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Augmenting neuroprosthetic hand control through evaluation of a bioacoustic interface

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Abstract— **The majority of neuroprosthetic interfaces, linking amputee to prosthetic hand, utilise proportional-based control through electromyography (EMG). The clinical translation of these interfaces can be attributed to their relative simplicity, usually requiring only two EMG electrodes to be placed on the flexor and extensor of the forearm. This bi-electrode setup enables opening and closing of hand grasp with an additional manual input used to cycle through the various grip patterns. In recent literature, the main focus has been on higher degree-of-freedom control leading to more complicated interfaces which can be considered the main barrier preventing their clinical utility. As such, new methods for grip pattern switching have not been explored with this fieldable strategy lacking any serious attention. In this work, a novel input, augmenting neuroprosthetic hand control, is proposed. This interface is based on bioacoustic signals generated through prescribed tongue movements. We demonstrate that such an interface can provide comparable performance to existing proportional-based systems without requiring any additional movements of the upper extremities.**

I. Introduction

A. Neuroprosthetic control

In the last decade, significant advances have been made in the electromechanical design associated with prosthetic hands. A plethora of multi-functional commercial prostheses are available to amputees with the potential for fully restoring their functional loss [1]. These devices provide highly realistic replacements which in many cases can mimic the design and dynamics associated with all 22 degrees of freedom (DoF) of the human hand. Although this is a significant achievement, appropriate and relevant control strategies are still vary much lacking [2]; see [3], [4] for recent surveys. Therefore, neuroprosthetic integration and control can be considered the major barrier to complete restoration of motor function for amputees. The majority of current control strategies utilise surface electromyography (sEMG) which allow physiologically relevant control signals to be generated. However, issues such as, the number of available electrode sites, signal selectivity and signal reproducibility, limit the controllability of the prosthesis [5]. Therefore, new interfacing strategies which can replace or complement these existing methods is of upmost importance if prosthetics are to be fully integrated into daily living.

Due to their simplicity, commercial systems typically use antagonistic pairing of sEMG signals placed on the flexors and extensors of the forearm [3]. The differential motor activity is measured, amplified, demodulated and subtracted allowing flexion/extension of the wrist to open/close the grasp of the hand proportionally. Although this provides a physiologically relevant control signal and limits the number of control sites required, most of the DoFs become interdependent while an additional discreet input is required for switching between various predetermined grip patterns. This grip switching is often operated by the remaining functional hand through a simple push switch mechanism. Recently, a grip switching system based on radio frequency identification (RFID) technology has been demonstrated [6]. Although this no longer requires additional input from the remaining hand, physical movement of the prosthesis within the activating radio field is still required. The potential of mechanomyography (MMG), as an alternative to sEMG signals for proportional-based control, has also been demonstrated. Similarly to EMG signals, they are representative of muscle activity, but rather then being generated electrically are instead produced through mechanical oscillations [7]. Such signals offer significant advantages over sEMG, such as, not requiring conductive gel, less stringent sensor placement and no crosstalk occurring, although there is increased risk of enhanced skin and motion artifacts[1].

To enhance controllability and ultimately dexterity associated with a prosthesis, the number of control sites can be increased and combined with a feature based classification scheme. Various hand states, for example specific grasp patterns or static hand gestures, can then be classified based on features extracted from the multichannel signals [8]. These features are generally time domain based and include the mean absolute value, the number of zero-crossings and normalised energies, to name a few [9], [10]. By using a classification subsystem, based on the chosen feature set, the various hand states can be decoded with a relatively high degree of accuracy. The accuracy of the decoding strategy is generally proportional to the number of electrode sites and inversely proportional to the number of hand states. Pattern recognition techniques have also been used to decode individuated finger movements (flexion/extension) with over 90% accuracy using 32 sEMG signals [11]. However, the large number of control sites limit the practicality of such systems as well as requiring calibration whenever the electrodes are reattached to the arm. Furthermore, it is theorized that control of hand posture takes place in a lower-dimensional space of coordinated motions, or postural

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[1]MMG signals present a rich area for future research with regards to prosthesis control

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synergies and therefore individual control of each DoF is redundant when performing normal grasping tasks [12].

By implanting invasive EMG (iEMG) electrodes in direct or close proximity to the nerve fascicles within the peripheral nervous system enables electrophysiological signals with higher fidelity and spatial resolution to be recorded [13]. This allows specific nerve groups to be targeted using and their associated action potentials captured [14]. Apart from providing information rich signals for decoding purposes, this also enables bidirectional communication and therefore sensory feedback from the prosthesis. Although this technology has significant potential, its wide applicability is limited due to the costly and risky surgical procedures required.

