Fine detection of grasp force and posture by amputees via surface electromyography

Claudio Castellini[*,a], Emanuele Gruppioni[b], Angelo Davalli[b], Giulio Sandini[c]

[a] *LIRA-Lab, University of Genova, viale F. Causa 13, 16145 Genova (Italy)*
[b] *INAIL Centro Protesi, via Rabuina 14, 40054 Vigorso di Budrio (Bologna, Italy)*
[c] *RBCS Department, Italian Institute of Technology, via Morego 30, 16163 Genova (Italy)*

Abstract

The state-of-the-art feed-forward control of active hand prostheses is rather poor. Even dexterous, multi-fingered commercial prostheses are controlled via surface electromyography (EMG) in a way that enforces a few fixed grasping postures, or a very basic estimate of force. Control is not natural, meaning that the amputee must learn to associate, e.g., wrist flexion and hand closing. Nevertheless, recent literature indicates that much more information can be gathered from plain, old surface EMG. To check this issue we have performed an experiment in which three amputees train a Support Vector Machine (SVM) using five commercially available EMG electrodes while asked to perform various grasping postures and forces with their phantom limbs. In agreement with recent neurological studies on cortical plasticity, we show that amputees operated decades ago can still produce distinct and stable signals for each posture and force. The SVM classifies the posture up to a precision of 95% and approximates the force with an error of as little as 7% of the signal range, sample-by-sample at 25Hz. These values are in line with results previously obtained by healthy subjects while feed-forward controlling a dexterous mechanical hand. We then conclude that our subjects could finely feed-forward control a dexterous prosthesis both in force and position, using standard EMG in a natural way, that is, using the phantom limb.

Key words: learning and adaptive systems, support vector machines, hand

* Corresponding author

Email addresses: claudio.castellini@unige.it (Claudio Castellini), e.gruppioni@inail.it (Emanuele Gruppioni), a.davalli@inail.it (Angelo Davalli), giulio.sandini@iit.it (Giulio Sandini)

prosthetics, electromyography,

1. Introduction

As of today, the most common way of feed-forward controlling an active hand prosthesis is via forearm surface electromyography (EMG), a technique by which motor unit activation potentials are read from the amputee's stump skin and then used to command the prosthesis (De Luca, 1997). The clinical success of EMG is motivated by its non-invasiveness and relatively low cost (Parker et al., 2006). Still, even though multifingered hand prostheses have appeared on the market (for example Touch Bionics's i-LIMB, see `www.touchbionics.com`), it seems that EMG-based control is not keeping the pace, being limited to a few hand postures or a simple proportional estimate of force. Moreover, this control is quite non-natural, meaning that the amputee must learn to associate muscle remnants actions to unrelated postures of the prosthesis, e.g., phantom wrist flexion and hand closing.

It would be desirable, for a dexterous prosthesis, to let the amputee command a grasp posture and force just by performing the corresponding action with the phantom limb, resulting in a movement or force elicited by ”desiring” it. Also, a way to finely modulate the force involved in a grasp is paramount in daily life activities, for example to hold an egg without breaking it or to grasp a hammer without letting it slip. Lastly, the system should be able to work in real-time and to adapt continually to the changing nature of the EMG signal.

Actually, recent scientific literature indicates that plain, old EMG signals can be used in a better way in prosthetics, by improving the signal processing method, essentially by switching to machine learning. Excellent results have been shown on healthy subjects, but surprisingly, as far as we know, there is so far just one study on amputees (Sebelius et al., 2005). Willing to explore the issue deeper and further, we have devised a new experiment. Three below-elbow traumatic amputees, two of which were operated decades ago, were asked to perform grasp postures with their phantom limb at various speeds and forces, while their EMG activity was recorded using 5 commercially available electrodes, positioned without clinical help, and the desired force was estimated using a force sensor in three different ways. The EMG and force signals were used to train a standard machine learning system (a Support Vector Machine) in order to check how well phantom limb postures could be discriminated and the required force approximated. This paper is a report of the experiment, whose outcome is positive.

We now quickly revise related work highlighting the novel contributions of this work, then we describe the experiment and results and discuss them.

1.1. Related work

1.1.1. Myoelectric control

Myoelectric control, i.e., feed-forward control of prostheses using surface EMG, is in use since the Sixties to control (externally powered) upper-limb prostheses by amputees mostly due to its relatively low cost and non-invasiveness. It provides a simple yet effective way to control single degree-of-freedom (DOF) hand prostheses such as OttoBock's SensorHand for decades, also allowing for a simple force estimation, the so-called proportional control. Before 1975, the common control schema was based upon the identification of active muscle remnants in the amputee's stump and the coding of two, at most three levels of activity of each remnant to prosthesis commands, e.g. (Bottomley, 1965; Childress, 1969). From the mid-Seventies on probabilistic methods and pattern recognition techniques began to be used, including Bayes methods, artificial neural networks and nearest neighbors. A thorough and well-organised survey and historical account of myoelectric control for hand prostheses can be found in (Parker et al., 2006).

With the appearance on the market of multiple-DOFs hand prostheses, the myoelectric signal gains even more interest, since it represents the only non-surgical way of finely controlling such artifacts. (Englehart et al., 2001; Ferguson and Dunlop, 2002; Bitzer and van der Smagt, 2006) are examples of better and better posture discrimination using EMG, always on healthy subjects. The issue is important also outside the field of prosthetics, e.g., in robotic control and teleoperation (Fukuda et al., 2003; Kato et al., 2006).

In (Castellini et al., 2008; Castellini and van der Smagt, 2008) it has been verified on one single healthy subject that the problem, from the very point of view of machine learning, is easy, and that a Support Vector Machine (Boser et al., 1992), a standard multi-layer perceptron and an incremental local-approximation method such as LWPR (Vijayakumar et al., 2005) obtain similar results when applied to the plain EMG signal as extracted by Otto Bock's commercially standard electrodes, the Myobock (see `www.ottobockus.com`).

It seems then reasonable to say that surface myoelectric control will still be the standard for the years to come, even when the dexterity of commercial prostheses increases. Single-DOF control via EMG is being studied (Jiang et al., 2008) and looks extremely promising. As many as 127 EMG electrodes are used simultaneously in Targeted Muscle Reinnervation (Kuiken, 2006), probably the most spectacular use of myoelectric control so far, although it is out of the scope of this work since it involves surgery.

