34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

Grasp and release with surface functional electrical stimulation using a Model Predictive Control approach

Ard J. Westerveld[1], Alexander Kuck[1], Alfred C. Schouten[1,2], Peter H. Veltink[1] and Herman van der Kooij[1,2]

***Abstract*— Stroke often has a disabling effect on the ability to use the hand in a functional manner. Accurate finger and thumb positioning is necessary for many activities of daily living. In the current study, the feasibility of novel FES based approaches for positioning the thumb and fingers for grasp and release of differently sized objects is evaluated. Assistance based on these approaches may be used in rehabilitation of grasp and release after stroke.**

A model predictive controller (MPC) is compared with a proportional (P) feedback controller. Both methods are compared on their performance in tracking reference trajectories and in the capability of grasping, holding and releasing objects.

Both methods are able to selectively activate the fingers such that differently sized objects, selected from the Action Research Arm test, can be grasped. The MPC method is easier to use in practice, as this method is based on a single identification of a model of the biological system. The P-controller has more parameters which need to be set correctly, and therefore needs more time to initialise.

The current results are very promising. Evaluation in patients will be done to explore the possibilities to apply these methods in rehabilitation of grasp and release after stroke.

I. INTRODUCTION

Functional independence of stroke patients is highly influenced by their ability to perform a successful grasp. In many activities of daily living, like drinking or opening a door, grasp and release is an essential part of the required movement. For stroke patients, electrical stimulation of finger and thumb muscles can be helpful in training grasp and release movements [1]. Depending on the ability of the individual patient, the assistance may be increased or decreased to maximize the voluntary activity, which is important in relearning movements [2]

Many strategies have been used in controlling electrical stimulated muscle [3]: open loop methods, where predefined stimulation patterns are used to activate several, e.g. [4], [5] and several forms of closed loop control, e.g. [6], are described in literature. Most methods target all fingers as a single degree of freedom, thus allowing only gross movements. In addition, the ability to position the *thumb* is an important factor to successfully manipulate objects. Recently, we explored the possibilities for activating individual fingers by electrical stimulation [7]. We aim to use this selective stimulation to control fine movements of the thumb and fingers, like grasping small objects.

Simple systems often can be controlled quite accurately with a feedback controller. When systems become more complex, more sophisticated control methods might give better results. An accurate model of the system can be used to predict the system's response to changing control outputs and to optimally control the system. This forms the basis of a model predictive controller (MPC).

The human musculoskeletal system is a complex nonlinear and time-variant system. Therefore it is likely that a 'simple' feedback control method gives poor results and is outperformed by a more intelligent control system, like an MPC.

The aim of this study is to show the feasibility of using either a proportional (P) controller or a MPC for accurately controlling the position of the thumb and fingers by surface electrical stimulation of multiple finger and thumb muscles. We aim to demonstrate that these methods can be used for more fine motor control of the hand, like for grasp and release of small objects. In addition, the performance of both methods will be compared.

Currently, we are focusing on successful positioning of the thumb and fingers by surface electrical stimulation only. At this stage, the movement is fully performed by the stimulation control system. At a later stage the method can be tailored towards relearning movements after stroke by minimizing the assistance provided by electrical stimulation.

II. METHODS

A. Subjects

Currently, the control methods are compared in experiments with two healthy, male, right handed subjects, aged 26 and 27 years. The subject's non dominant hand is tested.

B. Experimental Setup

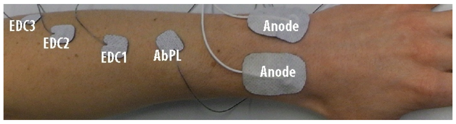
Two custom built 3 channel electrical stimulators (TIC Medizin, Dorsten, Germany) are used to apply the stimulation. One stimulator is used to target the thumb muscles, the other one targets the finger flexor and extensor muscles.

Hand and thumb positions are measured by a VisualEyez motion capture system (Phoenix Technologies Inc., Burnaby, Canada). Markers are placed at several bony landmarks at the back of the hand and the fingers. Finger flexion angles ($\phi_{1..3}$) are calculated from the finger marker positions. A fully extended finger is defined as zero degrees of flexion. Thumb positions are represented in 2 dimensions as abduction (ψ) and extension (θ) angles.

