

Neural Closed-loop Control of a Hand Prosthesis using Cross-modal Haptic Feedback

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Abstract—Due to the growing field of neuro-prosthetics and other brain-machine interfaces that employ human-like control schemes, it has become a priority to design sensor and actuation mechanisms that relay tactile information to the user. Unfortunately, most state of the art technology uses feedback techniques that are invasive, costly or inefficient for the general population. This paper proposes a feasible feedback method where tactile information during dexterous manipulation is perceived through multi-frequency auditory signals. In the interest of examining whether users are able to quickly learn and adapt to the audio-tactile relationship and apply it to the neural control of a robot, an experimental protocol was formed. Users were instructed to grasp several objects of varying stiffness and weight using an electromyographically-controlled robotic hand, and tactile information was provided to them in real-time through the proposed cross-modal feedback. Results show that users were able to adapt and learn the feedback technology after short use, and could eventually use auditory information alone to control the grasping forces of a robotic hand. This outcome suggests that the proposed feedback method could be a viable alternative for obtaining tactile feedback while staying non-invasive and practical to the user, with applications ranging from neuro-prosthetics to control interfaces for remotely operated devices.

I. INTRODUCTION

When utilizing a robotic end effector to interact with an environment, whether in neuro-prosthetics, exoskeletons or teleoperation of robotic devices, it is crucial for the user to be able to receive important feedback from the system. Current brain-machine interface systems rely heavily on visual feedback during control tasks, which lacks important details about the contact forces, textures, weights and material properties involved during object-manipulation tasks. In addition, there will be inevitable situations during the use of robotic end effectors in which visual feedback is not available or adequate, making use of such technology nearly impossible. Due to this limitation, it has become a crucial objective to develop feedback methods that can provide useful information during dexterous interaction between robots and the environment, regardless of the availability of visual feedback.

While the inclusion of visual feedback is known to greatly enhance the overall control experience for the user, this information can be of little use in instances where the user wishes to pick up an object or engage in a pressure-sensitive

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motion (e.g. handshake). Sufficient haptic feedback during closed-loop control operations will certainly aid the user in improving force regulation, in turn greatly improving the success of dexterous tasks and tactile exploration. Furthermore, results from a questionnaire administered through Orthopedic University Hospital Heidelberg indicate that the most desired additional prosthetic function of persons with upper limb amputations is force feedback [1].

The current haptic feedback methods being used in brain-machine interface technology come with austere limitations. Invasive and costly techniques are being implemented, such as intracortical microstimulation of brain sensory areas [2], electrical stimulation via brain implants [3] and targeted reinnervation of residual sensory nerves [4]–[6]. These procedures result in a form of phantom limb sensation through reassigning nerve pathways (reinnervation) and simulating somatosensory sensations through directly probing the associated brain regions. Other feedback methods in use include haptic tactors [3], which are tactile actuators in some chosen location (e.g. within the socket) that provide vibration pulses to other places on the arm or body. Various other forms of vibrotactile technology are also in use [7], [8], which can have useful applications in exoskeleton control or anthropomorphic robotic teleoperation, yet cannot be a solution for persons with a missing hand or limb. In order for an amputee to “feel” the vibrotactile sensations in a similar manner, innervation would still be required in most cases. All of the methods aforementioned can be useful, yet are invasive, often inefficient and certainly impractical for general application to prosthetic limbs. In response, this paper proposes an alternative feedback method where contact force information is perceived through sound. Using volume to represent force magnitudes and frequency to help map the location of those forces, the proposed sensory-substitutive feedback method can provide useful force feedback while staying practical and non-invasive to the user.

The central challenge in producing adequate haptic feedback is creating a learnable sensory substitution experience for the user to adapt to; since amputees no longer receive somatosensory feedback due to the missing limb or hand, there is a need for a sensory substitution method that can equitably transduce the tactile experiences of the robotic end effector into an alternative sensory modality. A notable example of successful sensory substitution is the use of Braille with blind persons, where tactile feedback represents information that is conventionally processed through visual and audial modal-

ties. Sensory substitution is shown to be successful even in contexts that seem non-intuitive or unusual; for example, one study converted information from haptic force sensors on a hand to the forehead of a person lacking peripheral sensation, and after some acclimation the individual was eventually able to embody the somatosensory experience of the glove while disregarding unrelated forehead sensations [9]. The mechanisms underlying this neural adaptation to sensory substitution are made possible through a well-studied characteristic of the brain called neural plasticity. In neuroscience, neural plasticity is assumed to enable adaptations to various functional demands from a person's environment or mental state, supporting a physiological reorganization of neural connections in the brain. The specific type of plasticity regarding the integration of two or more sensory modalities is referred to as cross-modal plasticity, where repeated input from a sensory substitution process is shown to reach and alter various brain structures, even those anatomically located in places associated with the lost sensory modality [9], [10]. It is believed that this capability of the brain to biologically adapt to new sensory convergence will make the cross-modal feedback technology easy to learn.

