Towards Adaptive Hand Prosthetics

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***Abstract*—The state-of-the-art in active (myoelectric) hand prosthetics is rather poor if considered from the point of view of control. Even the most advanced commercial prostheses, gifted with several degrees of freedom and able to mimic a number of human-like grips, provide no force control and enforce non-natural feed-forward actuation, so that the patient has to learn how to drive them from scratch. For instance, closing the hand is generally actuated using the remnant of the wrist flexor.**

We hereby describe an experiment in which three amputees train a machine learning system with surface electromyography signals, while asked to imagine, with their missing hands, complex grip postures and different degrees of force involved in the grip. Even though some patients have been operated *decades* ago, we show that they can still produce remarkably distinct and precise signals for each grip and force value, therefore potentially feed-forward controlling a dexterous active hand prosthesis to a degree of finesse unknown so far.

This result hints at a scenario in which prostheses adapt to the patient, entering a positive feedback loop of reciprocal learning, leading to shorter training times and a better quality of life for the patients.

I. Introduction

One of the most widely used ways of feed-forward controlling Active Hand Prostheses (AHPs) is forearm surface electromyography (EMG), a technique by which muscle activation potentials are gathered from the patient's stump skin, and then used to drive the prosthesis[1]. EMG [2] is relatively cheap, non-invasive and easy to use, and it has been around for some 40 years. Still, as it stands today, it is used in a way that is highly innatural for the patient, allows for a very limited number of grasp types, and enforces no control of the *force* involved in a grasp.

Force control, or at least a way to feed-forward modulate the force involved in a grasp, is paramount for daily-life activities of amputees, for example to hold an egg without breaking it and/or to hold a hammer without letting it slip. Moreover, due to the limitations in the signal processing techniques, so far large muscles, such as the wrist flexor and extensor, are used to drive the prosthesis; in the typical case the patient must learn to associate wrist flexing with hand opening, and this implies long training times. Lastly, such a rough schema cannot control more than a few standard grasping postures. This, notwithstanding recent advances in hand prostheses mechatronics, such as Touch Bionics's i-LIMB [3], a real leap forward as far as dexterity is concerned (even more dexterous non-prosthetic mechanical hands have already appeared, such as the DLR II hand [4]).

In this paper we show that plain, old surface EMG can be used to reach a much better form of feed-forward control of mechanical hands: similar grasp postures can be discerned easily, and the required force can be understood almost perfectly. The interesting point is that no specialised hardware is needed (five commercially available EMG electrodes suffice) and no careful positioning of the electrodes on the patients' stumps is required. The innovative bit is represented by the use of a machine learning technique, which means that the situation can be potentially radically improved without the need of surgery and complex electronics.

More in detail, three hand amputees were required to imagine performing different grasps with different levels of force with their missing limb; the obtained data have then been analysed using a Support Vector Machine (SVM) both for classification of the grasp and for regression upon the desired force. The machine is able to distinguish the required grasp in real-time with a high precision, and to understand the required force with an equally excellent performance. SVMs, as well as other machine learning techniques, have already been employed on the EMG signal to classify grasp postures and force required by healthy subjects (see, e.g., [5], [6], [7]), but as far as we know this is the first time such an analysis is carried out on patients with some systematicity, both for grasp and force control.

The task seems hard at first sight, since each patient's anatomy and residual muscle activity is different; moreover, one would expect people operated decades ago not to be able to imagine fine movements and postures of their missing limbs. Instead, rather surprisingly, our data analysis reveals that similar grasps such as a pinch and a tripodal grip can still be perfectly distinguished; that the requried force is delicately modulated and it can be estimated well; and that no anatomical / functional inspection of the stump is required.

This result hints at a scenario in which the prosthesis adapts to the patient as well as the other way round, entering a positive feedback loop of reciprocal learning, leading to shorter training times and a better quality of life for the patients.

The paper is structured as follows: Section II describes the experiment; Section III describes the data pre-processing and gives an idea of how the data look like; Section IV describes the experimental results; lastly, Section V contains a discussion

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NOTE for the reviewers of this paper: a preliminary, limited analysis of some of the data presented in this paper has been submitted to a rehabilitation medicine journal as a "short report", and is currently under review.

[1]Sensorial feedback is even less developed at the time of writing; thermic and vibrotactile feedback has been experimented with little success [1], so that visual feedback is so far the only effective way to close the control loop.

of the results and the conclusions.

