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SUPERNUMERARY ROBOTIC FINGERS: AN ALTERNATIVE UPPER-LIMB PROSTHESIS

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ABSTRACT

Conventional prosthetic devices substitute lost human limbs with mechanical proxies to enable amputees perform daily chores. We present an alternative approach that may replace or supplement traditional upper-limb prostheses by utilizing and enhancing the functionality of the remaining healthy limb with a new type of wrist-mounted robot: the Supernumerary Robotic (SR) Fingers. These SR Fingers are naturally and implicitly coordinated with the motion of the human fingers to provide assistance in a variety of prehensile tasks that are usually too difficult to carry out with a single hand, such as grasping a large/oddly shaped object or taking the lid off a jar. A novel control algorithm, termed “Bio-Artificial Synergies”, is developed so the SR Fingers can share a work load and adapt to diverse task conditions just like the real fingers do. Through grasp experiments and data analysis, postural synergies were found for a seven-fingered hand comprised of two SR Fingers and five human fingers. The synergy-based control law was then extracted from the experimental data using Partial Least Squares Regression (PLSR) and tested on the SR Finger prototype on a number of common tasks to demonstrate the usefulness and effectiveness of this new class of prosthetic device.

INTRODUCTION

When individuals have diminished dexterity and range of motion in their hands due to aging or disabilities, it can be difficult for them to perform routine tasks of daily living. According to the US Census, there are at least 52.6 million people currently suffering from some extent of dexterity and limb mobility impairment [1]. While various upper-limb prosthetic devices are available, they provide only limited assistance. For example, cosmetic prostheses, which are the preferred choice in Europe and Asia, are just rigid gloves with no functionality at all [2-4]. Hooks, due to the lower cost, higher durability, and higher functionality, are used by most (70%) US amputees, but manipulating delicate items with them is almost impossible [3, 4]. Despite the vast number of research on the design and control of robotic hands [5-10], the existing multi-joint prosthetic devices still cannot compete with the manipulation capabilities and dexterities of the human hand [11].

The aim of this paper is to introduce a wrist-mounted robot, the Supernumerary Robotic (SR) Fingers, that may complement or replace the conventional upper-limb prostheses. Previous work on other types of SR Limbs, for example waist and shoulder mounted robotic arms, has shown that additional limbs can aid the user in holding objects, supporting the body weight, and streamlining the execution of a task [12-16]. The robotic fingers discussed here is intended to enhance the functionality and capability of the remaining healthy limb to perform tasks that are usually too difficult to carry out with a single hand, such as grasping a large/oddly-shaped object or taking the lid off a jar.

A critical challenge is to control the motion of the SR Fingers so the human would eventually come to perceive the robotic limb as an extension of his/her body. The goal is to achieve a natural and implicit coordination such that the human and robotic fingers share the task load and adapt to diverse task conditions. This requires the motion of the SR fingers to conform to a functional relationship with the human fingers in a way that is perceived to be natural to the user. The SR fingers must also effectively assist the human without explicit visual or auditory commands.

Most hand prostheses use neural (electromyography) signals generated during muscle construction to extraction the intent of the user and control the movement of the device [17, 18]. Not only does this require considerable end-user training, the
measured EMG signals are also very noisy and must be filtered extensively [19-22]. Moreover, with only limited number of independent signals generated by the user, it is difficult to use EMG to control prosthesis with higher DOFs [23]. To coordinate the combination of innervated human fingers and non-innervated SR Fingers without using EMG, a control algorithm, termed “Bio-Artificial Synergies”, inspired by neuromotor control is developed.

A wealth of literature in neurophysiology and experimental brain science has reported synergy as an efficient strategy to achieve motion. Synergies are defined as the coherent activation, in space or time, of muscle groups by a single central control signal [24, 25]. Through the sequencing and superposition of only a small number of these muscle synergies, a large variation of complex, multiphasic movements can be accomplished [26, 27]. Muscle synergies have been used to explain posture and force-stabilization of prehensile actions [28-33]. In the realm of robotics, synergies have been utilized to control robot manipulators [34, 35], design robotic hands [36-39], and plan grasping actions [40-44]. Alternatively, nonlinear oscillators have used synergies to learn and reproduce complex rhythmic movements [45, 46].

