SoftHand Pro-D: Matching Dynamic Content of Natural User Commands with Hand Embodiment for Enhanced Prosthesis Control

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Abstract— **State of the art of hand prosthetics is divided between simple and reliable gripper-like systems and sophisticate hi-tech poly-articular hands which tend to be complex both in their design and for the patient to operate. In this paper, we introduce the idea of decoding different movement intentions of the patient using the dynamic frequency content of the control signals in a natural way. We move a step further showing how this idea can be embedded in the mechanics of an under-actuated soft hand by using only passive damping components. In particular we devise a method to design the hand hardware to obtain a given desired motion. This method, that we call of the dynamic synergies, builds on the theory of linear descriptor systems, and is based on the division of the hand movement in a slow and a fast components. We use this method to evolve the design of the Pisa/IIT SoftHand in a prototype prosthesis which, while still having 19 degrees of freedom and just one motor, can move along two different synergistic directions of motion (and combinations of the two), to perform either a pinch or a power grasp. Preliminary experimental results are presented, demonstrating the effectiveness of the proposed design.**

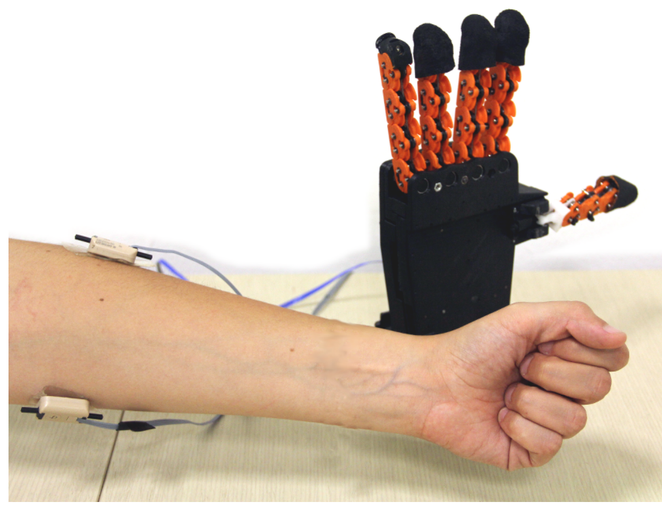

Fig. 1. The prototype of dynamic synergies prosthesis being tested. The two EMG electrodes are visible on the arm of a subject.

I. INTRODUCTION

Today, most prostheses in practical use are either merely aesthetic or extremely simple, while robotics-enabled prostheses are still too costly, fragile, and unintuitive to be widely used.

Although global-level statistics are difficult to extrapolate from the heterogeneous, sometimes difficult to access, data of medical records, the *status quo* of upper limb prosthetic aid is constituted by cosmetic prostheses (CPs): merely aesthetic devices, designed to maximize social and self acceptance by the patient in terms of body image, they offer a very limited, almost null, level of function. At the second place come body-powered prostheses (BPPs) that use an elastic grasping mechanism activated by the patient with a tendon, usually attached to a harness worn on the shoulders or some other body part. BPPs are widely used around the world for their robustness, ease of use and low cost. Both these category of prostheses are totally passive, whereas motion is either totally absent, as in CPs, or generated by the user, as in BPPs.

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A third type of prostheses that reached a good diffusion is that of myo-electric prostheses (MEPs). They have usually one motorized DOF, controlled by the patient thanks to signals fetched from the activation of two muscles on the surface of the residual limb. MEPs are active, meaning that they do no need the a physical effort from the patient in order to generate motion (as opposed to BPPs), with undeniable advantages in terms of fatigue. Unfortunately, a *cognitive* component of fatigue is now present, due to the concentration needed to operate the device.

Finally, the state of art of modern hand prosthetics is populated by devices which, in order to achieve a higher degree of dexterity, are characterized by a large number of articulated joints. Usually referred to as poly-articular prostheses (PAPs), they usually offer a broader set of movement capabilities, with the possibility to control up to 4 or 5 motors independently and achieve several different postures.

Despite their high active dexterity - or, as we claim, perhaps because of this - most state-of-the-art devices are often deficient in terms of functionality, durability, adequate cosmetic appearance, and affordability [1]. In particular, to control such a high number of motors, two surface EMG electrodes are not sufficient any more. In commercial devices this gap is usually bridged by the adoption of switching strategies (we describe some examples in section II) which often tend to be rather complex to use for the patient.

