Surface EMG suffices to classify the motion of each finger independently

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Abstract We introduce a learning method which can detect opening (extension) and closing (flexion) actions of all human fingers, as well as sideways movements (abduction/adduction) using lower arm surface EMG only. The method is shown to be used independently of the position of the arm. The method is ideally suited for the control of active prosthesis with a high number of active degrees of freedom. The method is successfully demonstrated on a robotic four-finger hand, and can be used to grasp objects.

1 Introduction

Todays hand prosthesis are combined in paper [1] to mainly active and passive prosthesis. According to paper [1] active, fully integrated, mechatronic, prosthetic hands become more and more important to give the patients the most possible functional capability back. Active prosthetic hands are commercially available of prosthesis manufacturers (e.g. *Otto Bock, Motion Control, Liberating Technologies*). On the manufacturers web pages there are only active hands with just one degree of freedom, which only allows the patient to close and open the prosthetic hand. Most of the prosthetic hands are controlled over myoelectric (EMG) interfaces measuring the muscle activity of a patients lower arm.
The motivation of this paper is to develop a control for a prosthetic, full integrated, robotic hand. The most important issue for the control of the robotic hand is the possibility to move all fingers of the robotic hand independently. For this task the

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control uses support vector machines (SVM), a method of machine learning, to distinguish different finger movements, because no unique mapping of EMG electrodes and finger movement is possible. With some preprocessing the support vector machine (SVM) has a quick response after muscle activation, robust classification and the most possible amount of different finger movements.
As shown in reference [2] the system works in supination and pronation and is robust between sessions. This paper continues the work of references [2],[3] and extends the system to eleven different classes. This device is tested on the DLR HIT hand [4],[5] with several subjects wearing ten EMG electrodes on their lower arm, the number of different finger movements is increased from five over eight to eleven movements during the experiments.

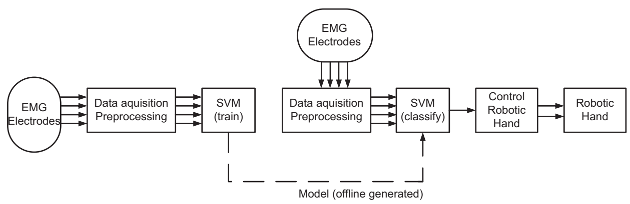

Fig. 1 Data flow plan of the rehabilitation system which consists mainly of EMG data acquisition, the support sector machine (SVM) and the robotic hand.

2 EMG Data Acquisition

EMG signals are recorded using ten commercial *Otto Bock* active double differential electrodes 13E200=50. Each electrode includes an amplifier with a factor of up to 100.000 changeable on a scale from 1 to 7 on the electrodes backside. The resulting measurement range goes from 0V to 4.49V.

2.1 Position of the EMG

The position of the EMG electrodes is the key for a successful distinction of the different finger movements. To distinguish many different finger movements the electrodes are placed all over the subjects lower arm. The placement of the electrodes, shown in figure 2, gives a general rough setup for the placement of the electrodes, where only small adjustments from subject to subject have to be made.
Since not every muscle is detectable with one sensor separately the paper is introducing SVM to distinguish different finger activity. The placement of the electrodes, figure 2 tries to map sensor to muscle as good as possible. Electrode 1 is placed on the flexor pollicis longus to detect the flexion of the thumb. Electrodes 2 is placed

on the flexor digitorum superficialis, where flexion of the index gives the highest response. Electrode 3 is placed on the flexor carpi ulnaris to detect the flexion of the pinkie. Electrodes 4-7 are placed on the flexor carpi radialis and the palmaris longus to detect flexion of the middle an the ring. Electrode 8 is placed on extensor pollicis longus to detect the extension of the thumb, electrode 9 is placed on extensor indicis to detect the extension of the thumb and electrode 10 is placed on extensor carpi ulnaris to detect the extension of middle, ring and pinkie.
The muscles for finger adduction/abduction are laying inside the hand, so they are not detectable directly, but their response is measurable in the muscles of the lower arm, so adduction/abduction of different fingers is distinguished with the combination of all EMG signals.

