The Fourth IEEE RAS/EMBS International Conference
on Biomedical Robotics and Biomechatronics
Roma, Italy. June 24-27, 2012

Continuous Vocalization Control Of A Full-Scale Assistive Robot

Mike Chung*, Eric Rombokas*, Qi An, Yoky Matsuoka and Jeff Bilmes

***Abstract*— We present a physical robotic arm performing real-world tasks using continuous non-verbal vocalizations for control. Vocalization control provides fewer degrees of control freedom than are necessary to directly control complex robotic platforms. To bridge this gap, we evaluated three control methods: direct joint angle control of a selectable subset of joints, inverse kinematics control of the end effector, and control in a reduced-dimensionality *synergy* space. The synergy method is inspired by neural solutions to biological body redundancy problems. We conducted several evaluations of the three methods involving the real-world tasks of water bottle recycling and grocery bag moving. Users with no prior exposure to the system were able to perform these tasks effectively and were able to learn to be more efficient. This study demonstrates the feasibility of continuous non-verbal vocalizations for control of a full-scale assitive robot in a realistic context.**

In the United States, there are over a quarter million individuals with spinal cord injuries, 47% of which are quadriplegic [1] (i.e., with restricted use of their upper limbs and hands). There are even more individuals with severe motor impairments such as paraplegia, amputations, arthritis, or Parkinson's disease. Individuals with limited mobility and motor control rely on others to assist them in their daily activities such as preparing meals, eating, lying down into bed, and personal hygiene.

Recent advances in assistive technologies have demonstrated several approaches to help these individuals. There are robots that semi-autonomously assist the users with spoken language and automatic speech recognition (ASR). They hold great promise due to the hands-free interaction they provide without significant investment in specialized hardware (other than the robot itself). Stanford's DeVAR is a desktop-mounted robot that utilizes ASR to assist users' daily activities including meal preparation, self-feeding, and certain personal hygiene tasks [2]. Another system called FRIEND I & II uses a robotic arm attached to an electric wheelchair [3]. The entire system is controlled by speaking relatively simple verbal commands which invoke arm movements or semi-automated high-level commands, such as motion planning for grasping, or navigating. Unfortunately, controls of this type require a structured physical environment to successfully execute high-level commands triggered by the user, or require a large number of voice commands to achieve high accuracy of movement control. Moreover, they rely heavily on robotic autonomy in human-environments, which is still an unsolved research problem [4], [5].

(a) (b)

Fig. 1. Experimental setup for the two real-world tasks. (a) In the pick-and-place task, users move water bottles into a trash can. (b) In the bag moving task, users pick up a grocery bag by the handles and move it to the specified region of another table.

Non-invasive brain control interface (BCI) via technologies like electroencephalography (EEG) may be a future option for providing hands-free interaction with the environment. There have been demonstrations of controlling a mobile robot and a wheelchair, as well as cursors [6], [7], and these systems continue to improve. However, noninvasive BCI systems, and even state-of-the-art invasive BCI systems, are currently limited in the richness and robustness of the control signal they provide and present practical hurdles to deployment such as cost, and susceptibility to electromagnetic interference.

There are other interfaces for controlling robotic devices, such as inductive tongue interfaces for robotic wheelchairs [8], eye-tracking for semi-robotic wheel chairs [9], and laser pointer and touch screen interfaces for high-level control of an autonomous robot [10]. Such autonomous or semi-autonomous systems provide discrete, as opposed to continuous, control signals and therefore provide a discretized suite of movement and manipulation options to the user. The Vocal Joystick (VJ) [11] provides real-time control signals from continuous human vocal qualities such as pitch, vowel formation, and amplitude, creating a control interface which is suitable for a complex robot. Previous work has demonstrated that the VJ can be successfully used for not only mouse control [12], but also simple robotic arm control [13]. The robot in that study was not simulated, and it demonstrated that users could successfully complete an object movement task in a reasonable amount of time. On the other hand, the robot was a relatively hobbyist's Lynxmotion Lynx 6 arm, which is too fragile and small for gross manipulation household tasks. Consequently, the task that was performed (moving a piece of candy from a starting position to a paper target) did not constitute a task typical of what one might wish to perform in the