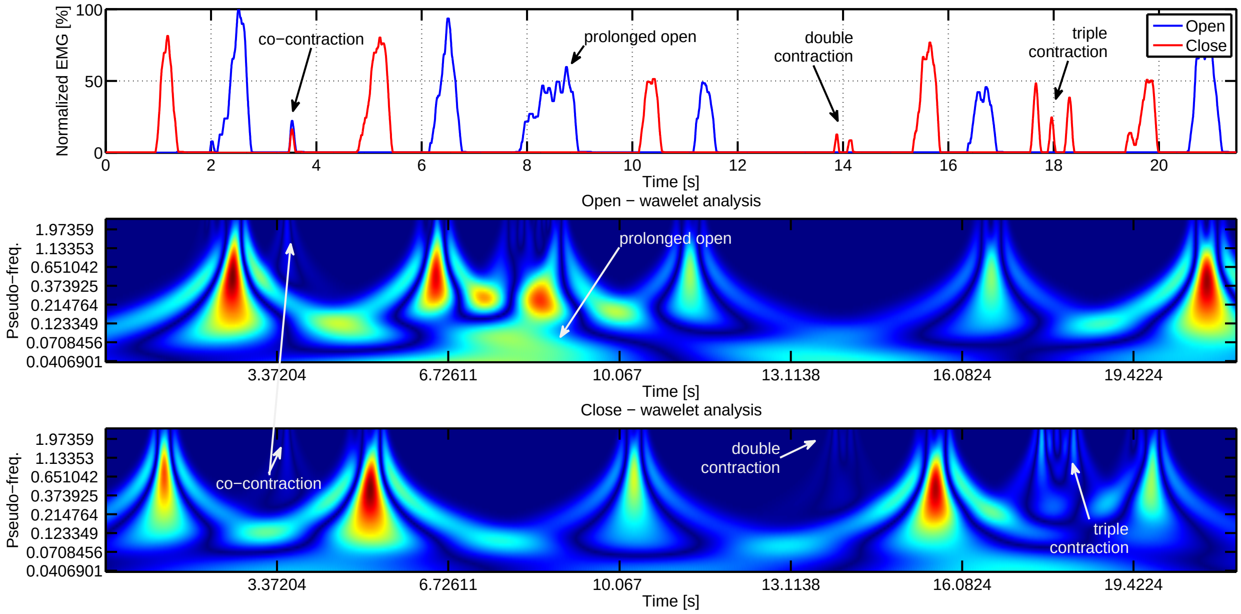

Fig. 2. Wavelet analysis of EMG control signals typically observed when operating a commercial PAP. Four arrows point to the switching commands, while the rest of the signals correspond to proportional operation of the hand (open and close). From the wavelet analysis it is possible to see that the the switching commands occupy the high frequencies (top of figures - activity is present in both signals for the co-contraction and in the closing signal alone for the double and triple contractions) and the very low spectrum of the frequencies (the prolonged opening is visible on the bottom part of the open channel), while the proportional control lies mostly in the middle - low slice of the spectrum. Note that the two signals are actual recording of EMG signals, acquired with two Ottobock electrodes at the frequency of 10Hz, on a sound person simulating the control modes described in section II.

Because of the former limitations, a consistent amount of research revolves around increasing the performance of EMG prostheses control. Two very successful recent approaches are those based on Targeted Muscular Re-Innervation [15] and Intra-Muscular Wireless EMG transceivers [19]. Both techniques substantially increase the reading precision achieved in recording the electrical muscle activation signal and have been demonstrated able to successfully control a multi-DOF prosthesis. Unfortunately, both these approaches are able to achieve such results at the cost of: (i) requiring larger number of electrodes, and moreover (ii) being invasive - both approaches, in fact, require some amount of surgery to be applied.

Other branches of research, on the other hand, try to overcome the limitation of standard surface EMGs by just increasing the number of electrodes and applying state of the art pattern recognition techniques [14], [17], [20], [11]. In particular the most ambitious goal for modern surface EMG interpretation [8] and prostheses control [4] is the extraction of modulating values, that is to be able to reconstruct signals that are somehow continuous in nature and carry magnitude information that can be used to modulate different control channels, while past techniques were just based on assessing the membership of the input to a particular class or cluster, out of a finite set.

In this paper we propose an approach that tries to exploit the frequency content of EMG in an innovative and natural way. A prototype of a dynamic synergies hand was designed and it was tested by using commercial EMGs electrodes. Rather than using the sort of frequency modulation that commercial EMG decoders adopt, we aim at shaping the posture of a PAP by using the velocity reference itself, associating different speeds with different movements. A slow muscle contraction was associated with a slow synergy while the fast synergy came from a fast muscle contraction.

The rest of the paper is organized as follows: section II exposes the open problem of controlling a multi-DOF prosthetic device with EMG signals, while section III presents and motivates our approach to its solution. Section IV shows how such a solution can be embodied in the hardware of a soft hand by introducing the concept of *dynamic synergies*. Section V describes a prototype designed following our methodology whose performance are demonstrated in experiments presented in section VI. Finally, section VII draws the conclusions of our work.

II. PROBLEM STATEMENT

As anticipated in the introduction, one problem that severely hinders the diffusion of multi-DOF prostheses resides in the barriers that the user needs to overcome to control them. While traditional 1 DOF MEPs are controlled by two sEMG electrodes, one for opening and one for closing, the control of a large number of DOFs is not this straightforward.