1.1.2. Artificial / prosthetic hands

In Section 3 of (Zecca et al., 2002) a full comparison among artificial hands, including the human hand, is shown; remarkable mechanical hands such as the Utah/MIT hand, the Stanford/JPL hand, the DLR hand and the Robonaut Hand are compared (see also the references in the paper for more details); but in those cases high dexterity means they are not usable as prostheses, either because they are too large, too heavy or too power-demanding. As well the DLR-II hand, appeared in 2004 (Butterfass et al., 2004), probably the most sophisticated mechanical hand at the time of writing, is far from being usable as a prosthesis.

As of 2004, a widely employed prosthesis was the Otto Bock / SUVA hand, which only had 2 DOFs and no opposable thumb. More recently, Touch Bionics's i-LIMB (`www.touchbionics.com`) has appeared, which has 5 independent DOFs and a passive opposable thumb. Its myoelectric control system enables the selection among 5 hand postures using 2 electrodes (information collected from the website); nevertheless, the impression is that most of the grasping effort is achieved through the underactuation of the hand, as it happens with the CyberHand (Carrozza et al., 2006), still at the prototype level, and the DLR Prosthetic Hand (Huang et al., 2006). Force control is a hot topic currently being studied in robotics (Ott, 2008; Wimboeck et al., 2008) as well as in hand prosthetics, among others in (Engeberg et al., 2008; Engeberg and Meek, 2008). There is a definite trend of transferring technology from mechatronics to prosthetics and we are probably going to see more and more dexterous prostheses built and marketed in the upcoming years; still, control lags behind, even without considering the crucial issue of sensorial feedback, dealt with in, e.g., (Cipriani et al., 2008) but completely open as yet.

1.1.3. Clinical applications

All aforementioned works and systems have been tested on healthy subjects. At the time of writing and to the best of our knowledge, (Sebelius et al., 2005) is the only test on amputees, done in the framework of Project SmartHand (`www.elmat.lth.se/~smarthand`). Sebelius had 5 below-elbow amputees, plus one subject with congenital malformation of the forearm, perform up to 10 hand postures (not grasping-related) while recording a 16-channel EMG signal. His results indicate that a rather high recognition rate is obtained by a neural network aided by a sort of decision tree, although not uniformly for all subjects; and that the age of amputation seems not to influence the subjects' ability.

1.1.4. Original contributions

To the best of our knowledge, this is the first time a position / force estimation is attempted on amputees somehow systematically. We apply a standard machine learning system to the EMG of three amputees both to recognise the grasping posture and to approximate the required force. Some considerations about the subjects' diversity as patients (age, age of operation, type of amputation) are drawn, also with respect to its impact on the results. Just 5 commercially available EMG electrodes are employed, and their signals are directly fed to the machine at 25Hz; classification and regression are performed sample-by-sample. (Traditionally, isometric/isotonic postures are classified after a certain amount of signal has been presented to the system, which introduces delay — this issue has recently been tackled in (Tsukamoto et al., 2007), too.) The encouraging results, and the simplicity of the tools used, indicates that surface EMG still has to be fully exploited.

2. Materials and Methods

2.1. Subjects

Three hand amputees, patients of the INAIL Centro Protesi in Vigorso di Budrio, Bologna, Italy, joined the experiment voluntarily after having been carefully informed of the procedure they were about to undergo, according to the INAIL patients care guidelines. All of them have lost their limb traumatically and, at the time of the experiment, the status of their muscle remnants was excellent.

Subject 1 is male, 63 years old, trans-radial one-third proximal, amputated in 1963; he is a pioneer of myoelectric prostheses, having started using them in the Sixties. The Subject 2 is male, aged 56, trans-radial one-third distal, amputated in 1972; he also started using myoelectric prostheses very early, actually in 1974. Subject 3 is male as well, aged 25, trans-carpal, amputated in 2007; he was in the process of learning how to use a standard myoelectric prosthesis at the time the experiment was performed (summer 2008). Subject 1 has about 9cm left of his forearm, Subject 2 has some 20cm, and Subject 3 has the whole forearm plus some of the carpus — see Figure 1.

[Figure 1 about here]

2.2. Setup

[Figure 2 about here]

We used a FUTEK LMD500 Hand Gripper force sensor (Futek, 2008), a strain-gauge based sensor with guaranteed low non-linearity and hysteresis factors, which can easily be gripped in various ways since it is light and small. The sensor returns a voltage proportional to the force applied to its narrow face (Figure 2, left). Also, 5 standard commercial surface EMG electrodes were used, namely OttoBock Myobock models (OttoBock, 2008), type 13E125=50 (Figure 2, center). The electrodes are dry bi-differential with a frequency bandwidth (-3dB) of 140-1500Hz, adjustable amplification gain from 0 to 50000, CMMR of 80dB and a double T notch filter at 50Hz (in the European version that we used) for power supply interference rejection. After a few initial experiments, we set the amplification at mid-range, which gave us an output voltage exactly matching the input range of the acquisition card. These electrodes are the state-of-the-art in commercially available myoprostheses, since their output is deemed exceptionally good, highly correlated with the force exerted by the muscle(s) whose activity the electrode is gathering. All in all, six signals were monitored (one per each EMG electrode and one from the force sensor), and sampled at a rate of 100Hz via a standard USB acquisition card, connected to an entry-level laptop.

The electrodes were placed around the stump just below the elbow, parallel to the forearm axis, equally spaced and held in place by an elastic band (Figure 2, right panel). This was done in order to detect signals from all muscle remnants uniformly, rather than try and associate electrodes to single muscles as is the case in normal one-DOF myo-devices. By the way, for Subject 1 this was the only possibility, since his stump would not allow the electrodes to be positioned anywhere else — this problem of "cluttered" electrodes on a subject's stump actually also appears in (Sebelius et al., 2005).

2.3. Experimental procedure

2.3.1. Grasping postures

The subjects were asked to perform with their phantom hand several different grasp postures, chosen according to suggestions by the INAIL Centro Protesi personnel and patients, and loosely based upon Cutkosky's taxonomy (Cutkosky, 1989):

1. the baseline *rest condition* (re);
2. the act of *pointing the index finger* (po), used when pressing buttons;
3. a *power grasp* (pw) in which the whole hand wraps around an object, used, e.g., when holding a heavy cylindrical object such as a hammer;
4. a *precision pinch grip* (pi) with thumb and index finger closing on an object, usually for lifting small objects such as a pen or an egg;
5. a *precision tripodal grip* (tr) similar to pi, but using the middle finger too, used for spherical objects;
6. the act of *stretching one's hand* (hs), used when an amputee is trying to put his hand inside a pocket.

