BIOSIGNAL ACQUISITION SYSTEM FOR PROSTHESIS CONTROL AND REHABILITATION MONITORING

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ABSTRACT

Simulation, modelling and verification are powerful methods in computer aided therapy, rehabilitation monitoring, identification and control. They are major prerequisites to face great challenges in medical technology. To realize tasks and services like an on-line data monitoring or a nerve signal based prosthesis control, smart, intelligent and mobile systems are required. Here we present data acquisition and learning systems providing methods and techniques to acquire electromyogram (EMG)- and electroneurogram (ENG)-based data for the evaluation and identification of biosignals. We focus on the development, integration and verification of platform technologies which support this entire data processing. Simulation and verification approaches are integrated to evaluate causal relationships between physiological and bioinformatics processes. Based on this we are stepping up efforts to develop substitute methods and computer-aided simulation models with the objective of reducing experiments on animals. This work continues the former work about system identification and biosignal acquisition and verification systems presented in (Bohlmann, Klinger, and Szczerbicka 2010; Klinger and Klauke 2013; Klinger 2014).

This paper focuses on the next generation of an embedded data acquisition and identification system and its flexible platform architecture. We present results of the enhanced closed-loop verification approach and of the signal quality using the Cuff-electrode-based ENG-data acquisition system.

Keywords: ENG-based prosthesis control, rehabilitation monitoring, system identification, system verification, simulation framework, simulation and modelling in computer aided therapy, robot-manipulators

1. INTRODUCTION

The use of electrical biosignals, like electro-encephalogram (EEG), electromyogram (EMG) and electroneurogram (ENG), gains a lot of importance for the assessment of functions in the human body. These signals are used as major indicators which provide medical professionals, patients or professional athletes during diagnostic and monitoring processes. In particular EMG and ENG are used to get information about the peripheral nerve system including information transfer due to sensual data and motion control by peripheral nerves. Based on these signals a multitude of applications is existing; they range from the achievement of a therapeutic goal up to prosthesis control, for example, to operate an artificial hand or an artificial forearm. There are several requirements existing to realize such these functionalities:

- Data acquisition and stimulation

  The EEG, EMG or ENG data has to be acquired and sampled according their signal characteristics, given in Table I. In particular applications stimulation is necessary, for example for the measurement of the nerve conduction velocity.

- Data processing

  The acquired data (action potentials) are disturbed by intrinsic noise. In addition they are overlaid by a substantial extrinsic noise, originated for example by EMG from surrounding muscles. Therefore we have to filter the recorded data with integrated analogue filter and additional digital filter. There are several specific high-pass, low-pass, band-pass and notch filter available. A further data processing is necessary, on the one hand to improve the data condition due to asynchronous and aperiodic samples, and on the other hand to generate events from the action potentials like the activity level of a muscle group or the detection of an exposure scenario.

Table 1: Biosignal Characteristics

Signal types	Amplitude range	Frequency range
EEG	$(100-1000)\ \mu$V	$(0.5-100)$ Hz
EMG	$(100-5000)\ \mu$V	$(0-8)$ kHz
ENG	$(1-400)\ \mu$V	$(0-12)$ kHz

- Identification

  The identification feature is required for prosthesis control or any type of high level signal evaluation. The identification is based on machine learning and recognizes movement commands and feedback signals. The identification method and the corresponding verification scenario has been introduced in (Klinger and Klauke 2013; Klinger 2014) based on results in (Bohlmann, Klinger, and Szczerbicka 2010; Bohlmann, Klauke, Klinger, and Szczerbicka 2011).

- Data archiving

After data acquisition and data processing the results has to be saved locally if there is no direct data transmission for an evaluation possible or desirable due to an offline analysis. Furthermore for identification a certain data amount is necessary to apply the identification algorithms during the operating phase (Klinger and Klauke 2013).

- Data interfacing

The data has to be transmitted for evaluation or monitoring purposes to a host system.

- User Interfacing

To select and execute certain functionalities and for online information an user interface must be available.

- Configuration

Due to the different application scenarios and system functions a configuration is necessary.

With regard to many different application scenarios and the corresponding requirements, the embedded system architecture is based on a modular hardware and software platform. We will present the system architecture and its characteristics including data acquisition, identification and data exchange in section 2. In section 3 we will discuss two specific applications to illustrate the platform character of the system. The results given in section 4 focus on the enhanced overall verification method, using modelling and simulation techniques and the verification of the data acquisition for ENG-based data.