To exploit all the possibilities offered by modern PAPs, up to 4 or 5 DOFs must be controlled simultaneously. To simplify this problem, usually PAPs embed a micro-controller unit that takes care of controlling the prosthesis motions by subdividing it in a series of pre-programmed gestures. Within each gesture the hand move in a proportional way using, once again, just two control signals: open and close. Unfortunately this approach does not solve the problem completely, but rather shifts it on the level of requiring some kind of mechanism to switch between strategies. Commercial PAPs usually rely on discrete triggering policies to let the patient switch the hand between different motion patterns. Some of the triggering policies adopted by products on the market include (all the following modalities are extracted from [12]) :

- EMG trigger sequences: specific muscle signals are used to switch between different postures, examples include
  - co-contraction (simultaneous activation of the two opposite muscle channels),
  - trains of impulses (e.g. doubles and triples of brief, strong muscle activations) and
  - held signals (keeping the open - or close - signal active for at least a fixed amount of time when the hand is already fully open - or closed).
- Gesture recognition: the hand uses a combination of muscle EMG triggers (as the former) and inertial measurements coming from an on-board IMU to recognize user gestures and select the grasp posture consequently.
- Smart-phone control: the hand posture is selected on a touch-screen with the other hand, and sent to the prosthesis via wireless or blue-tooth communication.
- Short-range beacons (also called proximity sensing): the prosthesis can be programmed to sense the proximity of small radio devices (based on NFC, RF-ID or other similar technologies), and to react by switching to a predefined posture. These beacons can be installed either:
  - in objects that are grasped frequently (object-installed beacons) or
  - on the user body (body-worn beacons), e.g. in clothes and pockets.

All of these strategies have limitations: some require the execution of unnecessary, potentially un-natural movements (gesture recognition and body-worn beacons), others require the operation of an additional device with the other hand (smart-phone control), and most of them charge the patient with non-negligible cognitive load, EMG trigger probably being the most cognitively-intense. The only one which minimizes the user cognitive load (object-installed beacons) requires prior adaptation of the surrounding environment and, as such, will never cover the totality of situations a user can live in.

Summing up, the problem we wish to tackle is the control of a PAP by using a reduced set of EMG measurements, ideally just two.

III. IDEA

In order to make a step toward the resolution of the described problem we propose here a paradigm shift, aiming to reach a more natural encoding of the user intentions.

Looking at the problem with the eye of the signal theory, commercial EMG-based approaches somehow *decode* the desired control of the PAP by operating a sort of *frequency division* of the EMG signals. In fact, if we look at the illustrative control signals of Fig. 2, and in particular at their frequency content, it is clearly possible to separate the phases of proportional prosthesis operation (i.e. when the prosthesis is controlled within a modality) from the phases of switching operation (i.e. when the user switches between postures) by just looking at the frequency content of the signal, in particular the very low range of the bandwidth and the higher band are dedicated to modality switching, while the middle part of the bandwidth is dedicated to proportional control. This approach, which can be implemented very efficiently, requires the user to *encode* the desired motion of the prosthesis in a rather unnatural sequence of frequency separated *packets* of information (performing almost a sort of Frequency Shift Keying modulation), burdening the user mind by forcing it to behave almost as a modem.

Hence we believe that forms of encoding that are more natural for the human beings has to be investigated. A simple model describing the transformation of action potential into muscle activation (proportional to the EMG signal associated with the muscle) is a low-pass filter. For limb muscles the effective cutoff frequency is $\sim 2\,Hz$ [3]. Hence a bigger effort is required in order to generate an high frequency activation w.r.t. a low-medium frequency one. Thus a natural way of encoding the desired behaviour of a prosthesis should favor encoding in the low-middle spectrum of the signal band.

A possible inspiration on how to approach this road comes from the observation (e.g. [16]) that precision tasks usually require higher attention, and are performed more slowly, with respect to strength tasks. In particular, Vainio et al. [22], [21] demonstrated that precision grip tasks on small objects require statistically longer times to be performed than power grip tasks on bigger objects.

So we assume that it could be more intuitive for a user to have slower controls associated with movements that are usually slow and faster signals associated with movements that are usually fast. We also believe that a smooth transition between the behaviors would be perceived as more natural rather than a discontinuous one.

We call this idea of smoothly encoding different postures with different speeds of the motion commands *natural encoding of user intentions*.

This idea can be implemented both on PAPs with many independent motors, by the *active* synchronized control of the different motors, or it can be *passively* embodied in the hardware of a prosthesis by using passive mechanical components as springs and dampers. In the next section we will demonstrate how this passive approach can be integrated in a synergy-based soft prosthesis.

IV. DYNAMIC SYNERGIES

Many experimental human motor studies (from [18] to [9]) suggest that a reduced basis of the hand joint space is sufficient for most of the total movement during grasping tasks. This basis is named *postural synergies*. We will refer to it through the matrix S. Based on this [2] proposes to generate reference motions, using a reduced set of the main postural synergies, which the real hand follows, compliantly attracted, while physically interacting with the environment.

An implementation of this concept, the adaptive synergies [10], was used for the design of the Pisa/IIT SoftHand [5], which with only one soft synergy is able to present excellent grasp capabilities.