* equal contribution

M. Chung, E. Rombokas, Q. An, and Y. Matsuoka are with the Neurobotics Laboratory, Computer Science & Engineering, University of Washington, Seattle, USA, {rombokas,mjyc,qian,yoky}@cs.washington.edu

J. Bilmes is with the SSLI Laboratory, Electrical Engineering, University of Washington, Seattle, USA, bilmes@ee.washington.edu

We thank Intel Labs Seattle for the use of the MARVIN robot.

978-1-4577-1200-5/12/$26.00 ©2012 IEEE

home. The task was extremely simple and ignored various control difficulties arising from using the proposed system in the real-world environment. For instance, there was no danger of collisions, and fewer relevant degrees of freedom both in the pose of the robot and in the objects. In this work, we demonstrate an improvement of the state-of-the-art in voice controlled robotics. The Vocal joystick (VJ) system [11] is used to control a complex robotic arm capable of performing real-world tasks. There are a number of novel aspects of our study over previous work. First, we use a real "industrial strength" robotic arm and hand, namely the WAM Arm [14] and the BarrettHand [15]. We demonstrate three control methods, each providing different tradeoffs for dealing with the complexity of performing real-world tasks that one might wish to perform in the home, including moving water bottles from a table into the trash, and moving a heavy shopping bag full of groceries.

We tested these two tasks under three control methods: *direct* joint angle control, *inverse kinematics* solving for end effector position, and dimensionality-reducing *synergy* control. A group of nine individuals participated in four sessions over the course of two days (two sessions per day). These studies allowed us to observe not only task and control method preferences and competencies, but also the rate of learning. Experiments on these nine users showed that, even though they had no prior experience with voice-controlled robotics, they could complete practical real world tasks and learn to perform more effectively over the course of four short sessions. To the best of our knowledge, this study demonstrates the first instance of a full-scale robotic arm being controlled by non-verbal vocalizations to perform real world tasks. It is also a pilot demonstration of task-specific synergies for robotic interface. Based on the results reported here, we believe further research of non-verbal voice controlled robotics and prosthetic limbs is warranted.

A. Sparse Control Problem and Synergy Hypothesis In Brief

While there has been active research in assistive interfaces, there has been relatively little work addressing the problem of interfaces providing fewer control dimensions than are required to control a fully functional assistive robot. In [16], this was named the *sparse control problem*. Jenkins addressed this problem by utilizing a subspace of a robot's position space, and demonstrated the results on a simulated robot. We compare the "default" solution of directly controlling a subset of joint angles with two other subspace methods. This default solution involves direct control of a subset of joint angles while being able to select which subset is currently active. The first alternative is to have the user control the cartesian position of the end effector, while an autonomous algorithm selects the appropriate joint angles. This control method we refer to as inverse kinematics control. The second subspace method is a new approach inspired by the Synergy Hypothesis in the study of neural movement control. Ignoring this inspiration, the method may be thought of as an Eigenvector dimensionality reduction technique based on an example of the desired task. In studies of neural control of movement, it remains unclear what fundamental output the higher nervous system controls,

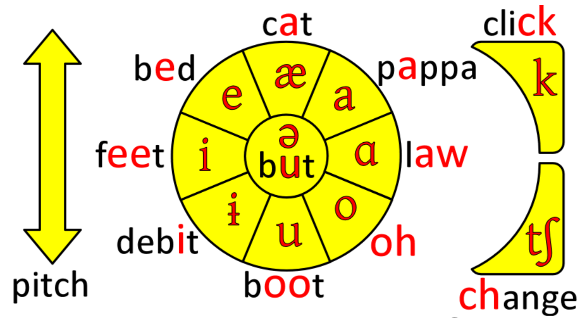


Fig. 2. The Vocal Joystick: Vowel sounds are used for control. Words include the nearest vowel in American English. Note that pitch was utilized as another continuous control dimension. Voice loudness controlled the speed of motion in combination with the other control dimensions.

