VERIFICATION CONCEPT FOR AN ELECTRONEUROGRAM-BASED PROSTHESIS CONTROL

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ABSTRACT

The use of nerve signals for a prosthesis control or limb stimulation is one great challenge in medical technology. It requires a recording of the electroneurogram (ENG) data and an identification of the motion-based action potentials of motoric, feedback and sensoric nerves within the corresponding neural bundle. We have realized a prototyping system for the data acquisition of ENG data, including an identification framework, described in (Klinger and Klauke 2013).
In this paper we introduce the verification concept of the identification process using synthetic datasets generated based on robot manipulator and electroneurogram simulator. The objective is to define a method to compare motion based trajectories and their corresponding ENG signals to prepare the future analysation and identification of human ENG data.

Keywords: ENG-based prosthesis control, system identification and verification, simulation framework, agent-based evolutionary computation, robot-manipulators

1. INTRODUCTION

The use of nerve signals to realize an intelligent control of prostheses or handicapped limbs is a key challenge in medical technology. Compared to the information acquisition via electroencephalogram (EEG) or electromyogram (EMG) signals, the use of ENG signals has several advantages (Klinger and Klauke 2013). So, our approach is the direct use of action potentials of peripheral neural bundles via an ENG (Gold, Darrell, Henze, and Koch 2007; Neymotin, Lytton, Olypher, and Fenton 2011). Based on these signals, a prosthesis, for example, an artificial hand or an artificial forearm, can be controlled specifically.
For the measurement of the very small electric signals up to sub-microvolt a technically optimized measuring circuit which permits the admission of electric axon signals in sub-µ area has been realized (Bohlmann, Klauke, and Klinger 2013}. The identification of the action potential movement patterns is based on methods of the machine learning (Bohlmann and Klinger 2010; Bohlmann, Klauke, Klinger, and Szczerbicka 2011). The proof of the identification concept is based on a verification framework described in this paper.

At first we present a short system overview and point out some aspects of the whole framework. Subsequently we give a brief description of the identification method. In subsection 1.3 we introduce the multipolar cuff electrode which provides some key characteristics for the used identification technique.
The main part of this paper is described in section 2. Here we present the verification concept based on a Matlab-based robot manipulator and explain the generation of stimulation patterns for the simulator, which is part of the verification concept. In section 3 we present results for the following aspects:

- Robot manipulator data based on specific sequence of motions
- Transformation into trigger pulses (action potentials) for the NEURON simulator
- NEURON simulation and generation of ENG data in accordance to the used multipolar cuff electrode
- Identification results

1.1. Overall System Architecture

In Figure 1 the overall concept, denoted as Smart Modular Biosignal Acquisition, Identification and Control System (SMoBAICS) in the following text, is shown in a block diagram. Two central components are to be recognized in this top-level: The data acquisition and signal conditioning in the analog front-end as well as the data evaluation and identification (Pattern Recognition, Learning).

In the data acquisition block the action potentials of the nerves are captured by a so called cuff electrode; the type of this electrode type is introduced in the following subsection. Following this the analog signals are being amplified and digitalized. Subsequently a two-stage evaluation and identification step follows. During these steps the ENG data stream has to be correlated to movement trajectories. We are using a multi-agent-based evolutionary algorithm optimized for a three step process (Klinger and Klauke 2013). The subdivision in two phases is necessary to allow a learning phase and an

