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Homeokinetic Proportional Control of Myoelectric Prostheses

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Abstract— **Self-organized control of myoelectric prostheses aims at an automatic selection of communication channels between a prosthetic device and its user. During training, the patient is instructed to generate control signals that follow the observed autonomous movements of the prosthesis. At the same time, the prosthetic controller maximizes both the diversity of movements and the coincidences of prosthetic movements and human control signals by varying the sensory features and control actions. This dual control algorithm is derived from the homeokinetic principle for robot control and is tested in a proportional control task for a hand prostheses.**

I. INTRODUCTION

Myoelectric prostheses have proved useful since several decades. However, the increased capabilities of prosthetic devices, especially for the upper limb, are not fully accessible due to limitations of their controllability.

Commercially available prostheses with more than one degree of freedom are often realized as state machines. This means that in dependence on the state the same muscle contraction leads to different movements. State transitions are realized by a co-contraction of flexor and extensor muscle. So complex movements of different degrees of freedom can only be executed in a serial order and the patient always has to keep in mind the actual state of the device.

The ability to control more than one degree of freedom without using state machines becomes more and more important as prosthetic devices with many degrees of freedom are becoming available. The control of the device should be realized in a proportional manner, where the velocity and grip force of the prosthesis are controlled proportional to the strength of the muscle activation, which is preferred by patients [1].

In order to fit a prosthesis usually a set of movement commands are generated by the patient while the produced myoelectric potentials [2] are recorded, see [3], [4], [5], [6], [7]. Based on the recorded patterns of myoelectric activity, characteristic features are calculated that enable the classification of the movement intentions of the user. The obtained class labels serve as the basis for prosthetic control. When using the prosthetic device the patient must generate similar movement commands as in the initial recording in order to support the classification.

Here we propose an algorithm that allows the patient to learn intuitive motion commands which are determined by a dynamical interaction of human and prosthetic control rather than by the unidirectional pattern-recognition approach mentioned above. Our approach takes into account the abilities of the patient, the reliability of the myosignals and the mechanical properties of the prosthesis. It is based on a closed-loop system that comprises both prosthesis and patient. The underlying principle is adapted from the homeokinetic approach to self-organizing control [8], [9]. In the following section the main ides of this principle will be shortly discussed (for details cf. [10], [11]). In Sect. III the idea of self-organization in prosthetic control will be described, followed by the technical details (Sect. IV). An illustrative example as a proof of principle (Sect. V) and an example for proportional control (Sect. VI) are presented. An application to a prosthesis with two degrees of freedom is given in (Sect. VII). The last two section discuss and summarize our results.

II. HOMEOKINETIC CONTROL

Homeokinesis follows the dynamical systems approach to robot control [12], [13], [14]. We will outline the main idea for a simple robot with one degree of freedom. At each time step the robot receives a vector $x_t \in \mathbb{R}^{n\times 1}$ of sensor values. The sensor values are predicted based on the earlier motor actions $y_t \in \mathbb{R}^{m\times 1}$ by a linear internal model

$$F(x_t, y_t) = a y_t \tag{1}$$

with a parameter matrix $a \in \mathbb{R}^{n\times m}$, where we assume $m = 1$. The robot acts in a sensorimotor loop which means that new sensor values are considered as being influenced by earlier motor outputs. In this way we can assume a functional dependence $x_{t+1} = \psi(x_t) + \xi_t$, where ξ_t contains all effects that are not under control by the robot. The function ψ is called the loop function and will be used here in the form $\psi(x_t) = a g\,(c x_t)$, where $c \in \mathbb{R}^{n\times 1}$ contains the controller parameters and the function g accounts for the hardware limits of the actions and is usually chosen as a $\tanh$.

Dynamically relevant properties of the robot can be described by a linearization that is given by the Jacobian L of the system $L_{ij} = \frac{\partial}{\partial x_j}\psi_i\,(x_t) = a_i c_j g'\,(z_t)$. The homeokinetic principle aims at modifying the eigenvalues of L by adapting the controller parameters c such that a marginally stable behavior is achieved. For this purpose the modeling error $\xi_t = x_{t+1} - F(x_t, y_t)$ is backpropagated

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through the internal model such that the previous sensor value is re-estimated. The re-estimated and the actual previous sensor value give rise to an error function which affects the stability properties of the system differently than for a direct minimization of the magnitude of ξ. This can be seen by considering the relation of the back-propagated error v and the forward error ξ via the the Jacobian: $Lv = \xi$. Because the inverse of L does not exist for $n > m = 1$, we can express the pseudo-inverse of L by the inverse in the direction of the vector a (1). Thus, the inputs x are considered as the deterministic part of the sensorimotor dynamics which can be captured by the model and, apart from the noise, a is proportional to x.