In addition to the brain's ability to quickly adapt and reorganize, there is a large volume of literature suggesting that an anatomical integration of touch and sound in the brain already exists. A recent study demonstrated extensive cross-modal activation in the auditory cortex of two monkeys during performance of a demanding auditory categorization task that involved pressing and releasing a bar during learned tones [11]. Other research studies also provide support for the existence of a somatosensory-responsible region in the auditory cortex, with the indication that a form of supra-additive integration of sound and touch occurs there [12]–[15]. Additionally, a study examining the benefits of force feedback methods (visual force plots, kinaesthetic and auditory) acting both alone and in combinations during a dexterous task showed that optimal force control occurred when coupling haptic and auditory feedback [16]. These implications support the notion that users may be naturally equipped to learn the cross-modal feedback method; while using auditory information as a way to “feel” an object or environment does not seem intuitive, there is evidence to believe that use of this cross-modal feedback technique could strengthen the pre-existing pathways in the brain responsible for integrating sound and touch, allowing habitual use of the technology to eventually become second-nature.

A prototype of the cross-modal feedback architecture was designed and implemented in the current study. The prototype was tested in the operation of a robotic hand in order to investigate the practicality of the technology. It was conjectured that merging the feedback method with a robotic control task would help the user embody the closed-loop experience and support the learning process. Using surface electromyography (sEMG), users were instructed to control grasping motions of the robotic hand through co-contracting

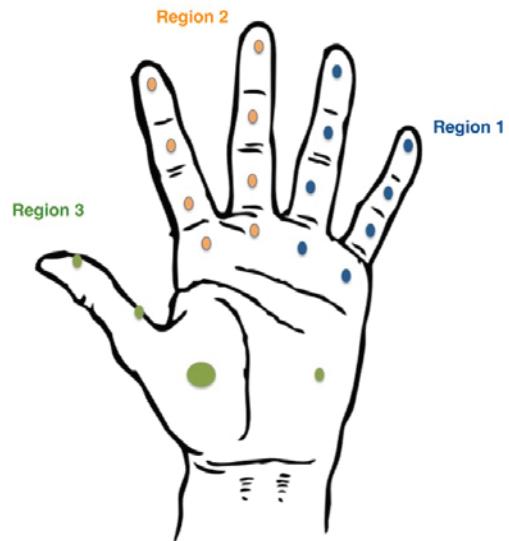


Fig. 1. Sensor map

specific forearm muscles. Both visual and audial feedback were apparent during the majority of the experiment to assist the user in forming associations between force and sound, and the last portion of the experiment involved audial feedback alone.

II. METHODS

A. Feedback Architecture

An i-Limb Ultra prosthetic robotic hand (Touchbionics Inc.) is equipped with a glove containing twenty 0.2in circular Force Sensing Resistor (FSR) sensors, split up into three different regions (R1, R2, R3) as shown in Fig. 1. The first region consists of the ring and pinky finger, while the second region consists of the index and middle finger and the third region consists of the thumb and palm area. Each region is comprised of two sub-regions (i.e. fingers), where those within the first and second region contain four each and those within the third region contain two each. Therefore, the first two regions (pinky-ring and index-middle fingers) include 8 sensors each, while the last region (thumb-palm) includes 4 sensors.

