Automatic Adjustment of Electromyography-Based FES Control

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***Abstract*— In this work, two EMG-based FES control approaches are investigated with the aim of allowing stroke patients to recover motor function of the upper limbs, especially the wrist. Often, patients have weak residual muscle activity but are not able to achieve high wrist extension angles. This residual volitional muscle activity can be continuously measured from the stimulation electrodes by using a customised EMG amplifier. The aim of both developed control approaches is to find the optimal FES support that uses the minimal required stimulation intensity to support the movement and that yields an almost linear relation between the measured volitional EMG activity (effort) and the resulting wrist-joint angle. The first approach is based on iteratively learning a static EMG-stimulation intensity relation from repeated EMG-reference tracking tasks, while the second approach maps the detected volitional EMG activity to a reference angle that is fed to a feedback controller. Both cases require the measurement of the wrist-joint angle, e.g. by an inertial motion unit. For both techniques, case studies with healthy subjects and stroke patients have been conducted. Advantages and disadvantages of both approaches are discussed in this contribution.**

I. INTRODUCTION

The idea to drive Functional Electrical Stimulation (FES) by electromyography (EMG) measurements obtained at the stimulated muscles has been studied by several research groups, see e.g. [1]–[5]. Residual volitional muscle activity was detected and the weak movements of the patients were amplified by FES-induced muscle contractions. The used systems measured the EMG from separate standard AgCl-EMG-electrodes or directly from the stimulation electrodes [6], [7]. In the past, research has been mostly focusing on the measurement of the EMG between stimulation pulses and the filtering process for extracting the information about volitional muscle activity, see e.g. [8]–[16]. The mapping from the measured volitional EMG activity to the stimulation intensity was usually static and linear. Parameters of this static mapping were selected by trial and error. No real procedure, neither manual or automatic, has been described or applied for finding optimal parameters.

An optimal EMG-based FES controller should enable the patient to determine the extent of the desired movement independently. Furthermore, the right stimulation intensity must be found automatically in such a way that the desired movement task can be achieved and that at the same time the maximal possible volitional contribution is demanded from the patient. These demands can be translated into the objective to find a controller that causes a linear function between the present volitional EMG activity and the resulting FES-supported wrist extension. It is obvious, that a simple linear relation in the control law between the measured volitional EMG activity and the applied stimulation intensity usually does not represent a solution for this problem.

This paper outlines two possible solutions for designing EMG-based FES controllers that fulfil the objective established above.

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II. MATERIAL AND METHODS

A. Experimental setup

The used experimental set-up is shown in Fig. 1. The wrist and finger extensors are stimulated through a pair of self-adhesive hydro-gel electrodes (RehaTrode 6x4cm oval, HASOMED GmbH, Germany) at a stimulation frequency of 20 Hz. Stimulation pulses are generated by a PC-controllable stimulator (RehaStim, HASOMED GmbH, Germany) with USB interface. The current-controlled stimulation pulses are bi-phasic with fixed current amplitude and modulated pulse width (stimulation intensity).

EMG-measurements are performed from the stimulation electrodes using a slightly modified version of the EMG amplifier STIMYO described in [6]. The amplifier uses PhotoMOS-switches to disconnect the amplifier inputs from the electrodes during the application of electrical stimuli and to shortly discharge the stimulation electrodes after each stimulus. After amplification and analogue band-pass filtering (200-700 Hz), the EMG-signal is sampled by an ARM Cortex M3 micro-controller (STM32F103RB, STMicroelectronics, Switzerland) at 4 kHz and a selected time window (27.5 to 49 ms after each stimulus) is filtered again through a non-causal digital high-pass filter with zero-phase shift and a cut-off frequency of 200 Hz. The resulting signal is windowed again to remove unwanted transients of the digital high-pass filter. Finally, the remaining signal is rectified

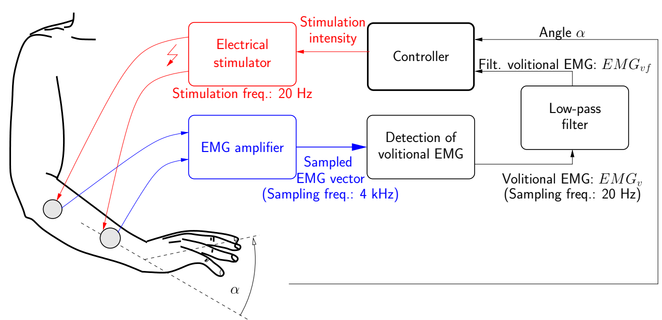

Fig. 1. Experimental set-up.