These consideration lead to the objective function

$$E = \|u_t\|^2, \tag{2}$$

where $u_t = \left(\tanh'(cx_t)\, R\right)^{-1} \xi_t \, {\xi_t}^T a$. The variable $R = ca$ denotes the linearized feedback strength of the sensorimotor loop. The minimization of Eq. 2 provides us with a rule for the dynamics of the parameters

$$\Delta c_i = \mu a_i - 2\mu c^T x \, x_{i,t} - \gamma \mu c_i. \tag{3}$$

An additional term $\mu = 2\varepsilon u^2/R$ and a small constant γ was introduced to produce a weak decay of the weights. In this way, the components of the initial conditions decay if they are orthogonal to a such that the assumption about the inversion of L is self-consistent.

In order to analyze the parameter dynamics we start with an initialization of the synaptic strength c such that the feedback strength is $0 < R \ll 1$. Then the motor command y is fluctuating around zero and the damping term $-2\mu \, c^T x \, x_i$ is small since the controller input cx is small. Hence the driving term in the learning dynamics dominates and produces $\Delta c_i = \mu a_i$, i.e. $\Delta (c_i a_i) = \mu a_i^2$ and hence $\Delta R = \mu a^2$. Obviously, the overall feedback strength R increases with channels of higher response strength $|a_i|$ being favored. Once R exceeds the critical value $R_c = 1$, activity in the system will be generated by amplification of sensory noise. If the system is active the sensor values x_i and the controller input $c^T x$ increase such that the anti-Hebbian term in Eq. 3 becomes effective. The parameter dynamics is stationary for $\gamma c_i = \left(1 - 2Ry_t^2\right) a_i$ or $R = \frac{1}{\gamma/a^2 + 2y_t^2} = \frac{a^2}{\gamma + 2x_{t+1}^2}$, so that $c_i = \alpha a_i$, where α can be considered as a constant here. Obviously the c_i reach values so that all sensors are integrated into the sensorimotor loop according to their response strength a_i as obtained from the internal model (1). Thus sensors showing a response to the motor commands are integrated in the sensorimotor loop with a synaptic strength $|c_i| > 0$. Non-responding sensors are barely integrated with $c_i \approx 0$.

These two properties of the homeokinetic control are not only interesting for autonomous robots but also for prosthesis control. On the one hand the generation of activity enables control the prosthetic device even with weak signals. On the other hand well responding sensors are selected in order to allow the patient to control the prosthesis.

III. HOMEOKINESIS IN PROSTHETIC CONTROL

The control loop proposed here will include two learning systems, namely the controller and the participant (or patient), compare Fig. 1. Motor commands of the controller are passed to the prosthesis. The movements of the latter can be visually observed by the participant. The reactions of the participant, measured via the surface electromyographic (sEMG) signal, are used as input to the self-organizing controller and build the basis for the generation of the next motor command.

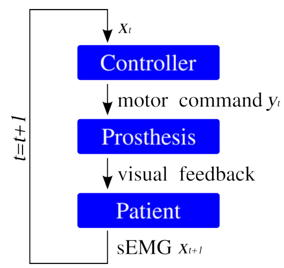


Fig. 1. Scheme of the control loop for a hand prosthesis with self-organizing controller. Motor commands from the controller cause movements of the prosthesis. The participant receives visual feedback and generates muscle activity the features of which are used as input to the controller and are used to calculate new motor commands.

In the beginning of the training period the prosthesis will start movements even if only noise is applied to the sensors, based on the driving term in the update rule in (3). In this way, patients who may initially produce rather weak signals get the impression to be able to cause the motion of the device and are thus encouraged to work with the system for longer periods. Thereby the involved muscle signals will be strengthened and the controllability is expected to improve. During the interaction the patient tries to support the movements shown by the prosthesis with motions he prefers and is able to generate. If after some minutes the prosthesis does not react to this movements, other movements have to be tried. The controller on the other hand will detect motion signals which are useful to control the prosthetic device. These control commands are not prespecified and therefore allow an adaptation to the individual patient. The learning algorithm is meant to be applied under supervision prior to the use in everyday life.