As shown in Fig. 2, the sensors belonging to a single sub-region are all connected in parallel to each other and then finally in series with a terminal resistor that accounts for electrical hardware constraints. A 5V voltage is connected in parallel to the total system, and the total voltage across the terminal resistor of each region is connected to an Analog Input port of a microcontroller (Arduino MEGA 2560 R3). When forces are not being exerted on an FSR, the force sensor acts as an infinite resistance and therefore the terminal resistor voltage drop is zero (open circuit). Conversely, during any applied force, the resistance of the force sensor linearly decreases with respect to the force magnitude, making the total analog voltage across a force sensor decrease as the exerted force on it increases. Consequently, the voltage drops across the terminal resistors increase, and therefore

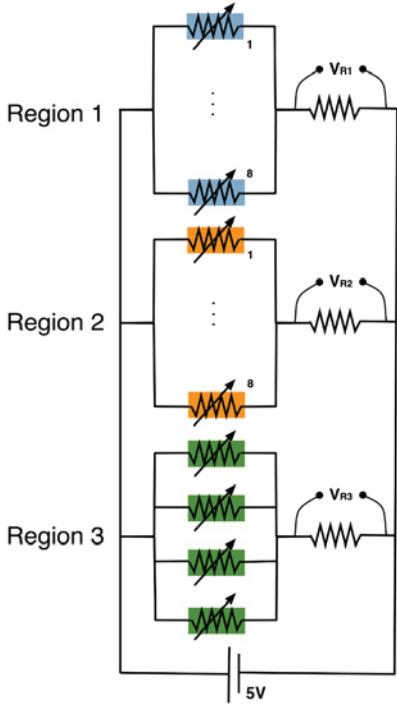


Fig. 2. Conceptual diagram of circuit

each region has an associated voltage input representing the sum of forces experienced in that region. If $V_R^{(i)}$ is the voltage across a terminal resistor within a region i ($i=1,2,3$), and $\sum_{n_i} F_{n_i}$ represents the sum of the forces exerted on the n_i sensors within that region, then the total voltage measured by the microcontroller for each region is given by:

$$V_R^{(i)} = K \sum_{n_i} F_{n_i} \quad (1)$$

where K is the arbitrary gain of the sensors converting the sensed force to voltage.

Using sound to represent forces requires a sound signal generation that is not only representative of force magnitudes, but also the location of the forces on the hand map. Therefore, if $X(t)$ is the sound signal representing all forces across all three regions, where t represents time, then $X(t)$ is given by:

$$X(t) = \sum_{i=1}^3 \frac{1}{3} \frac{V_R^{(i)}}{V_R^{max}} \sin(2\pi f_i t) \quad (2)$$

where the division by three ensures that each region is weighted equally. V_R^{max} is the maximum voltage that can be measured from each analog input (i.e. 5V), and f_i is the frequency assigned to that region. The current setup has region frequency assignments of $f_1=200$ Hz, $f_2=300$ Hz and $f_3=400$ Hz, which were chosen based off of results from a preliminary study regarding frequency perception. As a result, the signal $X(t)$ will always be within the range [-1,1]V and its frequency components will be a function of the total forces exerted within each region. For example, if

most of the forces are applied to the sensors within R1, then the frequency f_1 will dominate in the total sound signal. This resultant sound signal is output through a separate analog output of the microcontroller and received by Audio-Technica ATH-ANC9 headphones. The volume and frequency components of this sound signal are updated every 64ms to constitute a real-time experience with minimal delay.

B. EMG Control Algorithm

An EMG system with wireless electrodes (Trigno Wireless, Delsys Inc) was used for acquiring EMG signals from the forearm of human subjects in order to control the opening and closing of the fingers of the robotic prosthesis. Two electrodes were placed on two forearm muscles according to [17] in order to detect electrical neural signals. An extensor muscle (Extensor Carpi Ulnaris) on the forearm was chosen to be responsible for actuating the opening of the robotic hand at velocities directly correlated to the muscle co-contraction level; for closing the hand, a flexor muscle (Flexor Carpi Radialis) was chosen and utilized in an equivalent manner. Prior to using the system, each user is told to contract the extensor and flexor muscles to their maximum potential during wrist extension and wrist flexion so that each muscle's maximum voltage level, V_{max} , can be recorded. Each user is then instructed to relax the forearm so that each muscle's minimum voltage level, V_{min} , can also be recorded. After these parameters are collected, real-time use of the system can begin.

The raw EMG signals are sampled at 1kHz and undergo a pre-processing stage that is commonly used in the field of electromyography to compute the linear envelope of the signal [18]. The linear envelope performs full-wave rectification of the raw signals prior to passing them through a low pass filter (2nd order Butterworth, cut-off frequency of 8 Hz). After this step, EMG signals for each muscle are normalized with respect to the muscle's V_{max} [17]. This process essentially simplifies and reduces noise in the signals before quickly calibrating the system to the user's muscular characteristics.