Each posture was performed repeatedly by each subject a free number of times, ranging from 10 to about 25 (except the rest condition, obviously, which consisted of a few seconds of no-activity recording), with speeds ranging from 5Hz to ”slow motion” (about 20 seconds to complete a grasp, using various degrees of force). The postures were performed in the order described above, with a few seconds of rest inbetween. The experimenter would at times suggest the subject to go faster or slower, to press harder or softer, and at times the subject would be free to do whatever he wanted. We will call this sequence a *cycle*.

2.3.2. Training modalities

Since we employ a supervised learning strategy, a way of knowing what the subject is doing is required in the training phase. In particular, each sample must be associated to a label, denoting the current grasp posture, and to a force value.

Labels, one for each required posture (re,po,pw,pi,tr,hs), were attached to each sample simply according to the type of grasp required from the subject during a particular phase of the current cycle; for example, samples gathered while asking the subject to perform a power grasp would be labled with po, and so on.

Force values, on the other hand, were collected according to three *modalities* (see Figure 3):

1. *teacher imitation.* A healthy subject (the teacher) would place his arm besides the subject’s stump and ask him to imitate the teacher’s postures with his phantom limb. The subject was asked to grasp with maximum strength, while the teacher would grip the force sensor in order to mark the postures / grips.
2. *bilateral action.* The subject would grip the force sensor with his healthy hand while doing the same thing with the phantom limb.
3. *mirror-box.* Same as modality 2, but a *mirror-box* (Reflex Pain Management, 2008) was used.

[Figure 3 about here]

Each subject performed one cycle in each modality, resulting in a total of nine cycles, with a length of 5.7 ± 1.06 minutes (average $\pm$ one standard deviation). After all cycles were recorded, samples associated with force signal values lower than 0.01V were artificially given the label re. This threshold was detected by visual inspection of the signal, and checked by comparing it with the values during the baseline rest condition. Due to an error in the experiment protocol, Subject 1 did not record the pointing index grasp during the second modality, and Subjects 1 and 2 did not record the hand stretching posture.

Figure 4 shows some sample force and EMG signals obtained during the experiments. Notice that for Subject 3, two electrodes (blue and red curves) suffer of a non-null baseline and slowly drifting components, later on determined to be due to sweat. This is common when dealing with surface EMG (De Luca, 1997, 2002).

[Figure 4 about here]

2.4. Data pre-processing and preliminary analysis

Both force and EMG signals were digitally filtered to remove high-frequency noise components (II order low-pass FIR filter with cut-off frequency at 5Hz). After filtering, spectral analysis reveals that the relevant bandwidth of the EMG signal, as recovered form the elctrodes, and of the force signal, lies below 10-12Hz, so both signals were subsampled at 25Hz.

Principal Component Analysis (PCA) was applied to the 5 EMG signals in each cycle, revealing that they can be linearly reduced to two losing, on average, only $7.7\% \pm 4.4\%$ of the signal variance. Although this loss would probably hinder classification and regression, and therefore the 5-dimensional original signals were used later on, this reduction enables us to visualise the samples, tagging them according to the labels (and therefore according to the grasp), and to qualitatively check how well the subjects can produce different EMG patterns when they are asked to perform different grasping actions. Figure 5 shows the results, according to each subject and modality.

[Figure 5 about here]

As is apparent from the Figure, all subjects can produce distinct signals according to the required type of grasp. In particular, notice how two very similar grasp types, i.e., pi and tr, are qualitatively discernible on almost each graph. Notice that PCA being so effective in reducing the dimensionality of the EMG signals two does not imply that two electrodes would suffice to obtain the same results. In fact, PCA coefficients consistently show the same magnitude, meaning that each electrode is required.

2.5. Classification / regression method

The good performance of Support Vector Machines (SVMs) applied to similar problems is known since (Bitzer and van der Smagt, 2006). SVMs are statistical learning machines (Vapnik, 1998) which build an approximated map between samples drawn from an input space (under the standard i.i.d. sampling hypothesis) and a set of labels (classification) or a real value (regression). The map is a weighted sum of basic functions chosen a priori via the so-called kernel (hence the term *kernel methods*), each of which is centered on a sample. The weights are found by minimising a cost functional which is the sum of a loss function, punishing the error on the samples, and a regulariser, punishing over-complex solutions. For a comprehensive tutorial on SVMs please refer to (Burges, 1998; Smola and Schölkopf, 2004).

Maps found by SVMs are sparse, meaning that some (practically, most) of the weights found by minimisation are zero. Those samples for which the weight is not zero, that is, those which actually contribute to the map, are called *Support Vectors* (SVs), and their number is usually much smaller than the total number of samples used in the training phase — this is why prediction with SVMs is in practice rather fast (Cristianini and Shawe-Taylor, 2000). The ratio between the number of SVs and the number of samples is then a good index to measure how difficult a problem is: the smaller the ratio, the easier the problem, indicating that a few samples are sufficient to fully determine the map. In classification, this means that samples with different labels are well separated in the input space; in regression, it means that a simple relationship exists between the samples and the target values. The sparsity of SVM models is extremely useful in our context, since smaller models also mean higher chance of miniaturising them and using them in pratice on a prosthesis.

In our case, the input space is $\mathbb{R}^5$, one coordinate for each EMG electrode; EMG signals are fed to the SVM as they are, sample by sample. The labels are (a subset of) $\{\mathsf{re}, \mathsf{po}, \mathsf{pw}, \mathsf{pi}, \mathsf{tr}, \mathsf{hs}\}$ while the regression value is exactly the force value as read from the force sensor. No feature extraction besides the low-pass filtering is, therefore, employed on the signals.

As is standard, we use a Gaussian kernel both for classification and regression. Multi-class classification is realised via the all-pairs schema, in which a quadratic number of SVMs are trained to discriminate pairs of grasp postures, and then a final decision is made according to a voting criterion. Regression is done using the ϵ-SVR technique, which neglects errors smaller than a tolerance threshold $\epsilon > 0$, here set at the default value of 0.1. Multi-class classification and ϵ-SVR are provided by *libsvm* v2.83 (Chang and Lin, 2001) in the Matlab wrapped version.