IV. METHODS

Data were recorded by two purpose-built electrodes with four contact surfaces each. The electrodes were placed at the superficial digital flexor and at the digital extensor of the forearm. Ground connection was established with an additional electrode. Per electrode three voltage signals U_i were obtained by calculating the differences between the measured potentials of neighboring contacts. The data were high-pass filtered with a 10 *Hz* cut-off frequency. A band-stop filter was applied to remove 50 *Hz* power-line artifacts. These preprocessing steps were performed using the LabVIEW software (National Instruments). For the data reported here the motor commands were realized by a three-dimensional realistic physical simulation of a sixteen degrees of freedom hand prosthesis (Fig. 2) which was created using the Open Dynamics Engine (www.ode.org). To match the properties

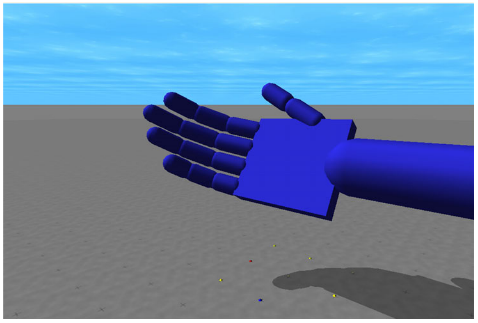


Fig. 2. Screen shot of a three-dimensional simulation of a human hand with 16 degrees of freedom which is used for visual feedback to the participant. In the experiments only wrist rotation and the hand aperture are actuated.

of an existing hand prosthesis (SensorHand, Otto Bock HealthCare) the degrees of freedom of the simulated hand were coupled, so that two independent and simultaneously controllable degrees of freedom remained (open/close hand and rotation of the wrist).

V. A 1DOF EXPERIMENT

The first experiment is intended to give a proof of principle of the homeokinetic approach to prosthetic control. Various features of the six-dimensional sEMG signal from the forearm of the participants were used as input to the homeokinetic controller. The goal of the experiment was to find out what feature would be chosen by the algorithm in order to enable control of the prosthesis by the participant. The selection process is performed in interaction of participant and prosthesis during a training period, prior to the practical use of the device.

The first input to the controller was the difference between the root-mean-square (RMS) values of two voltage signals obtained with different electrodes, i.e. above antagonistic muscles. The RMS values were averaged over 512 time steps corresponding to one sixth of a second at a sampling rate of the analog-to-digital converter of 3000 samples per second. The second, third and forth input were obtained analogously as differences between RMS values of two voltage signals within the same electrode. In order to simulate unusable channels the two remaining controller inputs received merely white-noise signals.

The first channel turns out to be best suited for control. We should expect the weights of the input lines to the controller to increase for the first channel and to decrease more or less quickly, resp., for the fifth and sixth and second to fourth channel.

The adaptation of the controller parameters was stopped when the patient reported the feeling of being able to control the prosthetic device which for the used averaging times and learning rates occurred typically after five minutes. After this time the weight of the channels had developed into a configuration that allowed the participant to control the prosthesis. Then a test was conducted and the participant was asked to operate the prosthesis according to a presented reference signal. The experiment was conducted with a healthy participant.

Fig. 3 shows the six input signals x_1 to x_6 and the controller-generated motor command y. Obviously, x_1 reflects the strongest response to the movement commands initiated by the participant. While the motor command is very noisy initially, it becomes more and more similar to x_1 subsequently due to the adaptation of the controller parameters.

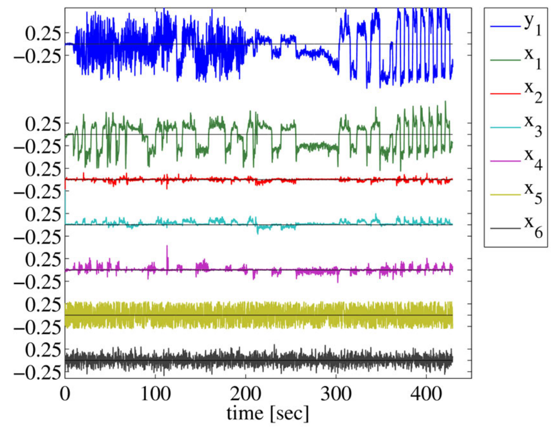
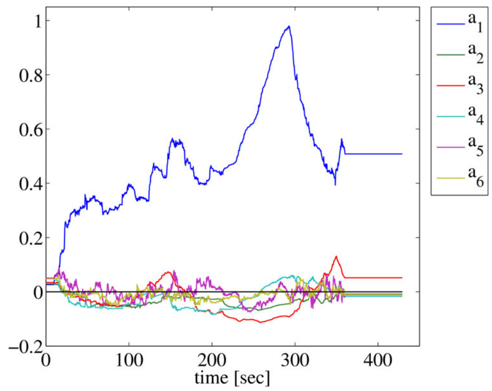