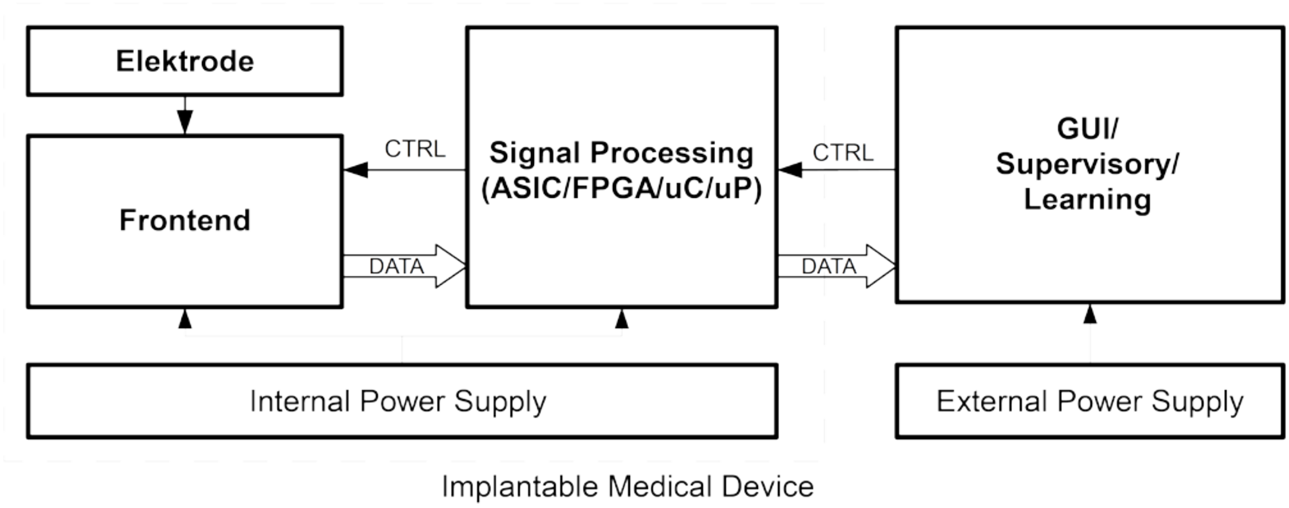

Figure 1. System architecture of SMoBAICS

operation phase. In the learning phase the base identification which allows a correlation between nerve signal and movement is carried out. The operation phase is using the identification results of the learning phase to realize a customization and adjustment due to parameter drift or electrode movement and to control the exoprosthesis. Therefore the base identification from the learning phase is used by a mobile processing device, which supports continuous learning. The objective is to integrate the necessary components for this phase within the organism using a system in package (SIP). New technologies, like energy harvesting, have to be used to operate this body mounted part.

1.2. Identification

The huge number of signal lines within a nerve - the axons - and the combination from actuatory, reactuatory and sensory information lines makes it practically impossible to perform a detailed analysis with the objective of a manual or automatic prosthesis control without using algorithmic tools. Therefore the machine learning and identification part is the most complex and the most important system module (Wodlinger and Durand 2011; Verdult2002). We are using a multi-agent-based evolutionary algorithm optimized for a three step process described in (Klinger and Klauke 2013). This work continues the former work about system identification presented in (Bohlmann, Klauke, Klinger, and Szczbericka 2011; Bohlmann, Klinger, and Szczerbicka 2009; Bohlmann, Klinger, and Szczerbicka 2010). At first a data pre-processing is executed to filter the data and to improve the data condition regarding the signal-noise ratio (SNR). The identification is subdivided into three-levels. In the first-level, the algorithm recognizes patterns of axon related action-potentials. This set of solutions is checked to well-known parameters, like impulse frequency, the relative magnitude of the nerve impulse amplitude and the refractory period. In addition, clusters are build up to model the different groups of activation and their related sensory information (feedback by proprioceptors). So, certain clusters in the neural bundle can be arranged to map muscle groups and their corresponding receptors. In the second level the agent-based set of solutions is combined to global solutions taking the causality between actor and sensory information into account. The third level correlates the first- and second-level solutions with trajectory information from a camera-system or a micro-electro-mechanical system (MEMS) for trajectory information, using inverse kinematics algorithms.

Once the identification procedure based on the recorded action potentials is successful, the recognized pattern can be used to drive a robotic prosthesis. Such devices are typically similar to serial manipulators, which can be modeled and controlled by applying well established methods from the field of robotics (Craig 2004; Sciavicco and Siciliano 2000; Khalil and Dombre 2002). Given the known direct and inverse kinematics of the serial mechanism, the task planning can either be performed in the joint space or in the task space. For the considered case, each motion pattern recognized by the action potential classifier corresponds to a predefined trajectory given in joint coordinates. Using the internal control unit of the prosthesis, the joint angle commands translate to the desired motion of the robotic device.

1.3. The Cuff Electrode

This type of electrode is put around the neural bundle to be examined. The single electrodes, part of the multipolar cuff-electrode, are inserted within biomedical silicone. This silicone protects the single electrodes and fixes them within the specific measurement arrangement. The main advantage of such an electrode is the non-invasive character. Properly designed this electrode can be used without cutting or traumatizing any nerves within a neural bundle. In contrast, using a sieve electrode the probability of an irreparably damage of the nerves is very high.