For classification, the performance index is the *weighted accuracy*, that is the average of the percentages of correctly predicted labels of type i, divided by the number of labels i in the testing set:

$$\sum_{i \in \{\mathsf{re},\mathsf{po},\mathsf{pw},\mathsf{pi},\mathsf{tr},\mathsf{hs}\}} \frac{c_i}{n_i}$$

where n_i is the number of samples tagged with the label i in the testing set and c_i is the number of correctly predicted labels of type i. This measure, as opposed to the more standard overall ratio of correctly predicted labels and number of samples, has the advantage of adjusting the importance of each label according to how often it appears in the testing set. For example, in general there are more re labels than others, since the resting condition appears both at the beginning of the experiment and in-between the grasps, therefore this label must be weighted *less* than the others, since it is more easily found in the testing set. For regression, the performance index is the root mean-square error (RMSE), normalised over the range of the force signal. This values characterises the error in regression as a percentage of the maximum amplitude of the target signal.

In both cases, in order to avoid the ominous danger of overfitting the data, two hyperparameters have to be found, γ and C, which account in turn for the width of the Gaussians used to build the approximated solution and the weight assigned to the regulariser during minimisation of the cost functional. We find optimal values for C and γ, as is standard, by logarithmic grid search: for each pair (C, γ) for $C = 10^{1,\ldots,3}$ and $\gamma = \frac{10^{0,\ldots,2}}{5}$, the generalisation error of a machine trained using that pair is estimated via 5-fold cross-validation; at the end the pair resulting in the best performance is chosen as optimal. Training samples are normalised by subtracting the mean values dimension-wise and dividing by the standard deviations; testing samples are normalised using the mean and standard deviation of the training set.

After the optimal parameters are found, the generalisation error of the optimal machine is evaluated via an *outer* 10-fold cross-validation, in which for each fold the optimal parameters found during the previous step are used to train an optimal machine on the training set of the split; the optimal machine so obtained is then tested on the testing set left of the split. This method, called *nested cross-validation*, is deemed to be among the best ways to get an unbiased estimate of the generalisation error of a machine learning method, since (a) it de-couples the estimation of the optimal parameters from that of the generalisation error, and (b) it never tests a machine on data which have been used for training, avoiding the so-called resubstitution bias (Varma and Simon, 2006).

3. Results

Figure 6 shows the performance results obtained by the SVMs in classification and regression for each subject and modality; Figure 7 shows four examples of predicted targets.

[Figure 6 about here]

[Figure 7 about here]

Classification performance ranges from $95.74\% \pm 1.15\%$ (Subject 2, bilateral action) to $79.72\% \pm 1.70\%$ (Subject 1, mirror-box). Highest performances per subject are $92.67\% \pm 0.74\%$ (Subject 1 in teacher imitation modality), $95.74\% \pm 1.15\%$ (Subject 2, bilateral action) and $93.26\% \pm 1.11\%$ (Subject 3, bilateral). Notice that bilateral action and mirror-box are not significantly different as far as Subjects 2 and 3 are concerned. A definite descending trend is observed for Subject 1 from imitation to bilateral to mirror-box, while this trend is reversed for Subjects 2 and 3, which perform much better in the last two modalities than in the first one. Modality-wise, teacher imitation is the best modality for Subject 1, while the other two are best for Subjects 2 and 3.

Regression performance[1] ranges from $6.54\% \pm 0.31\%$ (Subject 2, bilateral) to

[1] Notice that the regression performance index is an *error*, while the classification performance is an *accuracy*; therefore in the case of classification, the higher the bars, the better, whereas it is the other way around in regression.

$17.76\% \pm 1.06\%$ (Subject 3, teacher). Subject 1 has little or no significative difference among modalities, obtaining the best performance while doing bilateral action ($9.29\% \pm 0.73\%$); Subject 2 is best in bilateral action ($6.54\% \pm 0.31\%$) while Subject 3 performs best in mirror-box ($7.17\% \pm 0.43\%$) with high overlapping with the bilateral modality. Subject-wise, Subjects 2 and 3 perform remarkably bad in teacher imitation modality if compared with the other two; while modality-wise, we here notice again that teacher imitation gets worse and worse as we move from Subject 1 to 2 to 3. A reversed trend is almost consistently observed for the other two modalities.

Figure 7 indicates that (upper row) most errors in classification appear at the onset of grasps (transitions to/from label re), although for Subject 1 pw and pi are also frequently mistaken. Regression (lower row) appears good both when force is approximated during slow (left panel) and fast (right panel) grasps. The only significant disturbance is a high-frequency but low-amplitude modulation of the predicted force. Confusion matrices for each subject and modality (Figure 8) actually confirm that re is easily mistaken for any other label (first row and column of each matrix), in particular for Subjects 2 and 3. Subject 1 has a more complex schema of label confusion, depending on the modality. In particular, during teacher imitation, pi and tr are easily confused; during bilateral action, pi and pw are as well confused; and in mirror-box modality the pointing index and the power grasp are those most easily mistaken. Actually, this is qualitatively confirmed by considering again the PCA-reduced sample scatterplots of Figure 5, first row.

[Figure 8 about here]

Lastly, Figure 9 shows the percentages of SVs for each subject and modality, for the optimal models both for classification and regression. Comparing this Figure with Figure 6, an almost uniform inverse correlation is apparent, between performance and percentage of SVs, as predicted. Lowest percentages of SVs per subject in classification models are $19.73\% \pm 4.10\%$ (Subject 1, teacher imitation), $24.59\% \pm 0.22\%$ (Subject 2, bilateral action), and $15.83\% \pm 1.36\%$ (Subject 3, bilateral action again). For regression, we have $12.98\% \pm 0.19\%$ (Subject 1, teacher imitation), $8.28\% \pm 0.32\%$ (Subject 2, bilateral action), and $9.97\% \pm 0.13\%$ (Subject 3, bilateral action once again).

[Figure 9 about here]

4. Discussion

4.1. Quality of the results

In (Castellini and van der Smagt, 2008) it was shown that a dexterous mechanical hand such as the DLR-II could be feed-forward force and position controlled in real time by a healthy subject using surface EMG. Although this opens interesting possibilities, e.g., in teleoperation, virtual reality and robotic surgery, it is in the field of hand prosthetics that it has the most immediate applications. The question remained open then, whether comparable results could be *in principle* achieved by amputees:

1. is there enough fine muscular activity left in a stump?
2. how do the age of operation, the type of amputation and the use of myoelectric prosthesis affect the results?
3. does the essential uniqueness of each single stump challenge the general applicability of the method?

The results of our experiment show that, at least in the case of our subjects, the answer to the first question is positive. In the aforementioned paper, a classification accuracy of about 90% and a normalised RMSE of about 10% were sufficient to correctly control the DLR-II hand. Comparing these figures with those presented in the "Results" Section, we conclude that our subjects would actually be able to do the same, even possibly a little better.

