Exploiting Inherent Human Motor Behaviour in the Online Personalisation of Human-Prosthetic Interfaces

Ricardo Garcia-Rosas[1], Tianshi Yu[1], Denny Oetomo[1], Chris Manzie[1], Ying Tan[1], and Peter Choong[2]

***Abstract*—Human-prosthetic interfaces require their settings to be tuned to individual users. This can potentially be done autonomously while the prosthesis user performs a task by using online personalisation algorithms. These online personalisation algorithms adjust the interface parameters to optimise a given measure of performance. For convergence to be reached, both the human and the personalisation algorithm need to optimise towards the same objective. To date, task-oriented measures of performance have been utilised as the objective, requiring explicit feedback of the measure of performance to the prosthesis user, which is not practical. In this paper, the use of inherent human motor behaviour as the measure of performance for online personalisation algorithms is proposed and investigated. This allows the personalisation procedure to occur without the prosthesis user needing explicit knowledge of the measure of performance. The methodology for formulating inherent human motor behaviour within the framework of online personalisation of human-prosthetic interfaces is presented and validated through an experiment with nine able-bodied subjects. Experimental results demonstrate the efficacy of inherent human motor behaviour-based measures of performance in the design of an intuitive human-prosthetic interface specifically, applicable to human-robot interaction in general.**

***Index Terms*—Prosthetics and Exoskeletons; Human-Robot Collaboration; Optimization and Optimal Control.**

I. Introduction

Human-prosthetic interfaces (HPIs) require their parameters to be tuned to each individual. In motion-based synergistic HPIs, this involves finding the synergy parameters for any given individual [1], [2]. This adjustment can be done autonomously while the user performs a task with the prosthetic device [3], [4]. These methods utilise online optimisation approaches which use a measure of performance to tune the parameters of the HPI, referred to as "online personalisation of HPIs" henceforth. So far, these methods have been used under the assumption that the task is known a priori.

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In [4], a task-oriented measure of performance was used for the personalisation of a synergistic elbow prosthesis in a reaching task scenario. The use of a task-oriented measure of performance required the user to explicitly know the measure of performance being used for optimisation in order to achieve convergence of the algorithm [4]. This was ensured in [4] by displaying a score proportional to the measure of performance to the user after each repetition of a reaching task, which was possible due to the use of virtual reality (VR).

From a practical perspective, continuously displaying the measure of performance of a prosthetic reaching task is not desirable. Firstly, this requires the knowledge of the task being performed, which may not be available. For example, when using reaching-accuracy and reaching-time as in [4], it would require the knowledge of the pose of the target object and the accuracy of the positioning of the hand, as well as the exact time the intended motion is initiated and concluded. Secondly, displaying this information to the user at all times may be cumbersome to the user, as there is a need for a display mechanism to be present at all time. Furthermore, the user needs to be conscious of its performance for various movements all the time, which is mentally taxing. Therefore, the use of task-oriented measures of performance may not be a feasible approach for the online personalisation of HPIs.

Not being able to explicitly inform the human on the measure of performance introduces a new challenge to the online personalisation of HPIs, which is ensuring that both the human and personalisation algorithm have the same objective (measure of performance). This challenge also applies more generally to the wider human-robot interaction and shared control problems [5], [6], [7]. In human-robot collaboration, there needs to be an alignment between the objective functions that the robot and the human optimise towards. If there is no alignment between these, the convergence of the adaptation of the two agents (the human user and the online adapting prosthesis) cannot be ensured. In [8], an example of the case when the human converges to a different motor behaviour than intended when no explicit information on the measure of performance is provided to the user is presented.

A possible approach for performing online personalisation of HPIs without explicitly informing the human user what measure of performance is being optimised by the prosthesis is to utilise a known inherent human motor behaviour associated with the task as the measure of performance. The literature has provided well studied and established models of human motor control behaviour for upper-limb reaching tasks [9], [10], [11].

While these are able to describe reaching motion of the upper-limb, it is important to consider the practical limitations around what can be measured in a prosthetic setting. Based on clinical studies in prosthetics [12], [13] and the theory of metabolic effort [10], the extent of trunk compensation during a reaching motion was found to be an appropriate measure of metabolic and biomechanical efforts that can be conveniently measured, such as with wearable Inertial Measurement Units (IMUs).

In this paper, the methodology for formulating measures of performance based on inherent human motor behaviour into the framework for the online personalisation of HPIs is presented. The advantage of using inherent human motor behaviour as the measure of performance is that the personalisation algorithm does not require the human to be explicitly informed of the measure of performance being optimised, which is experimentally demonstrated in the context of this work. The methodology is presented in the context of a point-to-point reaching task with a transhumeral synergistic prostheses [4], [14]. Upper-body compensation motion is used as the measure of performance, inspired by the concept of metabolic cost optimisation [10] and clinical outcomes in upper-limb prosthetics [12], [13], which suggest that humans minimise trunk movement during reaching. While the concept is implemented specifically on a prosthetic application, on a specific formulation of online personalisation, the idea is applicable more generally to a collaborative human-robot interaction, with the appropriate choice of inherent human control behaviour for the intended task.