The cuff-electrode used in this application is a special cuff-electrode depicted in Figure 2. It consists of several electrodes organized in rings and segments. As elementary simulation set-up with minimal configura-

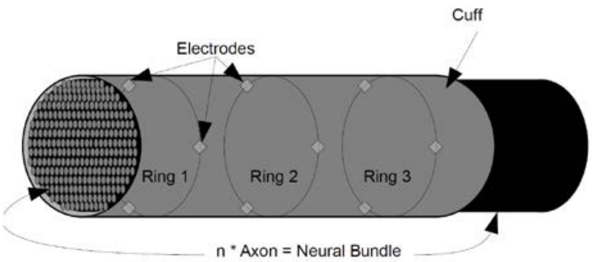

Figure 2. The Cuff Electrode

tion there are three segments (120°) and three rings necessary.

The three electrodes depicted there are evenly distributed on the circumference of the cuff (0°, 120°, 240°) to guarantee an uniform coverage of the action potentials triggered by the neural bundle for example via triangulation. Higher order of rings and segments depends on the space for the implanted cuff-electrode and the best available precision for electrode manufacturing. The number of axons of a neural bundles ranges up to several tens of thousands depending on the type of neural bundle and the selected application localization, like nervus ischiadicus, nervus radialis or nervus medianus.

2. VERIFICATION CONCEPT

To verify the identification process, it is necessary to generate well defined verification vectors. So, these vectors, called SimVectors, are used instead of recorded action potential data to allow specific verification scenarios. In addition, it is possible to reduce the number of animal trials using the verification and simulation framework.

To generate data according to the real existing biology mechanism we are using the well established NEURON framework for empirically-based simulations of neurons and networks of neurons (Carnevale and Hines 2006; Coates, Larson-Prior, Wolpert, and Prior 2003; Law and Kelton 2000) .

The different constraints, like myelin structures, all-or-none, two directions of information flow, frequency borders of the action potentials, etc. has been taken into account. We have configured the simulator and realized a complex neural bundle including our cuff electrode setup to generate verification data for several information transfer scenarios. The action potentials used for the NEURON-simulator are derived by human arm modeling via Matlab Robotics Toolbox (Corke 2011). With this model for verification we are able to concentrate on specific muscle groups and their reactuatory answer and therefore we are able to generate verification patterns.

Our first simple model which will provide proof of verification concept consists of 121 individual axons which run in parallel being arranged in a square grid. The dimensions of this array are depicted in Figure 3. Each axon has a diameter of 10 µm and a total length of 20 mm which is subdivided by 20 equally spaced nodes of Ranvier. Each Ranvier node has a length of 50 µm. These parameter are used with regard to the anatomical data from the selected laboratory animals (here: rats). It is obviously possible to redefine these parameters according other laboratory animals or later on human beings.

The simulation environment uses the Hodgkin-Huxley model to simulate the axon internal membrane, the ion channels and the extra cellular space (Hodgkin and Huxley 1952). So, the propagation of action potentials along the axons is modeled used these equations. Furthermore, the mechanisms concerning the passive membrane channels are included. In this context, each axon is considered myelinated while the Ranvier nodes are characterized by the absence of this surrounding sheath. In order to enable extra cellular recording, a mechanism is implemented that reports the contributions of local membrane currents to the total signal acquired by a recording electrode placed at a defined location with respect to the axon grid. Here, we consider the cuff electrode, introduced in subsection 1.3, which has three electrical contacts equally distributed along the interior wall of the cylindrical cross section. For simulation purposes, we define the radius of the circular contact arrangement according the dimensions of the defined nerve bundle. Furthermore, during simulations, this cuff electrode can be translated along the axon array in order to acquire the extra cellular potential at multiple locations as well as multiple time steps in accordance the multiple rings of the electrode.