It must be taken into account that, with respect to (Castellini and van der Smagt, 2008), the duration of each cycle is short (a few minutes versus one and a half hour) and that the electrodes were left in the same position for each subject. Nevertheless, these problems have been tackled and solved in that paper, and the very same techniques proposed therein can be employed in this case, in a practical setting. Moreover, a number of simple strategies can be used to further improve the performance: since most classification errors happen at the onset of grasps, for example, the regression machine can be used to start the classification only when the predicted force is above a threshold, when the chance of mistaking the posture is close to zero. Buffering, i.e., considering a few samples before switching category, would also help. The regression output signal can further be low-pass filtered to accommodate for the high-frequency oscillation noticed in Figure 4. All this is, of course, subject to experiments once a practical implementation is realised.

As far as the second question is concerned, of course more subjects and more cycles per subject are needed for a full answer; but if we restrict to our experiment, we see that our subjects obtain good results regardless of the age of operation (decades for Subjects 1 and 2, one year for Subject 3) and type of amputation (Subject 1 has a very short stump, Subject 2 has a longer one and Subject 3 retains his full forearm). Lastly, all our Subjects have been using myoelectric prostheses, (Subject 3 was actually being trained at the time of the experiment); this probably gives them a little advantage, but not that much, since commercial myoelectric prostheses, so far, mainly employ the wrist flexor and extensor; so we would expect a stronger fitness of these muscles, but not necessarily of all the others in the forearm. A similar consideration appears in (Sebelius et al., 2005), actually the only work we can compare with.

Question 3 seems to have a negative answer: the same uniform electrode positioning strategy worked fine for all Subjects, notwithstanding their diversity. If confirmed, this finding would definitely simplify the clinical training procedures as well as the manufacturing of prosthetic sockets, to the benefit of the patients.

4.2. Practical issues

Regarding the practical issue of manufacturing such a system, one wonders how easy it will be to miniaturise the optimal models obtained for each subject, both for classification and regression; we have conducted a preliminary study which indicates that it should be possible with a reasonable effort using standard micro-controllers. To this end, the above mentioned sparsity of the solutions built by SVMs (see Subsection 2.5) is an advantage. Anyway, the low percentages of SVs in the best models found (Figure 9) indicate that the problem, in general, is easy from the point of view of machine learning: in case SVMs proved too hard to implement in practice, even a less sophisticated method such as, e.g., nearest neighbours, could obtain acceptable performance values.

This consideration suggests that the rehabilitation community should probably stop looking for more and more sophisticated features and machine learning methods, and concentrate on other issues such as the prosthesis itself (dexterity, impedance control, humanoid-ness) and sensorial feedback. As well, knowing the state-of-the-art of hand prostheses, we claim that invasive techniques such as, e.g., electroneurography (Cipriani et al., 2008) will not be necessary for a long time to come, at least for trans-radial amputees. We have *just begun* to exploit plain, old surface EMG.

4.3. EMG patterns

The form of feed-forward control enforced by this method is, we claim, "more natural" than the standard single-muscle activation technique, since here we detect real-time *phantom movements* and *forces*. No claim is made about the physiological resemblance of the EMG patterns found to muscular patterns elicited for the same grasps in a healthy arm. As long as each subject can generate a distinct pattern for each grasp posture, this pattern can be detected and the appropriate command can be sent to the prosthesis. The net effect is that the amputee could obtain, e.g., a 20N power grasp just by doing it with the phantom limb — what he used to do naturally before the trauma.

As a matter of fact, we find amazing that long-term amputees, one of which has had almost *no forearm* for 45 years, can still produce such distinct signals for anatomically similar phantom movements such as, e.g., a pinch grip and a tripodal grip. (Indeed all subjects are users of conventional myoelectric prostheses, but in that case movements are required which can be at best defined gross, if compared to the precision obtained in this experiment.) It is common understanding that, due to cortical plasticity, motor/sensory brain areas devoted to amputated limbs are in the long run reassigned to other functions. The wonderful accuracy we have seen seems to go against this belief, and is in agreement with recent neurological studies on above/below elbow amputees (Mercier et al., 2006; Reilly et al., 2006). Trans-cranial magnetic stimulation and EMG detection on such subjects has revealed that stable, precise EMG patterns appear in subjects with long-term amputations when they are required to move their phantom limbs. (Hamilton and Pascual-Leone, 1998) is an earlier study of the same kind, performed on Braille-proficient blind. In (Reilly et al., 2006) such a pattern is even observed in an *above-elbow* amputee, asked to perform phantom thumb flexion, due to residual muscle synergies. This lets us hope that our technique could be applied, although probably not to the same extent, to more severe amputees such as trans-humerals.

4.4. On the training modalities

The three modalities were devised in order to provide a simple and effective way to obtain labels and force values for each EMG sample. For healthy subjects, this is usually done using a force sensor gripped with the hand (Castellini and van der Smagt, 2008) or a dataglove (Sebelius et al., 2005); obviously these ideas will not work with an amputee. The competing use of three different modalities has proven effective in finding the best way for each single subject to train the system; as it turns out, almost consistently for classification and regression (consider Figure 6 again), performances *differ* significantly as the modality changes for each subject. This is an important issue, since a better and quicker training could be obtained if we could know in advance what modality suits best an amputee. We have no general answer to this question so far, but some considerations are at hand.

The teacher imitation and bilateral action modalities were essentially suggested by common sense, while the mirror-box is inspired by Ramachandran's experiments on amputees of the mid-Nineties (Ramachandran and Rogers-Ramachandran, 1996), where it was noted that the illusion of seeing one's hand moving would reinforce the visual feedback loop and decrease the phantom limb pain in monolateral hand amputees. We figured out that such a device could actually improve the subject's ability to control EMG activation patterns at least with respect to the bilateral action modality; but it turns out that there is little or no difference between their performances, and indeed mirror-box is *worse* than bilateral action for Subject 1 in classification. Probably, a certain amount of training with the mirror is required, before a subject becomes proficient with the device.

Let us then restrict our attention to imitation and bilateral action. Imitation is predictably the less accurate modality, since it is the teacher who presses the force sensor in order to simulate the force applied by the subject; as well, the only way the subject has to know when to start grasping is visual feedback, which indeed introduces a delay. (Anyway let us notice that teacher imitation is the only possibility if we want to extend this method to *bilateral* hand amputees, whose quality of life can really be low after the amputation.) Both regression and classification performances are worse in this modality for Subjects 2 and 3; but it is best for Subject 1, and it degrades as we go to Subject 2 and 3. An interesting observation is that Subject 1 has the shortest stump left, Subject 2 has more, and Subject 3 has it all; this qualifies 1 as having a high degree of de-afferentiation (sensorial feedback deprivation). It has been noted (Lajoie et al., 1992; Miall and Cole, 2007) that de-afferented patients perform *better than normal subjects* in tasks involving a conflict between what they perceive from their moving limb and what they see; and this might explain why Subject 1 obtains better results then the others when imitating someone rather than figuring out his own movements. This is, of course, just a hypothesis so far.