from low-level activation of individual muscles to high-level task specifications which are acted on by a hierarchy of lower-level controllers [17]. The synergy hypothesis states that the neural system combines the activations of small groups of muscles that operate cooperatively as structural units of an overall control solution. These synergy components bridge the gap between the relatively simple movement goals of a task and the highly redundant variety of possible controls to achieve it. For the purposes of this paper, synergy components provide a way of mapping few controllable dimensions to a rich, task-specific set of poses for the robotic arm. Synergies used for robotic control or interface are sometimes constructed by hand [18] but here we demonstrate automatic synergy construction given examples of task completion. There are a variety of strategies for constructing synergies, from simple ratios of joint angle changes to more complex methods incorporating time dependence and delays [19], [20]. Here we use synergies in their simplest form, a linear weighting of joint angle displacements, to act as a small number of control knobs that each affect the joint angles by a fixed amount. This weighting is advantageous because it incorporates examples of the movements necessary to achieve the goal to provide a task-specific interface.

I. METHODS

The Vocal Joystick engine provided the control inputs to the robotic hardware. The engine provided controls at 100Hz in the form of vowel quality velocities, pitch, loudness, and discrete identifiers as shown in Fig. 2. (For detailed information about the Vocal Joystick engine, please refer to [11]) Pitch values were in log-scale frequency, which is closer to the human perception of pitch than linear frequency. To be consistent with units of vowel quality velocities, we used the derivative of pitch values, the pitch velocity, instead of absolute pitch values for our system. Two-dimensional continuous values from vowel quality velocities and the one-dimensional continuous signal from pitch velocity were used as joint angle controls, while the loudness of the user's voice determined the speed of motion. The two discrete phonemes, [k] and [tʃ], were used for commanding discrete actions of the robot, such as opening/closing of the robot hand. These correspond to the sounds beginning the words *kill* and *chill*, respectively.

A. Arm and Hardware Overview

The MARVIN Mobile Manipulation Platform was assembled by Intel Labs Seattle, and is a WAM Arm [14] and a BarrettHand [15] mounted on a Segway RMP 100 [21]. The WAM Arm has 7 degrees of freedom (DoF): shoulder rotate, shoulder bend, elbow rotate, elbow bend, wrist rotate, wrist bend, and a redundant wrist rotation. The WAM Arm is controlled by a real-time Linux PC at a rate of 500hz. Joint limit safety checks, high-level smoothing of joint movements, the inverse kinematics solver, and network communication with the Vocal Joystick engine were all executed on another computer and communicated to the robot via TCP network. The end effector of the WAM Arm is a BarrettHand. The BarrettHand has 4 DoF, but for this study is used as a simple 2-prong gripper with pre-tuned open and closed positions. A computer monitor was used to display simple feedback information about robot state as shown in Fig. 1-(a) (a monitor on right side of the robot).

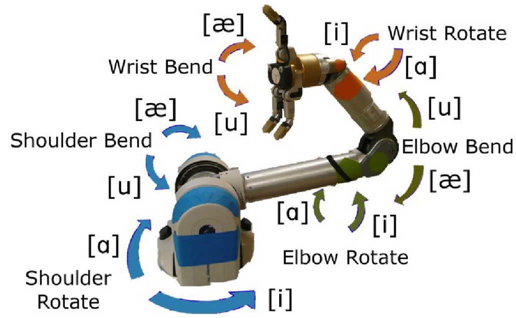
B. Control Methods

The Vocal Joystick provides four simultaneous control signals, to interface with the 7-DoF robotic platform. Therefore, the system operates under the sparse control problem [16], and cannot produce a one-to-one map between control data from the VJ engine to robot joints. We explored three control methods for bridging this gap, each involving a trade-off among simultaneousness, ease of understanding, and expressiveness.