II. Preliminaries

In this section, the preliminary information on the human-prosthesis system and the personalisation algorithm are presented. The following notation is used throughout the paper. The set of real numbers is denoted as $\mathbb{R}$, and the set of positive real numbers as $\mathbb{R}_+$. The term "synergy" is used to describe the parametrisation of a HPI, and in the context of this work is used to refer to the coordination between multiple degrees of freedom in the human body to achieve a task [15] as opposed to dimensionality reduction such as used to discuss muscle synergies [16]. The synergy parameters of a HPI are given by $\boldsymbol{\theta}_i \in \Theta$, where Θ is a compact set in $\mathbb{R}^n$ representing the parameter set of interest. For a given static mapping $y_x = h(x) : \mathbb{R} \to \mathbb{R}$, its gradient is expressed as $y_x^{'} = \partial h(x)/\partial x$, and curvature (Hessian) as $y_x^{''} = \partial^2 h(x)/\partial x^2$. The subscript x_i is used to indicate the iteration domain, such that x_i indicates the i^{th} iteration of x, where an iteration represents a repetition of the task.

A. Human-Prosthesis System

The system considered in this paper consists of a human user wearing an upper-limb prosthetic elbow who is performing a reaching task with the prosthesis. A block diagram of this system, including the HPI personalisation algorithm is presented in Figure 1. This formulation assumes that the human generates a residual limb trajectory ($\mathbf{q}_h$, $\dot{\mathbf{q}}_h$), which is used to produce the prosthesis' trajectory in the case of a synergistic HPI. Similarly, the synergistic prosthesis generates a trajectory ($\mathbf{q}_p$, $\dot{\mathbf{q}}_p$) based on the synergy parameters ($\boldsymbol{\theta}$) and the residual limb trajectory ($\mathbf{q}_h$, $\dot{\mathbf{q}}_h$). The human and prosthesis trajectories are then combined to describe the human-prosthesis arm dynamics and kinematics, which result in hand trajectories. Given that these trajectories are task dependent and the dimensionality problem observed in HPIs, the synergy parameters ($\boldsymbol{\theta}$) are task dependent. This means that $\boldsymbol{\theta}$ is identified for each task, or family of tasks. Then, the user selects the relevant "synergy" for the desired task, or an intention detection system is employed. Another potential avenue to address task dependency could be to incorporate sEMG [17] or task information [18] into the synergistic HPI.

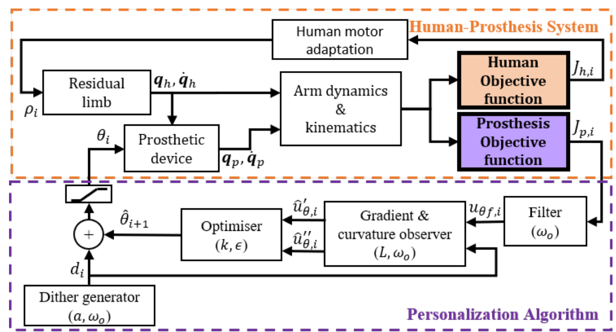


Fig. 1: Human-prosthesis system with synergy personalisation. This work focuses on J_p.

The human is assumed to have an internal measure of performance for the task ($J_h \in \mathbb{R}_+$), which is optimised throughout the human's motor learning process. This measure of performance may include both task-oriented [9] and inherent human motor behaviour components [10]. It is assumed that human motor learning occurs over iterations of the task and can be described by LTI dynamics as in [4], [19].

Similarly to the human, the prosthesis system has its own measure of performance ($J_p \in \mathbb{R}_+$), which is a design choice and is used in the personalisation algorithm to tune the synergy parameters (θ). The design of J_p is of utmost importance to achieve the desired behaviour with the prosthesis as the personalisation algorithm will drive θ to optimise J_p. The online HPI personalisation algorithm proposed in [4], which tunes θ to optimise J_p, is summarised in Section II-B.

In order to ensure the human and prosthesis achieve the same objective, it is necessary for J_p and J_h to be matched. In [4], this was done explicitly through a visual feedback mechanism to the human user which was proportional to J_p, such that $J_h \to J_p$. Alternatively, such as proposed in this work, one can design J_p in such a way that it resembles the human measure of performance, such that $J_p \to J_h$. This follows the concept of collaboration in the wider human-robot interaction and shared control formulations [5], [6], [7].

B. Online Personalisation Algorithm

The objective of the personalisation algorithm, such as proposed in [4], is to determine the synergy parameter (θ) that optimises the measure of performance (J_p). The algorithm works under the assumptions that the kinematic synergy parameter

θ and the performance of the resulting movement measured by J_p are related, i.e., J_p is a function of θ, $J_p(\theta)$; and that it is possible to obtain a measurement of J_p, represented as $\hat{J}_p$. The transient characteristics of human motor learning, and their effects on $J_p(\theta)$, are already addressed in the algorithm design as presented in [4]. Details of this are omitted in this manuscript for brevity.