Acknowledgments

The authors would like to thank Mr. Cesare Stagni of INAIL Centro Protesi for kindly helping us finding the patients who have joined the experiment. We also thank Benoni B. Edin of Umeå University, Sweden, for a helpful comment on the paper.

References

Bitzer, S., van der Smagt, P., May 2006. Learning EMG control of a robotic hand: Towards active prostheses. In: Proceedings of ICRA, International Conference on Robotics and Automation, Orlando, Florida, USA. pp. 2819–2823.

Boser, B. E., Guyon, I. M., Vapnik, V. N., 1992. A training algorithm for optimal margin classifiers. In: Haussler, D. (Ed.), Proceedings of the 5th Annual ACM Workshop on Computational Learning Theory. ACM press, pp. 144–152.

Bottomley, A. H., 1965. Myoelectric control of powered prostheses. J Bone Joint Surg B47, 411—415.

Burges, C. J. C., 1998. A tutorial on support vector machines for pattern recognition. Knowledge Discovery and Data Mining 2 (2).

Butterfass, J., Fischer, M., Grebenstein, M., 2004. Design and experiences with DLR Hand II. In: Proceedings of the World Automation Congress, Seville, Spain. Vol. 5. pp. 105—110.

Carrozza, M., Cappiello, G., Micera, S., Edin, B. B., Beccai, L., Cipriani, C., 2006. Design of a cybernetic hand for perception and action. Biological Cybernetics 95 (6), 629—644.

Castellini, C., van der Smagt, P., 2008. Surface EMG in advanced hand prosthetics. Biological Cybernetics 100 (1), 35—47.

Castellini, C., van der Smagt, P., Sandini, G., Hirzinger, G., 2008. Surface EMG for force control of mechanical hands. In: Proceedings of ICRA-08 - International Conference on Robotics and Automation. pp. 725—730.

Chang, C.-C., Lin, C.-J., 2001. LIBSVM: a library for support vector machines. Software available at `http://www.csie.ntu.edu.tw/~cjlin/libsvm`.

Childress, D. A., 1969. A myoelectric three-state controller using rate sensitivity. In: Proceedings 8th ICMBE, Chicago, IL. pp. 4—5.

Cipriani, C., Zaccone, F., Micera, S., Carrozza, M. C., 2008. On the shared control of an EMG-controlled prosthetic hand: Analysis of user prosthesis interaction. IEEE Transactions on Robotics 24 (1).

Cristianini, N., Shawe-Taylor, J., 2000. An Introduction to Support Vector Machines (and Other Kernel-Based Learning Methods). CUP.

Cutkosky, M., 1989. On grasp choice, grasp models and the design of hands for manufacturing tasks. IEEE Transactions on Robotics and Automation 5 (3), 269—279.

De Luca, C. J., 1997. The use of surface electromyography in biomechanics. Journal of Applied Biomechanics 13 (2), 135–163.

De Luca, C. J., 2002. Surface electromyography: Detection and recording. Copyright 2002 by DelSys, Inc.

Engeberg, E. D., Meek, S., 2008. Improved grasp force sensitivity for prosthetic hands through force-derivative feedback. IEEE Transactions on Biomedical Engineering 55 (2(2)), 817—821.

Engeberg, E. D., Meek, S. G., Minor, M. A., 2008. Hybrid force-velocity sliding mode control of a prosthetic hand. IEEE Transactions on Biomedical Engineering 55 (5), 1572—1581.

Englehart, K., Hudgins, B., Parker, P. A., 2001. A wavelet based continuous classification scheme for multifunction myoelectric control. IEEE Trans Biomed Eng 48 (3), 302—311.

Ferguson, S., Dunlop, G. R., 2002. Grasp recognition from myoelectric signals. In: Proceedings of the Australasian Conference on Robotics and Automation, Auckland, New Zealand. pp. 83—87.

Fukuda, O., Tsuji, T., Kaneko, M., Otsuka, A., apr 2003. A human-assisting manipulator teleoperated by EMG signals and arm motions. IEEE Transactions on Robotics and Automation 19 (2), 210–222.

Futek, 2008. Futek LMD500 medical load cell (hand).
URL `http://www.futek.com/product.aspx?stock=FSH00125`

Hamilton, R. H., Pascual-Leone, A., 1998. Cortical plasticity associated with Braille learning. Trends in Cognitive Sciences 2 (5), 168—174.

Huang, H., Jiang, L., Zhao, D., Zhao, J., Cai, H., Liu, H., Meusel, P., Willberg, B., Hirzinger, G., 2006. The development on a new biomechatronic prosthetic hand based on under-actuated mechanism. In: Proceedings of the 2006 IEEE/RSJ International Conference on Intelligent Robots and Systems. pp. 3791–3796.

Jiang, N., Englehart, K., Parker, P., 2008. Extracting simultaneous and proportional neural control information for multiple degree of freedom prostheses from the surface electromyographic signal. IEEE Transactions on Biomedical EngineeringTo appear.

Kato, R., Yokoi, H., Arai, T., 2006. Competitive learning method for robust EMG-to-motion classifier. In: IAS. pp. 946–953.

Kuiken, T., 2006. Targeted reinnervation for improved prosthetic function. Phys Med Rehabil Clin N Am. 17 (1), 1—13.

Lajoie, Y., Paillard, J., Teasdale, N., Bard, C., Fleury, M., Forget, R., Lamarre, Y., 1992. Mirror drawing in a deafferented patient and normal subjects: Visuoproprioceptive conflict. Neurology 42, 1104—1106.

Mercier, C., Reilly, K. T., Vargas, C. D., Aballea, A., Sirigu, A., 2006. Mapping phantom movement representations in the motor cortex of amputees. Brain 129, 2202—2210.

Miall, R. C., Cole, J., 2007. Evidence for stronger visuo-motor than visuo-proprioceptive conflict during mirror drawing performed by a deafferented subject and control subjects. Experimental Brain Research 176, 432—439.

Ott, C., 2008. Cartesian impedance control of redundant and flexible-joint robots. Vol. 49 of Springer Tracts in Advanced Robotics (STAR). Springer-Verlag.