We introduce here the dynamic synergies, an evolution of the adaptive synergies which permits to embed the passive intention encoding concept into the system mechanics. Using a set of dampers, connected to the hand joints through a generic transmission system, we are able to generate different closures, i.e. different sets of synergies S, as the input speed change. With respect to the add of new degrees of actuation, this solution permits to maintain low encumbrance and weight and a simple structure.

Assuming a PAP hand is under-actuated by means of a differential mechanism with transmission distribution matrix R, it is possible to write

$$Rq = \sigma \Rightarrow \tau_\sigma = R^T u \, , \tag{1}$$

where σ is the displacement of the motor, τ_σ is the vector of torques acting on the joints and u the force from the motor. Similarly we call T the transmission distribution that maps joint angles q into dampers positions x.

$$Tq = x \Rightarrow \tau_x = T^T (C\dot{x}_d) = T^T C T \dot{q} \, , \tag{2}$$

Note that the matrix C can always be chosen full rank and diagonal. Moreover without loss of generality, eventually rearranging σ and x, we can take both R and T orthonormal.

Writing the equilibrium of the joint torques, we obtain the dynamic system:

$$T^T C T \dot{q} + Eq = R^T u + w \, , \tag{3}$$

Since $Rank\{T^T CT\} = n_d \leq n$, this system falls into the class of the so-called descriptor linear system [7]. Being the system regular (E is invertible), the problem results well posed, i.e. there exist always an unique solution.

We consider here the hand behavior for two extremal conditions: fast and slow closure. We call *slow closure* an hand closure such that $\dot{q} \simeq 0$, i.e. where the damping force effect is negligible, giving:

$$Eq = R^T u + w \, , \tag{4}$$

which is the adaptive synergies force balance. It is worth to be noticed that the imposed condition corresponds to say that the system follows a quasi-static trajectory, since it is in the equilibrium condition. This also means that the synergy that we derive here is the hand steady state. Now grouping yields the equation:

$$\begin{bmatrix} -E & R^T \\ R & \emptyset \end{bmatrix} \begin{bmatrix} q \\ u \end{bmatrix} = \begin{bmatrix} w \\ \sigma \end{bmatrix} \, . \tag{5}$$

Solving it we obtain:

$$\begin{cases} q & = S_s \sigma + N_s w \\ S_s & = E^{-1} R^T (R E^{-1} R^T)^{-1} = R^+_{E^{-1}} \\ N_s & = E^{-1} - E^{-1} R^T (R E^{-1} R^T)^{-1} R E^{-1} = P_R^\perp E^{-1} \, . \end{cases} \tag{6}$$

Hence by proper choice of E and R we can design any slow closure (e.g. for $E = kI$, we have that $S_s = R$).

Now, following descriptor system theory, we can perform a standard decomposition of the system (3), into a *fast* and a *slow* subsystems, through the pre-multiplication of the matrix $[T^T, T_\perp^T]^T$, where $T_\perp$ is a base completion of T, such as $T\,T_\perp^T = 0$ and $T_\perp\,T_\perp^T = I$. Hence it results:

$$\begin{bmatrix} T \\ T_\perp \end{bmatrix} T^T C T \dot{q} + \begin{bmatrix} T \\ T_\perp \end{bmatrix} E \begin{bmatrix} T^T, T_\perp^T \end{bmatrix} \begin{bmatrix} T \\ T_\perp \end{bmatrix} q = R^T u + w \, , \tag{7}$$

Hence, calling $y \triangleq T_\perp q$

$$\begin{cases} C\dot{x} + TET^T x + TET_\perp^T y & = T(R^T u + w) \\ T_\perp E T^T x + T_\perp E T_\perp^T y & = T_\perp (R^T u + w) \end{cases} \tag{8}$$

Where x is the state of the *slow* system. Now we explicit y and we substitute it in the first equation. The resulting standard decomposition is (we pose $w = 0$):

$$\begin{cases} \dot{x} & = Ax + Bu \\ T_\perp E T_\perp^T y & = -T_\perp E T^T x + T_\perp R^T u \\ q & = Tx + T_\perp y \end{cases} \tag{9}$$

Where

$$\begin{cases} A & = -C^{-1}(TET^T - TET_\perp^T (T_\perp E T_\perp)^{-1} T_\perp E T^T) < 0 \\ B & = C^{-1}(T - TET_\perp^T (T_\perp E T_\perp^T)^{-1} T_\perp) R^T \end{cases} \tag{10}$$

We call a *fast closure* the period of the hand closure in which the force u is sufficiently fast to approximate[1] $T^T C T \dot{q} \simeq 0$ and $\dot{q} \neq 0$. In this hypothesis, deriving w.r.t. the time the second equation of (1) and (9) we obtain:

$$\begin{bmatrix} -T_\perp E T_\perp^T & T_\perp R^T \\ R T_\perp^T & \emptyset \end{bmatrix} \begin{bmatrix} \dot{y} \\ \dot{u} \end{bmatrix} = \begin{bmatrix} \dot{w} \\ \dot{\sigma} \end{bmatrix} \tag{11}$$