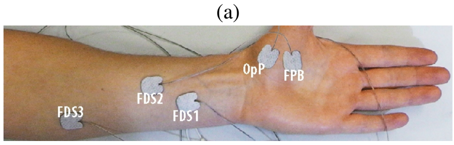
This study is funded by Interreg IV, part of the European Regional Development Fund

[1]A.J. Westerveld, A. Kuck, A.C. Schouten, P.H. Veltink and H. van der Kooij are with the Institute for Biomedical Engineering and Technical Medicine (MIRA), University of Twente, 7500 AE Enschede, The Netherlands `a.j.westerveld at utwente.nl`

[2]A.C. Schouten and H. van der Kooij are with the Department of Biomechanical Engineering, Delft University of Technology, 2628 CD Delft, The Netherlands



(a)



(b)

Fig. 1: Overview of electrode placement on the dorsal (a) and palmar side (b) of the arm and hand. Electrodes are placed above the finger extensors (EDC1..3), finger flexors (FDS1..3), abductor pollicis longus (AbPL), opponens pollicis (OpP) and the flexor pollicis brevis (FPB).

For the P-controller, a custom built setup is used to measure the isometric thumb forces in two directions (horizontal/vertical) perpendicular to the axis of the thumb. Forces are measured by two 45.3 N load cells (Futek, Irvine). Additional motion capture markers are attached to the setup to reconstruct the position of the force sensors.

Matlab/Simulink (The Mathworks, Nattick, USA) is used to set up the custom built controllers. Matlab XPC is used for real-time control. Ethercat I/O systems (Beckhoff Automation GmbH, Verl, Germany) is used to capture analog data from the force sensors and to set the stimulator parameters.

C. Experimental Protocol

Electrodes are placed at the motor points of selected muscles, see Fig. 1, based on exploration of the responses to electrical stimulation at a frequency of 30 Hz and a pulse width of 80 μs. For the fingers, the little finger is not specifically targeted. However, when stimulation currents become larger, the little finger is also activated.

Subject specific muscle properties are determined first. Thresholds and maximal stimulation amplitudes are determined for each electrode based on observation of evoked movements. Subsequently, the thumb is fixated in the isometric setup to measure the force directions for the three thumb muscles, which are used in the P-controller.

D. Control methods

Both control methods are schematically shown in Fig. 2. Fig. 2a shows the block scheme for the MPC, Figs. 2b and 2c show the block schemes of the proportional control methods for the fingers and the thumb respectively.

1) MPC controller: For the MPC, a model of the system is obtained, which is used by the controller to predict the best system inputs in order to push the system in a certain reference state. Hereby the system is described by a second order linear dynamic polynomial model (ARX) with 9 inputs (# of stimulating electrodes) and 5 outputs ($\theta, \psi, \phi_{1..3}$). To obtain data for model calculation, the actual control routine is preceded by a data acquisition procedure of approximately 2-3 minutes, in which the output angles are recorded while all inputs are individually excited by a semi random step signal. The obtained raw data is preprocessed by removing drifts and low pass filtering, the model is derived and fed into the controller. The MPC operates at a rate of 10 Hz using the general model predictive control objective function [8]. In order to avoid uncomfortable or harming stimulation behavior, the system inputs are constrained to the determined maximum stimulation amplitudes and the maximum rate change was constrained to 1 mA per controller step. Prediction and control horizon were set to 6 and 5 steps respectively.

2) P-controller: All determined parameters are used in the P-controller, which runs at a rate of 10 Hz. The determined threshold and maximal amplitudes are used to offset and saturate the stimulation output, respectively. Thumb muscle activation is based on the errors (ψ_ϵ and θ_ϵ) between desired thumb angles and the actual thumb angles. Based on these angles, the thumb force direction, ϕ_{ref}, is calculated based on the four quadrant inverse tangent, see (1). Based on this reference angle, the magnitude of the position error, Δx, the identified angles of movement of the two adjacent muscles, $\phi_{[1..2]}$, and their proportional gains, $K_{Th[1..2]}$, the activation amplitudes of both muscles, $A_{Th[1..2]}$, are determined, see (2). The proportional gains are set empirically based on observation of the finger movement to improve response times, while preventing oscillatory movements.

$$\phi_{ref} = 2tan^{-1}\frac{\theta_\epsilon}{\sqrt{\psi_\epsilon^2 + \theta_\epsilon^2} + \psi_\epsilon} \tag{1}$$

$$A_{Th1} = K_{Th1}\Delta x \frac{sin(\phi_{ref} - \phi_2)}{sin(\phi_1 - \phi_2)} \tag{2.1}$$

$$A_{Th2} = K_{Th2}\Delta x \frac{sin(\phi_1 - \phi_{ref})}{sin(\phi_1 - \phi_2)} \tag{2.2}$$