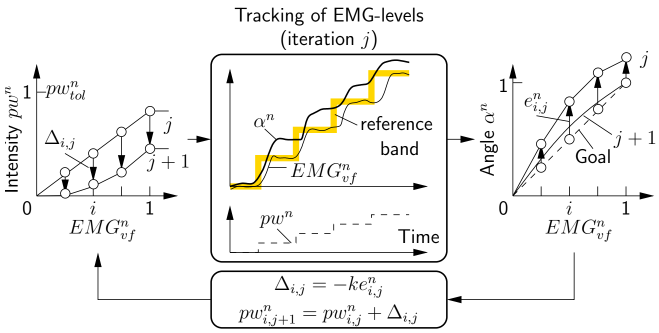

Fig. 2. Principle of iteratively learning EMG-based FES.

and the mean is calculated yielding a scalar measurement $EMG_v(k)$ of the volitional muscle activity within the last stimulation period. The index k is the sampling index of the control system and the sampling period $T_s = 50\,\text{ms}$ is determined by the stimulation period. The measurement $EMG_v(k)$ is transmitted through an optically isolated USB interface to a Laptop running Linux with RTAI real-time extension. At the PC-side the still noisy signal $EMG_v(k)$ is low-pass filtered by a digital first order filter with a cut-off frequency of 0.25 Hz.

Beside the filtered volitional EMG EMG_{vf}, the wrist-joint angle α is recorded by mounting an inertial-measurement unit (MTx, Xsens Technologies B.V., The Netherlands) at the hand. This measurement is precise as long as the lower arm is lying flat on a table.

Scilab 4.2.1[1] together with the HART toolbox[2] are used for controller design, real-time code generation, and interfacing the hardware. In addition, the tool QRtaiLab[3] is employed for signal monitoring and on-line parameter adjustment of the generated real-time executable.

B. System calibration

During an initial calibration phase, EMG_{vf} at rest and during maximal voluntary contraction are determined and stored as EMG^{min}_{vf} and EMG^{max}_{vf}, respectively. Then the minimal stimulation intensity pw_{min}, at which a visible muscle contraction can be observed, as well as the maximal tolerated stimulation intensity pw_{tol} are determined. The angle α_{min} at rest as well as the maximal desired angle α_{max} under FES support are detected. In a last step, the necessary stimulation intensity pw_{max} for generating the angle α_{max} is manually assigned. The volitional EMG and the angle are normalised (to the range [0,1]) between the *min* and *max* values yielding the signals EMG^n_{vf} and α^n, respectively. For the stimulation intensity, the range $[pw_{min}, pw_{tol}]$ is mapped to the range $[0,1]$, yielding the normalised intensity pw^n.

C. Iteratively learning EMG-based FES

The idea of an iteratively learning EMG-based FES is depicted in Fig. 2. The patient is asked to track iteratively a set of N distinct EMG-levels $EMG^n_{vf,i} = i/N$, $i = 1, \ldots, N$, which are equally distributed over the range (0,1]. He/she must keep the generated volitional EMG for a certain duration inside some pre-defined band. For each EMG-level, a constant supportive stimulation intensity $pw^n_{i,j}$ is applied which, is calculated for $EMG^n_{vf,i}$ from a static EMG^n_{vf} to pw^n relation that is valid during the iteration j. For the first iteration, a linear relation between EMG^n_{vf} and pw^n is chosen ($pw^n_{i,1} = pw_{max}/pw_{tol} \cdot EMG^n_{vf,i}$). For each tracked EMG-level with FES support, the resulting steady-state wrist-joint angle $\alpha^n_{i,j}$ is stored and the deviation $e^n_{i,j}$ from a linear relation between EMG^n_{vf} and α^n is computed. In order to drive these errors to zero the static relation between EMG^n_{vf} and pw^n will be updated as follows from iteration to iteration: $pw^n_{i,j+1} = pw^n_{i,j} - ke^n_{i,j}$. This learning may be stopped when the observed relation between EMG^n_{vf} and α^n becomes almost linear. The found piecewise linear static relation between volitional EMG and stimulation intensity may be used in EMG-based FES afterwards.

[1] http://www.scilab.org
[2] http://hart.sf.net
[3] http://qrtailab.sf.net

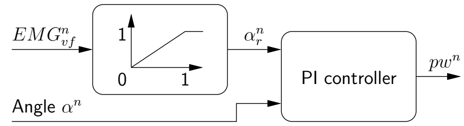

Fig. 3. Feedback EMG-based control.