2. SYSTEM ARCHITECTURE

In Figure 1 the overall concept is shown in a block diagram. Two central components are to be recognized in this level: The data acquisition and signal conditioning in the analog frontend as well as the data evaluation and identification (Signal Processing, Learning). In the data acquisition block the action potentials of the nerves are captured by a so called Cuff-electrode (Klinger 2014; Klinger and Klauke 2013). Following this, the analog signals are being amplified and digitalized. Afterwards there occurs a two-stage evaluation and identification step of the data (Bohlmann, Klauke, Klinger, and Szczerbicka 2011; Bohlmann, Klinger, and Szczerbicka 2009; Bohlmann, Klinger, and Szczerbicka 2010).

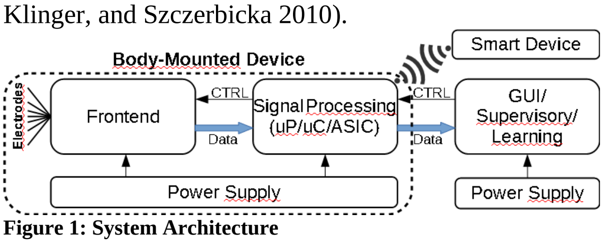

Figure 1: System Architecture

This subdivision in two phases is necessary to allow a learning phase and an 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.

Based on the overall system concept the system is designed as a platform providing a modular hardware and software architecture. The different modules, like analog frontend, analog digital converter (ADC), processing elements, application specific integrated circuits (ASICs), interface solutions or memory devices are important for specific use cases, like the operating mode, an online data evaluation, a long-term data archiving, etc.. The complexity of the hardware platform requires lots of software features, e.g. for the data management, the system configuration, the system programming, the development and for the graphical user interface. In addition, several use cases are existing with regard to different areas of operation, like medical test, the clinical application, the use by patients, long term or short term signal evaluation. To be able to fit all these requirements and constraints, the platform paradigm is valid for the hardware domain as well as for the software domain. Here a software platform is conceived which is based on the RichClient-Platform of Eclipse and uses the capabilities of the open system gateway initiative (OSGI).

In this paper, however, we would like to focus on the flexibility of the platform based architecture. To improve the first design we have taken several aspects into consideration. At first the system has been shrinked to realize a body-mounted system. Figure 2 shows the 1st and 2nd generation of the smart modular biosignal acquisition, identification and control system (SMoBAICS). Our first prototype has been used for the examination of the platform architecture and of the module design. Besides, the modules, in particular the analog frontend module, were subdivided in several submodules to be able to learn from the measuring campaigns efficiently. Here we have used a backplane architecture for the whole system to realize a fast and easy module replacement of the ADC, the amplifier, etc.. In addition, most of the components are configurable by software to guarantee high flexibility. With the help of this first prototype platform important knowledge about the signal characteristic features was obtained. The second platform approach reduces the system dimensions; now the area per module is 33x60 mm^2. The height per module ranges from amounts from 5.4 mm to 6.4 mm. Using a system configuration consisting of 5 modules, the overall volume is less than 80 cm^3, compared to the old system platform with $\approx$ 1750 cm^3. The next step will be the system in package platform (SIP) to realize an implant-