II. Materials and Methods

A. Patients

Three hand amputees, patients of the INAIL Centro Protesi in Vigorso di Budrio, Bologna, Italy, joined the experiment.

The first subject is male, aged 63, trans-radial one-third proximal, amputated in 1963; he is a pioneer of myoelectric prostheses, having started using them in the Sixties. The second subject is male, aged 56, trans-radial one-third distal, amputated in 1972; he also started using myoelectric prostheses very early, actually in 1974. The third subject is male again, aged 25, trans-carpal, amputated in 2007; he was in the process of learning how to use a standard myoelectric prosthesis at the time of writing.

A set of three patients is obviously not sufficient to gather statistics about the applicability of our method, but we are lucky enough that they present a rather wide variety of operations and conditions. In particular, subject 1 has about 9cm left of his forearm, subject 2 has some 20cm, and subject 3, a trans-carpal amputee, has the whole forearm plus some of the carpus (Figure 1 shows the subjects' stumps). Moreover, subjects 1 and 2 were amputated a very long time ago, although they have been using myodevices since then, whereas subject 3 is freshly operated. Lastly, subject 3 is rather young as opposed to the other subjects.

B. Setup

We placed on each subject's stump 5 surface EMG electrodes without searching for the best anatomical position, but rather in a standard way for all, around the stump, near the elbow (for subject 1 this was actually the only possible choice!) and at uniform angles from one another, in such a way to "wrap" the stump. See the "Discussion and Conclusions" Section for more about this issue.

The electrodes we employed are standard commercial surface EMG devices, namely OttoBock Myobock models [8], two of the 13C7=50 type and three of the 13E125=50 type. Myobock electrodes enjoy an excellent noise rejection ratio and pre-amplify the signal — an amplification gauge can be set for each electrode, and here it was set at a mid-range value for all electrodes. Moreover, they perform a run-time root-mean square evaluation of the signal; this results in an exceptionally good output, which is already highly correlated with the force exerted by the muscle(s) whose activity the electrode is gathering.

Each subject was also given a FUTEK LMD500 Hand Gripper force sensor [9] in order to detect the required force during the experiment. Data were gathered via a standard digital acquisition card, namely a National Instruments NI-DAQ 6122 USB card, connected to the EMG electrodes and force sensor on one side, and to an entry-level laptop on the other side. We employed National Instruments's SignalExpress application to sample the (synchronised) data at a sampling rate of 100Hz.

C. Experiment Design

The patients were induced to imagine performing with their missing hand 5 different postures / grips: no action, pointing index, pinch grip, tripodal grip, power grasp; subject 3 was also asked to stretch his hand — a posture which most amputees deem very useful for, e.g., slipping the hand in a pocket. The postures / grips were performed with free force and speed by the subjects, while we would record the EMG and force sensor activity.

Since the beginning we decided to employ a *supervised learning* strategy to build our models, as has been done in literature so far. To this end, three ways of training the system (*modalities*) were designed and employed:

1) *teacher imitation.* A healthy subject (the teacher) would place his arm besides the patient's stump and ask him to imagine replicating the teacher's postures and grips. The subject was asked to imagine gripping with his maximum strength, while the teacher would grip the force sensor in order to mark the postures / grips.
2) *bilateral action.* The patient was asked to grip the force sensor with his healthy hand while imagining doing the same things with his missing hand.
3) *mirror-box.* Same as modality 2, but a simple, plain mirror (in the case of subject 1), or a *mirror-box* (for subjects 2 and 3, see [10]), was placed in-between the patient's arms, in order to increase the visual feedback.

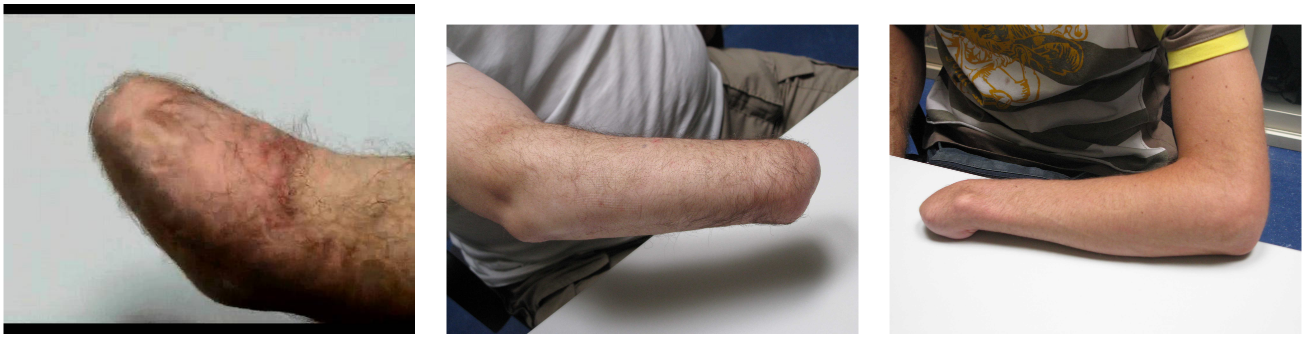
The idea behind the mirror-box modality is inspired by Ramachandran's experiments on amputees of the mid-Nineties [11], where it was noted that the illusion of seeing one's hand moving would reinforce the visual feedback loop and ease the ghost limb pain in monolateral hand amputees. We figured out that such a device could actually reinforce the patient's ability to produce different activation patterns.