To achieve the desired “natural and implicit coordination”, we explored the concept of postural synergy between the human fingers and the SR Fingers, describing it as “Bio-Artificial” to differentiate it from those reported in neurophysiology literature, since nerves do not extend to the SR Fingers. We tested this concept on grasping postures that involve all seven fingers, five healthy human fingers and two SR Fingers that are attached to the human wrist. The postural synergies among the seven fingers were analyzed using Principal Components Analysis (PCA). Moreover, Principal Components Regression (PCR) and Partial Least Squares Regression (PLSR) were examined as possible synergy-based control methods for the SR Fingers. Finally, real time control was implemented using PLSR and a few common grasping tasks were performed to validate the data-driven methodology for coordinating human-robot fingers.

SUPERNUMERARY ROBOTIC FINGERS

The quality of performance, ease of control, and comfortableness of the wear are the basic functional requirements of a prosthetic device. Since fewer DOFs means easier to control and less weight but also limited ability to perform motor tasks, as pointed out in [47], the optimal prosthesis often compromise between functionality and wearability depending on the user’s personality and need. It is worth noting that a functional prosthesis does not require strict accuracy, since the user can adjust his/her body to compensate for the errors. The quality of performance, therefore, is viewed as the user’s level of satisfaction in accomplishing activities of daily living.

Often, prosthetic limb only serves supplementary role since the users can modify their behavior and conduct most of the activities of daily living with the remaining healthy limb [48]. However, it is difficult to perform tasks with a single hand, even with the assistance of simple prosthesis, when delicate movements or substantial forces from the distal extremities are required, for example tying shoe laces, buttoning shirts, opening a bottled beverage with a bottle opener, and cutting material with scissors [2]. We propose the SR Fingers, which are mounted directly to the remaining human hand, as a means to expand the functionality of the hand and enable the user to more comfortably and easily perform manual tasks.

Since the SR Fingers are not as limited in size, range, and motion as the human fingers are, they are especially beneficial for grasping objects that are usually deemed difficult to grip, including objects that are large, oddly-shaped, heavy, slippery, too hot, or too cold. The SR Fingers can also hold an object in place while the human fingers perform more precise and delicate actions to the object, such as holding down a bottle while taking the cap off. Additionally, tools can be attached to the SR Fingers to facilitate tasks that require more than the bare hands. Figure 1 illustrates some examples of possible configurations and applications of the SR Fingers.

A preliminary prototype of the SR Fingers was developed as a proof of concept and a test bed for human-robot coordination control (Fig. 2). Feasibility studies of different finger layout and optimization of the mechanical design are to be investigated beyond the proof of concept stage and are thus out of the scope of this paper. In view of the difficult daily living tasks, as listed in [2], the SR Fingers need to be able to grip and carry the weight of an object by themselves. Thus, at least two SR Fingers are needed, one similar in orientation to the thumb and the other similar to one of the long fingers, to deliver the desired performance. Each robotic finger has three DOFs, and the joints are actuated by Dynamixel AX-12A servos (Robotis, South Korea), which are rated at a maximum torque of 1.5 Nm and provide at least 300 degrees of motion in anticipation of a wide range of grasping conditions. To give the robotic fingers the largest workspace possible around the human hand, and at

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the same time keep the design relatively simple, the two SR Fingers, called RT and RF, are fixed to opposite sides of the wrist via a 3D printed (fused deposition modeling) brace. The weight of the device (<250 g) is evenly distributed along the wrist and part of the forearm for better comfort. For the ease of controlling the SR Fingers, we used a data-driven method, keeping the human in the loop, to more naturally perform the desired tasks. This is discussed in more details in the next two sections.

BIO-ARTIFICIAL SYNERGIES

To set the SR Fingers apart from conventional prostheses, these robotic fingers must collaborate with the human fingers and achieve motion that feels and looks natural to the user. We want to extend the postural synergies found in the human hand to the SR Fingers and utilize that synergy for motion control. To do so, we captured static grasping data of a 7-fingered left hand and synthesized the most significant variables that explain the data variance with PCA.

During the experiment, the user was shown 40 objects with diverse shapes and sizes. The objects, for example a basketball, a book, and a bottle, were selected so all seven fingers can be used to perform the grasp. As a result, small objects such as pencils or cards were not used. The user was asked to approximate the general grasping posture of each object in air. Five trials were performed for each object and the average was used for analysis.