For general upper limb neuroprosthetic control, a paradox exists whereby the higher the disarticulation the more DoFs are lost whilst the number of functional sEMG sites is also reduced. Having said this, the nerves bundles serving the arm, although severed higher up the arm are generally functional. Based on this notion, a new technique called targeted muscle reinnervation (TMR) has been recently pioneered [15]. It involves transferring the residual nerves from the shoulder onto alternate denervated muscle groups, which are no longer 'biomechanically functional', since they are are no longer attached to the missing extremity. The target muscle group is generally located in the chest or back areas, for example the pectoralis muscle, as these provide a large surface for post-operative electrode placement. This combined with feature based pattern recognition allows for decoding of various arm and hand states for individuals with shoulder-disarticulation or transhumeral amputations.

By directly interfacing with the cortex, the motor signals relevant for neuroprosthetic control can be captured at the source of their generation. In the past, this has been done using noninvasive electroencephalography (EEG) signals [16], [17]. However, the associated hardware lacks cosmetic appeal and due to low spatial resolution, low-level control of multi-functional peripherals is generally very limited. More recently, invasive interfacing to the motor cortex has been established through chronic recording of action potentials associated with reach and grasp movements [18], [19]. This has led to the ability for paralysed individuals to have control, in three dimensional space, over robotic manipulators alongside performing simple grasp actions. This technology has the scope for enabling even the most physically disabled individuals, such as those with locked-in-syndrome, but is completely unwarranted for the majority of amputees.

Based on these observations, current neuroprosthetic control strategies with the aim of restoring hand function, can be broadly categorised by two main characteristics. The first being the method by which the hand states are generated from the physiological signals, that is, are they either proportionally controlled or based on the classification of features extracted from the biosignals. The second is the proximity of the sensor to the nervous system with either the electrodes positioned invasively or non-invasively within the individual. Table I highlights this taxonomy and shows some examples within each category of physiological signals which can be used to drive a prosthesis.

TABLE I
SOME EXAMPLES OF NEUROPROSTHETIC HAND CONTROL

		Control signal	
		Proportional	**Feature based**
Sensor location	**Noninvasive**	sEMG, MMG	sEMG, MMG, EEG, Gaze
	Invasive	iEMG, Cortical	iEMG, Cortical

Currently, control strategies utilised by commercially available prosthesis are based on proportional sEMG signals only (as highlighted in Table I). Due to the limited number of electrode sites for this type of control, these systems still require the active involvement of a healthy extremity to switch grip patterns. Therefore, a fieldable interface that does not rely on such physical input and is robust enough for use outside of the laboratory environment is still highly desirable.

B. Hybrid control

Hybridisation of various interfacing systems can potentially be used to extend the capabilities of neuroprosthetic control strategies [20]. For example, gaze tracking and computer vision techniques can be used to extract information regarding a object, acting as a high-level prehension controller, while the low-level grasping action can be initiated through sEMG. Such hybrid systems can lead to a higher level of control of the multiple DoFs associated with neuroprosthetic targets. Furthermore, independently operated interfaces can be used in collaboration to expand the instruction set based on synergistic design between the multi-modal inputs.

Tongue-movement ear pressure (TMEP) signals have recently been highly as a noninvasive, wearable and imperceptible human-machine interface for command and control of peripherals [21], [22]. In this work, we demonstrate the utility of TMEP signals for synergistic control of a prosthetic hand using control strategies similar to current commercial practises.

Validation is performed with regards to a timed manipulation task whereby various everyday objects are moved within a tabletop environment. Evaluation is based on task completion time and the strategies compared include natural manipulation using a real hand, proportional control using force sensitive resistors (FSR), full TMEP control and a hybrid strategy (comprising FSR & TMEP). It should be noted, that the FSR inputs simulate proportional sEMG control without the additional user training and subject variability. For this strategy, similarly to commercially available control setups, a contralateral hand-operated push button (PB) is used for switching between primary grip patterns [1]. The task is performed by three healthy individuals with ten repetitions per subject and control strategy. The following sections describe TMEP signals and their decoding, the prosthetic hand and control hardware, system integration and evaluation of the four control strategies.