Figure 2 shows various subjects performing the required actions in the three modalities.

The patients were left free, to a large extent, to exert the postures / grips with the amount of force and the speed they liked; in some phases of the experiment, the teacher would command them to grip faster or slower, or with a certain desired force. The result is that the patients applied a wide range of gripping speeds and forces, which helped test whether our approach would work equally well with signals gifted with diverse frequency and amplitude components. Figure 3 shows some sample force and EMG signals. On average, each modality lasted something more than 5 minutes and no subjects reported fatigue or pain. At the aforementioned sampling rate of 100Hz, we gathered a total of about 270000 samples.

D. Methods

As already pointed out in literature, Support Vector Machines (SVM) [12] are a good machine learning method to solve this problem, so we employed them. For an explanation of how SVMs work in the context of EMG signals, please refer to, among others, [13], [7], whereas, for a comprehensive tutorial on SVMs in the more general framework of classification and regression, refer to [14], [15]. SVMs are a statistical



subject 1 subject 2 subject 3

Fig. 1. the subjects' stumps. Subject 1 has a trans-radial one-third proximal amputation, with a stump about 9cm long; subject 2 is trans-radial one-third distal, stump about 20cm long; and subject 3 is trans-carpal, retaining the full forearm.

teacher imitation bilateral action mirror-box

Fig. 2. 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.

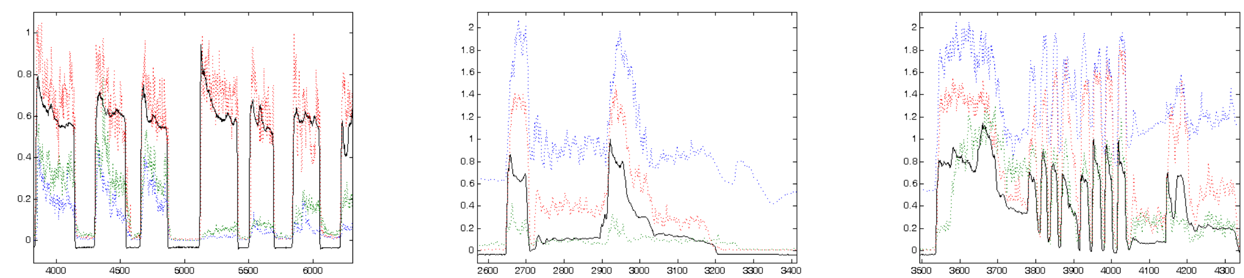


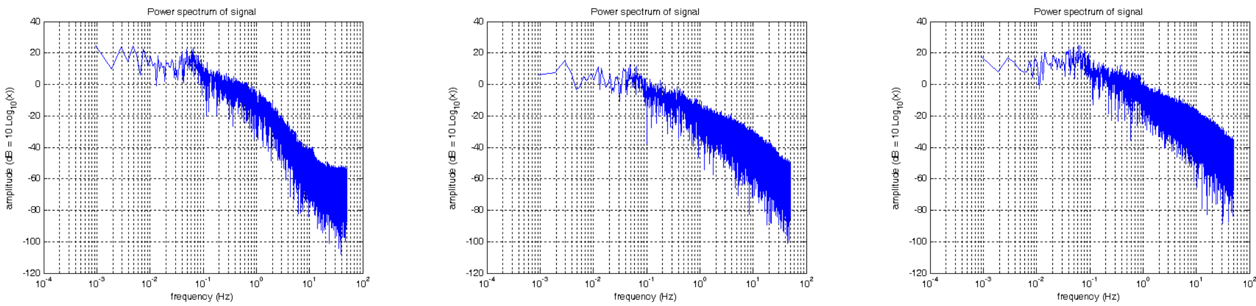
Fig. 3. three examples of force (black, continuous line) and EMG signals (coloured and dotted lines) during subjects' activity. (left panel) Modality 1: around the 5000th sample a switch from pointing index to power grasp appears — notice the related change in magnitude of the EMG. (center and right panels) Modality 3, slow and fast power grasping — notice two EMG electrodes spoiled by a non-null baseline and a slow drifting component, which was later on determined to be due to sweat.