In [4], the human subject is assumed to operate an elbow prosthesis as a function of the shoulder displacement, related through the kinematic synergy parameter θ. The measure of performance of the arm forward reaching motion is evaluated by a cost function $J_p(\theta)$, which is given in the form of a score to the human subject at the end of each attempt. The prosthesis adjusts the kinematic synergy parameter at the end of each attempt. It is assumed and shown in that study that the human user also updates their shoulder movements to improve the performance at the next attempt.

For a given measure of performance $\hat{J}_p$ and synergy parameterisation θ, the following conditions on $\hat{J}_p(\theta)$ need to be satisfied as established in [4]. These conditions layout the methodology presented herein.

Condition 1: There exists a $\theta^* \in \Theta$ such that $\hat{J}_p(\theta^*) < \hat{J}_p(\theta)$ for all $\theta \in \Theta$.

Condition 2: Given a unique $\theta^* \in \Theta$, there is a $\hat{J}^*_p(\theta^*)$, such that $\hat{J}'_p(\theta) = 0, \text{iff} \quad \theta = \theta^*$, and $\hat{J}''_p(\theta) > 0, \forall \theta \in \Theta$.

Demonstrating that Conditions 1 and 2 are satisfied for a designed $\hat{J}_p$ is necessary. The steps in the methodology presented herein verify the validity of a proposed measure of performance to the online personalisation of HPIs.

The personalisation algorithm uses an online optimisation approach and in [4], an extremum seeking technique [20] was employed, whose components are shown in Figure 1. The algorithm has the following tuning parameters: the dither frequency (ω_o), the dither amplitude (a), the optimiser gain (k), the optimiser threshold (ϵ), and the observer gain (L). For further details on the algorithm please refer to [4]. These parameters need to only be tuned once for a given synergy parameterisation and measure of performance, and can be used with any individual as shown in [4]. The purpose of this manuscript is to extend [4] by incorporating a J_p that approximates J_h, where the human user is not provided with explicit feedback on J_p, and validate the applicability of inherent human motor behaviour-based measures of performance in the online personalisation of HPIs.

III. Methodology

This section presents the methodology for formulating measures of performance based on inherent human motor behaviour for the online personalisation of HPIs, the experimental set-up, and the experimental protocols followed at each of the steps in the methodology.

A. Formulating Measures of Performance based on Inherent Human Motor Behaviour

The steps proposed as part of the methodology are detailed in this section while a specific example is presented in Sections III-C and IV. It is important to highlight that throughout these steps, the prosthesis users should not be informed of any particular metrics being used to evaluate their performance. The following steps are carried out:

1) Identify the relationship between the synergy parameters (θ) in the range of interest (Θ) and the measured variables, e.g., sensor measurements, deemed relevant to the inherent human motor behaviour that is to be used as the measure of performance. Validate that these measured variables are suitable, i.e., that they are sensitive to θ.
2) Construct a measure of performance ($J_p \in \mathbb{R}_+$) using the suitable measured variables (from Step 1) to define the inherent human motor behaviour-based measure of performance. Verify that it satisfies Conditions 1 and 2.
3) Validate that the personalisation procedure successfully converges without the user knowing the proposed inherent human motor behaviour-based measure of performance and that the human user also converges to a steady state over iterations.

Step 1 involves evaluating the prosthetic user's behaviour for a range of synergy parameters (θ) in order to determine the relationship between θ and the candidate metrics. This can be done by having the prosthesis user perform the task with a wide range of synergy parameters settings. The result of Step 1 would be the relationship between the synergy parameters and the candidate metrics in plot form. From this relationship it can be determined whether an optimal exists within the range of interest. The definition of what the "optimal" is will depend on the application. For instance, one may want to maximise some metric such as a score or minimise a behaviour such as compensation motion.

In Step 2, an objective function (J_p) is constructed which combines the relevant variables identified in Step 1 to achieve a convex relationship (for minimisation) between the synergy parameters θ and J_p. A synergy to measure of performance mapping ($J_p(\theta)$) is constructed to verify the satisfaction of Conditions 1 and 2. Given that a human-in-the-loop system is considered, this is typically done experimentally. The same data from Step 1 could be used for this purpose as it already contains a sweep for a range of synergy parameters.

Step 3 involves performing the personalisation procedure on a range of individuals using the HPI to ensure the proper operation of the algorithm. The convergence of the algorithm to a synergy parameter value which optimises the measure of performance J_p is considered as a successful result.

