significantly less reliable when used in untrained positions [5]. In this respect, it is important to evaluate the utility of a prosthesis over a broad activity envelope in order to accurately report its efficacy.

Furthermore, the vast majority of validated outcome measures are subjective in nature, relying on clinician or user feedback to quantify quality. For example, the Activities Measure for Upper Limb Amputees (AM-ULA) [6] includes a measure of "movement awkwardness" as judged by a trained evaluator. Similarly, the modified Disabilities of the Arm, Shoulder and Hand survey (QuickDASH) [7] is completely dependent on the experience of the observing clinician and the personal opinions of the amputee. The aforementioned qualitative measures are useful; however, because they are qualitative, it is difficult to translate that usefulness across the wider patient population. There is a need for a more comprehensive, quantitative outcome measure through which assessment correlates to utility. This paper describes the Prosthetic Hand Assessment Measure (PHAM) as an alternative outcome measure to aid in the quantitative functional assessment of prosthetic systems.

KEY REQUIREMENTS

With the primary goal of accurately assessing prosthesis utility, the PHAM must:

- require the completion of tasks that approximate real-world use cases;
- explore typical DOFs over a significant 3D volume;
- be quantitative in nature;
- be scalable to future technological advances;
- be clinically deployable.

The PHAM approximates real-world use cases by requiring multi-DOF manipulation of common geometric primitives, combining features from both the SHAP and CRT. While each manipulation currently only requires open / close and wrist rotation, the PHAM is scalable in that each protocol can easily be modified to require further DOFs, such as wrist flexion / extension or ulnar / radial deviation, with no extra hardware. Additionally, the activity envelope of the PHAM is large enough to robustly investigate the effect position variance has on task completion rate and quality. Finally, the PHAM uses kinematic information to quantitatively assess quality of motion. While traditional motion capture schemes use optical or magnetic tracking, these systems are expensive in both cost and space; they are not clinically feasible [8]. Since the PHAM is to be clinically deployable, a flexible, multimodal motion capture system is implemented instead.

SYSTEM ARCHITECTURE

Hardware

The PHAM frame is a windowpane structure made from 1.5” diameter PVC pipes. The height and width of the windowpane are adjustable, ensuring that a user of any height is able to reach all segments of the windowpane with his or her prosthesis. The windowpane can be decomposed into twelve segments, six vertical and six horizontal, each containing LED strips and a PHAM testing environment (Fig. 1a). With each testing environment, the PHAM evaluates four different grips: power, tripod, pinch, and key. These grips are necessary to manipulate the four geometric primitives: cylinder, prism, block, and card. Each grip-object pairing is designed to be mutually exclusive, wherein each grip can only manipulate a single object and each object can only be manipulated with a single grip. These grip-object pairings are each targeted to simulate activities of daily living (ADL). These relationships are outlined in Table I.

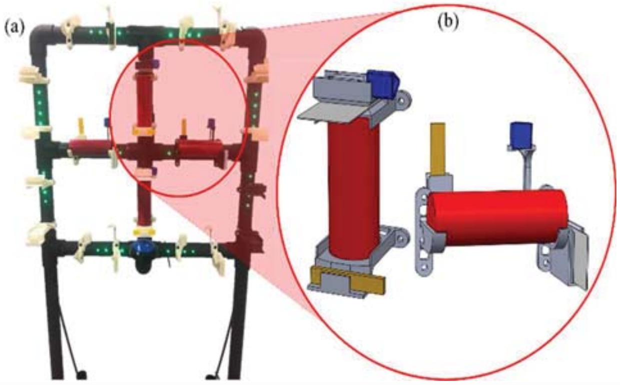

Figure 1: (a) An image of a complete PHAM windowpane. (b) Note that the horizontal and vertical testing environments are not the same. Slightly different designs are necessary to reduce the chance of collision while still guaranteeing each object can only be manipulated with one grip. The grip required to manipulate each primitive is represented by its color, the code of which can be found in Table I.