The five-fingered robotic prosthesis controller allows for the control of each finger's velocity within the range of 25 to 65 deg/s. Each finger is underactuated, therefore only one motor controls the flexion or extension of each of three finger joints (proximal, middle, distal). There are 14 different values for velocity that can be commanded to each finger, namely $\pm 1 \dots \pm 7$, which correspond to 7 different values equally spaced in the range of 25 to 65 deg/s, for positive (opening) and negative (closing) velocities. When a velocity value is commanded to a finger, the finger will start moving with that velocity until it encounters a pre-defined maximum opposing force, which is a function of that velocity. Therefore, in the case that a finger physically interacts with the environment, control of velocity results in indirect control of force exerted from the finger on the environment. Consequently, the control of velocity for each finger can be associated with the control

of each finger's force when the finger is in contact with an object, i.e. grasping. The maximum power grip force of the prosthesis is 100N.

The processed EMG signals are used in real-time to directly control the velocity at which the robotic hand opens and closes, where increased muscle contraction results in an increase in velocity in the direction associated with that muscle. To create greater disparity between muscular signals for opening and closing the grasp, users are instructed to extend the wrist to open the hand and flex the wrist to close the hand. While the extensor and flexor muscles both play a role in each of these opposing motions, prior research [19] and electromyography convention [17] suggest that extensor muscle activation is much higher for wrist extension while flexor muscle activation is much higher for wrist flexion. These relationships provide a basis for the EMG-control algorithm, which quantitatively compares the averages of the normalized signals in 100ms windows. If the maximum value of the processed EMG signal u within the window is greater than 2.5 times the relaxation voltage V_{min} of the specific muscle, the hand is commanded to either close or open all fingers simultaneously, depending on the muscle activated. The velocity at which the hand then actuates the chosen motion is directly correlated to the magnitude of the normalized signal, i.e. the degree of muscle co-contraction above the threshold value. The function that determines actuation velocity from normalized EMG signals employs the user-specific V_{max} and V_{min} collected prior. Once the muscle reaches a level greater than 40% of the user's V_{max} , the velocity is at maximum. This relatively low percentage value was chosen in order to make the system easier to control while minimizing the potential for muscle fatigue. The function that gives the absolute finger velocity v_f based on the processed EMG signal u is given by:

$$v_f = \begin{cases} 0 & , u < 2.5V_{min} \\ \lceil \frac{7}{0.4-V_{min}}u + 7 - \frac{2.8}{0.4-V_{min}} \rceil & , 2.5V_{min} \leq u < 0.4V_{max} \\ 7 & , u \geq 0.4V_{max} \end{cases} \quad (3)$$

where $\lceil x \rceil$ represents the ceiling function, i.e. rounding of the number x to the nearest integer towards plus infinity. Fig. 3 shows the relationship between EMG magnitude and actuation velocity.

III. RESULTS

In order to test the feasibility and efficiency of the proposed cross-modal feedback in the EMG-based closed-loop control of a hand prosthesis, we designed an experimental protocol consisting of two parts: (a) Learning the cross-modal feedback, and (b) Testing human subject adaptation to the method. Ten healthy subjects (23-30 years old) participated in the experiments. All subjects gave informed consent according to the procedures approved by the ASU IRB (Protocol: #1201007252)

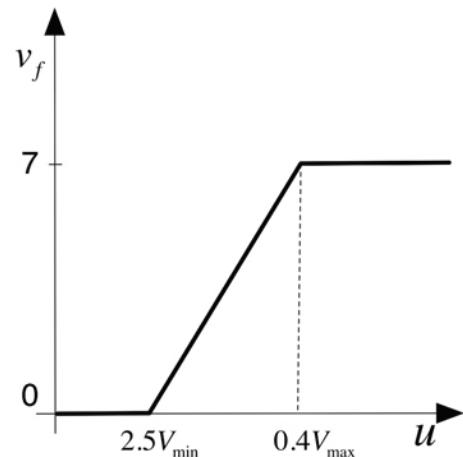


Fig. 3. Commanded absolute finger velocity as a function of normalized EMG signal



Fig. 4. Objects used in the learning phase from left to right: Empty plastic cup, an un-opened soda can and a partially full water bottle

A. Learning

The first part of the experiment required the user to grasp three different objects with the i-Limb Ultra robotic hand: a thin, partially full plastic water bottle, a slightly thicker plastic empty cup and a full, un-opened soda can. The objects are shown in Fig. 4. The water bottle was very easy to deform under minimal force, with the plastic cup being moderately deformable and the soda can being most resistant to deformation. Additionally, the objects have weight differences. The experimental setup is shown in Fig. 5.