Fig. 3. Time course of the sEMG input features $x_1 \dots x_6$ and the motor command y during the experiment. The motor commands are very noisy initially since the inputs x_5 and x_6 have relatively strong weights c_5 and c_6 (compare Fig. 4(b)). Later the weights of the inputs ($x_1 \dots x_4$) increase resulting in a motor command that follows the shape of input x_1. After around 360 seconds the participant reported confidence in the ability to control the prosthesis and learning was disabled for a test (see Fig. 5).

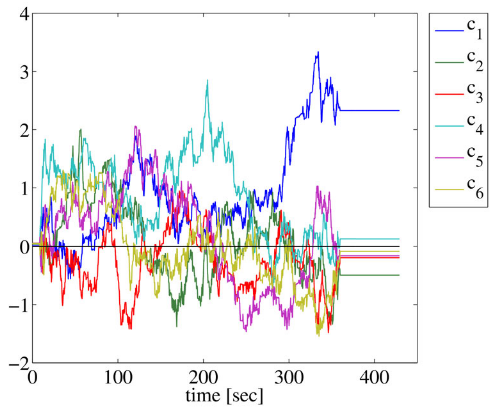
The development of the parameters of the controller and the model is shown in Fig. 4. The model parameter a_i serves to predict the myosignal feature x_i by linearly weighting the current output value of the controller. Clearly the weight corresponding to the sensory feature x_1 is quickly assuming the largest value while the other sensor values depend on the motor command to a lesser extent such that the corresponding weights remain smaller.

At the same time the controller parameters undergo fluctuation that test different constellations of the input weights to the controller. At some point the weight c_4 belonging to a suboptimal input channel reaches a certain strengths, but is soon replaced by c_1 as expected. The contribution of the other sensor values to the generation of the motor command are negligible. With this parameter setting the participant reported to be able to control the prosthetic device. Hence the adaptation of the controller parameters was stopped for the test of controller and selected features.

During the test a combined visual and acoustic stimulus r was used to indicate the required test movements. The motor command y depicted in Fig. 5 shows that the patient was able to generate the desired sequence of input signals and hence the desired motor commands.



(a)



(b)

Fig. 4. **(a)** The model parameter a_1 quickly develops to assume the largest absolute value. This implies that the motor command y contains predictive information mainly about the input x_1, see Fig. 3. **(b)** Initially, the controller parameters c_i change continuously and probe many different configurations. From about 300 seconds the weight c_1 is dominating in correspondence to the values of the model parameters. At about 360 seconds the adaptation of the parameters of model and controller was disabled for the test.

This result is not surprising. The input signal s_1 was the most promising signal provided and is also used in nowadays prosthetic devices. The interesting point, however, is that this solution *was* found. The self-organizing controller, in interaction with the participant, was able to select this signal for the control of the prosthetic device from a set of given signals, without further information provided.

VI. PROPORTIONAL CONTROL

This experiment is intended to investigate the possibility of proportional control using the proposed paradigm and the features introduced in the previous experiment.

The first input to the controller was the difference between the (RMS) values of two voltage signals obtained above antagonistic muscles. The second and third input were again obtained as differences between RMS values of two voltage signals within the same electrode. In order to simulate an unusable channel the input x_4 received merely a white-noise signal. The input signals were averaged over five time step.

The first channel is best suited for control and was also selected for control in the previous experiment. We should expect that with a RMS signal selected as contributing input a proportional control of the motor command is possible. In order to check this, we modified the test after the adaptation of the control parameters. The participant was asked to generate motor commands with different amplitudes.