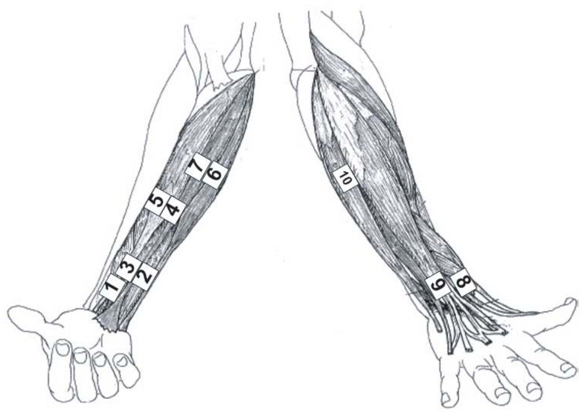

Fig. 2 Position of the EMG electrodes on the lower arm.

2.2 *Characteristics of EMG Electrodes*

Many characteristics and problems of the EMG electrodes are given in the references [8] and [7], moreover he electrodes measure a higher potential when the were just put on the lower arm, as when were put on the lower arm for some minutes. The reason for this is the different temperature of the EMG electrodes, so the subject should wait some minutes until he starts using the system. Still the electrodes measure a quasi constant potential in relax position, see left figure 3, which can differ from electrode to electrode and is also a function of time. The amplification gain is chosen to be large enough to detect muscle activity, possible noise is eliminated with a lowpass filter.

2.3 Detection Muscle Activity

A finger movement is described as a flexion, extension, adduction or abduction of a certain finger from relax position to a linked position, where the muscles of the lower arm has to apply little force to the finger. The active movement of the finger translates to a peak detected by the EMG electrodes, see left figure 3.
The most robust method to detect this peak is using a constant threshold $t_c(t)$ which just one electrode has to reach for a certain amount of time. To use the same constant threshold $t_c(t)$ for all EMG signals $s(t)$, the EMG signals must be on the same level, so the EMG signals are transformed to zero voltage axis with a high pass filter and noise is eliminated with a low pass filter

$$s^*(t) = \frac{1}{s+1}\frac{20s}{s+20}[s(t)], \tag{1}$$

given in the Laplacian domain. The filters parameters were easily found through experiments and only data satisfying condition

$$s^*(t) > t_c(t) \tag{2}$$

are stored for later preprocessing.

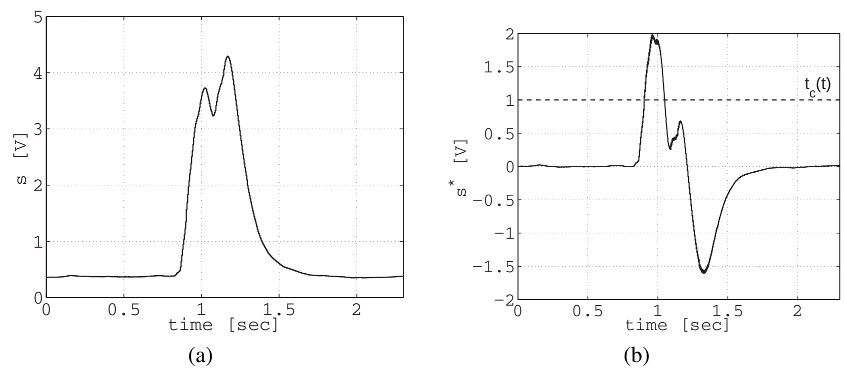

Fig. 3 Muscle activation recorded by one EMG electrode (a) and the same signal high pass filtered (b).

3 Learning Finger Movements with SVM

To learn human finger movements we use support vector machines (SVM) [9], [10] using a gaussian rbf kernel [11], with an implementation from *SPIDER* toolbox [12]. The EMG signals are preprocessed to feed the SVM with the most unique data as possible. The learning process consists of a training phase, where a model with the gaussian kernel is created and a classification phase, where online EMG data is compared with the generated model. After this comparison the SVM should classify the finger movement of the subject correctly.