Using the NEURON simulator, predefined or randomized excitation patterns can be applied to the modeled axons. An excitation is achieved by injecting a defined current in one end of an axon. The functionality of the simulation framework is further increased by the given ability to specify the number, duration and period length of the injection. By running the simulation, each

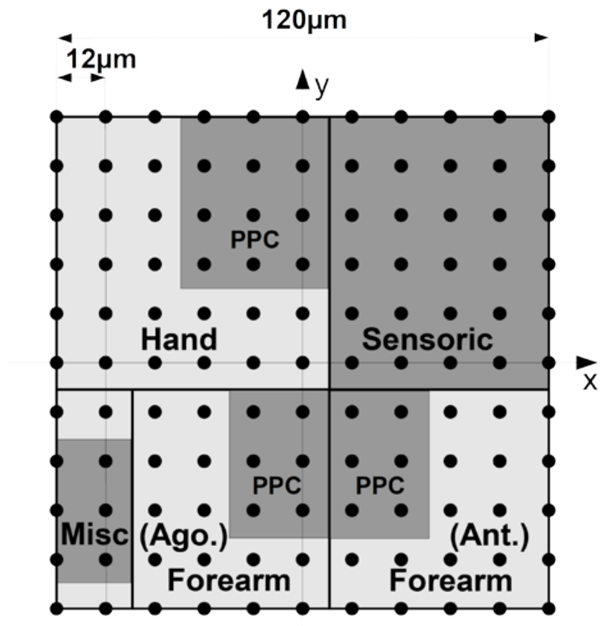

Figure 3. Used model for axon bundle

excitation pattern is translated into potentials acquired by the recording cuff electrode. Hence, identification algorithms processing time series of such potentials can easily be validated due to the fact that the excitation pattern, i.e., the ideal identification result, is known.

As an enhancement of the previously described simulation framework, the simplified model of a human arm was implemented in Matlab using the Robotics Toolbox. Based on this human arm model specific scenarios can be defined to generate sets of SimVectors for the verification process which provide complex interactions of muscle activities (actuatory) and feedback via proprioceptors (reactuatory).

The kinematics of the human arm can be approximated by a serial mechanism consisting of 7 active joints (Grecu, Dumitru, and Grecu 2009). The base coordinate frame is assumed to be located at the shoulder while the coordinate frame associated with the endeffector of the mechanism coincides with human wrist, see Figure 4. Both hand and fingers are omitted here. Following this approach, the simplified kinematics of the human arm can be expressed in terms of the Denavit Hartenberg parameters.

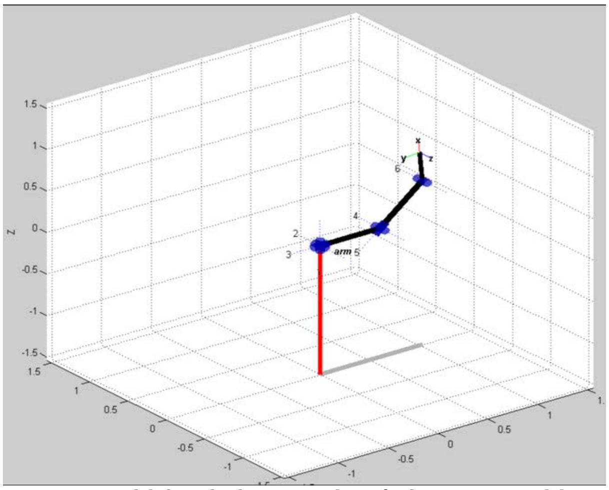

Figure 4. Matlab-based robot manipulator for human arm modeling

3. RESULTS

In order to validate the identification procedure proposed in this paper, we present here one scenario based on the movement of the forearm and the hand where the generation of the StimParameters is focused on the movement of the forearm. The resulting time series of simulated extra cellular recordings are fed to the identification algorithm.

In Figure 5 the joint acceleration, the joint moments, the joint angles and the joint velocity for the selected sequence of motion are shown. The process of movements demanded by the selected scenario and generated by the Matlab Robotics Toolbox is transformed into a sequence of action potentials according to the following criteria:

- Position of the axon according the axon membership to the specific muscle and proprioceptor sensors depicted in Figure 3.
- The frequency of actions potentials is set in accordance to the force vectors and the physiological data like maximum frequency and refractory period.
- The sequence of actuatory and reactuatory (proprioceptors) signals is set with regard to the causal relationship and the signal propagation times.

The sequence of signals is transformed into actions potentials and simulated by the NEURON simulator using the axon bundle configuration and the cuff electrode setup. The data acquired by this simulated cuff electrode is shown in Figure 6. In this Figure the frequency of the action potentials and their signal amplitudes, caused by the superposition of several actions potentials, is shown.

The Figures 7 and 8 show two different details from the overall signal sequence in Figure 6. Figure 7 shows the simulated data for three adjacent rings of the cuff electrode. The three time series are different because of the superposition of actuatory and reactuatory signals during the zoomed time period.