While similar to one another, the horizontal and vertical testing environments are slightly different in order to accommodate subtle, orientation-dependent requirements. While each testing environment houses a full set of geometric primitives, each object receptacle within the environment is not in the same relative position. This is to allow for proper hand clearance as well as reduce the chance of collision during task completion (Fig. 1b).

Table I: Geometric Primitives

Primitive	Grasp	Color	Activity of Daily Living
Cylinder	Power	Red	Pouring a Glass of Water
Prism	Tripod	Blue	Picking Up a Pencil
Block	Pinch	Yellow	Picking Up Coins
Card	Key	White	Grasping a Credit Card

Motion Capture

The PHAM system uses two sensing modalities in concert with one another in order to capture the dynamics of a subject during task completion: orientation tracking and force dispersion. Orientation tracking is accomplished through the use of five inertial measurement units (IMUs). Four IMUs are affixed to an anchor point on the subject’s body while the final IMU is located at the base of the PHAM unit, serving as a reference. With the method outlined in [9], the network of IMUs is able to return the orientation of each body segment of interest, including the subject’s trunk, upper arm, forearm, and hand. Using these orientations, normalized against the reference, it is possible to extract the corresponding joint angles, effectively reconstructing relative body position from frame to frame.

In order to maintain inter-subject consistency, ideal IMU anchor points were determined as such: the scapulae midpoint, the dorsal midpoint of the upper arm, the dorsal midpoint of the forearm, and the dorsal center of the hand. It is unlikely that each sensor will be placed in the same exact orientation from subject to subject and, so, a calibration routine is necessary to correct for sensor misalignment. For calibration purposes, ideal local reference frames are defined for each sensor and the transformation relating each adjacent frame can be found in Fig. 2. During calibration, the subject must attain the calibration position for one second, over which the average orientation is computed [10]. Once averaged, the apparent joint angles are calculated as the transformation relating each IMU’s orientation to that of its successor in the chain. The calibration angles are then simply the difference between the measured angles and the ideal transformations.

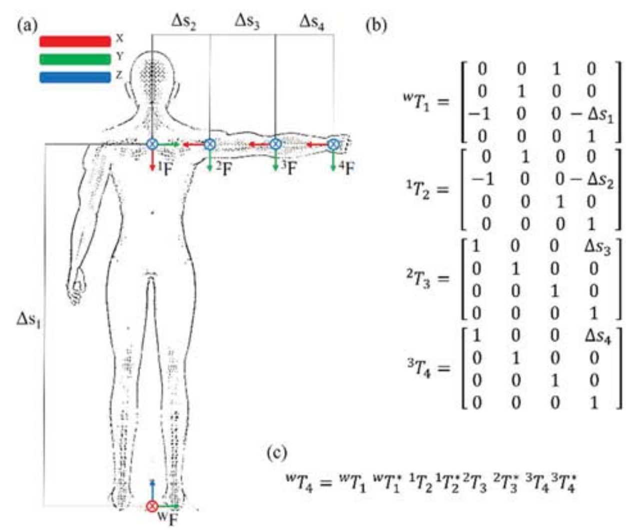

Figure 2: (a) The calibration pose with each IMU’s ideal reference frame defined. (b) The ideal rigid body transformation relating each adjacent reference frame, ^BT_A. (c) Hand position, in the world reference frame, is given by chaining these transformations with the calibration transforms, $^BT^*_A$.

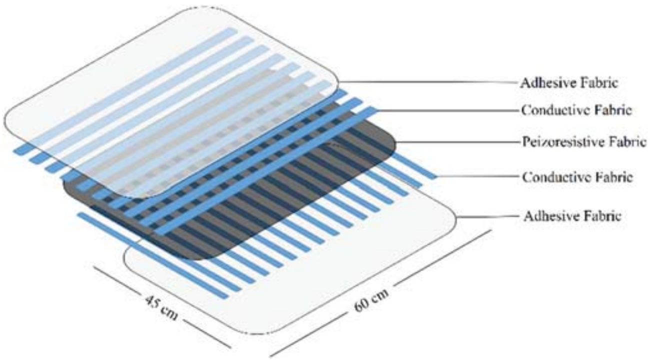

Figure 3: The mat is fabricated by adhering a peizoresistive fabric (black) between two orthogonal sets of conductive fabric strips (blue). When force is applied to a section of the grid, the resulting decrease in resistivity causes a change in voltage. The textile mat uses these voltage changes to track the 2D translational motion of the subject during assessment.