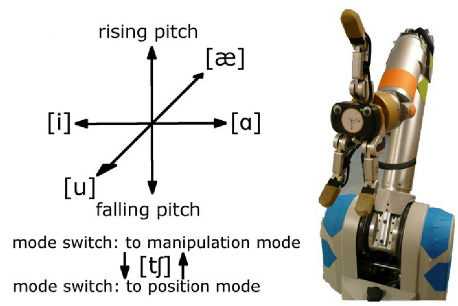
1) Direct Joint Angle Control: The direct joint angle control method solves the sparse control problem by allowing the user to switch active control joints. The user controlled two joint DoFs at any given time: rotation and bend of a joint connecting two segments of the robotic arm. The discrete sound [tʃ] was used to switch between the currently active DoFs. Default control started with controlling shoulder rotation/bend, switching to elbow, then wrist, and back to shoulder 3. This control method did not make use of the second wrist rotation joint. The monitor displayed a unique color indicator of current state: blue for shoulder, green for elbow, and orange for wrist. For example, in Fig. 1-(a), the user is controlling the shoulder joint and blue is being displayed on the monitor. The discrete sound [k] is used to command the hand to open or close.

Direct joint control is the most expressive control method since the user has direct access to the most number of joints (6 out of 7 DoFs), giving the most freedom to the user in the robot's joint space. The number of simultaneously controlled DoFs is very low, which can increase the time needed to perform tasks, but is easy to understand conceptually for an inexperienced user.

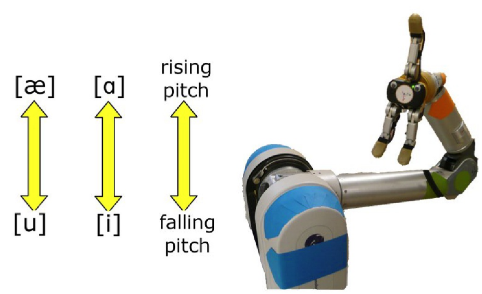
2) Inverse Kinematics: Two modes were available for this method: *positioning* mode and *manipulation* mode. Positioning mode was designed for gross positioning of the end effector, but preliminary explorations indicated that more expressive control is required for fine interaction with the objects. In positioning mode, inverse kinematics control solves the sparse control problem by finding joint configurations which produce a controlled cartesian position of the end effector. Users of



(a) Direct Joint Control



(b) Inverse Kinematics Control



(c) Synergy Control

Fig. 3. Instructional figures provided to the users, describing each control method. (a) Reference for direct joint angle control details the sounds necessary to move the joints. (b) The endpoint position of the robot is controlled in cartesian coordinates. (c) It is difficult to depict the motions produced by synergy control in a still frame, so the reference simply reminds the user of which axes of vocal joystick control are used.

inverse kinematics control are able to control all 7 joints, but only through specification of end effector position, not directly. As in Fig. 3-(b)) the end effector is positioned by making [u] and [æ] sounds to move towards and away from the user, and the sounds [i] and [ɑ] are used to move left and right. Rising pitch and falling pitch raise and lower the effector. Loudness is used in combination with these sounds to control speed.

The manipulation mode allowed the user to directly control wrist rotation bend for close-range, fine manipulation of objects. It was identical to the wrist control interface (orange) of the direct joint angle control method. The discrete sound [tʃ] was used for switching between positioning and manipulation mode. As above, the monitor displayed the unique color indicator of current mode: grey for positioning mode, and orange for wrist mode. The discrete sound [k] is again used to command the hand to open or close

Inverse kinematics control can be intuitive for the users because it provides a control interface in Cartesian space, which most users find to be comfortable. Having only two modes instead of three as in direct joint control, inverse kinematics was a more simultaneous control interface. On the other hand, inverse kinematics was the least expressive control method; when the user is in position mode, they cannot configure the joints of the arm because the controller set the joint angles autonomously. The user could only configure the two joints of the wrist directly in manipulation mode, which limited the overall expressiveness of inverse kinematics control.