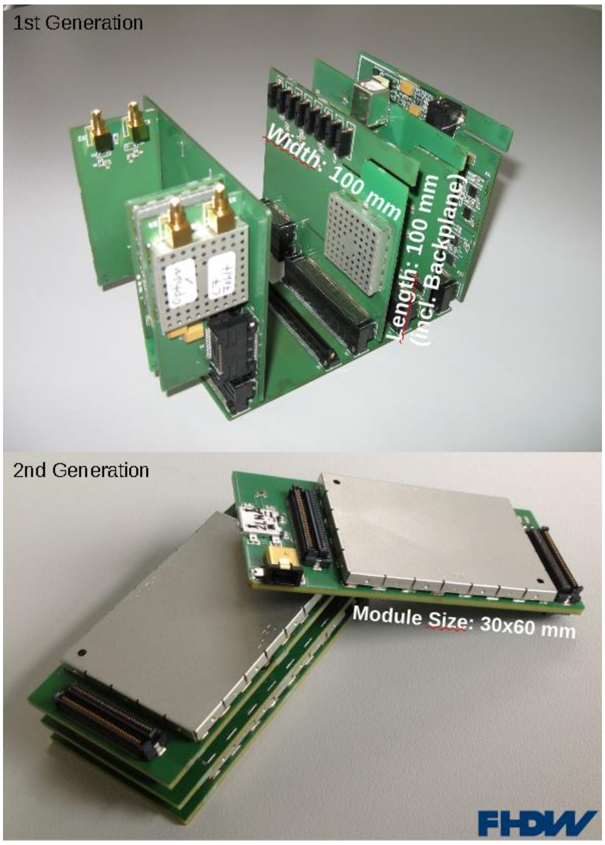

Figure 2: System evolution

table medical device. The additional design specifications for the new system are:

- Mobility

The measurement period of the EMG- or ENG-based biosignals and an optional stimulation has to be several hours to integrate the monitoring process into the user's life and satisfy long-term measurements.

- Considerable Improvement in Communication Options

The system has to realize a communication channel to medical staff informing about critical situations or therapy-relevant events. This communication channel has to be established using a smart phone which is connected via Bluetooth or Wi-Fi to the system.

- Local Intelligence

To trigger the measurements and to realize an event based communication with the user or external staff, local processing power is necessary. In addition, the local identification, used in the operation and mobile mode, needs local intelligence for event and pattern matching.

In the following text we present the design of the new CPU-module extending the system capabilities. This CPU-module provides a better local data management and more computing power for the online identification algorithms during mobile operation and the ongoing system evolution. In addition, the connectivity of the

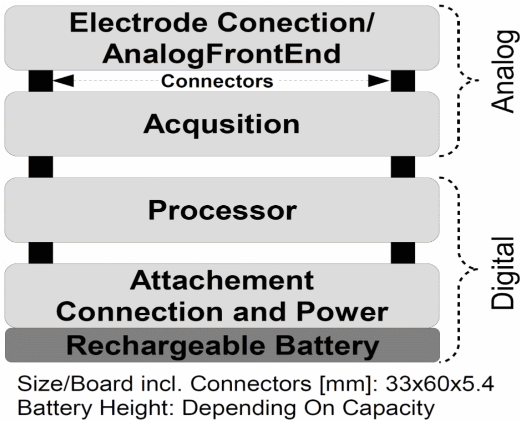

Figure 3: Module stack of the embedded data acquisition and identification module

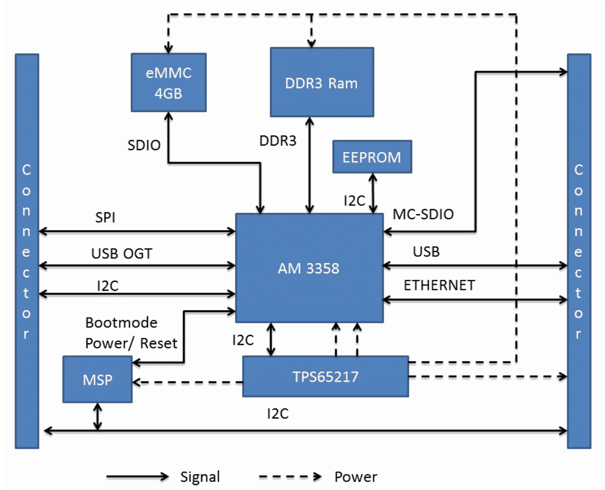

Figure 4: CPU-Module: Processor Board

system can be improved using for example the full Bluetooth/Wi-Fi stack based on Linux operating systems. The overall module stack of the system is shown in Figure 3. This module stack contains the whole functionality of the block diagram in Figure 1 including power supply by a rechargeable battery. The new CPU-module has been developed according the platform design guidelines. Using a high performance microprocessor (Sitara AM3358), the system capabilities, in particular the communication can be improved considerably. This board takes the data from the Acquisition Board, processes the data and either sends the data via communication channel. The CPU-module is split into two modules due to design considerations. The first module contains the ARM Cortex A8 processor along with the RAM, ROM as well as the power management chip. In Figure 4 the block diagram of the board is shown. The system is based on the AM3358 processor which is capable of running at 1GHz speed, along with support from a DDR3 RAM and a flash memory system. The AM3358 is best to be paired with the TPS65217 Power Management IC which provides all the supply voltages that are needed for operating the processor as well as the peripherals. The support for the USB, SPI and the