Hence $E_y = T_\perp E T_\perp^T$ assumes the role of an equivalent stiffness matrix, and $\mathfrak{R} = R T_\perp^T$ the role of an equivalent ratio matrix. Solving w.r.t. $\dot{y}$ we obtain:

$$\dot{y} = \mathfrak{R}^+_{E_y^{-1}} \dot{\sigma} \tag{12}$$

where $\mathfrak{R}^+_{E_y^{-1}}$ is the pseudo-inverse of $\mathfrak{R}$ weighted on E_y. Integrating, it gives:

$$y = y_0 + \mathfrak{R}^+_{E_y^{-1}} \sigma \Rightarrow q = q_0 + T_\perp^T \mathfrak{R}^+_{E_y} \sigma \, . \tag{13}$$

Thus we call fast dynamic synergy matrix:

$$S_f = T_\perp^T \mathfrak{R}^+_{E_y^{-1}} , \tag{14}$$

which identifies the obtainable hand closures when the hand is closed fast. This matrix depends on the same parameters of the slow synergy S_s (i.e. E and R) and on the damper topology T (it is worth to be noticed that S_f does not depends on the choice of the completion matrix $T_\perp$, as we show in appendix).

As results from previous considerations, the hand follows the fast synergy reference $S_f \sigma$, only for a limited period of time (i.e. until the condition $T^T C T \dot{q} \simeq 0$ holds), converging finally to the slow synergy equilibrium S_s. Hence S_s has to

[1] Note that this condition is true for any signal for a sufficiently small period of time.

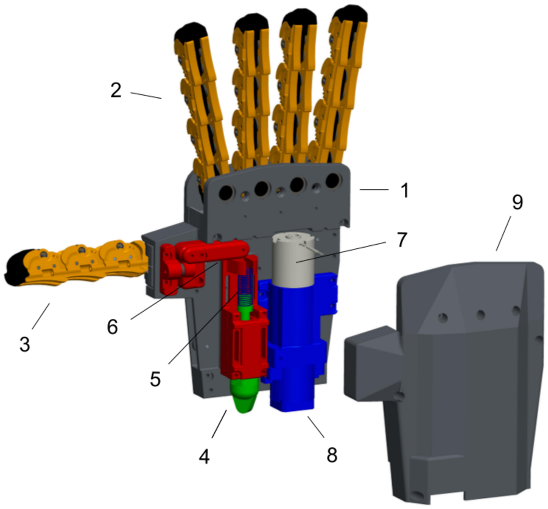

Fig. 3. CAD Model of the prototype of the dynamic synergies hand. The viscous element is placed in the dorsal side of the palm, directly connected with the distal and proximal joints of the thumb.

be used for task that requires a finite time to be executed (e.g. in-hand manipulation), or in a context where hand pre-shaping, together with external constraints, lead to achieve different steady state positions.

In the prototype proposed in this work, we fall in the second case, taking advantage of the constraint represented by the contact between fingers, and/or between finger and object.

V. PROTOTYPE IMPLEMENTATION

A. Design choices

In [13] authors present a statistical study of daily life hand movements. It results that movements of the four long fingers are closely related. In contrast the movements of the thumb are quite independent from each of the four fingers, and its percentage of exclusive movements is twofold more frequent than those of the index finger. Thus, among the other things, different relative positions of thumb and index fingers permit to pass from precision to power grips [6]. The importance of these skills in every-day life is well known (e.g. [24]), such as their role in the human evolution [23].

For this reason we focus in the design of dynamic synergies which differ for thumb motion. The pulleys R and the springs E are designed as in the PisaIIT SoftHand [5], implementing the first synergy of grasp. One damper with transmission ratio $T = [0\ \frac{1}{\sqrt{2}}\ \frac{1}{\sqrt{2}}\ 0 \dots 0]$, where the non zero elements refer to distal and proximal thumb joints, results sufficient in order to implement the researched behavior. The corresponding fast synergy is $S_f \simeq [\frac{1}{4}\ 0\ 0\ \frac{1}{4} \dots \frac{1}{4}]$.

B. Hand description

As shown in Fig. 3, the hand prototype is an evolution of the Pisa/IIT Softhand. The palm structure (1) and the fingers (2-3) are the same of the previous version. The actuation is guaranteed by a 24V DC motor (7), placed in the dorsal side of the palm and integrated in a support structure (8). The damping element is a small hydraulic piston (4) filled with silica oil. The oil can be changed in order to obtain different viscosity coefficients. The damper is placed in the dorsal side of the hand, parallel to the motor. It is directly connected with a compression spring (5), to ensure the return at the rest position of the damper piston during the hand reopening phase. Only the thumb (3), and in particular its distal and proximal joint, are directly connected with the damper through a tendon. A support structure (6) hosts the damper and, thanks to two slots, provides the possibility to regulate its position. Furthermore the damper remains continuously connected with the thumb through a tendon that routes over a group of bearings. Finally a cover (9) allows to have a more smooth and pleasant design, in addiction to providing protection to the elements placed in the dorsal part of the hand in case of impact.