learning method able to build an approximated map between an input space and a label (classification) or a real value (regression). Classification is here used to classify the type of grasp according to the EMG signal, whereas regression is used to understand how much force the subject is exerting, independently from the grasp type.

The input space is chosen to be $\mathbb{R}^5$, one coordinate for each EMG electrode; the labels are five integer numbers, one for each grasp type (six for subject 3, who also performed the hand stretching posture); and the real value is exactly the force value read off the force sensor. Notice that we work in real-time, that is, our machines associate a grasp type and a force value to an EMG value at each instant of time. This approach enables us to detect a grasp type almost at the onset of the grasping movement.

III. Data Pre-processing and Preliminary Analysis

The data related to each subject and modality were chronologically juxtaposed exactly in the order the experiments were performed; then a label was attached to each sample, according to the type of grasp required from the subject. Samples associated with a low force value were given the label 0, since they denote no activity of the muscles, that is, a resting condition. Subject 1 actually needed the no-action data set to be replicated for each modality, since we did not record its baseline each time — a mistake which was corrected with the second and third subject. Moreover, we could not record



force | electrode 1 | electrode 3

Fig. 4. frequency analysis of the force signal and two typical electrodes.

the "pointing index" activity for this subject in the second modality, which is therefore null.

Spectral analysis of the EMG signal as read from the electrodes, in agreement with the literature, shows that its relevant bandwidth lies below 10-12Hz (see Figure 4), so we could safely subsample the signals at 25Hz, that is, considering one sample in four of the original data stream. This made the data set to be dealt with much smaller and computationally tractable. Subsequently, we applied a II order low-pass filter with cutoff frequency at 5Hz in order to remove all possible high-frequency noise. This has proved to be a very effective way of getting a good signal in early experiments (see [16]).

Principal Component Analysis (PCA) reveals that the 5 signals can be linearly reduced to two losing, on average, only $7.7\% \pm 4.4\%$ of the signal variance; therefore, we can visualise the samples, tagging them according to the labels (and therefore according to the action) and visually detecting how well the subjects can produce different EMG patterns when they are asked to simulate different grasping actions. Figure 5 shows the results, according to each subject and modality.

As is apparent from the Figure, all subjects can produce remarkably well separated and distinct signals, according to the elicited type of grasp. In particular, notice how two very similar grasp types, i.e., pinch grip (thumb and index come together as to precisely grip, e.g., a pen) and tripodal grip (the same, but done with the middle finger, too) appear well separated on almost each graph — look at the black and pink coloured samples.

Notice, as well, that the graphs have not all the same scale and that they appear incongruent with one another, but this is due to having positioned the electrodes irrespective of their order number on the stumps of the patients. This is anyway ininfluent, since SVMs are exaclty supposed to automatically find patterns and regularities among the samples for each subject.

One last point is that PCA being so effective in reducing the dimensionality of our data to two does not necessarily imply that we could use two electrodes only to obtain the same results; this depends on the PCA coefficients, which show consistently the same magnitude (except in the case of subject 3, where a heavy drift was observed on two electrodes, very likely due to sweating — this is a well-known problem of EMG-controlled prosthetics). This means that each electrode is required to give a uniformly-weighted contribution to the PCA-transformed 2-dimensional samples. Of course reducing the required number of electrodes is a requirement, since this would make the prosthesis cheaper. We are invesitigating the issue.

IV. Experimental Results

For each patient we hereby present a performance result both for classification and regression.