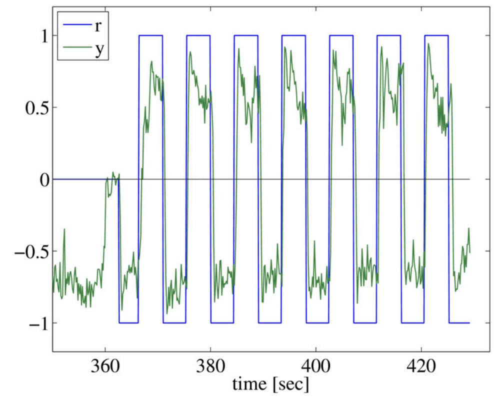


Fig. 5. The time course of the reference signal r and controller output y during test after successful training. The reference signal r represents the task to be performed by the participant, i.e. a required movement of the prosthetic device. The motor command is the signal generated by the controller based on input from the muscle activity of the participant. The traces indicate that the participant succeeded quickly in generating the desired sequence of motions of the prosthetic device.

The adaptation of the controller parameters was stopped when the (healthy) participant reported to be able to control the prosthetic device (after circa five minutes). In this experiment not only the RMS signal of the antagonistic muscles (x_1) but also the other RMS signals (x_2, x_3) had a noticeable contribution to the controller input, as determined by the vector of synaptic strength c. The noise input x_4 was barely integrated. During the test the participant was asked to operate the prosthesis according to a presented reference signal.

The test lasted circa 15 min with several minutes break. The participant was able to generate motor signals with discriminable amplitudes, see the exemplary time course in Fig. 6. Counting generated discriminable motor commands versus all desired motor commands (as indicated by the reference signal) a ratio of 77% was achieved. Uncertainty about the correct hand gesture for the desired motor command is the main reason for not discriminable motor commands. Hence a longer training/testing period is expected to increase performance in the test considerable. However, the results show a first proof of principle that, depending on the features used as input to the self-organizing controller, motor commands can be generated in a proportional way.

VII. CONTROL OF A 2DOF PROSTHESIS

As above we assumed that appropriate data features of the sEMG signal are provided and ask whether it is possible to equip a myoelectric prosthesis with a self-organizing controller, in order to select those features of the sEMG signal which allow the participant to control a two-dimensional prosthetic device. The adaptation of the controller is done in

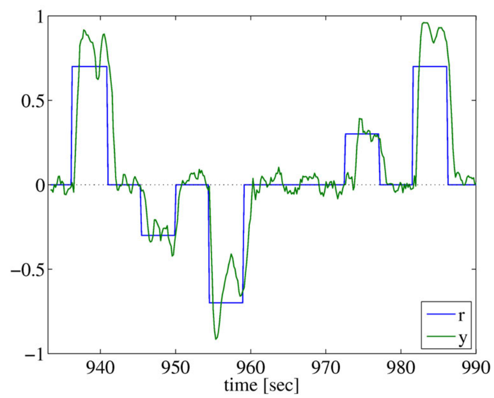


Fig. 6. Time course of the reference signal r and controller output y during test after successful training. The reference signal r represents the task to be performed by the participant, i.e. a required movement direction and amplitude. The motor command is the signal generated by the controller based on input from the muscle activity of the participant. The traces indicate that the participant succeeded in generating the desired sequence of motion commands with corresponding amplitudes.

interaction of participant and prosthesis in a training period, prior to the use of the prosthetic device.

A superposition scheme [5] was used for the feature extraction in this setup. It requires little computational effort and provides information about the motor unit action potential propagation that varies with different motions. Before running the reported experiments we tested the earlier observation [5] that this superposition scheme performs usually better than other time-domain and frequency-domain features. The superposition feature is calculated as

$$f_i = \frac{\mathrm{RMS}(U_i + U_j) - \mathrm{RMS}(U_i - U_j)}{\mathrm{RMS}(U_i + U_j) + \mathrm{RMS}(U_i - U_j)},$$

where j refers to the right neighbor of site i except for the last difference potentials of each electrode where it refers to the first site.

The first two inputs to the controller are determined according to the formula above, $x_1 = f_5$ and $x_2 = f_1$. The input lines three and four contain differences of the signals of this type, i.e. $x_3 = f_2 - f_5$ and $x_4 = f_3 - f_6$. The last input is similar to the one used in the previous section i.e. a difference of two RMS values of antagonistic muscles. The homeokinetic controller generates a two-dimensional output using two five-dimensional weight vectors. These outputs are used directly for the control of the two degrees of freedom prosthetic device.

The experiment was conducted with a healthy participant and lasted about one hour. Seven trials of about the same duration were performed. During the first trials the two degrees of freedom could not be independently controlled. Hence, several hours of interaction are required in the current setup to eventually be able to control the prosthesis. Unlike in the first experiment, no preferred feature can be identified in the input signals.