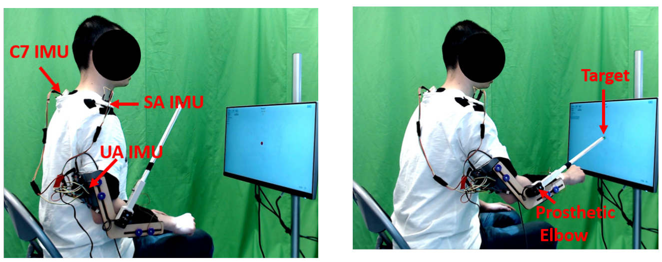
The specific example used to demonstrate these steps is presented next. The example involves a point-to-point upper-limb forward reaching task with a synergistic prosthetic elbow, where trunk and shoulder displacement are used as the candidate metrics for the measure of performance.

B. Experimental Set-up

This section presents the experimental set-up utilised to demonstrate the methodology presented in this work. Following the experimental set-up in [4], a point-to-point reaching task with a synergistic elbow prosthesis is utilised for the experiments to exemplify the proposed methodology. The HPI for the synergistic prosthetic elbow is given by

$$\dot{q}_e = \theta \dot{q}_s, \tag{1}$$

where $\dot{q}_e$ is the prosthetic elbow extension angular velocity and $\dot{q}_s$ the shoulder extension angular velocity. This set-up was chosen to keep the movement and the kinematic synergy to be of low order of complexity to allow the study to focus on the validity of exploiting human motor behaviour for online personalisation. This HPI implements the standard synergy control widely used in the literature to regulate elbow flexion from shoulder flexion, such as shown in [1], [14], [21], where the synergy represents the first principal component of shoulder-elbow coordination for forward reaching tasks [22], [23]. More complex kinematic synergies for the upper limb have often been expressed through PCA or artificial neural networks [1]. Without loss of generality, the method proposed herein can be applied to higher-dimensional parameterisations of kinematic synergies. The experimental set-up is shown in Figure 2.



(a) Starting position for the reaching task and sensor location for the prosthetic case.

(b) Example of the target reaching task with the emulated prosthetic elbow and forearm.

Fig. 2: Experimental set-up for a point-to-point reaching task.

The task required subjects to reach forward from a neutral seating position and touch a target on a (computer display) touch screen. The starting position is shown in Figure 2a, with the target location being a red circle on the screen. The screen location was adjusted to for each subject's arm length. The forward distance and height of the screen were set at the position of the subject's wrist joint when the arm was held forward. The lateral position was set such that the centre of the screen was aligned with the centre of the subject's chest.

Two experiment configurations were included in this study: an able-bodied (AB) and a transhumeral prosthetic (TH) configuration. The able-bodied configuration required subjects to reach the screen with their dominant hand (without prosthesis). The prosthetic configuration utilised a prosthetic elbow and forearm attached to the subject's dominant arm, as shown in Figure 2b. The able-bodied subject's actual elbow is held in place by a mechanical brace. The prosthetic elbow was configured to operate with the kinematic synergy interface as described in (1). The range of θ used in this study is $[0.8, 2.7]$.

Bosch BNO055 IMUs were mounted on the subject's C7 vertebrae to measure trunk motion (C7), on the shoulder acromion (SA) to measure shoulder motion, on the upper-arm (UA) to be used for the synergistic HPI and measure upper-arm motion, and on the lower-arm (LA) to get able-bodied elbow motion data, which was used only in the able-bodied configuration. For the prosthetic configuration, a joint encoder at the prosthetic elbow unit was used to gather elbow motion data. Sensor placement is shown in Figure 2a.

The C7 and SA sensors were used to determine the trunk and shoulder forward displacement, respectively. Displacement was calculated using the subject's body measurements, trunk length and C7 to shoulder acromion distance, and the estimated joint angle from the IMUs. The upper-body was considered to be a set of rigid links. Data gathering was done using an Arduino M0 Zero and an application developed in Visual Studio/C#.

C. *Experimental Protocol*

The experimental protocol followed for the experiments required in Steps 1 and 3 are presented next. The procedure was approved by the University of Melbourne Human Research Ethics Committee, project number 1750711.2. Informed consent was obtained from all subjects in the study.

1) Step 1 Experiments: Able-bodied Reaching and Relationship between Synergy and Upper-body Motion

Step 1 verifies that there is a synergy parameter that achieves minimal upper-body motion (trunk and shoulder displacement). Minimal upper-body motion is utilised as it has been found in able-bodied studies that humans do optimise their trunk motion in reaching tasks, with the trunk being recruited primarily for targets outside of the arm's workspace [24], [25], [26]. From a prosthetics perspective, achieving minimal compensation motion is desirable as upper-body compensation may lead to long term health issues such as musculoskeletal pain and overuse syndromes [27], [28].

A) Able-bodied Reaching (AB Configuration): Three subjects were asked to perform the point-to-point reaching task with their arm (able-bodied) for 30 iterations to obtain their able-bodied motor behaviour as a reference. Subjects were only asked to touch the target on the screen and to return to the start position after each repetition, no other instructions related to the task were given. The subject's C7 and SA displacement from the starting position was measured throughout the experiment.