VI. EXPERIMENTAL RESULTS

In this section we demonstrate the capabilities of the prototype hand designed using the method of the dynamic synergies.

A. Experiment 1

In a first experiment, the hand is controlled through a Matlab/Simulink interface, based on the software of the SoftHand, available online in the repository of the Natural Machine Motion Initiative website[2]. The system is fed a fast ramp command, to demonstrate the fast synergy, a slow ramp, to demonstrate the slow synergy. The fast ramp is setted at the maximum closing speed of the hand. Figures 4 shows the slow and fast dynamic synergies motions of the prototype hand. As it was designed, the two different motions lead the hand toward the two postures corresponding to the power grasp (the closed fist) and to the pinch (thumb-index opposition). A dynamic fast to slow motion, to show the natural continuous sliding from fast to slow motion is shown in Fig. 5.

B. Experiment 2

In a second experiment, the hand was controlled with a mechanical interface in order to grasp some objects, thus showing the advantage of having a spectrum of possible grasps from where to choose. The images in Fig. 6 show the ability of the prototype in grasping objects of several sizes and shapes, adopting grasps that lie in the full spectrum that goes from the pinch grasp posture to the power grasp posture.

C. Experiment 3

Finally, the prototype of dynamic synergies prosthesis was controlled using two Ottobock surface EMG electrodes. The experimental setup is shown in Fig. 1, where the EMG electrodes are connected, as input, with the electronic board of the hand. Fig. 7 shows the wavelet analysis on some EMG signals used to effectively drive the prototype. It can be seen

[2] `www.NaturalMachineMotionInitiative.com`

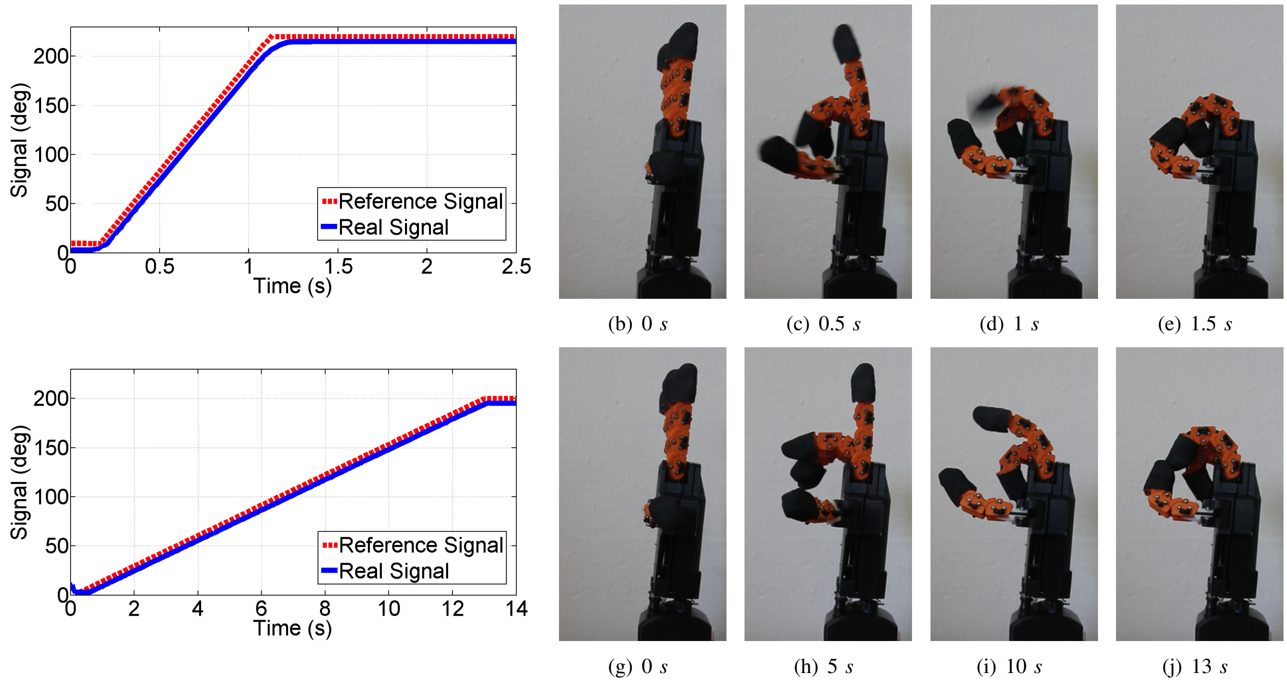

Fig. 4. The prototype moving along the fast synergy (top row) and along the slow synergy (bottom row), the two plots (leftmost panels) show the reference value and the effective position of the motor. The snapshots show the hand closing. It is possible to see that the fast synergy closes the hand in a fist (the primitive synergy of the power grasp) while the slow motion closes the hand in a pinch grasp. Note that the snapshots are extracted at different instants of time for the two sequences; this is in accordance with the fact that the slow synergy takes longer to close than the fast synergy. Note also that in order to maximize the decoupling, the speed of the slow synergy is very low, resulting in a rather long closure time. The closure time to obtain a pinch grasp needs not to be so slow, as it is show in Fig. 5.