During each trial, the object was lowered by the experimenter into the robotic hand's grasping range and the user employed EMG-control of the grasping motion while watching the interaction and listening to the audial feedback on the headphones. Once the user verbally confirmed that they had reached the optimal grasping configuration (no slipping or deformation), the trial ended. During the training phase, users were instructed to grasp each object for eight different trials, resulting in a total of twenty-four timed trials. The duration of the training phase ranged from 40-60 minutes for each user, where each trial lasted between 3-15 seconds.

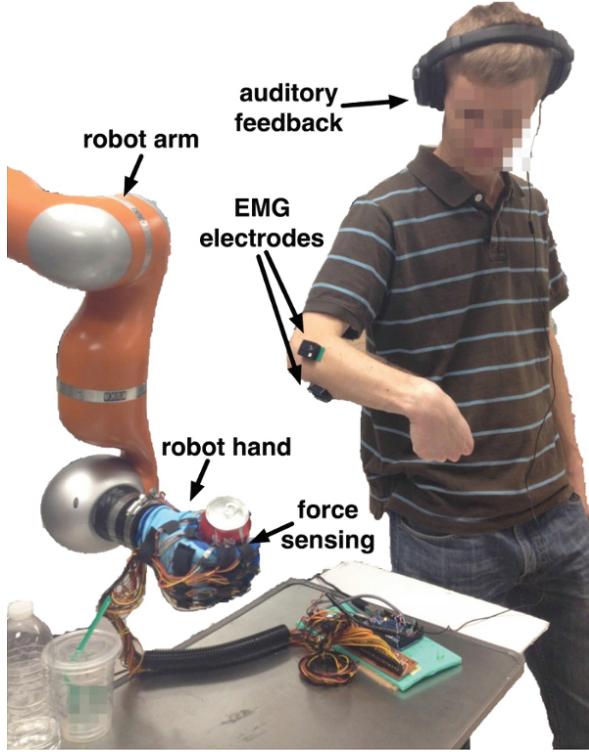


Fig. 5. Experimental setup: The subject controls the robot hand in grasping a soda can using myoelectric signals (forward control) and auditory feedback to moderate the grasping force.

The completion times for each trial were normalized with respect to the maximum trial time for each subject. The normalized completion times across all subjects and trials are shown in Figs. 6, 7, 8 for the soda can, water bottle and plastic cup, respectively. There is strong support for learning and adaptation to the feedback method during the trials involving the soda can and plastic cup; over the course of the 24 training trials, the average task completion time and variance between users decreases significantly. While results for these two objects demonstrate a learning process, Fig. 7 shows that the completion times for the water bottle trials have averages that fluctuate, and the variance between users' scores does not change significantly throughout training. Self-reports from users after the experiment suggest that the water bottle was hardest to grasp due to both the resolution of grasping control and being easily deformable.

A linear fit was created for each object's normalized completion times as shown in Fig. 9, showing decreasing trend for the soda can and plastic cup trials with coefficients of determination of 0.92 and 0.91, respectively. For the water bottle, the sporadic trend in completion times shown in Fig. 9 has a low and meaningless coefficient of determination of 0.34 with its fitted line.

B. Validation

The second part of the experiment involved a test in which the user grasped objects while blind-folded, where three of