The adaptation of controller and model parameters during the experiment is more complex than in the first experiment. Converging to the map of motor commands to the features, the internal model does not end up with a single dominating channel. Instead all model parameters show considerable values, i.e. all sensors develop some dependency on the motor command. According to the model structure, all sensors become included in the generation of the motor command (compare Sect. II). The parameter adaptation was disabled, when the participant reported the feeling of being able to control the prosthetic device, which happened after about half an hour.

During the following test the participant was instructed to generate movements of the prosthetic device as indicated by visual and acoustic stimuli (reference signal r). The motor commands generated by the homeokinetic controller and the reference signal r are depicted in Fig. 7.

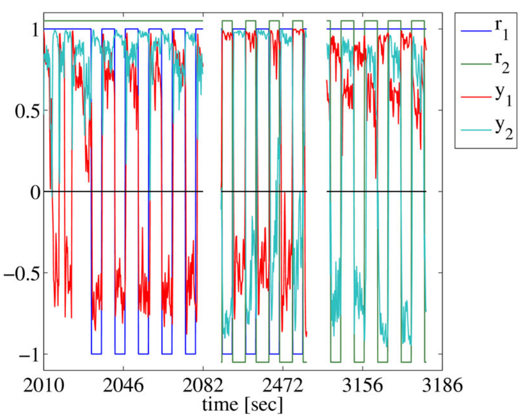


Fig. 7. During the test the participant was able to control two degrees of freedom independently. In the first part of the diagram y_1 oscillates between positive and negative values while y_2 remained at positive values, as indicated by the reference signals r_1 and r_2. In the second part both motor commands change sign but keep opposite sign. The third part shows an oscillation of y_2 while y_1 stays at positive values.

Three different combinations of the two motor commands y_1 and y_2 were generated by the participant, plotted as three distinct parts in the diagram. The first part shows movements where the motor command y_1 oscillates between positive and negative values while the motor command y_2 stays at positive values. This means the wrist rotates inwards (pronation) and outwards (supination) while the prosthesis is open. The second part shows an oscillation of both motor commands, with opposing sign. This corresponds to a supination with simultaneously opening of the hand alternating with a pronation with simultaneously closing of the hand. The third part shows motor command y_2 oscillating between positive and negative values while y_1 stays positive. In this case the hand opens and closes while the wrist rotates inwards. This experiment shows that during an interaction period of a participant and a prosthesis equipped with a self-organizing controller input signals are automatically selected, which allow the participant to control the two degrees of freedom of the prosthetic device.

VIII. DISCUSSION

By the results reported here we could show that the selection of appropriate input channels by interaction of a self-organizing controller and a human is a feasible approach which allows also for proportional control is possible. It is interesting to note that the selection of input features from the myoelectric signals adapts, too, together with the increase in signal quality when the participants improve. Hence, patient-specific adaptation remains possible even when the performance changes during training.

In some cases the superposition features were observed to be sensitive to small changes of the finger positions which made it problematic for participants to remember the allocation of motor commands by hand positions. This aspect is a side effect of the flexibility of the controller during training and requires further habituation by the patient. For the self-organizing controller the sensitive patterns seemed to indicate the possibility of controlling more degrees of freedom. For future work the use of larger electrode arrays or ring electrodes, perhaps incorporating different features, is expected to ease and improve the possibilities of the feature selection, since more input channels and hence more information about the muscle activity can be exploited.

In general, if several degrees of freedom are available it is possible, that some actuators start to connect to the same input provided to the controller, since there is no direct (physical) feedback from actuators to sensors such that coupled degrees of freedom result. Due to the properties of the homeokinetic approach these modes, as all others, will be left after some time [15]. Nevertheless it would be preferable to avoid these modes completely. Hence for future work, especially for more than two degrees of freedom, competitive learning, cf. e.g. [16], can be used for the adaptation of the internal model to reduce the appearance of these modes and so shorten the required training time.

The approach is clearly not restricted to prosthesis control. Control problems where the selection of input features has to be negotiated with the controllability of a device represent a possible field of application. This could include the control of a vehicle by body movements or of an avatar in a computer game by means of EEG signals.