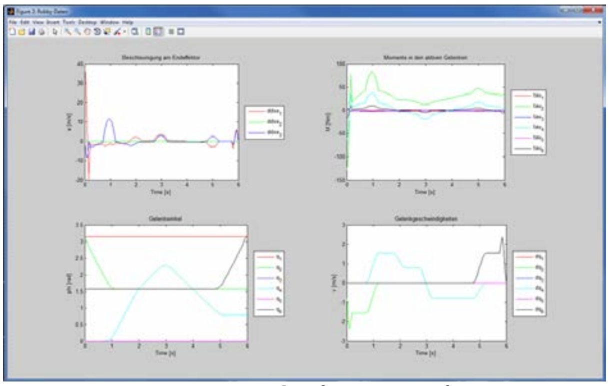

Figure 5. Joint data for sequence of motion

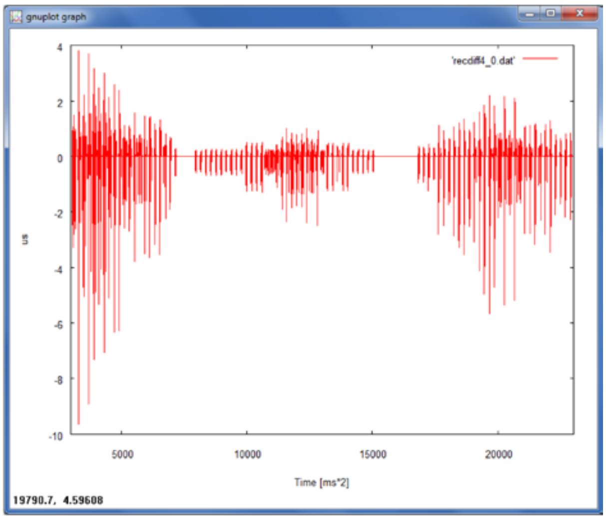

Figure 6. NEURON simulation of the actuatory and reactuatory action potentials of the selected sequence of motion (simulated ENG)

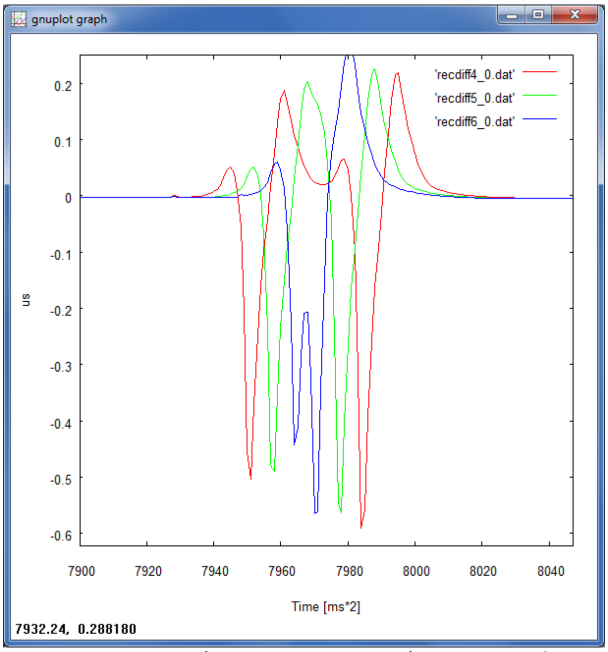

Figure 7. Zoom of Figure 6: Movement of action potentials

In Figure 8 the data acquired by three different segment electrodes of one electrode ring are shown. With regard to the position of the axon within the axon bundle the amplitudes are differing.

The identification method is using only the data acquired by the cuff electrode, no additional information. Here two different aspects of the identification process are shown:

- The detection of the direction to identify actuatory and reactuatory signals, and
- the clustering of action potentials to enable an assignment of the action potentials to specific areas.