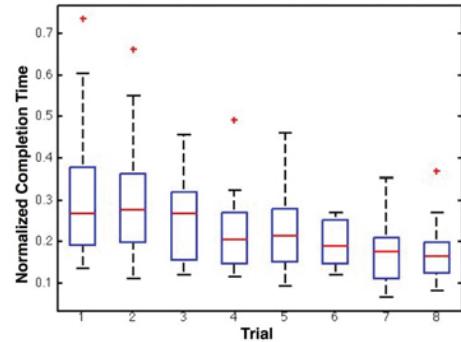


Fig. 6. Normalized grasping completion time for the soda can for all users

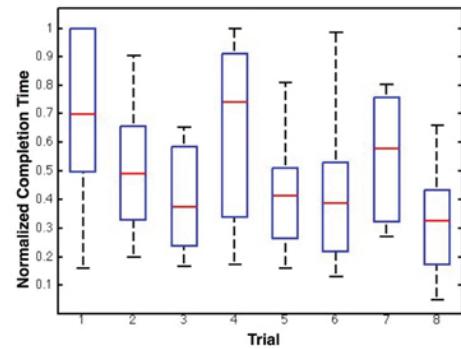


Fig. 7. Normalized grasping completion time for the water bottle for all users

TABLE I
GRASPING ACCURACY SCORES, MEAN AND STANDARD DEVIATION FOR ALL USERS

Users	1	2	3	4	5
Score	100%	79%	86%	86%	79%
Users	6	7	8	9	10
Score	86%	86%	100%	86%	100%
Mean Score		Standard Deviation			
88.8%		8.2%			

the objects were those used in the training portion and four objects were new, totaling to 7 objects. The new objects consisted of an easily deformable foam block, a ceramic cup, a full plastic water bottle and a thin glass sphere. The users were required to do the same task as before, i.e. grasp and hold the objects with the robot hand; although, the users were blindfolded this time in order to eliminate visual feedback, and therefore the grasping force information was perceived solely through the cross-modal feedback.

While these testing trials were still timed, a qualitative performance score was determined for each user: for each of the seven objects, a successful trial was considered one involving minimal deformation and no slipping ($score = 1$), whereas an adequate trial involved some deformation and no slipping ($score = 0.5$) and a failed trial involved unnecessary deformation or slipping ($score = 0$). The user's final grasping accuracy was then determined by adding up the trial scores and dividing by the total trials in order to get

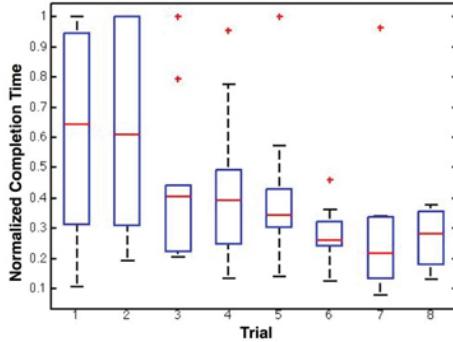


Fig. 8. Normalized grasping completion time for the plastic cup for all users

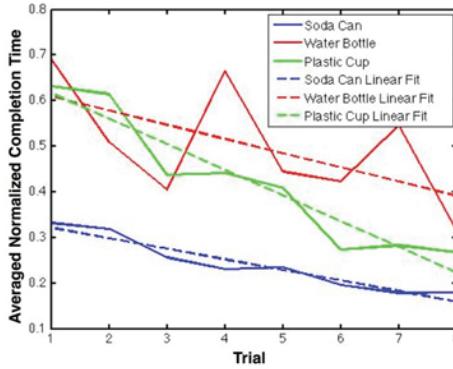


Fig. 9. Averaged grasping completion time for all objects across all trials

a percentage reflective of test performance. Scores for all users are shown in Table I, where the average score ended up being 88.8% with a standard deviation of 8.2%. Even though trial completion time didn't significantly decrease for the water bottle during the training portion of the experiment, users demonstrated successful grasping force control of both this item and novel ones of similar stiffness during the blindfolded test.

While qualitative, the performance scores portray the grasping precision and accuracy that users were able to obtain using audial feedback alone. In addition, there weren't any specific objects that were associated with a higher failure rate during the blindfolded test, so users' accuracy scores portray their success in grasping objects of varying stiffness and weight. Moreover, the fact that the users were able to successfully grasp objects that they had no prior information about provides support for the feasibility and generalizability of the proposed scheme.

IV. CONCLUSION

This paper proposes and investigates an alternative haptic feedback method for use in brain-machine interface technology that proves to be practical and feasible for the user. Throughout a short training phase, users show rapid learning and adaptation to the sensory-substitutive feedback modality. After users make connections between visual force implications and perceived sounds during grasping, they are able to use audial feedback alone to precisely control such

motions around several different objects, some of which are novel. As non-invasive and easy to learn technology, the current feedback method can be a more efficient and inexpensive alternative for receiving force feedback during anthropomorphic robotic operation. An interesting direction for future research would be to investigate which frequencies and volumes optimize the user's performance with this system.

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