II. Tongue-movement ear pressure signals

It has been previously established, that bioacoustic signals generated through impulsive tongue actions can be noninvasively captured from the ears of an individual [21], [22], [23]. The user expresses their intention through tongue flicks, creating acoustic signals within the ear canals. These have been coined as TMEP signals, due to the nature of their generation and evolution within the oral and auditory regions. The actions themselves involve placement of the tip of the tongue at the base of the central incisor, left or right first molar and flicking the tongue up (bottom, left or right action) and placing the tip of the tongue against the top of the palate and flicking down (top action). This instruction set was chosen as it directly relates to the cardinal control scheme of up, down, left and right, with any instruction subset chosen based on the application. Fig. 1 illustrates the described action set and tongue trajectory during a specific movement. Based on their unique bioacoustic signatures, the prescribed tongue movements are distinguishable from one another as well as normally occurring activity, such as speech, coughing and swallowing [24]. This is due to the motions not typically occurring in daily activity, although they feel natural to execute implicating their repeatability.

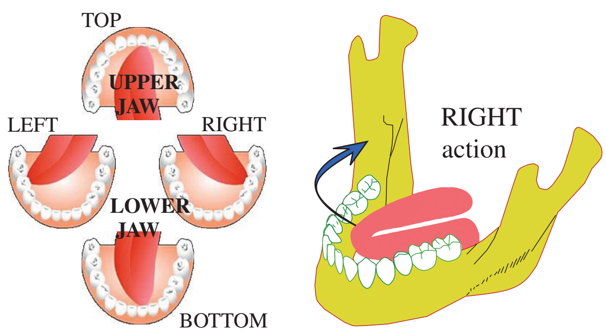

Fig. 1. Left side - Starting point of the tip of the tongue prior to the execution of the four predefined actions. Right side - 3D representation of the idealised trajectory of the tip of the tongue during execution of the right action

To capture the bioacoustic activity from the TMEP signals a generic earpiece is used. Fig. 2 shows this, both extracted and inserted, within the ear canal. In this work, a stereo channel setup is utilised whereby two generic earpieces are located in both ears of the individual. Although this has the effect of slightly inhibiting the user's ability to hear, it also provides a sufficient increase in decoding information for this to be considered an insignificant hinderance.

Extraction and decoding of the bioacoustic activity associated with the dual TMEP channels utilises a bioacoustic processing framework. Fig. 3 depicts this extraction and decoding architecture and the various subsystems involved. Initial processing consists of activity detection and signal segmentation to extract a 200ms length for each bioacoustic data channel containing the impulsive temporal waveforms associated with the volitional TMEP activity [25]. This is

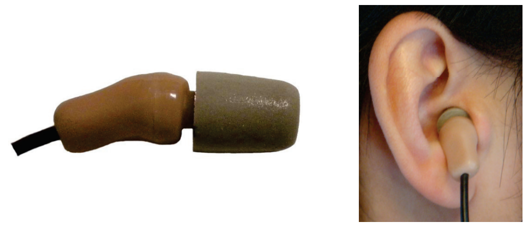

Fig. 2. Photos showing the generic earpiece both removed and inserted into the ear

based on a short-term energy contour in combination with amplitude and time thresholding. Due to the potential for interfering bioacoustic activity to merge with the signals in real-time a dedicated dichotomous interference rejection (IR) block is implemented prior to inter-action classification [24]. This has been shown to be effective at rejecting higher frequency interference, such as speech and coughing, in both off-line and online environments.

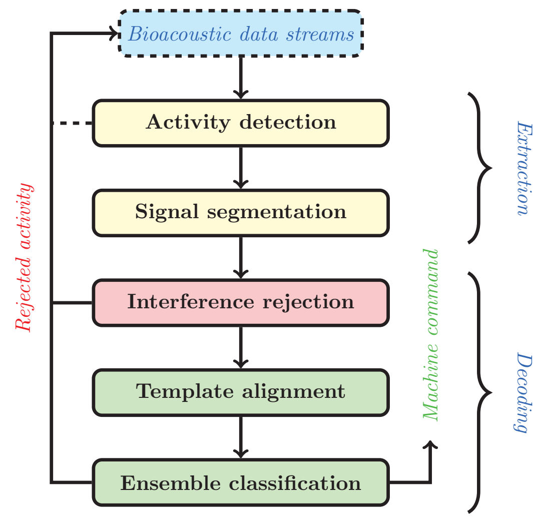

Fig. 3. The real-time bioacoustic processing framework for extraction and decoding the TMEP activity