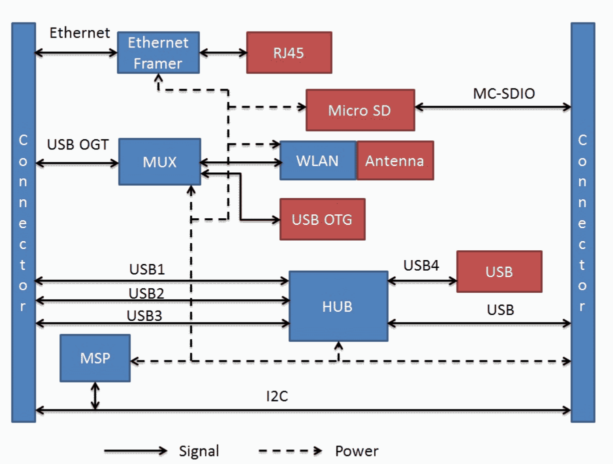

Figure 5: CPU-Module: Attachment Board

Ethernet ports are fed to the stack connectors as the ports are located on the Attachment Board along with the Memory Card slot. In addition, the board level controller (MSP430) is integrated, acting as the board identification and overall control system. Using the I2C protocol the various boards are able to identify and configure themselves accordingly. On the Processor Board, the MSP430 microcontroller also serves as a secondary control device with regard to low power operation. On the Attachment Board all peripherals are combined that are connected to the Processor Board, like USB ports, Ethernet port and also a micro SD card slot which can be used to store the data that is processed by the Processor Board. The overview of the Attachment Board is seen in Figure 5. The Attachment Board interfaces to the processor board through the stack connectors. It provides all external connectivity and the base plate for the rechargeable battery.

3. APPLICATION FIELDS

There are numerous applications in the field of biosignal measurement and signal processing. We will focus on two specific examples, demonstrating the flexibility of the platform concept.

3.1. Rehabilitation and Long-term Treatment Monitoring

There appears a whole array of diseases where it is necessary to monitor specific parameters for a long term treatment, for recovery from illness or for rehabilitation. Several reasons for such a decrease in nerve conduction are well known but not understood, like demyelinating or axonal injury. Neurophysiological measurements and tests are available to improve the knowledge and to improve the curing prospects. But in most cases these measurements are used rarely, once a week some even less often. It is necessary to provide a continuous

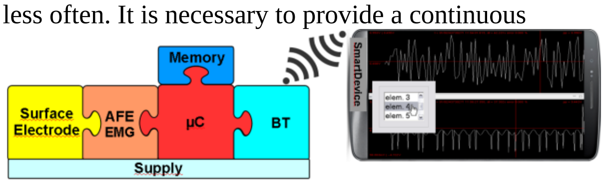

Figure 6: System for NCV (AFE: AnalogFrontend; µC: Microcontroller; BT: Bluetooth)

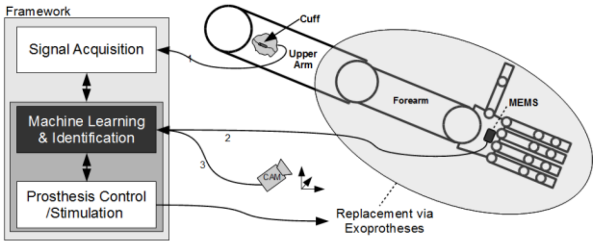

Figure 7: SMoBAICS Appplication

monitoring to get a better understanding of the interference of other parameters, like temperature, time of day, state of exhaustion, etc.. To fit all these requirements, a mobile system is necessary which provides the key functions described in section 1. One common examination is the measurement of nerve conduction velocity (NCV) in which impairments can be identified. While determining the nerve conduction, the nerve to be examined will be electrically stimulated at least at two places in its course. In Figure 6 the adequate system configuration is shown. It combines from surface electrode up to Bluetooth interface all modules to acquire and save data and to connect to a widely used smart device.