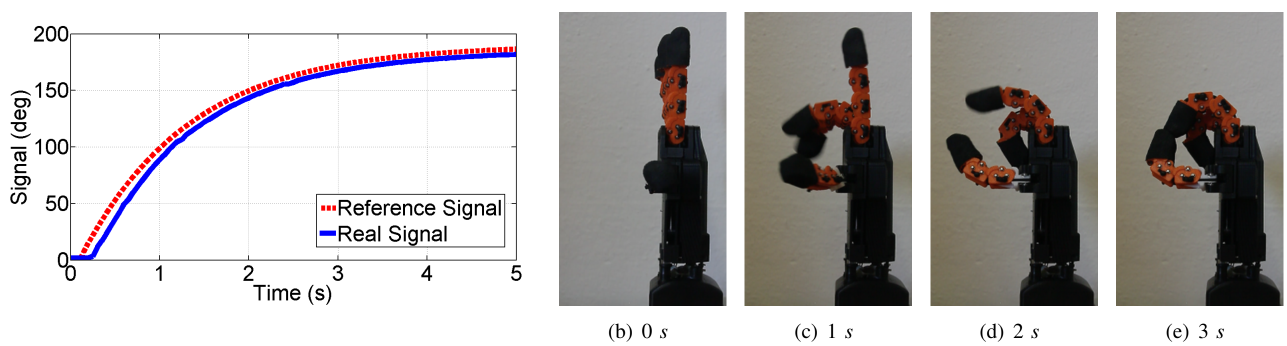

Fig. 5. Shortest time needed to obtain a pinch grasp, reference and actual motor position (a) and snapshots of the hand closing (other panels). By optimizing the reference, it is possible to seamlessly shift from the fast to the slow synergy, and thus minimize the time to closure while still obtaining a pinch grasp closure.

that signals are more spread in frequencies because there is no need to separate frequencies as in Fig. 2.

Additional details can be found on the video attachment.

VII. CONCLUSIONS

This paper intended to tackle the problem of encoding different movement intentions of the user of a poly-articular prosthesis using the dynamic frequency content of the control signals in a natural way. To achieve this objective we drew inspiration from how human movements normally present a correlation between precise and slow motions on one side and strong and fast motions on the other. Moreover, we demonstrated how this approach can be passively embedded in the hardware design of a soft synergistic hand by using dampers. We derived a method to place the dampers in order to design a given set of motions, that we call the method of *dynamic synergies*. Using this method we designed a prototype prosthetic hand which has 19 degrees of freedom and just one motor and can move along two different synergistic directions of motion, to perform either a pinch or a power grasp. The prototype function was demonstrated in some preliminary experiment. Future works will address proper validation of our approach with patient studies.

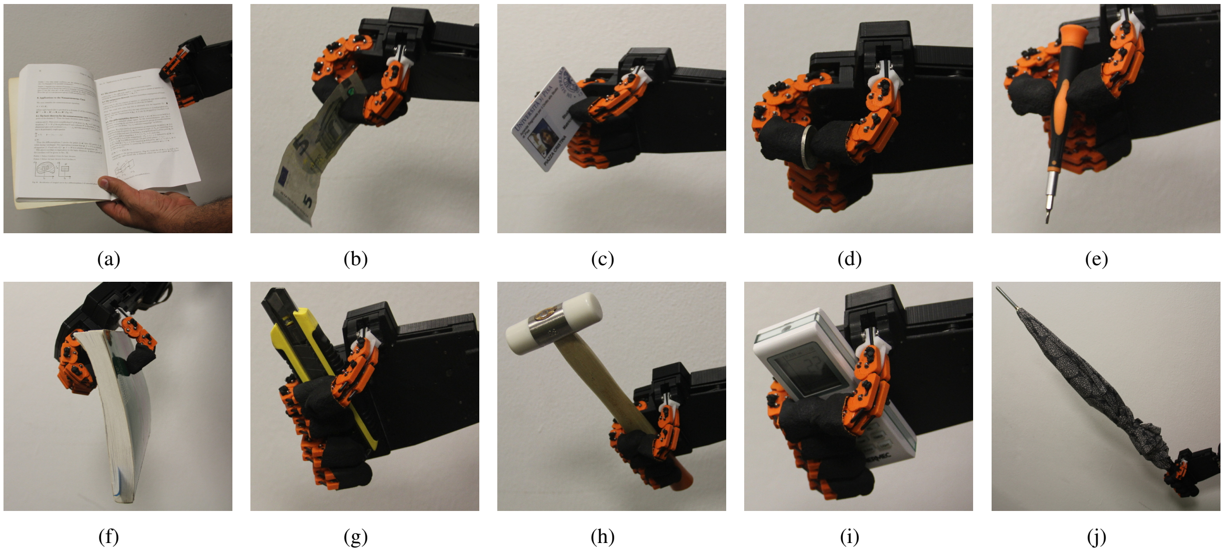

Fig. 6. Some example of grasps using SoftHand Pro-D: pinch grasps (a-e) and power grasps (f-j).