Preceding inter-action classification the extracted TMEP segments are aligned to class-specific templates. The templates are created from representative data-sets of each action, collected from each subject, prior to classification. This enhances the classification performance associated with the individual classifiers. Inter-action discrimination uses a heterogeneous ensemble architecture and is depicted in Fig. 4. This framework is described in detail in [23]. The output from the ensemble is based on a majority vote between the two channels of data classified through seven individual base classifier models and implies a total of fourteen heterogeneous members. The seven classification strategies comprise various combinations of feature extraction, feature selection and classifier models and include: (1) Euclidean distance classifier, (2) Matched filter classifier, (3) Decision fusion classifier, (4) Autoregressive classifier, (5) Discrete Fourier transform classifier, (6) Principal component analysis classifier, and (7) Discrete cosine transform classifier.

The heterogeneous ensemble helps to reduce the effect

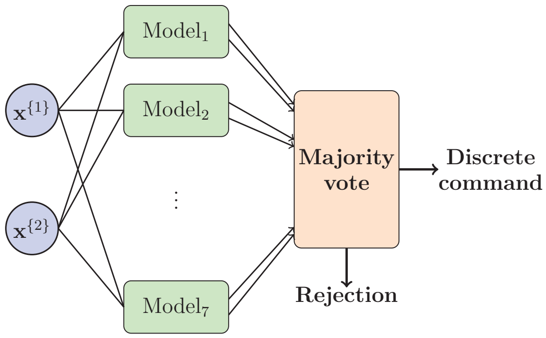

Fig. 4. Heterogeneous ensemble classification architecture using dual earpiece channels, seven base classifier models and a majority voting strategy to fuse the outputs of the ensemble members

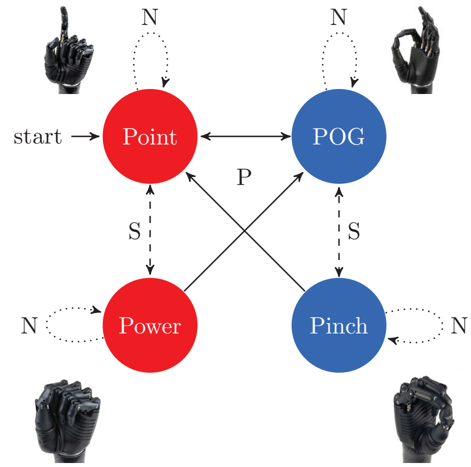

Fig. 5. Bebionic v2 hand shown in the four grip patterns utilised during this study. Also shown is a state diagram indicating how the grip patterns are accessed. P - Primary switch (solid line), S - Secondary switch (dashed line), N - No action (dotted line), Red states - Group A grip patterns and Blue states - Group B grip patterns

of the 'no free lunch theorem', especially in circumstances where there is limited data available to the classification machine. This helps to minimise the misclassification error whilst also increasing the overall classification accuracy based on ambiguity amongst the members. A further advantageous byproduct is its natural IR capabilities. Interfering signals which are potentially missed by the IR block, for instance, due to them having a similar frequency response as the TMEP actions, can now potentially be rejected based on this mechanism.

III. Prosthetic Hand Control

The prosthetic hand used in this study is a Bebionic v2 manufactured by RSL Steeper, UK [1], [26]. The hand allows the user to achieve everyday manipulation tasks using common grip patterns with the opening and closing of the hand designed to be proportionally controlled using two sEMG signals. A discrete switch located on the rear of the hand allows two primary grip patterns to be toggled. A secondary method allows two further grip patterns to be accessed based on when the hand is fully open followed by a subsequent short duration open signal (<1s on the falling edge). Currently, there is no other way of accessing this secondary set of grip patterns, for example, by using an independent PB. Four different grip patterns can be accessed on the hand at any one time and are preset by the user from a total set of fourteen. These are intended for different manipulation tasks and include, but are not limited to, a precision open grip (POG), precision closed grip (PCG), key and point grip. Fig. 5 shows a state diagram indicating how the grip patterns can be accessed using the described primary (P) and secondary (S) switching methods. Shown alongside is the Bebionic v2 hand in the grip patterns utilised in this study.

Fig. 6 shows the proposed system setup linking the TMEP decoding framework to the Bebionic hand. Also shown is the physical interaction between the user and their environment. The prosthetic hand is shown in the standard open position which is the default position for all grip patterns when the hand is fully extended.