3.1 Preprocessing

Muscle activation results in peaks, see figure 3, which have different widths depending on several aspects (e.g size of muscle, the position of the electrode, the speed of the finger movement). Feeding data to the SVM only satisfying equation (2) fails because the SVM requires constant input space which is a priori not the given due to the different lengths of the peaks. Data fed to the SVM is called feature which consists of ten subfeatures which equals the amount of electrodes. The paper introduces a mapping

$$\mathbf{R}^n \to \mathbf{R}^c, \tag{3}$$

which generates an equal dimension for every subfeature, where n is the amount of samples who satisfy equation (2) and c is an arbitrary constant value. Examples for mapping (3) are

$$f_s = max(s^*(t)) \qquad \forall \;\; s^*(t) > t_c(t) \tag{4}$$

$$f_s = n \tag{5}$$

$$f_s = \sum_{i=0}^{n} s^*(t) \qquad \forall \;\; s^*(t) > t_c(t) \tag{6}$$

$$f_s = \frac{1}{n}\sum_{i=0}^{n} s^*(t) \qquad \forall \;\; s^*(t) > t_c(t) \tag{7}$$

or any combination of these subfeatures. The reduction of the input space has the big advantage that the SVM can classify much faster, which is very important using this method in a prosthesis control.

3.2 Training and Classification

To train the SVM the subject repeats the finger movement ten times for each finger which makes it for one class. If the subject trains eleven different finger movements (classes) it will take him around two minutes. The user has to choose two SVM parameters called C and σ, therefor a heuristic method is used called 2-fold cross-validation with gridsearch. The result of 2-fold crossvalidation is the probability for wrong classification which is a good indication for the quality of the training set.
In classification phase the subject is moving an arbitrary finger and the SVM should be able to find which finger the subject was moving. The time for classification of

the *SPIDER* toolbox [12] is around 0.024s for eleven classes and ten repetitions per class in training phase.

4 Experimental Results

Experiments with six different subjects were made to test the system online. For this task pictures of random gestures, see table 1 are shown on the screen, where each gesture appears ten times. The subject must accomplish the same gesture given on the screen. After the experiment the given gestures and the classified gestures are compared and a the amount of misclassified gestures is calculated.
The amplification gain of all EMG electrodes is set to maximum through all experiments. The values for σ are 2 ± 1 and the values for C are 40 ± 20, the threshold for peak detection is set to 1 ± 0.2, depending on the different subjects. Through all experiments the number of electrodes is ten and the amount of classes is increased from five over eight to ten/eleven.
As shown in figure 4 the amount of correct classified classes decreases if the amount of classes increases. Thus it is harder for the SVM to distinguish the different finger movements. The improvement from ten to eleven classes is due to only half of the subjects were able to accomplish class ten, see table 1. Subjects being able to accomplish all classes, were able to move their fingers independently which is one reason for the better results with eleven classes.
The amount of expected correct classes, calculated with 2-fold crossvalidation does not increase that strongly, see figure 4. Thus subjects were able to create a mathematical model, which performance the subjects could not achieve in online experiments. Reasons for this phenomena are given in later discussion.
Figure 5 shows the experimental results of each gesture (class). As shown in figure 5(a) all classes are classified with nearly the same performance. The standard deviation with five classes is small, so the systems works well with every subject. The performance with eight classes, see figure 5(b) is still very good, because on average more the nine of ten classes are classified correctly. Figure 5(c) shows the standard deviation gets higher compared to eight classes. The performance of the system depends more and more on human factors, see discussion. Nevertheless the system performs well for the first seven classes and only misclassifies some of the new classes. The highest amount of misclassification takes place in class nine which is index abduction. The muscles for this movement are laying inside the hand, where no electrodes are placed. There is only a response measurable on the lower arm, which differs a lot from movement to movement. Class eleven (all fingers abduction) works perfectly because a muscle response is measurable in nearly all electrodes. Figure 5(d) shows that the system can perform well if the subjects know the system and the muscle activation is measurable in a sufficient way.