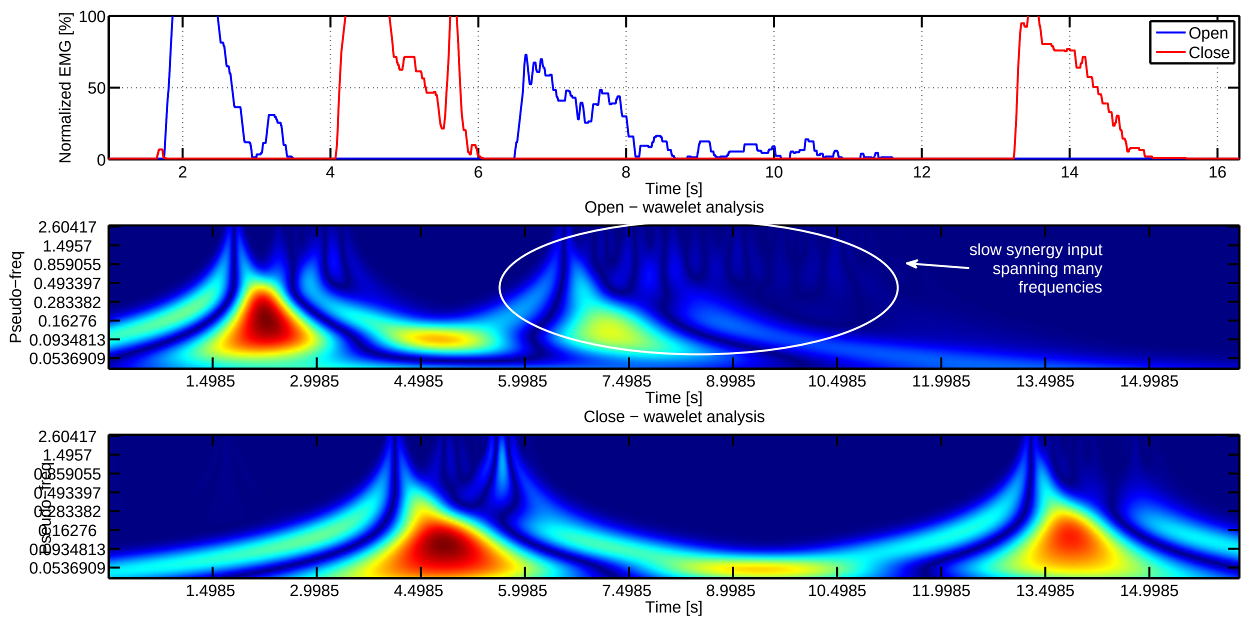

Fig. 7. Wavelet analysis of EMG control signals used to control the prototype hand. The signals are more spread in frequencies because there is no need to separate frequencies as in Fig. 2. Note that the signals were acquired on a sound individual.

APPENDIX

Taking the fast dynamic synergy expression:

$$\begin{aligned} S_f = & T_\perp^T \mathfrak{R}^+_{E_y^{-1}} = \\ & = T_\perp^T E_y^{-1} \mathfrak{R}^T (\mathfrak{R} E_y^{-1} \mathfrak{R}^T)^{-1} = \\ & = T_\perp^T (T_\perp E T_\perp^T)^{-1} (R T_\perp^T)^T ((R T_\perp^T)(T_\perp E T_\perp^T)^{-1} (R T_\perp^T)^T)^{-1} \end{aligned} \tag{15}$$

We write a different choice of $T_\perp$ as the generic change of variables $T_\perp \to U T_\perp$, with U unitary. We call S_f^U the associated fast dynamic synergy. From which:

$$\begin{aligned} & T_\perp^T U^T (U T_\perp E T_\perp^T U^T)^{-1} (R T_\perp^T U^T)^T = \\ & = T_\perp^T (U^T U^{-T})(T_\perp E T_\perp^T)^{-1} (U^{-1} U)(R T_\perp^T)^T = \\ & = T_\perp^T (T_\perp E T_\perp^T)^{-1} (R T_\perp^T)^T , \end{aligned} \tag{16}$$

and:

$$\begin{aligned} & (R T_\perp^T U^T)(U T_\perp E T_\perp^T U^T)^{-1} (R T_\perp^T U^T)^T = \\ & = (R T_\perp^T)(U^T U^{-T})(T_\perp E T_\perp^T)^{-1} (U^{-1} U)(R T_\perp^T)^T = \\ & = (R T_\perp^T)(T_\perp E T_\perp^T)^{-1} (R T_\perp^T)^T \end{aligned} \tag{17}$$

Hence we have that

$$S_f^U = S_f \quad \forall U \; s.t.: \; U^T U = I \tag{18}$$

i.e. the result is independent from the choice of $T_{\perp}$.

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