IV. Control Strategies

To demonstrate the potential of discrete tongue movements for prosthetic hand control it has been compared to various control strategies, including natural manipulation using the human hand, FSR-based and synergistic control. FSR inputs have been used as an alternative to sEMG as they provide a similar control signal and remove additional human factors including required subject training, varying proficiency levels and signal fidelity based on electrode placement. The similarity between the control signals is due to sEMG preprocessing involving (half- or full- wave) rectification and filtering [27]. Therefore, to simulate antagonistic muscle control as used by proportional sEMG control schemes, dual FSRs are utilised providing similar analogue open and close signals in response to applied pressure from fingers on the contralateral (unused) hand of the subject. This requires no prior training with the generated signals more responsive and requiring less exertion than standard sEMG based inputs. The following subsections describe the four control strategies tested.

A. Natural

Performing the task using a normal human hand. This is used as a benchmark when evaluating the three remaining strategies. The same grip patterns are simulated by the healthy hand as stipulated in the task protocol.

B. FSR

This strategy involves the use of FSRs to produce a control signal which opens or closes the hand at a speed which is proportional to the pressure exerted. Primary grip switching is achieved via a PB which is located on the control terminal adjacent to the FSRs. Therefore, from Figure 6, the control inputs are open - FSR 1, close - FSR 2 and primary grip switch - PB.

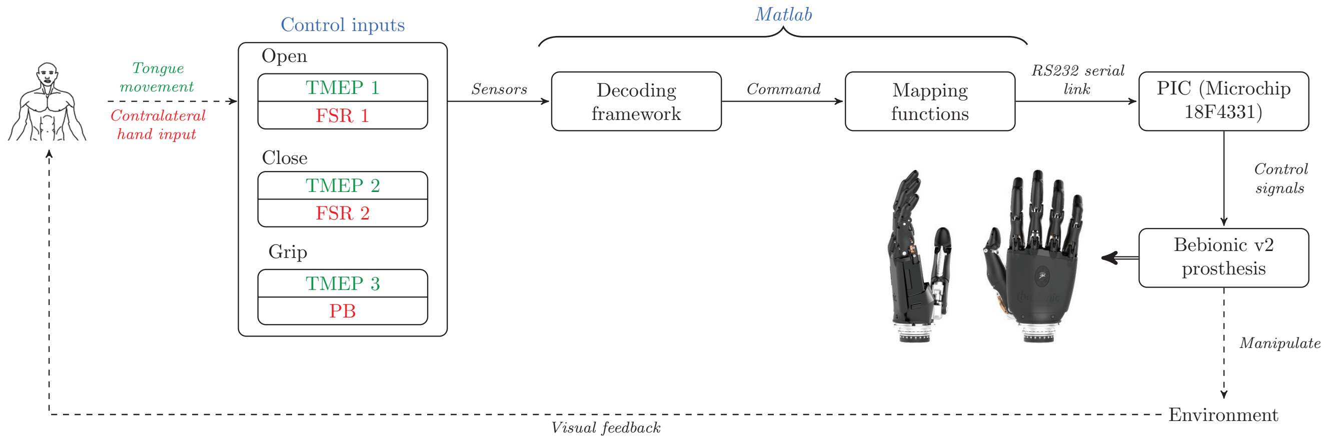

Fig. 6. System setup for controlling the Bebionic v2 prosthetic hand with potential control inputs for opening, closing and primary grip switching highlighted (TMEP - tongue-movement ear pressure, FSR - force sensitive resistor, PB - push-button). Dashed lines are indicative of human connections while solid lines indicate hardware connections

C. Tongue

This strategy involves the use of three distinct TMEP signals for the opening, closing and primary grip-switching of the hand. Due to the output of the TMEP decoding block being discrete, an on-off strategy is employed. A single open/close action starts opening/closing the hand at a constant speed with a repetition of the same action stopping it. As the duration and delay in processing a TMEP event is short ($\sim$300ms), this still provides very fine control during manipulation tasks. The tongue actions which correspond to the specific control actions are customizable depending upon user preference. Hence, it is possible to 'rank' the tongue actions such that the most commonly used control signal is assigned to the tongue action which the user is most comfortable with. Therefore, from Figure 6, the control inputs are open - TMEP 1, close - TMEP 2 and primary grip switch - TMEP 3.