The human hand posture was measured by a ShapeHand data glove (Measurand, Toronto, Canada), which contains fiber optics sensors that capture the positions of the wrist, finger tips, and finger joints in Cartesian coordinates. On a laptop with 6 GB RAM and 2 GHz CPU, the sensor was able to update the data at 80 frames per second, with a resolution and accuracy of 0.1 mm. Figure 3 shows the joint locations measured by the data glove. The robotic fingers were moved by the user via LabVIEW (National Instruments, Austin, TX) until the subjectively decided best grasping position is reached. Similar to [28], the grasping posture of the 7-fingered hand was obtained without contacting the objects so the general form of

the posture is only affected by the geometry of the hand and not by external factors, such as contact forces and slippage.

The 19 joint positions, as shown in red in Fig. 3, were converted into 19 joint angles of the human fingers. The inward circumduction of the thumb, the abduction of each finger, as well as the flexion of the metacarpo-phalangeal and interphalangeal joints were defined as positive; the joint angles were set to 0° when the fingers were straight, close together, and in plane with the palm. For the robotic fingers, six joint angles were measured. Angles of the robotic finger joints were defined as 0° when RF was pointing straight forward like the human fingers, and RT was in plane with the palm but perpendicular to the long fingers.

PCA was selected for analyzing the grasping data because it is particularly effective at dealing with situations with large number of system variables (r=19+6=25) and small number of observations (N=40). In [28], it was shown that the first two principal components (PCs) can account for approximately 80% of the data variance in 5-fingered grasps. Similarly for a 7-fingered hand as shown in Fig. 4, the first two or three PCs together can account for most of the data variance. The
significant reduction in the DOFs necessary to form grasping postures suggests that Bio-Artificial postural synergy can be a valid and efficient way to control the SR Fingers. Figure 4 also compares the PCA result of the postural data measured in different coordinate systems. Even though the number of system variables in Cartesian coordinates is three times larger than the number of variables in joint angle coordinates, the percentage variance explained by the most significant PCs are comparable between the two. This suggests that the postural synergy between the seven fingers incorporates some type of inherent human preferences in motion execution that are not influenced by the frame of reference. Therefore for future development of the SR Fingers, detecting and measuring finger postures can be accomplished by a wide range of sensor technologies, which may enable more compact and ergonomic design, as well as more versatile control of the robotic fingers.

SYNERGY-BASED CONTROL

The Bio-Artificial postural synergy of the 7-fingered hand analyzed with PCA suggests that as long as the task is to grasp a class of objects with all seven fingers, the motion of the SR Fingers is strongly correlated with the motion of the human fingers. To obtain a useful control law for natural and implicit coordination between mechanical and biological limbs, we need to capitalize on the postural synergy found earlier and predict the posture of the SR Fingers based on the posture of the human fingers.

We split the experimental data, in finger joint angle coordinates, into an input matrix \(X\), consisting of data from only the five human fingers, and an output matrix \(Y\), consisting of data from the two SR Fingers.

\[
X = [x_1, \ldots, x_n] \in \mathbb{R}^{n \times m}, \quad Y = [y_1, \ldots, y_n] \in \mathbb{R}^{n \times m},
\]

where \(x_i = [x_{1i}, \ldots, x_{7i}]^{\top}\) is an observation of mean-centered joint angles of the human fingers and \(y_i = [y_{1i}, \ldots, y_{10i}]^{\top}\) is that of the SR Fingers \((n=19, m=6)\).

Ordinary multivariate linear regression methods approximate the output matrix with the input matrix via a regression coefficient matrix \(B\),

\[
Y = XB,
\]

where \(B\) is calculated by

\[
B = (X^{\top}X)^{-1}X^{\top}Y. \tag{3}
\]

However, \(B\) is unsolvable if \(X^{\top}X\) is singular, which is caused by either a non-square \(X\) or collinearities between input variables. PCR can circumvent this problem by decomposing \(X\) into orthogonal score matrix \(T\) and loading matrix \(P\) via singular value decomposition (SVD),

\[
X = (UD)VT^{\top} + E = TP^{\top} + E, \tag{4}
\]

and performing regression on the first \(n\) columns of \(T\), also known as the first \(n\) PCs, to find \(B\)

\[
B = P_n(\hat{T}_n^{\top}T_n)^{-1}\hat{T}_n^{\top}Y. \tag{5}
\]