OttoBock, 2008. Otto Bock MYOBOCK 13E125=50 electrodes.
URL `http://www.ottobock.com`

Parker, P. A., Englehart, K., Hudgins, B., 2006. Myoelectric signal processing for control of powered limb prostheses. Journal of electromyography and kinesiology 16 (6), 541—548.

Ramachandran, V. S., Rogers-Ramachandran, D., 1996. Synaesthesia in phantom limbs induced with mirrors. Proceedings of the Royal Society B: Biological Sciences 263 (1369), 377—386.

Reflex Pain Management, 2008. Folding mirror therapy box.
URL `http://www.reflexpainmanagement.com`

Reilly, K. T., Mercier, C., Schieber, M. H., Sirigu, A., 2006. Persistent hand motor commands in the amputees' brain. Brain 129, 2211—2223.

Sebelius, F. C. P., Rosén, B. N., Lundborg, G. N., 2005. Refined myoelectric control in below-elbow amputees using artificial neural networks and a data glove. Journal of Hand Surgery 30A (4), 780—789.

Smola, A. J., Schölkopf, B., 2004. A tutorial on support vector regression. Statistics and Computing 14 (3), 199–222.

Tsukamoto, M., Kondo, T., Ito, K., 2007. A prosthetic hand control based on nonstationary EMG at the start of movement. Journal of Robotics and Mechatronics 19 (4), 381—387.

Vapnik, V. N., 1998. Statistical Learning Theory. John Wiley and Sons, New York.

Varma, S., Simon, R., February 2006. Bias in error estimation when using cross-validation for model selection. BMC Bioinformatics 7 (1).

Vijayakumar, S., D'Souza, A., Schaal, S., 2005. Incremental online learning in high dimensions. Neural Computation 17, 2602—2634.

Wimboeck, T., Ott, C., Albu-Schaeffer, A., Kugi, A., Hirzinger, G., 2008. Impedance control for variable stiffness mechanisms with nonlinear joint coupling. In: Proceedings of the 2008 IEEE/RSJ Intl. Conf. on Intelligent Robots and Systems, Nice, France. pp. 3796—3803.

Zecca, M., Micera, S., Carrozza, M. C., Dario, P., 2002. Control of multifunctional prosthetic hands by processing the electromyographic signal. Critical Reviews in Biomedical Engineering 30 (4–6), 459–485.

Figure 1: the subjects' stumps. Subject 1 (left) has a trans-radial one-third proximal amputation, with a stump about 9cm long; Subject 2 (center) is trans-radial one-third distal, stump about 20cm long; Subject 3 (right) is trans-carpal, retaining the full forearm.

Figure 2: parts of the experimental setup. (left to right) the FUTEK LMD500 Hand Gripper; an Otto Bock Myobock EMG electrode; placement of the electrodes on a subject's stump, parallel to the forearm axis, equally spaced, held in place by an elastic band — the electrodes' wires are clearly seen.

Figure 3: the three training modalities. (left to right) Subject 1 imitating a pinch grip; Subject 3 bilaterally performing a pinch grip; Subject 2 assuming the pointing index posture while looking in the mirror-box.

Figure 4: three examples of force (black thick line) and EMG signals (coloured thin lines). (left panel) Subject 1 in the teacher imitation modality switches from po to pw at about 200 seconds of activity — notice the sharp change in relative average magnitude of the EMG signals, before and after the switch. (center and right panels) Subject 3 in the mirror-box modality, slow and fast power grasping.

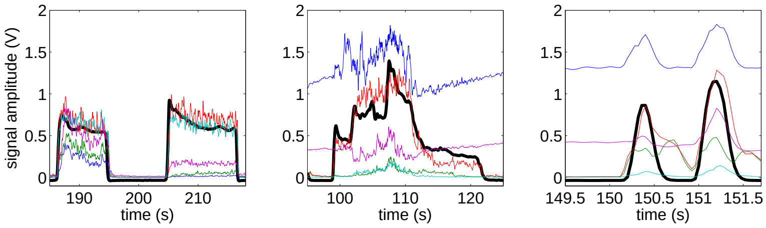
Figure 5: visualisation of the PCA-reduced EMG signals.

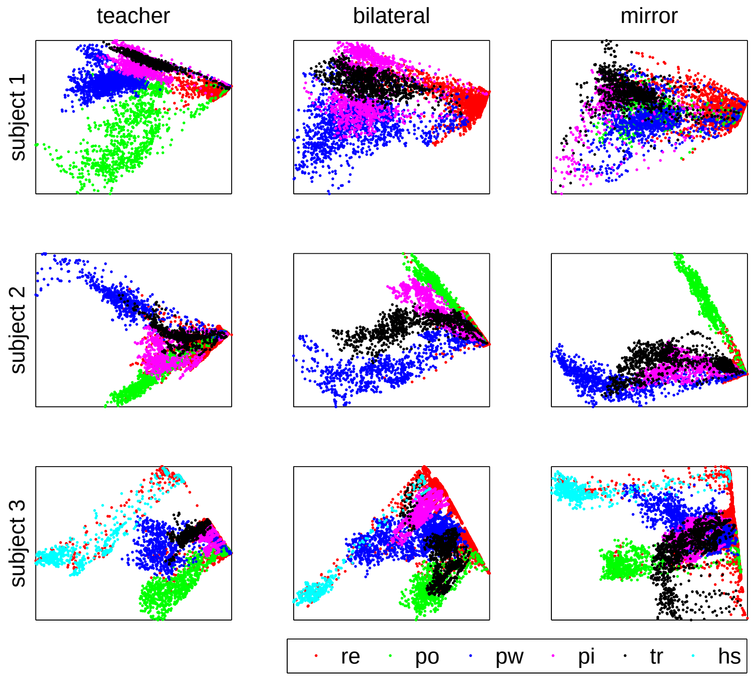
Figure 6: classification (left) and regression (right) performance for each subject and modality. Histogram bars are mean values over the 10 splits of the outer cross-validation, error bars denote one standard deviation.