D. Hybrid: FSR & Tongue

This hybrid control strategy involves the use of the FSRs to open/close the hand and a single tongue action for primary grip switching. Again, it is possible to assign which tongue action is used via the action ranking feature in the software. Therefore, from Figure 6, the control inputs are open - FSR 1, close - FSR 2 and primary grip switch - TMEP 3.

V. Experimental Protocol

Fig. 7 highlights the task space used during the evaluation of the various hand control strategies. The setup consisted of the tabletop divided into three sections (each 15 $\times$ 25 cm) with a filled bottle, tray and lid placed at the centre of each. A circular block was placed at the top of the middle section.

Fig. 8 highlights the task protocol and shows for a single trial, the order that the objects were manipulated alongside the associated grip patterns and grip changes required. The task was chosen as it resembles an everyday object manipulation task.

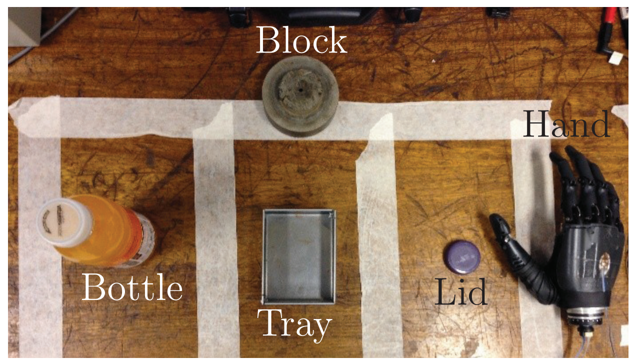

Fig. 7. The proposed task environment and objects to manipulate

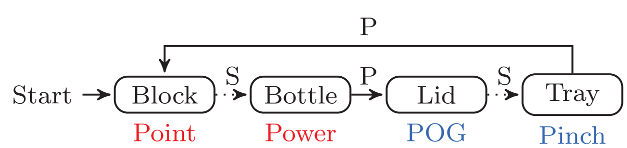

Fig. 8. Flow diagram highlighting the task protocol: P - primary grip switch, S - secondary grip switch

Each trial consisted of the following: Start timer by touching the block using the point grip, pick up the bottle using the power grip and place into the tray, pick up the lid using POG and also place into tray, pick up and lift the tray into the right area using the pinch grip and finish by touching the block again using the point grip, thus stopping the timer. During the trial, the prosthetic hand is grasped in the right healthy hand of the individual.

The experiment was performed by three healthy subjects who had previous experience in making all four tongue actions. Subject training is detailed in [22]. Specific actions were assigned to each of the control signals (open, close and primary grip switch) based on user preference with the task performed ten times per control strategy. The TMEP decoding block was trained using 30 subject-specific signals of each action and 162 generic interfering signals.

VI. Results and Discussion

Fig. 9 shows timing results for each trial across the three subjects (A, B, C) and four control strategies. Also shown are boxplots created from each of the ten trial groupings and is indicative of the distribution of the timing results. As expected while using the natural control strategy, on average, the subjects were able to execute the task in the fastest time ($\{7.7, 7.7\} \pm 0.8, \{6.5, 6.6\} \pm 0.6, \{15.5, 15.4\} \pm 0.8$ seconds; $\{$median,mean$\} \pm 1$ STD). In all cases, operation of the prosthetic hand was always slower than this. For subjects A and B, this was at least a minimum of a factor of two times slower. In all cases full tongue control was the slowest on average ($\{46.6, 44.3\} \pm 15.1, \{38.5, 40.8\} \pm 13.7, \{37.5, 46.7\} \pm 22.1$). The hybrid control method ($\{26.9, 32.2\} \pm 15.7, \{20.1, 21.7\} \pm 5.6, \{29.6, 32.2\} \pm 10.8$) performed comparably to the FSR method ($\{32.7, 33.6\} \pm 11.6, \{22.2, 26.3\} \pm 9.2, \{24.2, 24.2\} \pm 4.6$).