While the aforementioned modality is capable of capturing subject movement anchored at an immutable reference point, it is unable to capture the translational lower body movements often necessary to complete everyday tasks. As to not limit a subject's maneuverability during assessment, a simple translational motion capture subsystem is implemented using a force-sensitive mat. The mat is constructed using both conductive and peizoresistive fabric with the method illustrated in [11]. Using this design, the pressure matrix covers a 60 cm × 45 cm area with 150 discrete analog measuring units (Fig. 3). As the subject stands, the mat records the pressure distribution and locates the center of mass (CoM). All translational deviation in the XY-plane is computed as the movement of the CoM. Using this scheme with the IMU orientation tracking, it is possible to determine a subject's 3D kinematics during a task.

User Interface

The operation of the PHAM is controlled by a Python 3.5 GUI. After connecting all PHAM components, this user interface prompts the assessor to enter in experiment parameters, such as body segment lengths and task timeout. Before assessment, the user must choose a protocol, which determines the order and way in which the geometric primitives must be manipulated. A valid manipulation requires the movement of a single object from either a horizontal or vertical testing environment to a perpendicular testing environment. The PHAM supports three forms of protocols: preset, random, and custom. After the protocol is chosen and parameters are set, the PHAM LEDs flash orange to signify the start of a trial. This is an indication for the subject to press the large blue button to begin the first manipulation. After the initial button press, two PHAM segments light up, only one of which houses a geometric primitive. The subject will move the object from this lighted segment to the other lighted segment. The object to be moved is indicated by the color of the LEDs, outlined in Table I.

After this movement is completed, the subject must press the button again to indicate the end of that manipulation. In order to indicate a successful manipulation, all PHAM LEDs turn green. Immediately afterwards, two new PHAM segments light up, instructing the subject to complete the next manipulation. Should the subject take more than the allotted time to complete a manipulation, the PHAM lights will indicate failure by turning red and then turning off. Pressing the button will start the next manipulation. A total of four manipulations complete a trial for a preset or random protocol while this set size is arbitrarily large for a custom one. After a trial, the subject is allowed to rest while the assessor resets the positions of the PHAM objects in preparation for the subsequent trial. During all manipulations, regardless of completion status, the GUI records the kinematic data from the motion capture system.

PERFORMANCE EVALUATION

From the kinematics of a single manipulation task, several efficiency metrics are first computed. These metrics are defined as such: the 3D deviation of the subject's chest ($\overrightarrow{\delta_C}$), the 3D deviation of the subject's shoulder ($\overrightarrow{\delta_S}$), the 2D translational displacement ($\overrightarrow{\lambda}$), and the completion rate (η). The 3D deviation of any joint, $\overrightarrow{\delta_X}$, is defined as the summation of the absolute differences between 3D orientation in adjacent time intervals, seen in Equation (1).

$$\overrightarrow{\delta_X} = \begin{bmatrix} \delta_X^{\varphi} \\ \delta_X^{\theta} \\ \delta_X^{\psi} \end{bmatrix} = \sum_{n=1}^{N} \left| \begin{bmatrix} \varphi_X \\ \theta_X \\ \psi_X \end{bmatrix}_n - \begin{bmatrix} \varphi_X \\ \theta_X \\ \psi_X \end{bmatrix}_{n-1} \right| \tag{1}$$