For classification, the performance index is the *weighted* percentage of correctly guessed labels, that is, the average of the percentages for each label i, divided by the number of labels i in the testing set. This measure, as opposed to the more standard ratio of correctly guessed labels, 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 0 labels in any testing set than other labels, since 0 appears both at the beginning of the experiment and in-between the grasps, as it represents rest. 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 standard Pearson correlation coefficient evaluated between the predicted force signal and the real one (remember that we work in real-time, so that this measure of correlation really is a measure of temporal correlation). The choice of the correlation coefficient, as opposed to the more standard mean-square error, is suggested by a practical consideration: when driving a prosthesis, or even a non-prosthetic mechanical hand, we are not interested in the absolute force values desired by the user/subject, since mechanical hands usually cannot apply as much force as human hands do, for obvious safety reasons[2]. We are rather concerned about getting a signal which is *strongly correlated* with the patient's will.

As is standard in machine learning, each data set was split in 5 folds and cross-validation was performed on it; this makes the evaluation robust against the problem of over-fitting. We employed a well-known freely available SVM package, *libsvm* v2.83 [17], in the Matlab wrapped flavour, with a Gaussian kernel. This particular kind of SVM, in our case employing the so-called Gaussian or Radial Basis Function kernel, requires

[2]or, e.g., in teleoperation scenarios, they could be able to apply *much more* force than a human hand can.

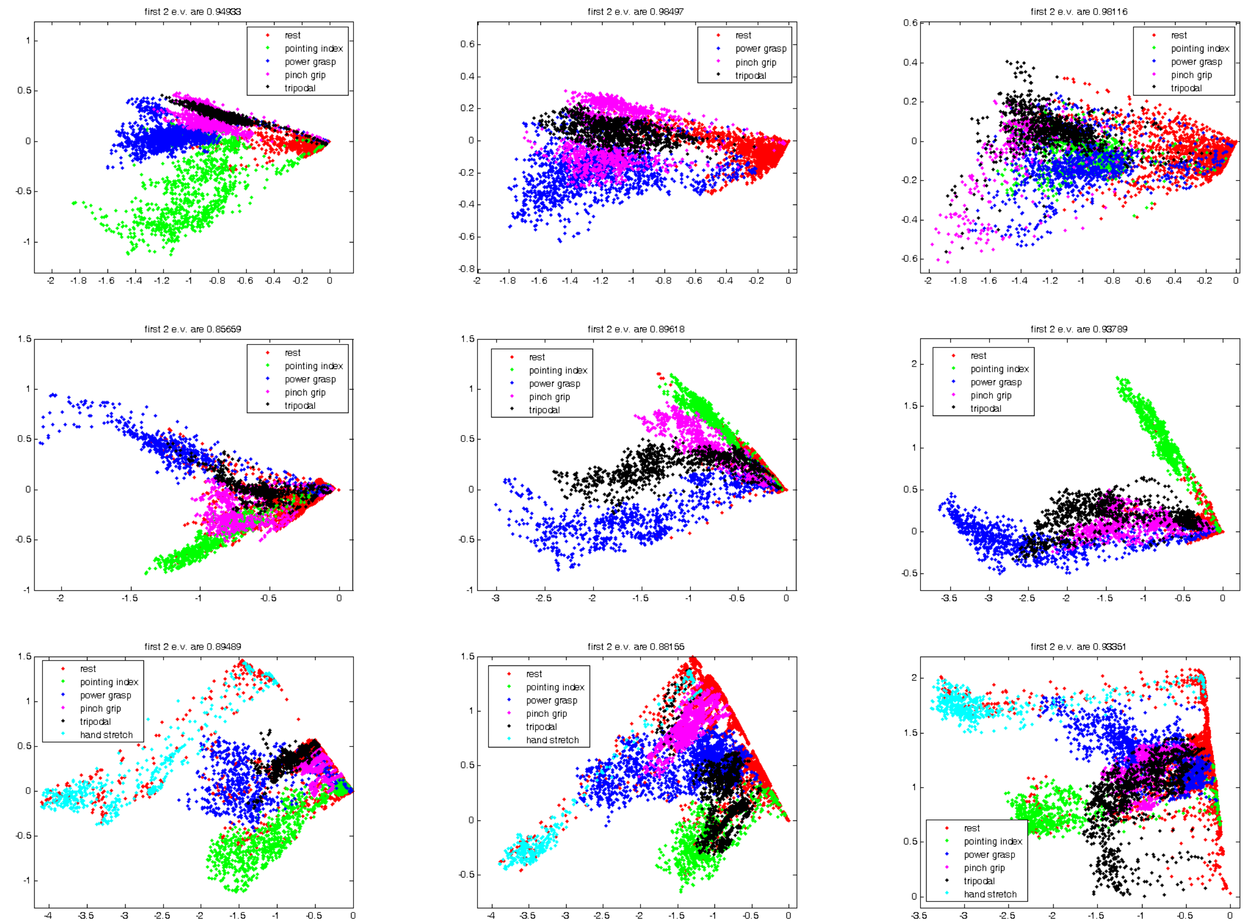


Fig. 5. PCA analysis of the subjects' data. (top to bottom) Subject 1, 2 and 3; (left to right) modality 1, 2 and 3. Notice that subject 1, modality 2 has no "pointing index" data, and that subject 3 has the "hand stretch" data.

setting two *hyperparameters*, called γ and C, which were found by grid search using the aforementioned performance indexes.