Since PCR only takes into account of variances of the input data, it may not be sufficient for predicting the output in situations where a minor component of \(X\) is highly correlated with \(Y\). PLSR, on the other hand, further expands upon the idea of PC-based regression and uses correlation between the input and output to define the score and loading matrices [49]. The components, called latent variables (LVs), are obtained by iteratively performing SVD on the matrix \(X^{\top}Y\), where \(X\) and \(Y\) are initialized as \(\bar{X}\) and \(\bar{Y}\), respectively. Projecting the first left singular vector, \(w\), onto \(X\)

\[
t = \bar{X}w,
\]

the resulting LV is then normalized to calculate the loading in the input and output space.

\[
p = \bar{X}^{\top}t \tag{7}
\]

\[
q = \bar{Y}^{\top}t \tag{8}
\]

A similar LV for the output space can also be found using the first right singular vector, but it is not necessary for performing regression. To continue the iterative process, \(\bar{X}\) and \(\bar{Y}\) are deflated by subtracting the information accounted for by the LVs, and SVD is performed on the cross product of the new \(\bar{X}\) and \(\bar{Y}\).

\[
\bar{X} = \bar{X} - \hat{p}t^{\top} \tag{9}
\]

\[
\bar{Y} = \bar{Y} - \hat{q}t^{\top} \tag{10}
\]

Putting the vectors \(t, w, p,\) and \(q\) into the columns of matrix \(T, W, P,\) and \(Q\), respectively, the regression coefficient matrix \(B\) based on the first \(n\) LVs, or the first \(n\) columns of the matrixes, becomes

\[
B = W_n(P_n^{\top}W_n)^{-1}(T_n^{\top}T_n)^{-1}T_n^{\top}Y. \tag{11}
\]

Figure 5 compares RMSE of the predicted output using PCR and PLSR. The two methods yielded comparable errors, although PLSR generally performed better than PCR. With three components, RMSE drops to about \(10^6\) for both methods. However, after the third component, the rate at which RMSE decreases becomes much lower: between component 3 and 10, the change in RMSE is less than \(1^\circ\). For the purpose of defining general grasping postures while retaining an efficient control scheme with reduced variable space, approximating the output using three components is sufficient. In [50], it was shown that dividing the input and output variables into smaller groups, for example using the thumb motion to predict the motion of RT and the other fingers for RF, can significantly improve the prediction accuracy. Other control algorithms, perhaps arranged in a hierarchical system with Bio-Artificial Synergy placed at the lowest level, are also needed to fine tune the posture of the
SR Fingers for more specific tasks. Figure 6 illustrates the prediction results of the two methods using three components each. All six output variables are plotted together, and the green line indicates the ideal case where the prediction perfectly approximates the measured result. The two regression methods predicted very similar output, so it would seem either method could be used to perform coordinated control of the SR Fingers. The advantage of PLSR is that, unlike PCs, LVs exist in both input and output space. The patterns of motion used to approximate grasping posture can be interpreted by examining the corresponding input and output LV pairs. Instead of blindly mapping a set of input to a set of output, PLSR allows for extraction of meaningful information from the data to form a better understanding of grasping posture. In that sense, PCR is less useful since PCs are only representative of the input space.

Figure 7 illustrates the first and second LV pairs in input and output spaces. The first two input LVs represent in-phase and out-of-phase motion of the human fingers. Correspondingly, the output LVs exhibited a similar pattern. Furthermore, there is also heavier emphasis on the motion of the first three human fingers these LVs, while the ring finger and little finger contributed much less. Hence, for grasping postures that require all seven fingers, a reduced number of sensors that are mostly concentrated on the first three fingers may still be sufficient.