2D translational displacement can be trivially calculated with the analogous method in two dimensions. Completion rate, η, is meant to most directly capture the utility of the prosthesis as the ratio successful tasks to attempted tasks. From these individual metrics, a succinct performance score, P, is computed as follows:

$$P = \frac{\left\| \overrightarrow{k^T \lambda} \right\|_1 + \left\| \overrightarrow{\delta_C} \right\|_1 + \left\| \overrightarrow{\delta_S} \right\|_1}{\eta} \tag{2}$$

Note that the L1 norm of $\overrightarrow{\lambda}$ is multiplied by the scaling vector k, proportional to the force mat dimensions. This is to balance the effect that units have on the final performance score. For assessment, a lower performance score equates to higher quality of motion and is more desirable.

RESULTS & DISCUSSION

To illustrate the quantitative analysis available through using the PHAM, a simple case study involving an able-bodied volunteer was conducted with their informed consent. The subject performed a custom PHAM protocol containing 16 object manipulations six times in total: three as a control and three again with their wrist braced. Performance for each manipulation is computed using the aforementioned metrics. The results can be seen in Table II.

Table II: Protocol Performance

Metrics		*Control*	*Braced*	*% Change*	*Units*
$\overrightarrow{\delta_C}$	φ	2.4849	2.3044	-7.26	rad
	θ	0.2418	0.3837	+58.68	rad
	ψ	0.9868	1.9303	+95.61	rad
$\overrightarrow{\delta_S}$	φ	1.3219	0.9122	-30.99	rad
	θ	0.2064	0.3091	+49.76	rad
	ψ	0.8840	0.9920	+12.22	rad
$\overrightarrow{k^T\lambda}$	X	1.6646	1.1469	-31.10	cm
	Y	2.1181	3.9590	+86.91	cm
η		1.000	0.875	-12.50	--
P		**9.9083**	**13.6429**	**+37.69**	**--**

The subject achieved a worse performance score with a wrist brace than they did on their control; however, the individual compensatory trends are not so black and white. While the reduced dexterity resulted in an overall increased L1 norm for every deviation metric, the composite deviations are not all positively trended. Unsurprisingly, the task completion rate, η, was significantly worse in the braced case than in the control. Interestingly, while the metrics displayed in Table II undoubtedly show increased compensation in the braced case, the 3D path travelled by the hand remains remarkably similar in both cases (Fig. 4). This suggests that while a reduction of DOFs results in an increase in compensatory movements, the redundancy of the human anatomy allows for near-optimal path tracking.

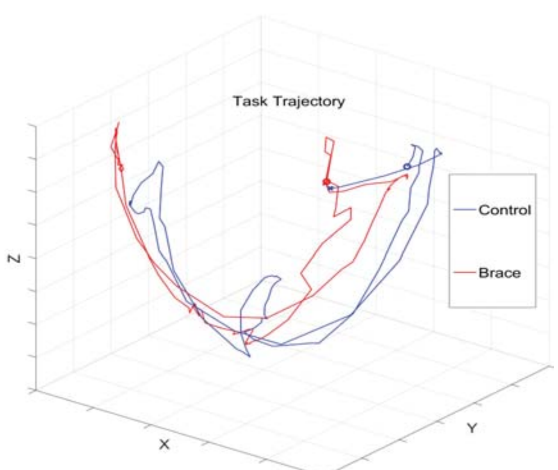

Figure 4: 3D hand path over a single manipulation in both the control (blue) and braced (red) condition for a single subject. Despite reduced DOFs in the braced case, both paths are quantitatively similar.

In this paper, we have introduced the PHAM as an alternative outcome measure used to quantitatively assess the efficacy of upper-limb prostheses. Furthermore, the system has shown that in-depth kinematic analysis is both possible and useful in a preliminary case study. Moving forward, we would like to compare the accuracy of the motion tracking subsystem to more traditional methods, such as optical or magnetic tracking. Additionally, we expect the kinematics of amputees to be significantly different even to braced, able-bodied subjects. As such, we need to validate the PHAM with amputee subjects in a large-scale study in the near future.

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