Table I shows the main results obtained by the SVMs.

TABLE I
CLASSIFICATION/REGRESSION PERFORMANCE FOR EACH SUBJECT (ROW) AND MODALITY (COLUMN).

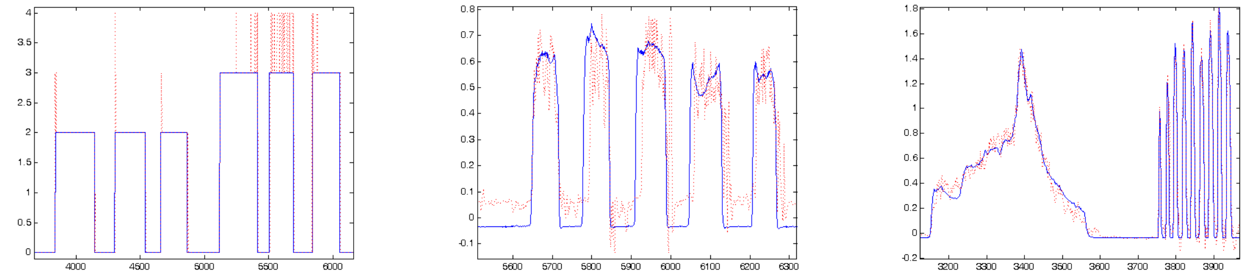
	Imitation	Bilateral	Mirror
Subject 1	93.11% / 0.96	90.41% / 0.95	82.39% / 0.93
Subject 2	88.67% / 0.86	95.98% / 0.96	96.07% / 0.94
Subject 3	84.07% / 0.81	92.40% / 0.92	91.98% / 0.91

The first consideration is that for each subject, at least one modality produces excellent results, both in classification and regression. Subject 1 works best by imitation, whereas subjects 2 and 3 exhibit best results via bilateral action and mirror-box. If we consider the modality with the best results for each subject, we get an average classification accuracy of 93.86% and an average regression correlation of 0.95. The system can predict almost perfectly, as is apparent from Figure 6 in which a comparison is shown between bits of real target labels and values and the corresponding guessed targets.

It is unclear why modalities produce better or worse results according to the subjects, but see Section V for a couple of hints on why this phenomenon appears.

Consider the Figure, panel (a): the major problem seems that of pinch grips which get mistaken for tripodal grips, and this is intuitively clear, since these two types of grips are quite similar from an anatomical point of view. This fact is corroborated by the fact that (consider Figure 5 again, pink and black dots) the two grips lie, almost consistently, in the same regions of the 2-dimensional PCA-transformed input space.

Actually, the confusion matrices related with each subject / modality pair (see Figure 7) confirm this feeling only for subject 1 and only partially. Really, most mistakes in classification involve label 0, both in the sense that 0 is mistaken for something else and vice-versa (consider the first row and first column of each matrix). This happens especially (consider rows 2 and 3 of the Figure) for subjects 2 and 3, whereas subject 1 presents more uncertainty as far as other confusion pairs are concerned. This phenomenon is also clearly justifiable, since misclassifications involving label 0 (the "rest" position) happen at the onsets / endings of grips — this is confirmed by visual inspection, in the cases of modalities 2 and 3 (in modality 1 the teacher was pressing the force sensor, so the data are unreliable for this kind of analysis), and for subjects 2 and 3. In these cases, willing to obtain an even more accurate classification rate, one can think



(a) (b) (c)

Fig. 6. comparing true and guessed labels (a) and force values (b) and (c). Notice, in panel (a), that labels 3 (pinch grip) are easily mistaken for labels 4 (tripodal grip) but not to the point of hindering the performance of the system. Notice also, especially in panel (c), the almost perfect correlation between force and guessed force, both during a slow buildup/release and during quick applications of force.