B) Relationship between Synergy Parameter and Trunk Movement during Forward Reaching (TH Configuration): Three subjects were asked to perform the point-to-point reaching task with the prosthetic elbow and forearm unit, using the synergistic human-prosthesis interface. Subjects were only instructed to touch the target on the screen with the end-effector of the prosthetic forearm and to return to the starting position after each repetition, no other instructions related to the task were given. Subjects were provided with sufficient training with the device in order to minimise the effects of motor learning on the synergy-motion results. Subjects repeated the reaching task for 200 iterations, with the synergy value changing every 5 iterations ($\Delta\theta = 0.05$). The synergy in equation (1) was used with θ in the range of

$[0.8, 2.7]$. The subject's C7 and SA displacement from the starting position was measured throughout the experiment.

2) Step 2 Experiments: To complete Step 2, additional experiments are not necessary as the same upper-body displacement data from Step 1 experiments can be used to evaluate the proposed measure of performance.

3) Step 3 Experiments: Online Personalisation with Inherent Human Motor Behaviour as Measure of Performance

This experiment addresses the performance of the personalisation algorithm with the proposed measure of performance. It is important to highlight that the key aspect of this test is to observe the co-convergence of the adaptation of behaviour by the prosthesis and the human, without the explicit knowledge of the human of the measure of performance being optimised.

Nine subjects were asked to perform the point-to-point reaching task with the prosthetic elbow + forearm setup. Subjects were only asked to touch the target on the screen with the end-effector of the prothesis forearm and to return to the start position after each repetition, no other instructions related to the task were given. Subjects were provided with sufficient training with the device in order to minimise the effects of motor learning on the synergy-motion results. Subjects performed the task for 80 iterations, with a one minute rest after 40 iterations. The personalisation algorithm was used to iteratively adjust the synergy parameter (θ) after every repetition of the task. The tuning parameters for the online personalisation algorithm used in this study as summarised in (1) are: $\omega_o = \pi/4$, $a = 0.06$, $k = 0.0008$, $\epsilon = 0.1$, and $L = \begin{bmatrix} 0.3840 & 0.6067 & -0.2273 & -0.8977 & -1.0302 \end{bmatrix}^T$.

IV. Results & Discussion

The dataset for the results presented herein can be accessed at https://git.io/JTsxF.

A. Step 1 Results: Able-bodied and Prosthetic Upper-body Motion

Experimental results for able-bodied reaching and the relationship between the synergy parameter and trunk and shoulder displacement for the three subjects are presented in Figure 3. Comparing the trunk displacement resulting from the measurements by sensor C7: the blue lines represents average trunk displacement for the able-bodied (AB) cases while the blue circles for the prosthetics reaching (TH) cases. Similarly for the shoulder displacement, as measured by sensor SA and C7, the red line represents average able-bodied (AB) shoulder displacement while the red circles the prosthetics (TH) case.

It can be observed that trunk displacement for the able-bodied (AB) case is close to zero for the given reaching task. In the prosthetics (TH) case, trunk displacement has a near linear relationship with the synergy, which is desirable for formulating the objective function. Moreover, it can be seen that the TH case data intersects the subject's AB displacement line. Intuitively, if the prosthetic forearm is close in characteristics to the biological arm, then as the synergy value moves away from this intersection, the individual will recruit trunk motion to compensate for the elbow not extending enough, or over-extending. This behaviour is desirable for personalisation purposes as it suggests that there is a unique synergy that minimises trunk displacement. Moreover, the AB line intersection is at a different synergy value across subjects and the slope of the synergy-displacement map differs across subjects, highlighting individuality in motor behaviour.

It can be seen that shoulder forward displacement is always present in the reaching motion, with AB displacement of about four centimetres for the given task. In the TH case, different compensation strategies can be observed across subjects in the shape of the synergy-displacement map. This highlights individuality and preference in motor behaviour. Similar to trunk compensation, the TH curve intersects the AB curve for shoulder displacement as well, which in this case is at 4cm.

B. Step 2 Results: Synergy to Proposed Measure of Performance Map

Given that the results for Step 1 showed that the synergy-displacement relationship is close to linear, a candidate J_p that satisfies Conditions 1 and 2 is the convex combination of squared trunk (C7) and shoulder (SH) displacements:

$$J_p = \alpha(\bar{x}_t - x_t)^2 + (1 - \alpha)(\bar{x}_s - x_s)^2. \quad (2)$$

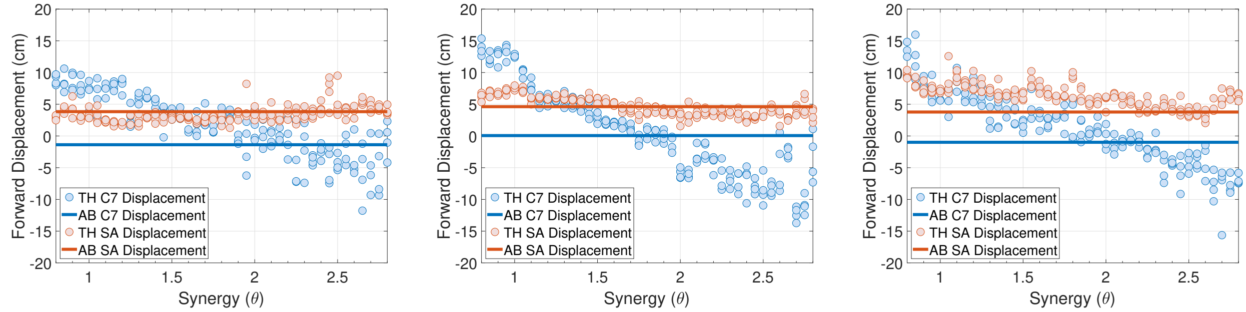
$0 < \alpha < 1$ is a weight to be determined, x_t the trunk forward displacement, $\bar{x}_t$ the desired trunk forward displacement (able-body-like), x_s the shoulder forward displacement, and $\bar{x}_s$ the desired shoulder forward displacement (able-body-like). As J_p is a measure of compensation motion, the objective is to minimise it.

A rigorous choice of the weight α would require determining the involvement of each joint in the reaching motion, and thus an analysis of human motor behaviour and the theorised internal optimisation mechanisms for human motion planning [9], [29]. For instance, by taking an inverse optimality approach [30]. This is out of the scope of this paper and will be investigated in future work. Therefore, it was chosen to equally weigh both trunk and shoulder displacement by setting $\alpha = 0.5$. $\bar{x}_t$ and $\bar{x}_s$ were chosen as zero so the objective is to minimise upper-body compensation.

The obtained synergy-cost maps ($J_p(\theta)$) for the three subjects are presented in Figure 4. The experimental data is represented by the blue circles, while the quadratic polynomial fit to this data is shown by the black lines. The estimated optimal synergies (θ^*), given by the polynomial, are 1.99, 1.91, and 1.92, for each respective subject. However, it is important to note from the experimental data that the minimum cost is observed for a range of synergy values. As expected, the synergy-performance maps ($J_p(\theta)$) show desirable features for online personalisation. These results shows that the proposed compensation motion-based objective function satisfies the conditions for the algorithm presented in [4].

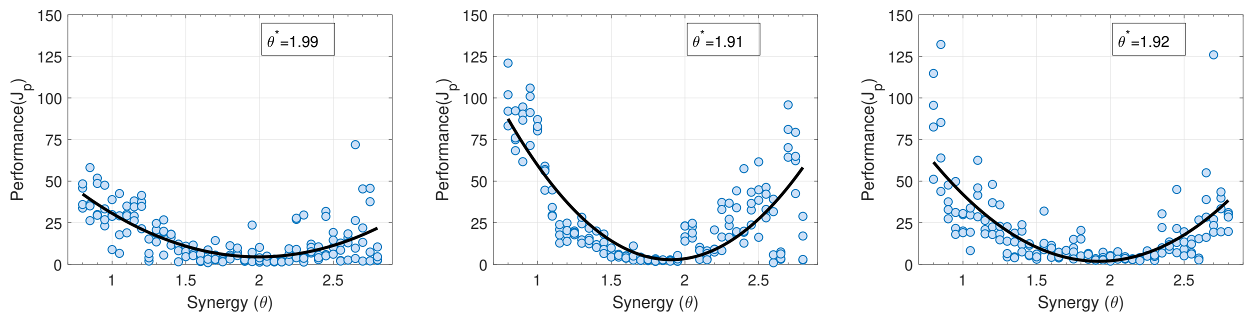
C. Step 3 Results: Inherent Human Motor Behaviour-based Online Personalisation of Synergistic Elbow

The results for the personalisation procedure for a representative subject (Subject 3) are presented in Figures 6 and



(a) Subject 1. (b) Subject 2. (c) Subject 3.

Fig. 3: Relationship between the synergy (θ), and trunk (C7) and shoulder (SA) forward displacement for three subjects. Blue and red lines represent mean able-bodied (AB) C7 and SA displacements, respectively. Blue and red circles represent C7 and SA displacements for the prosthetic case (TH), respectively.



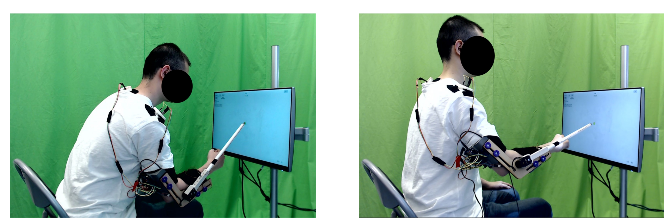
(a) Subject 1. (b) Subject 2. (c) Subject 3.