D. Feedback EMG-based control

Feedback EMG-based FES control represents another approach to obtain a linear relation between volitional muscle activity of the patient and the joint angle. This method is based on the use of a control loop. The measured angle $\alpha^n(k)$ is fed back. The angle reference $\alpha^n_r(k)$ is defined as follows:

$$\alpha^n_r(k) = EMG^n_{vf}(k) \tag{1}$$

The use of normalised signals allows the direct assignment from $EMG^n_{vf}(k)$ to $\alpha^n_r(k)$. As shown in Fig. 3, a PI (Proportional-Integral) controller is used in order to compute the stimulation intensity $pw^n(k)$:

$$\begin{aligned} e^n(k) &= \alpha^n_r(k) - \alpha^n(k) \\ pw^n(k+1) &= K_P e^n(k) + K_I T_s \sum_{l=1}^{k} e^n(l) \end{aligned} \tag{2}$$

Here, $e^n(k)$ is the error between desired and real angle. The controller parameters K_P and K_I are positive constants that are chosen by trial and error in order to avoid oscillations of the closed loop system and to maintain good tracking performance (rise time less than 8 s). The controller was implemented with an anti-windup feature [17] for the integrator as the control signal (stimulation intensity) may saturate at the level pw_{tol}.

III. RESULTS

A. Iteratively learning EMG-based FES

The iteratively learning EMG-based FES was evaluated with healthy subjects at first. To mimic a reduced muscle

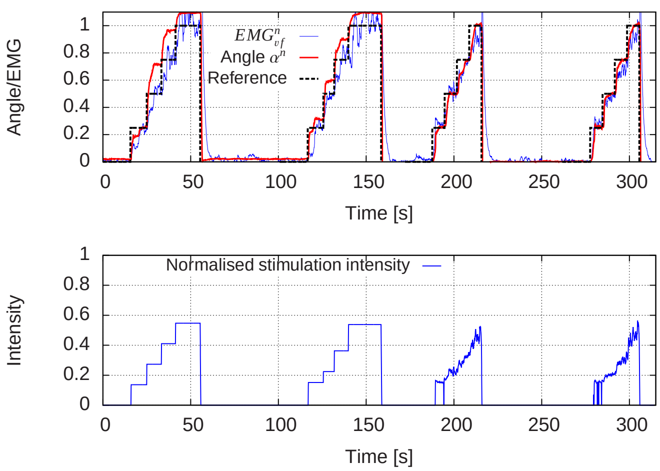

Fig. 4. Results of iteratively learning EMG-based FES with a healthy subject: 1st-2nd EMG reference staircase → learning, 3rd-4th angle ref. staircases → EMG-based control with fixed controller.

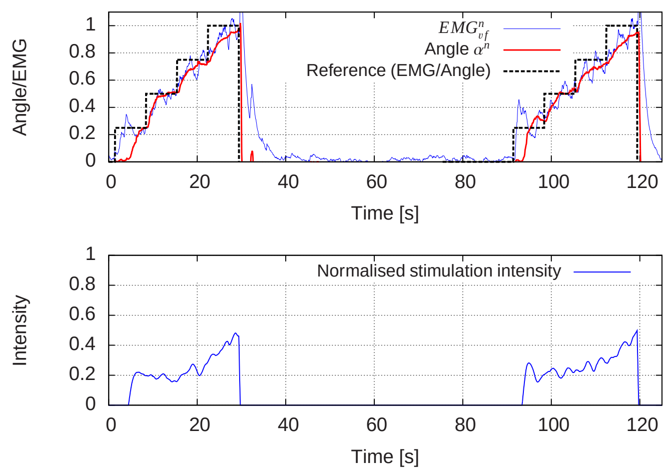

Fig. 6. Results of feedback EMG-based FES for a healthy tracking a displayed angle profile. Please notice that the shown pre-defined reference is NOT the internally used reference $\alpha_r^n(k)$ for the PI controller.

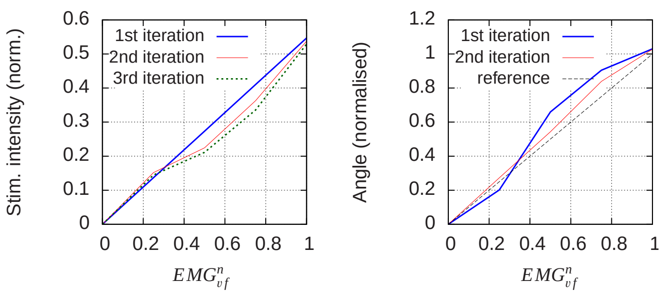

Fig. 5. Static relations for the trial with iteratively learning EMG-based FES shown in Fig. 4.