IX. SUMMARY

For prostheses with one or two degrees of freedom control could be achieved easily based on the features selected by the self-organizing controller. In the one-dimensional case the RMS feature was selected by means of which the test participant was able to control the prosthesis following a given reference signal with different amplitudes. In the two-dimensional case a combination of the provided features was selected which allowed the participant to control wrist rotation and hand aperture as advised through the reference signal. The system remained sensitive with respect to changes of finger positions which resulted in different inputs to the controller and, hence, a variability of the motor commands. This made it sometimes difficult for participants to reproduce the correct hand positions for the motor commands required during the test.

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REFERENCES

[1] H. H. Sears and J. Shaperman, "Proportional myoelectric hand control: an evaluation," American Journal of Physical Medicine and Rehabilitation, vol. 70, no. 1, pp. 20–28, February 1991.

[2] R. Merletti and P. Parker, Eds., Electromyography: Physiology, Engineering, and Non-Invasive Applications. Hoboken, NJ, USA: John Wiley & Sons, Inc., 2004. [Online]. Available: http://doi.wiley.com/10.1002/0471678384

[3] L. Eriksson, F. Sebelius, and C. Balkenius, "Neural control of a virtual prosthesis," in Perspectives in Neural Computing: Proceedings of ICANN '98, L. Niklasson, M. Bodn, and T. Ziemke, Eds. Berlin: Springer-Verlag, 1998.

[4] B. Karlik, M. Osman Tokhi, and M. Alci, "A fuzzy clustering neural network architecture for multifunction upper-limb prosthesis," Biomedical Engineering, IEEE Transactions on, vol. 50, pp. 1255–1261, 2003.

[5] H. Willburger, "Adaptive myo-signal processing for multidimensional prosthesis control," Ph.D. dissertation, Vienna University of Technology, September 2007.

[6] M. LUCAS, A. GAUFRIAU, S. PASCUAL, C. DONCARLI, and D. FARINA, "Multi-channel surface EMG classification using support vector machines and signal-based wavelet optimization," Biomedical Signal Processing and Control, vol. 3, no. 2, pp. 169–174, 2008. [Online]. Available: http://linkinghub.elsevier.com/retrieve/pii/S1746809407000791

[7] M. Khezri and M. Jahed, "An exploratory study to design a novel hand movement identification system." Computers in biology and medicine, vol. 39, no. 5, pp. 433–42, 2009. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/19342012

[8] R. Der, U. Steinmetz, and F. Pasemann, "Homeokinesis - a new principle to back up evolution with learning," in Computational Intelligence for Modelling, Control, and Automation, ser. Concurrent Systems Engineering Series, vol. 55. Amsterdam: IOS Press, 1999, pp. 43–47.

[9] R. Der, M. Herrmann, and R. Liebscher, "Homeokinetic approach to autonomous learning in mobile robots," in Robotik 2002, ser. VDI-Berichte, R. Dillman, R. D. Schraft, and H. Wrn, Eds., 2002, no. 1679, pp. 301–306.

[10] F. Hesse, R. Der, and J. M. Herrmann, "Modulated exploratory dynamics can shape self-organized behavior," Advances in Complex Systems (ACS), vol. 12, no. 3, pp. 273 – 291, 2009.

[11] F. Hesse, G. Martius, R. Der, and J. M. Herrmann, "A sensor-based learning algorithm for the self-organization of robot behavior," Algorithms, vol. 2, no. 1, pp. 398–409, 2009.

[12] G. Schöner and M. Dose, "A dynamical systems approach to task-level system integration used to plan and control autonomous vehicle motion," J. Robot. Auton. Syst., vol. 10, pp. 253–267, 1992.

[13] L. Steels, "A case study in the behavior-oriented design of autonomous agents," in SAB94: Proceedings of the third international conference on Simulation of adaptive behavior : from animals to animats 3. Cambridge, MA, USA: MIT Press, 1994, pp. 445–452.

[14] J. Tani and M. Ito, "Self-organization of behavioral primitives as mulitple attractor dynamics: A robot experiment," IEEE Transactions of on Systems, Man, and Cybernetics Part A: Systems and Humans, vol. 33, no. 4, pp. 481–488, 2003.

[15] R. Der, F. Hesse, and G. Martius, "Rocking Stamper and Jumping Snakes from a Dynamical Systems Approach to Artificial Life," Adaptive Behavior, vol. 14, no. 2, pp. 105–115, 2006.

[16] D. E. Rumelhart and D. Zipser, "Feature discovery by competitive learning," Cognitive Science, vol. 9, no. 1, pp. 75 – 112, 1985.