5 Discussion

Less performance with more classes is caused by different factors. The most limiting factor are the EMG electrodes because they have to detect muscle activity in a sufficient way otherwise every algorithm will fail. Human factors play the second largest role, where physical factors like motor skills or location of the muscles are important. Also mental factors like repeat accuracy of finger movements, fatigue, engagement and ability of concentration influences the performance of the system. If different finger movements result in equal EMG signals the SVM is the limiting factor due to impossibility of distinguishing classes.
To improve the actual results we should definitively use more electrodes, so their position on the lower is no factor anymore. It would also be easier for the SVM to distinguish the different classes due to more information. The systems also performs better if the subject uses it regularly, so he knows how to contract his muscles to get the desired result.

6 Conclusion

It is possible to distinguish finger movement with support vector machines (SVM) when the fingers are moved independently. The performance with eight classes is sufficient to forward this method to use it in a prosthesis hand. With ten electrodes successful classification of ten or more classes depends on several, mostly human factors which have to be eliminated in future work.

1	thumb flexion	2	index flexion	3	middle flexion
4	ring flexion	5	pinkie flexion	6	thumb extension
7	index extension	8	middle & ring & pinkie extension	9	index abduction
10	index & middle abduction	11	all fingers abduction		

Table 1 Description of the different gestures (classes).

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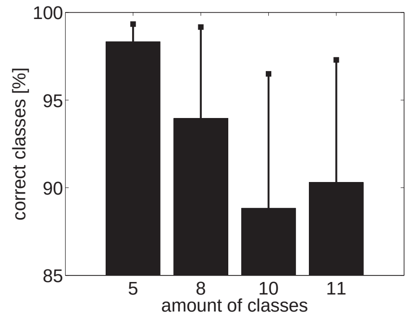

Fig. 4 Crossvalidation results (stems) compared with experimental results (bars).

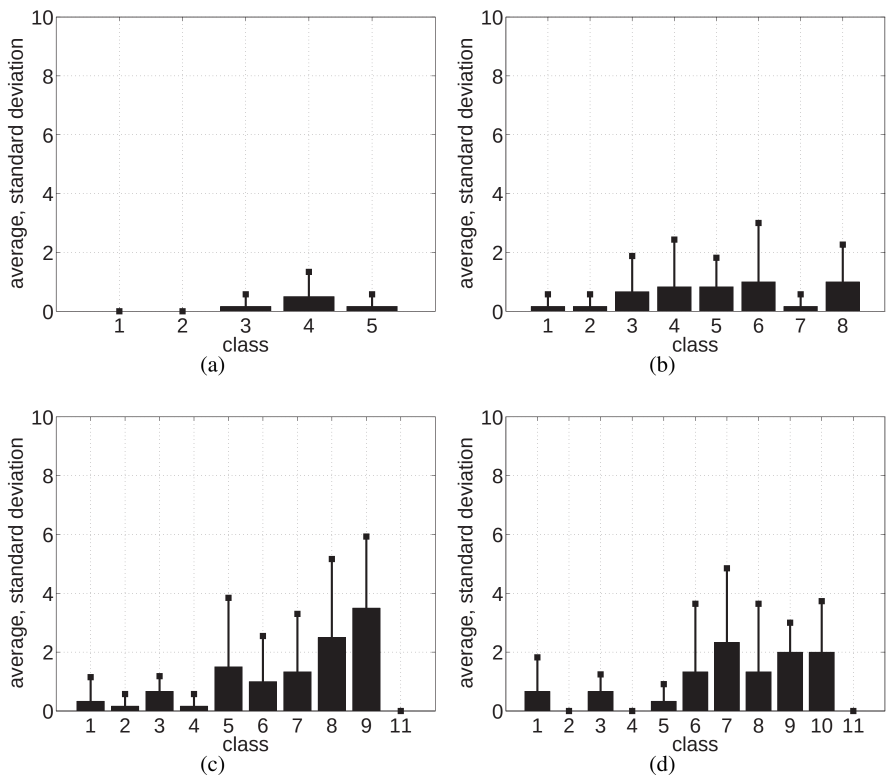

Fig. 5 Experimental results of six subjects with the first five classes (a); the first eight classes (b); the first nine classes and class eleven (c) and all classes (d) of table 1. Bars are the the correct classified classes (average of six subjects) and stems are the corresponding standard deviation.

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