Avoiding Training Reiterations by Early Forecasting using Stochastic Estimates for Human Pattern Recognition/Regression Training

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Introduction

For applying machine learning to prosthesis control, it is beneficial when prosthesis users produce repeating muscle actions with low spatial and temporal variability. Due to their complex nature, most machine learning approaches are statistically based. Machine learning needs to be robust against variability, but this works only up to a certain border. Changing environment produces data-shift between training data and test/application data, which may lead to higher recognition errors. In order to alleviate this, co-optimization between machine- and human learning appears as the most efficient approach.

Machine learning optimization is in focus of interest since decades of research. Human learning capabilities were long time neglected or underestimated for being component of a solution. This, because human variability in doing things appeared often too complex for a proper modeling, hence it was tried to better avoid involvement of human actions as much as possible. Thus, in rehabilitation and prosthetics, the human is the object of factual interest and is also part of the processing loop and therefore not neglectable at all.

However, since human physiotherapeutic training takes typically weeks, it is difficult to judge if the way a subject performs muscle contractions will certainly yield good separability between different motions at the end of the training. Therefore, a forecasting method is required, which shows if different motions will probably overlap too much after completion of training. This can help to avoid training which must be re-done in the end. Thus, when using the proposed method it becomes possible to change the way of doing a certain contraction at an early stage to avoid overlap with other patterns. Prosthesis users become substantially influenced by psychological factors, such as i) learning ability, ii) cognitive skills, iii) motor-skills, and iv) mental status (e.g. motivation, will, stress), which are situated in their mental-body. Thus, a prosthesis user needs time for adaptation and reorganization of their neuronal network. It appears that they may feel and imagine their original joints and they can also move them, which is described by the phantom-limb phenomenon. Hence, utilizing the phantom-limb phenomenon enables us to provide more intuitive prosthesis control to the prosthesis user, because they may simply try to move the phantom-limb joints as if they would use their original ones. By that, residual muscles of the prosthesis user-stump are activated, yielding ElectroMyoGraphic (EMG) signals on the skin surface from action potentials produced by the contraction of some muscle fibers of the stump. Finally, these surface EMG-signals can be taken by electrodes and utilized for prosthesis control.

Methods

The problem is that novice prosthesis user seldom produces repetitions of a movement with the same outcome, using certain joint and same contraction strength. There is some variation observable, thus motions appear over time somehow perturbed which can be attributed to some variability in motor control. This variability can be modeled as noise, which is added on the pathway from motor cortex along the spine via the motoneurons to the muscles. In order to average out this noise, “enough” samples from the contraction patterns must be used for building the average. The problem herein is to determine the number of samples required to get a proper result. Hence, as a solution, we modeled the interaction of two stochastic processes, with the first as the signaling process, which produces the signal plus noise, and the second as the averaging process which samples the first process to get data for building the average. Finally, after using a huge number of averages, the averaged result will no longer change when adding more samples, hence, the averaging has estimated correctly the underlying original signal. We show that the solution in fact is at the stopping time of a martingale process and as result, the variations of the mean and variance of the patterns fade out.

Results

Having this method in mind, we let the subject do a number of motions for every movement type to be supported and contraction level. Fig.1-top row shows early estimates before training, calculated for an individual subject. It can be seen there, that the subject has had for three out of five different movements almost one equivalence class and the other two were also very close to these. Fig.1-lower row shows the result after re-training the subject on six days within two weeks with three hours training per day. In the plots we see peaking directions of all movement classes now directed into different directions and the overlaps between the classes are no longer influencing the result. Finally, the subject improved offline classification rate from 62\% (average over all movement classes) to 99\% and the machine learning could therefore be successfully applied for five prosthesis functions (i.e. wrist supination, wrist pronation, hand opening, key-grip and fine-pinch functions of the Michelangelo®-hand Advanced Prosthesis System.

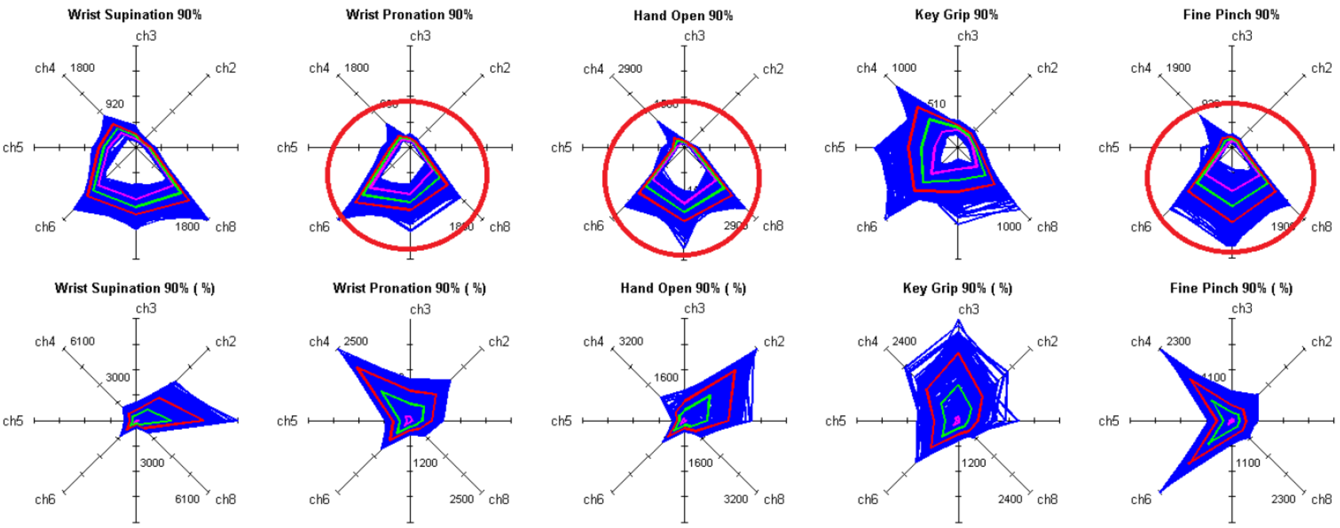

Fig.1: Polarplots: Vectors of RMS values of a huge number of trials are plotted as superposed octagons. Upper row -- initial polar plots for five intended movements. We can see that three out of five plots (circled) are member of the same equivalence-class. Therefore, this subject had to be trained differently in order to achieve distinct movement patterns.
Lower row -- the same subject after re-educated training. The patterns now appear distinctive and the subject could be fitted with a prosthesis

Conclusion

We have shown a method that enables acting individually with the required level of support for the fitting of EMG prostheses to users after amputation. The early estimation of movement performance enables to optimize training in order to get the best results in a direct way. We have applied this method for the training of several prosthesis users, both for laboratory sessions [Ge et al., 2013] and for real-live application [Amsuess, 2014].

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