3) Dimensionality Reduction: Synergy Control: The synergy control method was based on movement primitives, each a weighting of the robot joints which provided a particular motion tailored to the task. The weightings were constructed from a single recording of a user completing the task using the direct joint control mode. Each synergy component was an "Eigenmotion" which best captured the variance encountered in the recording. Principle Component Analysis (PCA) yielded the synergy components, and the three which explained the most variance were controlled by the user. Two dimensional motion control data from vowel quality velocities and one dimensional motion control data from pitch velocity controlled the activation of the three synergy components. Loudness, as before, controlled the speed of the motions. Since synergy control did not have different modes or states, the monitor feedback was not used. The discrete sound [k] was used to open or close the hand.

Synergy control was the most simultaneous method, since each control dimension of the VJ was used to move all of the joints simultaneously. These motions were tailored to the task, which limits the expressiveness to tasks for which synergy components have been created. The control dimensions of the synergy method are difficult to describe to users in graphic form, since they involve complex motions of all joints. This can lead to reduced perfomance, especially for users without exposure to the method. For instance, the first synergy component for the bottle task greatly rotates the shoulder joint, as if moving from the table surface to the trash bin, but it also pulls the hand toward the robot base. This combination is useful for completion of the task, but can take time to learn.

II. USER STUDY

A. Participants

We conducted user studies with nine naive healthy volunteers (eight male and one female). The participants, ages 20-35, had varying occupations (undergraduate / graduate students, department staff, and global health program), and native language (Mongolian, Korean, English, Chinese). The participants did not have any experience using the Vocal Joystick or similar systems. The study was approved by the University of Washington Human Subjects Division and each user gave informed consent.

B. Experimental Design

The user study was designed to evaluate the three control methods for performing two real-world tasks; it also investigated the learnability of the interface. The study took place over two days. The two real-world tasks were to throw away water bottles in a trash can, and to move a heavy grocery bag from one table to a subregion of another.

For the bottle task, six nearly empty water bottles were placed at pre-assigned positions on the table as shown in Fig. 1-(a). Bottles were separated so that users had enough room to allow error in grabbing a single bottle without hitting others. The table with bottles was placed 55cm away from the center of the robot. The recycle bin was placed 45cm away from the center of the robot's right wheel (the left side of table from the user perspective.) The goal of the bottle task was to put as many bottles as possible from the table to the recycling bin in 5 minutes. This task is challenging because it requires fine-grained control for positioning the hand and arm. The user can easily fail to achieve task goals by disturbing the target bottle before achieving a grasp, knocking out other bottles during transportation, or colliding with the table.

For the bag moving task, users were asked to move a paper grocery bag filled with 6 full 500ml water bottles, all together weighing about 3kg, from one table to another table. The first table was located 55cm from the center of the robot toward the user. The other table was located 55cm away from the center of the robot to the left from the user's perspective. The starting position of the bag was fixed for all users as shown in Fig. 1-(b). The goal of the bag task was to pick up the bag from first table and place it in the target region of the other table as fast as possible. A challenging aspect of this task is to successfully grasp the handle of the bag. It is necessary to grasp correctly as a first step for the task without dropping the bag while transporting fragile objects inside. Because the handle of the grocery bag was not rigid, but could deflect around and fold, firmly grasping the handle required fine-grained control.

C. Experimental Procedures

Two tasks combined with three different control methods yields a total of six different experiments. To see the learnability curve of each user, we asked each to participate on two consecutive days. One experiment day included two trials, each consisting of an experiment run for all six conditions. The order of experimental runs was randomized in order to minimize the ordering effects in learning as a confounding factor for comparison of control methods. The details of the study protocol are as follows:

1) *Introduction:* On the first day, users were given a brief introduction to the Vocal Joystick system, and the basic goals and methods of the study. The users were allowed to ask any questions regarding VJ research in general. On the second day, this step was skipped.
2) *Calibration:* Users were taught the nine vowel sounds used by the VJ system with the help of a graphical interface. The VJ system adapted its internal parameters to match the user by having them produce 2 second

segments of each vowel and each discrete sound. On the second day, this step was repeated to capture various changes of microphone setup, and any changes in user behavior due to experience using the VJ system on the first day.