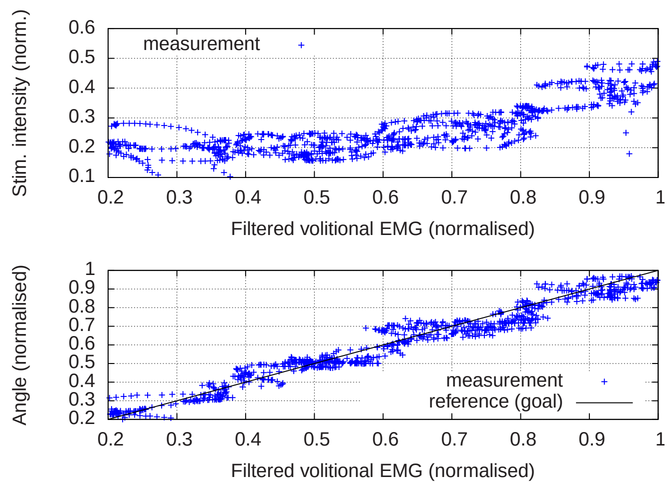

Fig. 7. Scatter plots of normalised EMG, stimulation intensity and measured angle for feedback EMG-based FES trial shown in Fig. 6.

activity, the maximal allowed volition EMG during the experiments was set to the EMG activity measured during 20° wrist-joint extension (hand flat on the table corresponds to 0°). For one subject, Fig. 4 shows the results from two iterations of learning followed by two iterations of angle tracking using the found static controller relation. The maximal wrist extension was 58°. The updated static relations between EMG and stimulation intensity/angle for the learning phase are shown in Fig. 5. It can be observed that already after two iterations of learning an almost linear EMG–angle relation could be achieved. From 180 s on, an angle tracking test was performed using the previously found nonlinear EMG–stimulation intensity relation.

B. Feedback EMG-based FES

Also the feedback EMG-based FES was evaluated with healthy subjects at first. Fig. 6 shows exemplary results of an angle tracking test. The angular reference was a staircase like signal. The scatter plots of normalised EMG, stimulation intensity and measured angle in Fig. 7 clearly show that an almost linear EMG–angle relation can be generated with the feedback EMG-based FES approach.

C. Clinical tests

The iteratively learning EMG-based FES was applied to stroke patients as well. Fig. 8 shows exemplary data. The first 50 s, the patient was asked to track a staircase like angular reference profile without FES support with a maximal wrist extension of 41°. The requested higher angles could not be reached. Then two iterations of iteratively learning EMG-based FES followed. The test concluded with two rounds of angle tracking with EMG-based stimulation (using the found EMG–stimulation intensity relation) and one round of angle tracking without FES-support. It is interesting to notice that an almost linear EMG–angle relation can be observed after the learning. However, one tracking round later the subject needs less volitional effort to produce the angle profile and after switching off the stimulation support he is even able to generate the angle profile completely alone.

IV. DISCUSSION AND CONCLUSIONS

The proposed methods automatically seek the stimulation support for achieving an almost linear relation between residual volitional muscle activity and wrist-joint angle. Both methods require an additional measurement of the joint

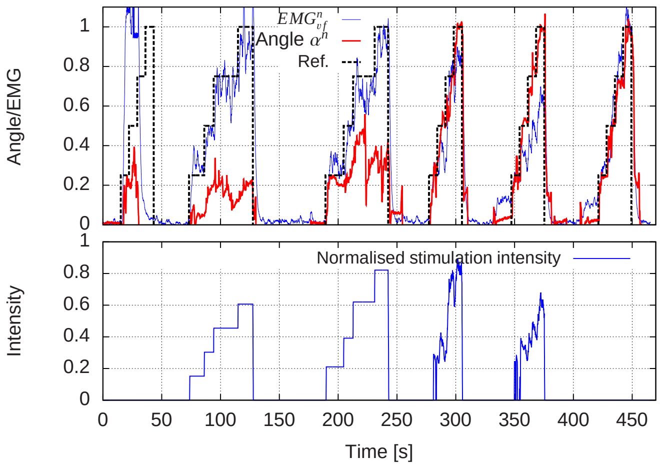

Fig. 8. Results of iteratively learning EMG-based FES with a stroke patient: 1st angle reference staircase $\rightarrow$ no FES, 2nd-3rd EMG ref. staircases $\rightarrow$ learning, 4rd-5th angle ref. staircases $\rightarrow$ EMG-based control with fixed controller, 6th angle ref. staircase $\rightarrow$ no FES.

angle. The iteratively learning EMG-based FES is bound to repetitive movements while the feedback EMG-based FES can also be applied to free non-repetitive movements. However, a badly tuned feedback EMG-based FES may lead to instability and oscillations.

Preliminary results with stroke patients indicate that the iteratively learning EMG-based FES should not be stopped after some iterations. Learning should always continue to adapt for changes in spasticity, muscle tone and fatigue. For the reported case, the muscle tone of the flexors was probably decreasing during the experiment. As a consequence, the patient could track the required angle profile at the end with the same extensor EMG activity which was initially not adequate. Another clinical observation is that the maximal volitional EMG of the supported muscle should be re-calibrated after a certain time to adapt for improvements/deteriorations of the patient's residual motor control.

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