Fig. 4: Synergy-Performance map ($J_p(\theta)$) for three subjects, where performance is given by eqn. (2). The blue circles represent experimental data. The fitted quadratic map is shown in black. The optimal synergy (θ^*) for each subject, given by the fitted quadratic map, is shown in each plot.

Figure 7. Figure 6 shows the synergy parameter value (θ) and the measure of performance (J_p) over iterations of the task. Figure 7 shows trunk and shoulder displacements over iterations of the task. The results from this subject exemplify the behaviour of the personalisation algorithm.

From Figures 6 and 7 it can be seen that as the personalisation algorithm updated the synergy setting, the subject was able to reduce compensation motion. This was as a result of the elbow extending further for a given residual limb motion. This was done until trunk motion was close to zero (around iteration 50), which at this point both the algorithm and the human behaviour co-converged. It is important to highlight that the shoulder motion was only changed slightly, suggesting that this motion occurs naturally in human reaching behaviour. As a result of the non-zero shoulder compensation, J_p was not driven completely to zero. Nevertheless, the algorithm achieved its objective and converged to a steady θ in the vicinity of an able-bodied-like forward reaching motion.

Figure 5a shows the subject's posture when reaching the target at the start of the experiment, when θ was not personalised. Figure 5b shows the subject's posture when reaching the target at the end of the experiment, when θ was personalised (and co-convergence to the steady state is achieved). This demonstrates the efficacy of personalising HPIs and the capabilities of the personalisation algorithm when using the proposed inherent human motor behaviour-based measure of performance. Statistical analyses of the results for the nine subjects are presented next. On average, the algorithm and human behaviour co-converged within 40 iterations of the task. This personalisation procedure behaviour is comparable to the results presented in [4].



(a) Subject posture at the start of the experiment with a non-personalised synergy parameter. (b) Subject posture at the end of the experiment with a personalised synergy parameter.

Fig. 5: Subject 3 posture when reaching the target at different stages of the experiment.

Statistical analyses of the C7 displacement, SA displacement, completion time, accuracy, synergy parameter, and measure of performance were performed for the first and last eight iterations of the reaching task.The first and last iterations in the personalisation process were selected as these compare the non-personalised and personalised cases. The metrics indicated are used as the dependent variables. The general linear model was used to perform two-way analyses of variance (two-way ANOVA) and comparisons between the first and last eight iterations with confidence levels of 95%

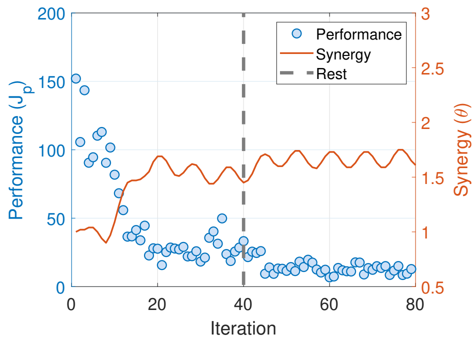


Fig. 6: Synergy value (θ) and measure of performance (J_p) over iterations for a representative subject (Subject 3). The red line represents θ, the blue dots J_p, and the grey dotted line the rest time.

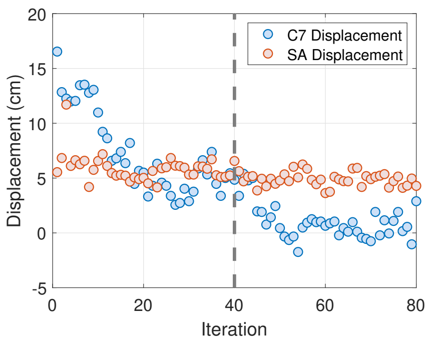


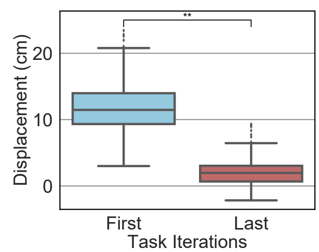
Fig. 7: Trunk (C7) and shoulder (SA) displacement over iterations for a representative subject (Subject 3). The blue circles represent C7 displacement, the red circles SA displacement, and the grey dotted line the rest time.

and 99% ($p < 0.05$, $p < 0.01$) after adjustment for multiple comparisons using Tukey's method. The analyses were used to determine whether statistically significant differences exist between the non-personalised and personalised cases in terms of the indicated metrics.

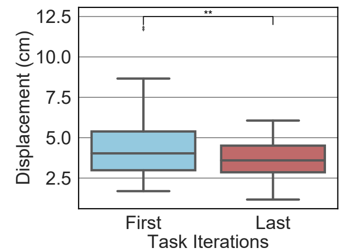
Figure 8 shows the statistical results for the trunk (C7) displacement, shoulder (SA) displacement, completion time and reach accuracy; comparing the metrics at the start and the end of the personalisation process for each subject. A statistical significance with $p < 0.01$ was found in trunk and shoulder displacement (Figs. 8a and 8b). This confirms that the reduction in compensation due to personalisation is significant.