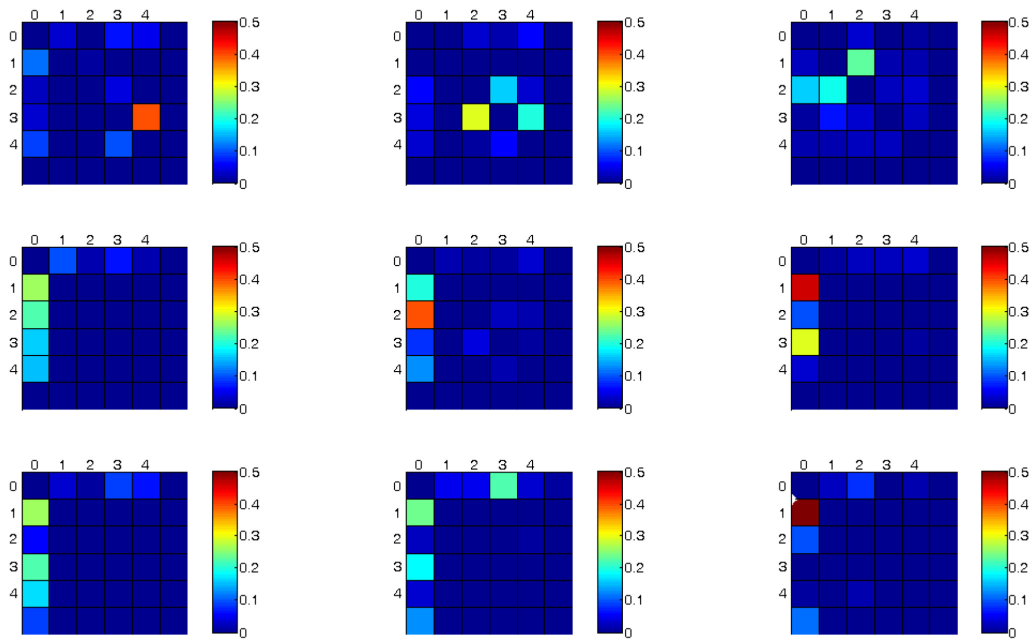


Fig. 7. confusion matrices for each subject / modality pair. Subjects are on each row, modalities are on each column. In each matrix C, the entry C_{ij} denotes the fraction of labels i which have been mistaken for j over the total mistaken labels of that particular subject / modality pair. The diagonals of the matrices are, therefore, identically zero.

of using the regression system to guess when the required force is above a reasonable threshold, and start the classification only at that point, when the chance of mistaking the posture / grip is close to zero. Also, in a practical setting, a simple buffering strategy (i.e., considering a few samples before switching category) would probably suffice to eliminate this problem completely.

As far as regression is concerned, consider now Figure 6, panels (b) and (c). If we neglect a high-frequency oscillation, the guessed force values are essentially replicating the true values — again, there are different offsets, but this is a direct result of choosing *maximum correlation* as the performance index. The signals in the Figure could easily be used in practice after a simple linear transformation; the oscillation can be removed by low-pass filtering the signal before sending it to the control system of the prosthesis, or by relying on the electro-mechanical time constants of the prosthesis itself, which would probably be hardly capable of accurately following such a high-frequency spurious signal. Notice in particular (panel (c)) how the system is smoothly able to correctly guess both low-frequency (left-hand side) and relatively high-frequency (right-hand side) oscillations of the target value.

Inspection of the hyperparameters C and γ is useful to narrow down the grid search and also to gather more abstract considerations about the problems at hand. Here we have that, in classification, (the logarithm of) C is 2.17 ± 0.83 and γ is uniformly 2. These numbers reveal that the problem is rather easy, since C is set at a quite high value, and as well γ is at the highest possible value in our grid search range. As far as regression is concerned, we find a similar pattern, with (the logarithm of) C being 0.56 ± 0.53 and γ being set, again, at 2 uniformly. Regression as well seems an easy task for SVMs, which in the end confirms the visual appearance of the PCA scatterplots of Figure 5.

One last hint at this comes from the analysis of the models themselves. SVMs enjoy the property of building *sparse* solutions to the problems on which they are trained; this means that the prediction function, for the selected kernel, both for classification and regression, is a weigthed sum of Gaussian functions. The Gaussians involved in the sum are centered around some of the training samples — the so-called *Support Vectors* (SVs), and their number is usually much smaller than the total number of samples used in the training phase.