For the fingers, the evoked angular movement directions are assumed to be constant in flexion/extension directions. Based on the error, ϕ_ϵ, between the actual and the reference angle, either the flexor muscle or the extensor muscle is selected for stimulation. The flexor muscle is selected when the error is positive, the extensor muscle when the error is negative. The absolute error is then fed back with the proportional gain, K_f and K_e for flexor and extension muscle respectively, to activate the selected muscle with the calculated amplitude, $A_f(i)$ and $A_e(i)$ respectively, see (3).

$$A_f(i) = K_f(i)|\phi_{\epsilon,i}| \quad A_e(i) = K_e(i)|\phi_{\epsilon,i}| \tag{3}$$

E. Controller evaluation

For evaluation of the control methods, two evaluation procedures are defined.

1) Tracking of step function inputs: To evaluate the performance of the control method on selective activation of different fingers, step function reference patterns are defined for each of the fingers, while the references for the other fingers remain constant. Although there is both biomechanical and neuromuscular coupling between the different fingers, we expect to keep movements of non-targeted fingers small relative to the targeted finger. From all step functions, steady

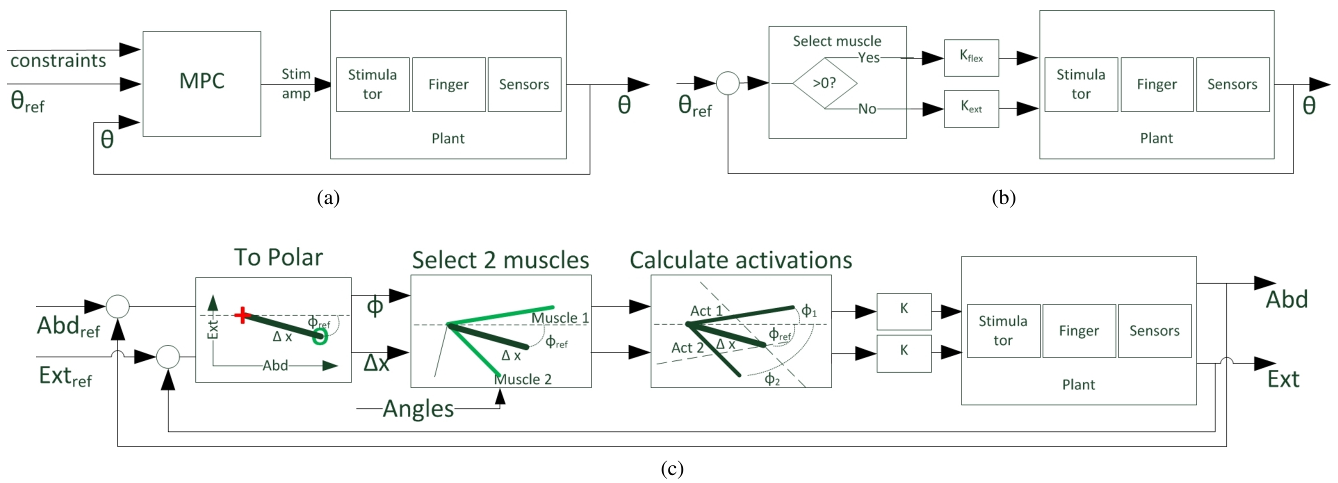
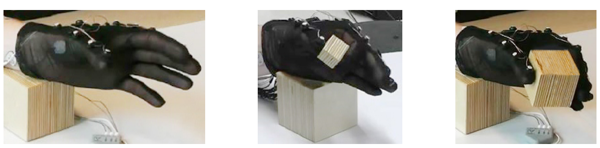


Fig. 2: Block schemes for the controllers. a) MPC, b) finger P-controller and c) control structure applied to the thumb muscles in the P-controller: first the angular error is determined, which is then used to select the appropriate muscles for stimulation and to calculate the stimulation amplitudes for these muscles.