A statistical significance with $p < 0.05$ was found in reach completion time (Fig. 8c). However, this cannot be attributed to the personalisation procedure as it could be a result of the human's practice performing the task. This will be investigated further in the future. The reaching accuracy was not found to be significantly different between the non-personalised and personalised outcomes (Fig. 8d).

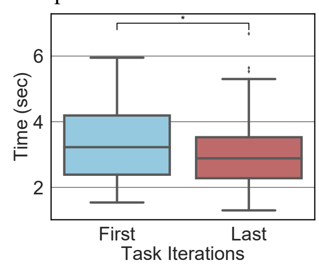
Results for the synergy parameter and measure performance for the last iterations for each subject are shown in Figures 9a and 9b. Figure 9a shows the wide range of personalised synergy values obtained across the subjects. Figure 9b shows the subjects' achieved performance reflected by J_p, which is proportional to trunk and shoulder displacements. Within the given time, only subject 4 was not found to reduce J_p



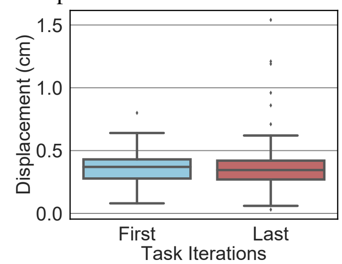
(a) Population C7 displacement box plots.



(b) Population SA displacement box plots.

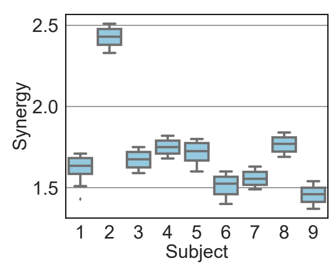


(c) Population reach completion time box plots.

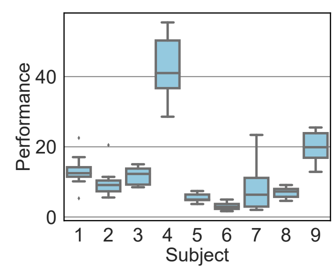


(d) Population reach accuracy box plots.

Fig. 8: Population statistical results for C7 displacement, SA displacement, reach completion time, reach accuracy for the first and last eight iterations.



(a) Box plots for each subject's synergy parameter.



(b) Box plots for each subject's measure of performance.

Fig. 9: Subject results for the last eight iterations.

below 20, which would be equivalent to $5cm$ in total trunk and shoulder displacement. Regardless, the reduction of trunk motion to able-bodied-like levels was achieved across the subjects in the experiment when using the proposed measure of performance constructed based on inherent human motor behaviour, while the subjects had no knowledge of the measure of performance. These results validate the proposed method.

D. Discussion & Future Work

In this paper, the idea of utilising the human motor behaviour to construct a cost function for the personalisation of a prosthetic arm was validated (and shown to be effective) on a simplified forward reaching task. Further work is still necessary to evaluate the extent of the validity over more complex tasks, which may be representative of the variety of practical tasks in daily living.

It should be pointed out that $\boldsymbol{\theta}$ is task dependent. In a practical implementation, there is a kinematic synergy controller (with different input signals and different synergy parameter $\boldsymbol{\theta}$) that is activated for each task. This selection can be done explicitly by the human user (e.g. by pressing a button) or through automatically detecting the intended task.

For each task (or family of task) the corresponding synergy parameter θ is updated through the mechanism presented here. It can be done in one session, or through multiple iterations spanning each time the task is selected. It should be noted that in a practical implementation, the prosthesis will come preloaded with synergy parameters identified through the average population of users which act as the initial values of the parameters for the personalisation process.

There are practical considerations of using wearable sensors in realising the proposed approach. These sensors will need to be easy to attach by using a single hand and the algorithm will need to be robust to the uncertainties in sensor placement reasonably expected in the scenario.

Lastly, the overall personalisation session took approximately 15 minutes for each subject. While it is comparable to the time it currently takes to set up a prosthesis, e.g., a clinician manually tuning the parameters, it should be noted that the proposed method can be run online to adjust the parameters during operation, using preset values as the initial parameter settings. The outcome reported here was the result of human motor adaptation during the relatively short period of the experimental sessions. The long-term validation of such adaptation and its convergence would require a longitudinal study in the future.

V. Conclusion

This paper presented the methodology to utilise inherent human motor behaviour as the basis for the online personalisation of HPIs. This methodology extends the previous HPI personalisation algorithm proposed by the authors in [4] to operate without the need to provide explicit performance feedback to the human and using only wearable sensors. An experiment with nine able-bodied subjects was performed to investigate the efficacy of utilising the human inherent tendency to minimise trunk extension during forward arm reaching motion as an implicit optimisation measure of performance in a synergistic prosthetic elbow. The experimental results validate the applicability of such measure of performance to the personalisation of HPIs. Future work will consider higher dimensional synergy parameterisation and evaluate multiple measures of performance.

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