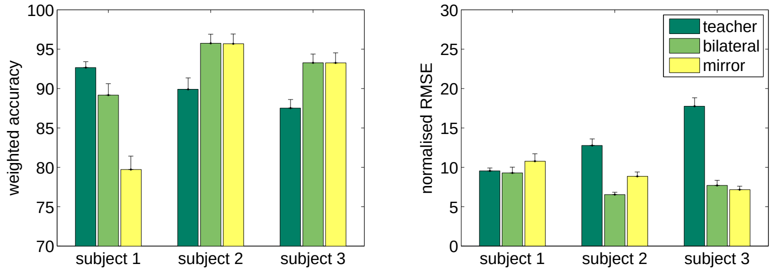
Figure 7: comparing true and predicted targets. (upper row) Classification of Subject 2 in bilateral action (left, weighted accuracy $95.74\% \pm 1.15\%$) and Subject 1 in mirror-box (right, $79.72\% \pm 1.70\%$). (lower row) Regression of Subjects 2 (left, normalised RMSE $6.54\% \pm 0.31\%$) and 3 (right, $7.70\% \pm 0.65\%$) in bilateral action.

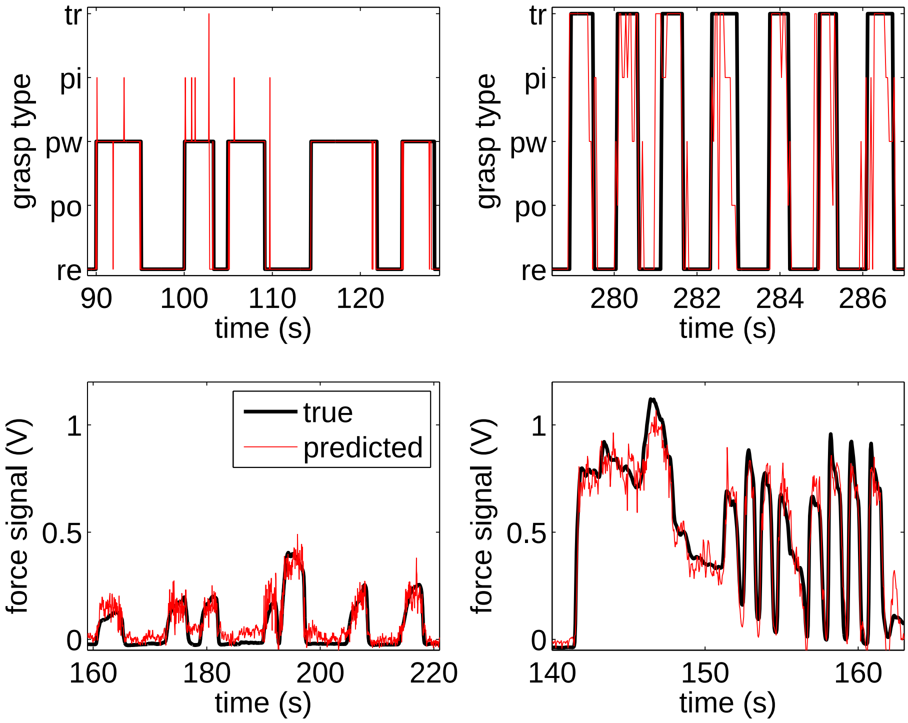
Figure 8: confusion matrices for each subject and modality. In each matrix C, C_{ij} denotes the fraction of labels i which have been mistaken for j over the total mistaken labels of that particular cycle. The diagonals of the matrices are obviously identically zero. Each matrix is the average of ten matrices, obtained from each outer cross-validation split.

Figure 9: percentages of Support Vectors obtained in the optimal models for classification (left) and regression (right) for each subject and modality. Histogram bars are mean values over the 10 splits of the outer cross-validation, error bars denote one standard deviation.

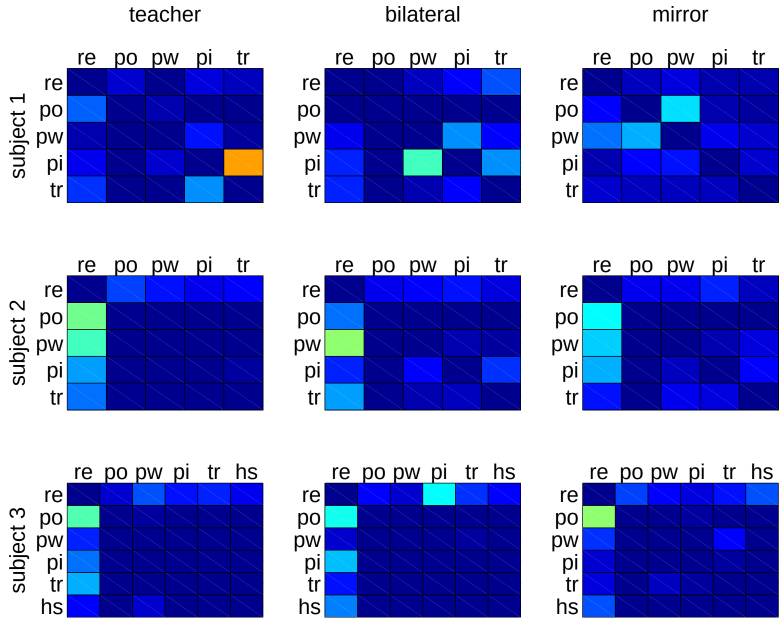

signal amplitude (V)
time (s)
time (s)
time (s)

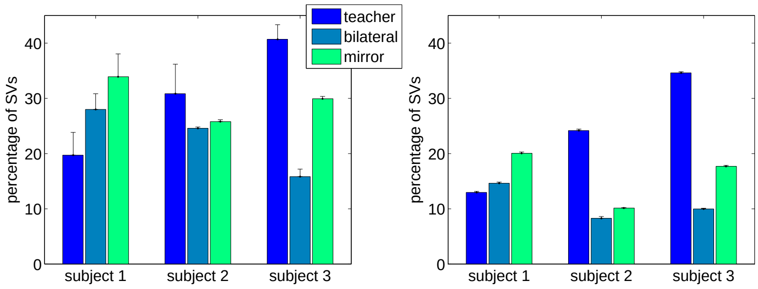

teacher
bilateral
mirror
subject 1
subject 2
subject 3
re
po
pw
pi
tr
hs


100
95
90
85
80
75
70
weighted accuracy
subject 1
subject 2
subject 3
30
25
20
15
10
5
0
normalised RMSE
teacher
bilateral
mirror
subject 1
subject 2
subject 3



tr
pi
pw
po
re
grasp type
90
100
110
120
time (s)
280
282
284
286
force signal (V)
1
0.5
0
true
predicted
160
180
200
220
140
150
160


teacher
bilateral
mirror
subject 1
subject 2
subject 3
re
po
pw
pi
tr
hs



teacher
bilateral
mirror
percentage of SVs
0
10
20
30
40
subject 1
subject 2
subject 3
percentage of SVs
0
10
20
30
40
subject 1
subject 2
subject 3