	θ_{ref}	ψ_{ref}	$\phi_{ref,1}$	$\phi_{ref,2}$	$\phi_{ref,3}$
Hand opening	20^o	40^o	5^o	5^o	5^o
Cylindrical grip	-10^o	20^o	60^o	60^o	60^o
Pinch grip	-10^o	20^o	60^o	35^o	35^o

TABLE I: Predefined reference angles for different states



(a) (b) (c)

Fig. 3: Example of the controlled hand states: a) hand opening, b) pinch grip and c) cylindrical grip.

state errors are calculated as the average RMS angular error between setpoint and actual angle when the response reached steady state. RMS errors of targeted and non-targeted fingers are then compared for both methods.

2) Grasping of differently sized objects: Three differently sized objects: cubes of 2.5 cm and 5 cm and a small marble are selected from the Action Research Arm (ARA) test. To simulate reaching, the objects are moved towards the hand, while the hand remains at the same position. Different states for the hand are defined: opening, cylinder grip and pinch grip. Constant reference angles are defined a priori for these states, see Table I. Examples of different states are shown in Fig. 3. To grasp a object, the setpoints are first set to the open state, then the object is moved towards the hand and then the setpoints are changed to close the hand. The cylindergrip is used for grasping the largest cube. The pinch grip is used to grasp the small cube and the marble. Successful grasp is defined as holding the object without any assistance, thus purely by muscle forces evoked by electrical stimulation, for at least ten seconds. Grasping trials are repeated five times for each object.

III. RESULTS

A. Tracking of step function inputs

Fig. 4 shows angular positions of the different fingers during the step function inputs. The figure shows that we are able to selectively activate a single degree of freedom (the index finger in this case) with both controllers. Small movement in especially the middle finger and thumb are observed when the setpoint for the index finger is changed. However, these movements are small compared to the index finger movement.

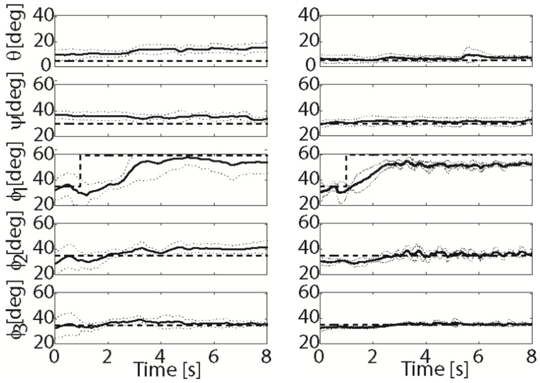
Similar results are obtained when step functions are applied as reference for other angles. These results are summarized in Fig. 5. Step response trials for all fingers are shown for both the MPC and the P-controller. In general, the MPC has lower steady state errors for the targeted angles. For the non targeted *finger* angles, the steady state errors are similar, for non-targeted thumb angles the P-controller shows smaller errors.

B. Grasping of differently sized objects

We are able to use the selective index finger activation of both methods functionally to perform the pinch grip for grasping a small cube and a marble. Both methods are also successful in evoking a cylindrical grip. All grasping trials have been successful for both methods. See also Fig. 3 for examples of actuated grasps.

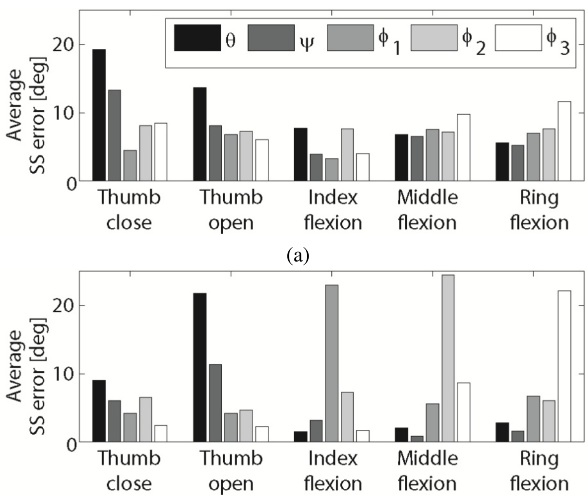
IV. DISCUSSION

In this study we evaluate the feasibility of both a MPC and a P-controller for the selective control of finger movements. Both methods are able to selectively activate the fingers such that differently sized objects can be grasped. The P-controller had smaller errors for keeping the thumb at the setpoint when each of the fingers were moved. On the other hand, the MPC controlled the targeted finger better towards the reference (Fig. 5). From a practical point of view, the MPC is easier to initialize, as this method uses a single initialisation phase



(a) (b)

Fig. 4: Step function responses for subject 1: a) MPC and b) P-controller. Sub panes show the different measured angles of the thumb (θ and ψ) and the flexion angles of the first three fingers ($\phi_{1..3}$) as solid lines. Angle setpoints are shown as dashed lines. Dotted lines indicate the standard deviations of the measured angles.