3.2. Prosthesis Control

Today prosthesis is even more than only easy spare parts for the human body. From the simple wooden butts of the past ingenious high-tech constructions have become. However, the modern medicine can substitute even more than only arms and legs. The main problem is the human machine interface of prosthesis and its movement control. The objective is to use biosignals for the information transfer between human being and prosthesis. Several possibilities are existing to realize such an interface. Our approach is the direct use of the action potentials of peripheral neural bundles via an ENG (Gold, 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. In addition, by using a direct nerve interface it is possible to realize a bidirectional interface, not only for the actuatory data but for the reactuatory and sensory signals. The acquisition and interpretation of nerve signals is one key challenge to realize an intelligent control of prostheses or handicapped limbs. The interpretation is one central aspect due to the high information density within a nerve. In Figure 7 overall flow of motion control including the feedback loop is shown. Part of the system is camera and micro-electro-mechanical system (MEMS) support to improve the movement identification by methods of inverse and forward kinematics. The system configuration to fit this scenario contains:

- Cuff-electrode

Using a special type of electrode, a Cuff-Electrode, the electrical potentials are recorded. The Cuff-electrode has been chosen for minimally invasive surgical and therapeutic applications (Klinger and Klauke 2013).

- Analog frontend for ENG

To record the very small signals, which are only of the order of a few microvolts, we have designed a special front-end hardware (Klinger and Klauke 2013).

- Microprocessor
  - System and data management

    The AM3358 processor provides data management and configuration from the analog sampling module and data preprocessing for identification and archiving.
  - Identification

    The information taken from the Cuff-electrode contains a superposition from all action potentials of all single axons within the selected nerve bundle. Therefore an identification process is necessary to extract the trajectory information and to build up a model of the nerve bundle due to its axon configuration. The AM3358 provides enough computing power for the evaluation of the online identification.
  - Connectivity

    The Am3358 provides the full driver and communication stacks to enable seamless integration into the communication environment.
- Wi-Fi or Bluetooth interface to host

  Necessary hardware and antenna for establishing the wireless or Ethernet interface.

Figure 8 shows the scenario related system configuration. The Cuff-electrode is connected via cable.

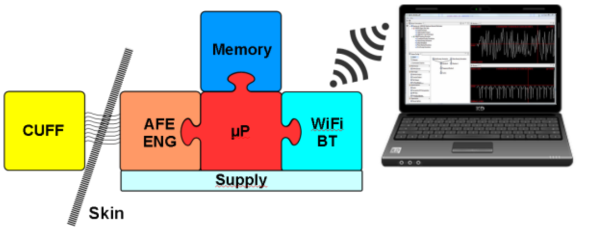

Figure 8: System for Prosthesis Control (AFE: AnalogFrontend; µP: Microprocessor; BT: Bluetooth)

4. RESULTS

In this paper two different aspects are in the focus due to the results. In subsection 4.1 we will present the enhanced verification method providing an all-level verification for the identification method. In subsection 4.2 we will focus on signal quality and interference ratio of the ENG-based analog frontend. The signal quality and accuracy is one of the key factors for the data based identification.

4.1. Enhanced Verification Method

The verification of the identification method is based on physiological data (Kandel, Schwartz, and Jessell 2000), and simulation knowledge (Law and Kelton 2000; Zeigler, Praehofer, and Kim 2000; Carnevale and Hines 2006). The new closed-loop verification provides an efficient and transparent verification process for the identification method. Causes and effects of certain sequence of motions can be investigated in detail. The used verification method allows different loops to check different characteristics using different levels of the identification method. In Figure 9 three different loops are shown taken the generated or motion-based generation of certain stimulation vectors and simulated action potentials into consideration.

- Verification of cluster assignment and physiological parameters (1)

  The first option verifies the disposition of the clusters or anatomic fascicles of the nerve bundles. Using certain stimulation vectors this verification approach is used to optimize the parameters of the identification method. Using real data, recorded with an analogue front-end system, it can be used to evaluate inter- or intra-individual differences of human beings to optimize the identification method with regard to adaptability. This verification step is based on the NEURON simulator modelling the intra- and extracellular nerve bundle (Carnevale and Hines 2006).
- Verification of action potential sequences (2)

  This verification approach can be used either to improve the identification method towards better action potential disintegration or to enhance the knowledge base regarding the peripheral nerve-muscle interface. The generation of certain stimulation vectors itself can be used to adapt the abstraction level and complexity of the identification task. This verification step is based on the NEURON simulator, Java Framework and Matlab (Carnevale and Hines 2006; Corke 2011). The stimulation vectors (StimVectors) are generated based on simulated movements data.