To validate the PLSR results, we gathered grasping posture data for 10 new objects, following the same protocol as described in the previous section. Based on the three LVs obtained earlier from the training data, the SR Finger joint angles were predicted for this new set of data. Figure 8 shows the error between the predicted SR Finger joint angles and the actual angles the user chose for each of the objects. On average, most of the errors are found in the first two joints of RT and the first joint of RF. Since the user can decide to support the object either from the side or from the bottom, the orientation of the proximal joints can vary significantly, even between grasping trials of the same object. Figure 9 shows the distributions of the prediction error. About 68% of the cases exhibited error less than $\pm10^\circ$. This result is acceptable since strict accuracy is not necessary for prosthetic devices when the user can always adjust his/her body and adapt to the errors. Additional data
REAL TIME CONTROL AND DISCUSSION

To demonstrate the usefulness of the SR Fingers, we implemented the synergy-based control and performed grasping tasks in real time with seven fingers. As illustrated in Fig. 8, the SR Finger joint angles predicted by three LVs can sometimes be much larger or smaller than the desired values. In actual grasping tasks, this would result in the SR Fingers going into or not touching the object. To compensate for such errors, the control algorithm was modified so the SR Fingers would only stop moving if 40% of the torque limit is reached. This limit prevents the servos from overheating and ensures contact with the object. Thus, if the SR Fingers reach the object while the human fingers are still moving, the motion of the robotic fingers would stop prematurely; conversely, if the human fingers stopped moving but no reaction torque is felt by the SR Fingers, they would continue to be actuated at the same rate until the object is reached. Figure 10 shows some examples of grasping various objects in real time using the SR Fingers.

As mentioned earlier, since the first three LVs place heavier emphases on the postures of the first three fingers, the coordinated control may be accomplished with a reduced number of sensors. To that end, we developed a simple data glove by attaching 3 stretch sensors (StretchSense, New Zealand) to the human hand, one on the thumb, one on the index finger, and one on the middle finger and streaming finger bending data into LabVIEW to control the position of the SR Fingers (Fig. 11). PLSR was performed to relate the stretch sensor reading to the robotic finger joint angles. With only three sensors, the motion of the SR Fingers can already be coordinated with the motion of the human fingers to perform synchronized in-phase and out-of-phase movements, similar to those shown in Fig. 7. With more optimally placed sensors, for example along one of the LVs found in the previous section, this coordinated motion can become more accurate and adapt to more specific grasping situations.
can also be accomplished with the help of the SR Fingers. As illustrated in Fig. 12, after the robotic fingers reach the desired positions, a hold function was initiated, allowing the user to perform 2-handed tasks with a single hand, such as stirring a cup of coffee, opening a container, or twisting the cap off a bottle.

FIGURE 12 THE 7-FINGERED HAND CAN PERFORM TASKS THAT WOULD USUALLY REQUIRE TWO HANDS.

CONCLUSIONS AND FUTURE WORK

In this paper, we presented an alternative approach to upper-limb prosthesis. Instead of replacing lost limbs, the SR Fingers serve to improve the capabilities of the healthy limb. Using the novel and effective synergy-based coordination control, we can correlate the motion of the SR Fingers with the human fingers in a natural and implicit manner. The Bio-Artificial Synergies generate low-level behaviors that play the key role in transforming a robot to act as part of the human body.

Since finger force and torque play an important role in grasp stability [7, 9], our next step is to add tactile sensors to the prototype and determine correlation of fingertip forces between SR and human fingers. Control of contact forces will be more effective than merely controlling the hand posture in adapting to the geometric irregularity and material uncertainty (e.g. hardness and coefficient of friction) of the object, hence enabling better grasp stability as reported in the literature of human fingers [29-33].

Besides finding the right finger morphology and attachment configuration for effective and secure grasps, the design of the SR Fingers must also be optimized through usability studies to ensure wear comfort and avoid secondary injuries that may be caused by repetitive use of the device. Recent studies on complaint robotic fingers have shown great potential in terms of dexterity, adaptability, and robustness [51, 52]. Incorporating soft actuators and sensors into the SR Fingers may be help make the robot more compact and lightweight.

The methodologies described in this paper can be extended to larger size SR Limbs in diverse tasks and contexts. It is our hope that with further development, SR Limbs and Fingers will increase the capability of senior citizens and people with disabilities, allowing them to enjoy a greater sense of independence or get employment opportunities that were otherwise not available to them. SR Limbs will be a promising and important branch of wearable robots that will infuse unique concepts of human-robot coordination. We hope this will provide a new direction for human-robot interaction and enable other prosthetic and assistive technologies to be developed in the future.

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