The sparsity of SVM models is extremely useful in our context, since smaller models mean higher chance of miniaturising them and using them in pratice. At the same time (see, e.g., [18]), it is well-known that the total number of SVs is inversely correlated to the model's generalisation power, and therefore to its overall performance. In our case, the percentage of SVs with respect to the size of the related training sets is systematically low and strongly inversely correlated with the perfomance attained. For classification, the percentage is $20.55\% \pm 6.07\%$ with correlation to the performance -0.96; for regression, we have $17.11\% \pm 9.53\%$ with correlation -0.93.

In practical terms, let us consider, for example, the models obtained for Subject 3 via bilateral action, a case in which the performance is excellent, and a complex case, since subject 3 performed five kinds of postures / grips, as opposed to the four performed by the other subjects: the classification model has 2059 SVs and the regression model has 1324, for a total memory occupancy (in Matlab) of, in turn, 207KB and 91KB. When optimised, these models are small enough to fit on a standard micro-controller (see the next Section for more details). Of course, things are supposed to get even *better* from this point of view, if we allow for a slightly worse performance and employ a sparsification technique such as, e.g., uniformisation [13], [7]; such a technique is anyway needed when we switch to a real online framework.

V. Discussion and Conclusions

The results hereby presented clearly show that the well-known surface EMG signal can be used to drive a mechanical hand / prosthetic hand in a much batter way than before: finer, force-controlling, more dexterous. Our results indicate that a machine learning approach such as Support Vector Machines will effectively detect well-separated grasping patterns in real time, as required by an amputee; at the same time, the system will be able to detect how much force is involved in the grasp. If the prosthesis has a sufficient number of DOFs, that is, it can be position-controlled to mimic the required grasps, and if it can be force-controlled, then a system such as the one described in this paper will be able to feed-forward control it in a natural way, that is, according to what the patient wants it to do.

The positioning of the electrodes, at least in the case of the three patients who joined the experiment, is uniform and not related to any anatomical consideration. Since the results we have obtained are uniformly good for all patients, it is probably possible to claim that careful positioning, as well as medical control to identify the best working remaining muscles in the stump, is not required. This would simplify the whole procedure.

The proposed analysis of SVM hyperparameters and percentage of Support Vectors with respect to the total number of training samples (see Section IV) indicates that the problem is rather easy, if considered form the pure point of view of machine learning. This lets us hope that, 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.

Lastly, in this work we are making no statement about the physiological resemblance of the patterns we deal with, with respect to the muscular patterns elicited for the same grasps in a healthy arm. Actually, we have not investigated what the patient's stump muscles do when the patient is asked to imagine, e.g., a pinch grip — this is indeed a very interesting issue, but is not the focus of this work. Since each and every amputation is different from one another, and therefore each stump has different muscular conditions, we can hope that the system works fine for a reasonable range of amputees and stumps. Although we have only 3 patients here, their diversity as far as age, age of operation and type of amputation lets us hope for the best. In the end, as long as for each patient, each grasp type or posture corresponds to a different pattern, then a system such as ours can detect it and send the appropriate command to the prosthesis. The patient will then be able to elicit from the prosthesis, say, a 5N pinch grip, or a 30N power grasp, just by "desiring" so. This is what we mean by a better quality of life for amputees and a shorter training time. The keyword *adaptive prosthetics* is meant, here, in the machine-learning sense, that is: the prosthesis is trained upon the patient's data and therefore adapts to her/him.

We have actually found it surprising that so much fine muscular activity can be elicited from elderly patients, such as our subjects 1 and 2, who, by the way, have been operated *decades* ago. Notwithstanding this, they are still perfectly able to produce, e.g., two very different patterns for similar grips such as the index / thumb pinch grip and the tripodal grip. This is maybe the most interesting scientific finding of this work and, if confirmed on more patients, it will be worth investigating with a deeper analysis from an exquisitely neuroscientific point of view.

The use of three different modalities has proven effective in finding the best way for each single patient to train the system. Actually, as one can see by considering Table I again, subject 1 obtains better results if he trains the system in the teacher imitation modality, whereas subjects 2 and 3 make it work better in the bilateral action and mirror-box modalities. It is unclear why this is the case, and anyway a broader range of patients is required to observe any stastically meaningful phenomena, in order to possibly relate the type of amputation to the preferred modality — a relationship which would be of great help when a new patient has to train the system.

The only reasonable note we can make here is that subject

1 is left with a very short stump, as opposed to subjects 2 and 3; this qualifies him as having a high degree of de-afferentiation, i.e., sensorial feedback deprivation. It has been noted [19], [20] 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.

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