(b)

Fig. 5: Steady state errors for all angles resulting from applied step functions. Averaged results for a) the MPC and b) the P-controller. Different bars represent the five measured angles. Bars are grouped for each step function input.

for model determination, instead of several parameters which need to be set individually as is the case for the P-controller.

Given the fact that the musculoskeletal system has a complex nature, one could expect that the controller based on a model of such system outperforms the P-controller. However, this will be highly dependent on the accuracy of the estimated model. In the current approach we use a linear model. Although the estimated models already show good ability to predict the system's behavior, the controller performance could be improved by the choice of a more complex model or by supplying additional inputs such as hand/wrist orientation. However, this will also further increase the computational power needed for predicting the system behavior.

For the P-controller, the targeted angle, i.e. the angle to which the step is applied, has the largest steady state errors compared to the other angles (Fig. 5). This could indicate that the gains for the angles were relatively low, which would result in less activation proportional to the angular error which occurs at the step transition. A more sophisticated method for tuning the gains, e.g. Ziegler-Nichols closed loop tuning [9], might be used to improve this. Also, integral action could be added to improve the performance of the controller and reduce the steady state errors.

To apply the current methods in a more clinical setting or a home environment, some modifications will be needed. A different system for measuring finger motions or angles is preferable, like accelerometers or bend sensors. In addition it would be preferable to estimate the directions of movement of the different thumb muscles without the isometric measurement setup. This might be achieved by measuring the position changes against a small load. Small leaf springs could be included to provide some additional stiffness to the fingers during identification phases and to bring the fingers back to a neutral position when the stimulation is ended. With such modifications the current methods might easily be transferred to a setting for rehabilitation of stroke patients.

The current results show great potential of both methods in fine motor control of the hand, where existing methods mainly focus on gross motor control of the hand and wrist [1,3,4]. Additional objects might be considered to seek the limits of both control methods. Objects even smaller than the currently used ones or heavier objects might be used to try to make the controllers fail in grasping/holding the objects. In the near future we plan to evaluate the control methods in more subjects, to get a better view at the reproducibility and adaptability of the methods for different subjects. Although the current results are promising, evaluation in patients is needed to explore the possibilities to apply these methods in rehabilitation of grasp and release after stroke.

References

[1] S. Micera, T. Keller, M. Lawrence, M. Morari and D. Popovic (2010), Wearable neural prostheses, Engineering in Medicine and Biology Magazine, vol. 29(3), pp. 64-69, May 2010.

[2] E. T. Wolbrecht, V. Chan, D. J. Reinkensmeyer and J. E. Bobrow, Optimizing compliant, model-based robotic assistance to promote neurorehabilitation, IEEE Trans. Neural Systems and Rehabilitation Eng., vol. 16(3), pp. 286-297, March 2008.

[3] P. E. Crago, N. Lan, P.H. Veltink, J. J. Abbas and C. Kantor, New control strategies for neuroprosthetic systems, Journal of Rehabilitation Research & Development, vol. 33(2), pp. 158-172, April 1996.

[4] K. L. Kilgore and P. H. Peckham, Grasp synthesis for upper-extremity FNS, Med. Biol. Eng. & Comput., vol. 31, pp. 607-614, 1993.

[5] M. B. Popovic, Control of neural prosthesis for grasping and reaching, Medical engineering and physics, vol. 25(1), pp. 41-50, January 2003.

[6] P. E. Crago, R. J. Nakai and H.J. Chizeck, Feedback regulation of hand grasp opening and contact force during stimulation of paralyzed muscle, IEEE Trans. Biomedical Engineering, vol. 38(1), pp. 17-28, January 1991.

[7] A. J. Westerveld, A. C. Schouten, P. H. Veltink and H. van der Kooij, Selectivity and resolution of surface electrical stimulation for grasp and release, IEEE Trans. Neural Systems and Rehabilitation Eng., vol. 20(1), pp. 94-101, Jan. 2012.

[8] E. F. Camacho and C. B. Alba, Model Predictive Control, Springer, 2nd ed., May 2004.

[9] J. G. Ziegler and N. B. Nichols, Optimum settings for automatic controllers, Trans. ASME, vol. 64, pp. 64-69, 1942.