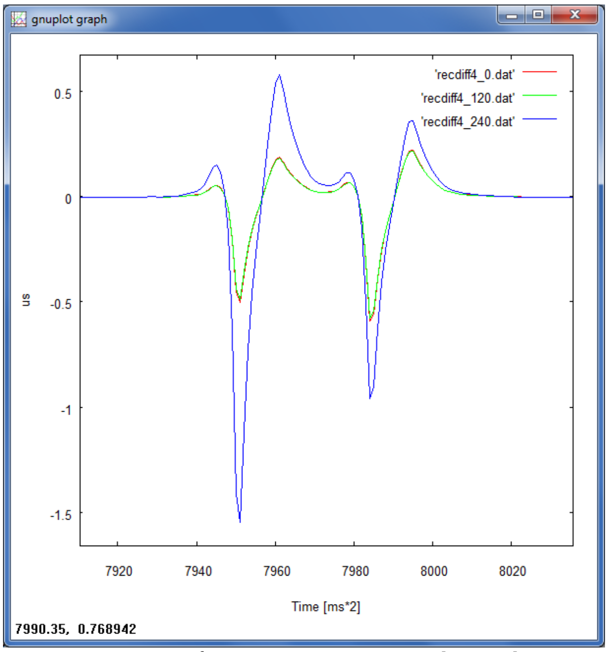

Figure 8. Zoom of Figure 6: Superposition and triangulation

Both aspects are necessary to realize a nerve signal based identification of the type of movement. In Figures 9 and 10 both aspects of the identification are shown, based on the SimVectors generated from the Robotics Toolbox. Figure 9 shows the direction detection, Figure 10 the cluster assignment.

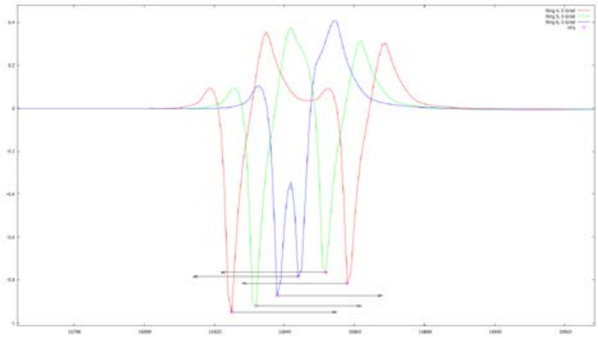

Figure 9. Restructured action potentials using the identification method and detection of actuatory and reactuatory action potentials

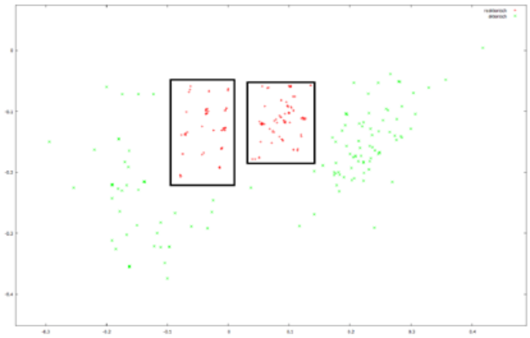

Figure 10. Clustering of the actuatory and reactuatory axons within the axon bundle according to the axon bundle model in Figure 3

4. SUMMARY AND FURTHER WORK

The SMoBAICS approach to identify of motion-based action potentials in neural bundles for exoprosthesis control or for handicapped limb simulation provides an integrated solution from ENG based action potential recording up to the identification procedure.

This paper focuses on the verification method based on generated action potentials used to enable the proof of the identification concept. On the basis of a movement trajectory, actuatory and reactuatory trajectory-based action potentials are simulated with the NEURON simulator according the axon bundle model. This simulation provides an ENG with regard to the special type of cuff electrode to enable a triangulation and direction detection. The identification method based on evolutionary algorithms (Bohlmann, Klinger, and Szczerbicka 2010; Klinger and Klauke 2013) reads these simulated ENG-data and reconstructs the action potentials, their motoric, feedback or sensoric characteristic and the location inside the axon bundle. Based on this identification a correlation between the action potentials and the corresponding movement actions is possible. Due to this solid foundation, the ENG-based motion detection for prosthesis control or limb stimulation offers considerable potential. The used method based on a on robot manipulator and electroneurogram simulator allows a complex verification process and can be used for a large number of movement scenarios. The most important tasks in the next month will be:

- Adding noise to the SimVectors to analyze the identification process regarding the loss of signal to noise ratio.
- Including sensory feedback from hand's sensory areas in the simulation to take these additional nerve signals into account.
- Starting the clinical tests to achieve measurement results according the real existing biology mechanism.

Based on clinical tests the robustness of the identification method has to be optimized. To start these test the new measurement platform has to be finished. In addition inverse kinematics algorithms have to be integrated into the identification procedure.

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