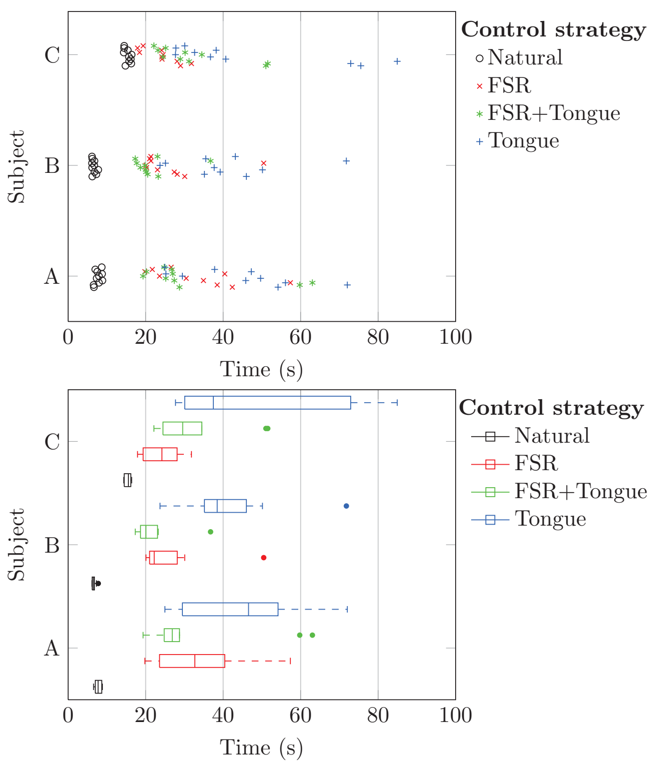

Fig. 9. Timing results of the hand control task (Top - raw results, Bottom - boxplots). Each subplot is associated with a subject (A,B or C) performing ten trials for each of the four control strategies

Statistical analysis was performed in SPSS version 20. Due to skewed distributions, the median was chosen as the descriptive statistic across each of the ten trial sample sets. Based on this statistic, a Shapiro-Wilks test identified that the data was normally distributed across all three subjects and four control strategies. Therefore, a one-factor analysis-of-variance (ANOVA) was performed, highlighting a familywise significant difference ($p = 0.029$) between the four control strategies at the 5% level. To elucidate specific differences, paired two-tailed t-tests were then performed.

This analysis highlighted that there was no significant difference ($p = 0.073$) between natural manipulation and the FSR method. This implies that the FSR method performs comparably to a real hand and although is not a standard control strategy (and is only simulating proportional sEMG control) is able to do so with a good performance level. Both methods involving tongue control were significantly different (hybrid: $p = 0.013$ and tongue: $p = 0.024$) from the natural baseline. Comparison between the hybrid and FSR method were highly insignificant ($p = 0.817$) indicating a very similar performance level. The FSR and tongue were also significantly different ($p = 0.004$) while the hybrid and tongue method were insignificantly different ($p= 0.054$). Therefore, apart from the hybrid method, full tongue control performed significantly slower than the remaining control strategies.

Although full TMEP control was the slowest control method, the ability to perform and complete the task in all cases was demonstrated. The slower completion time can, in part, be attributed to the increased cognitive load due to the subjects having no previous experience in controlling a prosthetic hand with their tongue. Subjects were often prone to making mistakes due to incorrect grip selection rather than TMEP signal misclassification. This confusion often occurred during incorrect selection between the two grip switching mechanisms. The hybrid method provides a good control solution as it performed comparably to the FSR method without involving an additional PB input when switching grips. In reality, this PB is located on the back of the Bebionic v2 hand, is operated using the contralateral hand and therefore would further reduce the task completion time. It is hypothesised that utilising normal sEMG, when compared to FSR, control is likely to further slow performance due to the steep learning curve and large forearm muscle contractions required.

VII. Conclusion

We have demonstrated that bioacoustic signals associated with tongue movements can be used as an input for neuroprosthetic control. This has comparable performance to standard proportional control methods when performing a timed object manipulation task. Utilising the tongue provides additional and synergistic control signals that would otherwise be unavailable if only proportional sEMG signals were employed due to the limited control sites available on the forearm. Furthermore, this interface can be used in the presence of interfering signals, caused by daily activity, due to a dedicated interference rejection subsystem. This robust subsystem prevents incorrect grasping from occurring caused, for example, by speech and/or coughing during conversation. In two out of the three subjects, this hybrid control strategy was on average faster than the standard FSR method and comparison between the two exhibited highly insignificant differences ($p = 0.817$), thus indicating comparable performance. The hybrid strategy has the additional advantage of not requiring a grip switching input from the contralateral hand. This paper has highlighted that additional heterogeneous control inputs, such as TMEP signals, can be used in conjunction with existing neuroprosthetic control methods; providing hands-free manipulation with comparable performance to current control strategies.

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