3) *Vocal Joystick Practice Session:* Each user was allowed 10 minutes to practice using the VJ with visual feedback. Within this practice time, users could ask questions.
4) *Experimental Run Description:* At this step, one of six experimental setups was selected randomly. Each user was provided a corresponding reference sheet (Fig. 3) explaining the selected control method. Users were shown a short instructional video of an expert demonstrating the currently assigned tasks using the currently assigned control method. Users were not allowed to ask any questions after this point. On the second day (trials 3 and 4) this step was skippable at the user's request.
5) *Experimental Runs:* Commencement of the experimental run was self-initiated by the user by producing their first sound to control the system. The experimental run was concluded after five minutes for the bottle task, and whenever the task was successfully completed for the bag task. The experimental run was recorded by video for performance analysis, with only the robot and task space visibile in the recording.
6) *Repeating Experimental Runs:* Each experimental condition was run once, corresponding to all combinations of the three control methods and two tasks. After completing all six runs, the user was allowed to take a short break before conducting a second trial of six experimental runs.
7) *Repeating Session:* On the second day, the users repeated the same procedure from *Introduction* to *Repeating Experimental Runs*.

D. Evaluation Metric

For the bottle task, we used two evaluation metrics: the number of bottles dropped in the recycle bin in 5 minutes and the time taken per bottle for the user to grasp and place in the bin. For the bag task, we used one metric: the time taken to successfully transport the bag from its initial location from one table to its end location. The metrics were measured by reviewing the video recordings of each experimental run for each user.

III. RESULTS

The three performance measures of both tasks indicate that all three control methods are learnable, with statistically significant performance improvement from trial one to trial four ($p < 0.05$, see Fig. 4). Average completion time for the bottle task decreased 45%, 50%, and 52%; time to complete the bag task also decreased 67%, 63%, and 78%; and the average number of successfully trashed bottles increased 88%, 86%, and 100% for direct joint, inverse kinematics, and synergy controller respectively. By the last set of trials, several users were able to place all of the bottles in the bin

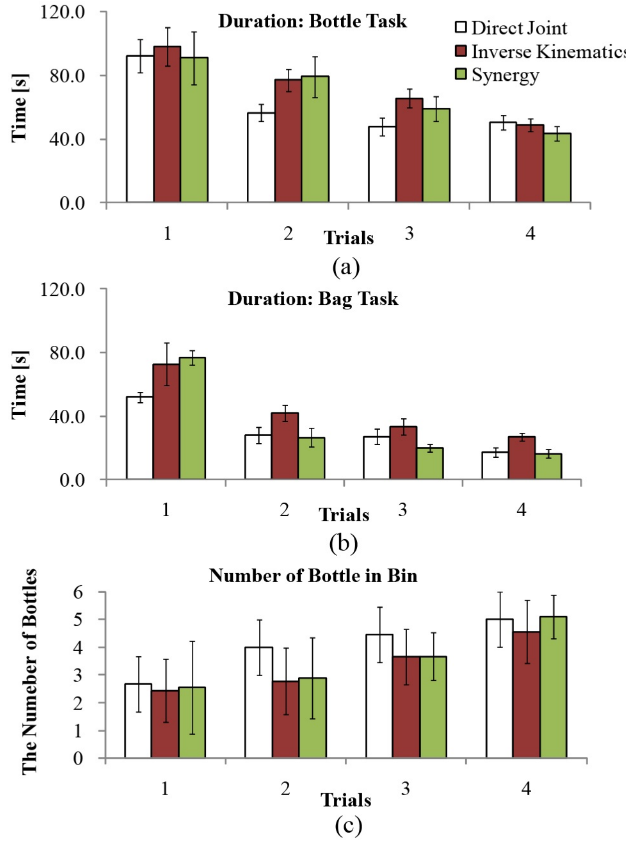


Fig. 4. Results of the user study. (a) The mean time taken per bottle. The users are able to improve their speed for all control methods. (b) Time taken to complete the bag task (moving the bag from one table to another). Again, the all users were successful and were able to improve their speed with practice. (c) Total number of bottles trashed in 5 minutes for bottle task.

