MULTI-SUBJECT / DLA ANALYSIS OF SURFACE EMG CONTROL OF MECHANICAL HANDS

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INTRODUCTION

This work is about smart control of Active Hand Prostheses (AHPs). An AHP is a hand prosthesis which can be voluntarily actuated, to some degree, by the patient wearing it. Among other characteristics, the ideal AHP is highly dexterous and naturally controlled, but at the time of writing even the best commercially available AHPs, Otto Bock's SensorHand and Touch Bionics's i-Limb, have just one or two DOFs; it comes as no surprise that they are controlled by, at best, three surface electromyography (EMG) electrodes, resulting in unnatural control which must be learned by the patient. Nevertheless, the mechatronics of AHPs is getting better, the i-Limb being an example, together with, e.g., the DLR prosthetic hand [1] and the CyberHand.

With the aim of enabling a patient to finely control the forthcoming AHPs, then, in [2] we already showed that forearm surface EMG can be used to detect in real-time both what kind of grasp a human subject is willing to use, and how much force is required. Actually, recent literature (see, e.g., [3,4]) points at surface EMG as a viable device to reconstruct the act of grasping, and therefore for a "natural" control of hand prostheses.

Here we extend that work, which was done in highly controlled conditions and on one human subject only, to (a) multi-subject and (b) Daily Life Activities (DLA) analysis. Issue (a) has involved multiple subjects whose EMG has been monitored and independently related to their way and force of grasping a force sensor, whereas issue (b) was tackled by letting the subjects freely walk, move their arm and pronate/supinate while doing the experiment. Although preliminary, our results are encouraging.

METHODS

Ten healthy subjects, two women and eight men, volunteered to join the experiment; they were given no knowledge of what the experiment was. Seven single-differential Aurion *ZeroWire* wireless electrodes for surface EMG were placed on their dominant arm (see Figure 1(a)); a FUTEK *LMD500* force sensor was used to detect the force involved in the grasping (Figure 1(b)). The electrodes were positioned as carefully as possible in order to detect the activity of the most relevant flexor and extensor muscles; their signal was gathered by a standard data acquisition card and sampled at 2 KHz.

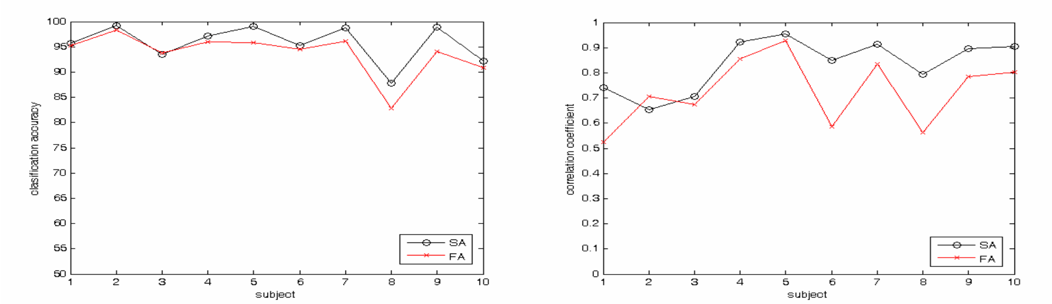
(a) (b) (c) (d) (e)

Figure 1: the experimental setup *(a–b)* and grasp types *(c–e)*.

In the first phase, each subject had his arm still and relaxed on a table; in this condition, he was asked to grasp the sensor, in turn, in three different ways (besides rest, which was sampled beforehand): index precision grip, other fingers precision grip and power grasp (Figure 1(c, d, e)). The subject freely repeated each grasping action for 100", resting for 30" in between grasps. All was repeated twice, in order to gather more data and smooth out as much as possible local, statistically irrelevant errors. This phase was called *Still-Arm experiment (SA).* A second, more interesting phase consisted in exactly the same exercise, but letting the subject freely move, walk around, lift and pronate/supinate his arm and forearm, as one is expected to do in DLAs. This latter phase was called *Free-Arm experiment (FA).* All in all, each subject's experiment resulted in something more than 1200" of data. We pre-processed the data, subject by subject, by first evaluating the Root Mean Square of the signal over a certain time-window, and then reducing it via Online Uniformisation (OU). The first step is well-known to make the EMG signal highly related to the muscular force [5]; OU is required in order to reduce the number of samples given to the machine learning system without degrading too much its performance [2], making it usable on-line and in real-time, which is the medium-term aim of this work. OU works by discarding samples which are too close to already-acquired samples, according to Euclidean distance. We employed Support Vector Machines [6] with a Gaussian kernel to estimate the map from the EMG signal to the type of grasp (classification) and the force involved (regression).

RESULTS AND DISCUSSION

Figure 2 shows initial classification and regression results, for the ten subjects involved.



(a) (b)

Figure 2: experimental results obtained for classification of grasp types (a – percentage of correctly guessed grasps for each subject) and regression on the applied force (b – correlation between guessed and actual force for each subject).

As one can see, results are overall excellent for classification (95.73% ± 3.76% for SA, 93.74% ± 4.32% for FA) and good for regression (0.83 ± 0.1 for SA, 0.73 ± 0.14 for FA); moreover, they are consistent by experiment *and* by subject. After some initial experiments, the RMS time window was set at 0.5” for classification and 0.1” for regression; classification actually benefits from a wider time window – a phenomenon which we will investigate in the short term. 5-fold cross-validation and grid search for the SVM hyperparameters, C and σ, were used; the training/testing sets have been acquired from each subject in a single-session experiment lasting about half an hour.

Summing up, this work shows that surface EMG can be used to classify grasps and predict the involved force, within a broad range of human subjects, and even if these subjects act in non-highly controlled conditions, that is, while performing DLAs (Daily Life Activities). This work can also be viewed as the natural extension of [2], where we posed four subproblems regarding this problem, and only solved two of them; here we are about to solve the remaining two. When this is done in a rock-solid way, we will be ready to test the approach on patients in a clinical setting, which is what we hope to do in the short to medium term.

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