before the time limit. The results indicate that performance using synergy control is competitive with the more standard methods. Especially for the bag moving task, completion using synergy control took 39% less time than with inverse kinematics control with statistical significance($p < 0.05$). Task performance appears to continue increasing at trial 4, which suggests that asymptotic performance levels may be further improved.

IV. DISCUSSION

These results demonstrate the feasibility of using non-verbal voice-controlled robots as practical assistive robots. We would be remiss, however, if we did not carefully discuss some limitations of the system as it appears here, how they may be addressed, and some promising future directions inspired by this study.

1) Feedback: Users must simply use vision of the robot for feedback of its state. Since there is a control interface in the form of a computer monitor, showing some enhanced visual feedback for the robot state, and even, enhanced visual feedback for the user voice input, could increase usability and rates of learning the interface. The synergy control method in particular could benefit from an intuitive indicator of the effects of user input. Additional measurement and indicators of the state of the robot and environment could make the system more safe and potentially more expressive. For example, depth-camera sensing can be used to prevent collisions, especially under the inverse kinematic control method when the system is making many kinematic pose decisions for the user. There is also potential for the use of force feedback from the robotic hand to improve manipulation performance [22], [23].

2) Hybrid/Adaptive Voice Control: Though continuous non-verbal robotic control offers a rich and robust controller, it is potentially quite tiring for users. Its use may also not be appropriate for quiet locations and could be conspicuous. Augmenting the system described here with a voice command system which leverages recent advances in robotic autonomy could provide a compromise. Adaptive interfaces, e.g. [7], the system that can learn often-repeated tasks, could be possible direction to explore.

3) Discriminative Synergy: The synergy control method can be further explored in following direction. The property captured by the synergy decompositions above is the *variation* in observed data. This criterion corresponds to squared error, but for many motor tasks, success is not defined by squared error. For instance, when dropping a bottle into the trash can, the task is likely to succeed for hand endpoints above the trashcan boundaries, but jumps discontinuously as the end effector moves outside those boundaries. We propose a synergy decomposition based on Linear Discriminant Analysis (LDA) of examples of task success and failure. This synergy prioritizes motion important to task success, and allows for variance when it is not relevant to the task.

Construction of the LDA synergies requires examples of joint configuration $\mathbf{x} \in \mathbb{R}^d$ for d joints, and their associated class labels $y \in (0, 1)$ where class 1 corresponded to success and class 0 to failure respectively. An initial session using direct joint control could be used to collect examples of success and failure. The joint configurations $\mathbf{x}$ are used to form a discriminant function $f(\mathbf{x})$ expressed as in eq.1. When $f(\mathbf{x}) > 0$, the joint configuration $\mathbf{x}$ is classified as success, and it is considered a failure when $f(\mathbf{x}) \leqq 0$.

The weight vector $\mathbf{w}$ best describing the data is the *LDA synergy* and can be used just as the previous synergy formulation. Pilot experiments using LDA synergy control are underway.

$$f(\mathbf{x}) = \mathbf{w}^{\mathbf{t}}\mathbf{x} - w_0 \tag{1}$$

V. CONCLUSION

To our knowledge the results presented in this paper are the first instance of using a non-verbal voice-controlled robotic arm for *practical tasks* in human environments, and using synergies constructed from task examples as a robotic control interface. Nine users with no prior exposure to the system were able to perform real tasks using a full-scale assitive robot in a realistic context. Though all users were able to accomplish the tasks to some degree immediately, the users appear to still be learning after four trials over two days, suggesting that further improvement may occur with more practice.

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