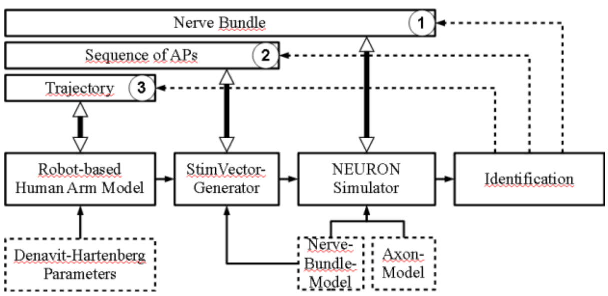

Figure 9: Verification architecture of SMoBAICS

- Trajectory verification (3)

  The trajectory verification is the most sophisticated verification approach. Starting with the sequence of motion the verification consists of the comparison of the initial sequence of motion (start trajectory) and the identified sequence of motion (result trajectory). The comparison between both trajectories allows a qualitative and quantitative evaluation of the whole identification loop. This trajectory verification includes the integration of camera- or MEMS-data within the identification method for the learning and the operating phase if there are no encoder data from prosthesis are available. It is well known that the human arm or total or partial prostheses are redundant manipulators therefore we have to use more than information from actions potentials to identify the position of the end-effector. During the operating phase we have to use MEMS, but it lacks in bias stability compared to the camera system. So we have to take this into account integrating the inertial navigation into the identification method (Woodman 2007). To evaluate a closed-loop verification system further, a robot-manipulator like a human arm (Denavit-Hartenberg parameters) including an MEMS device provides real movement data including real MEMS parameters. Closed loop verification consists of the causal chain:

1. Generating movement data using a robot-manipulator (Corke 2011)
2. StimVector generation based on the movement data and anatomical data (the calculated parameters are Denavit-Hartenberg parameters of the robot model according e.g. an anatomical data of an human arm.).
3. Simulation by NEURON simulator and extracting the data of the simulated Cuff-electrode.
4. Identification
5. Identification-based trajectory processing
6. Comparison of robot-manipulator movement and identified trajectory.

This verification step is based on the NEURON simulator, Java Framework and Matlab, too. It uses in addition inverse/forward kinematic algorithms (Craig 2004; Khalil and Dombre 2002).

4.2. Results from the Acquisition System

Focusing on the second application scenario (see subsection 3.2), the entire system uses data-based methods where the data are acquired by the Cuff-electrode; therefore data quality is one key parameter. In this subsection we present measurement data taken by the analog frontend (ENG) and a Cuff-electrode (Klinger and Klauke 2013) to evaluate the signal quality. The results were determined in an animal experiment with rats, carried out at the Medical School Hannover (MHH). All information in the following diagrams is scaled as follows:

- Abscissa: Time
  Relative timeline, corresponding to the number of cycles of the analog-digital converter, sample rate: 4 kHz.
- Ordinate: Amplitude
  All values are given in µV .

In Figure 10 one single impulse measured by the Cuff-electrode is shown. This impulse, a classical All-or-None-impulse, shows from the amplitude heave as well as from the temporal expiry the course to be expected for a capacitive electrode. Helpfully with this measurement are the appraisals which can be won with regard to the nerve isolating qualities by Epineuria as well as Perineuria and Endoneuria.

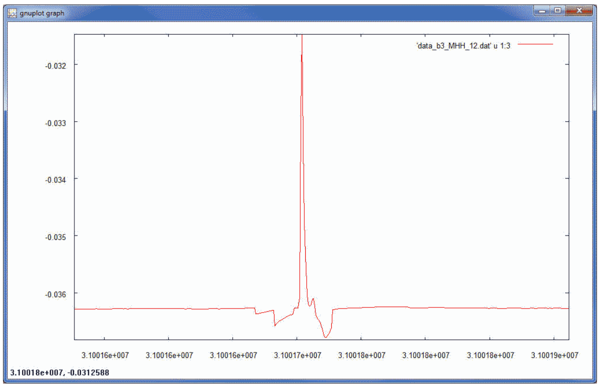

Figure 10: Measurement of a classical All-or- None-impulse with the capacitive Cuff-electrode

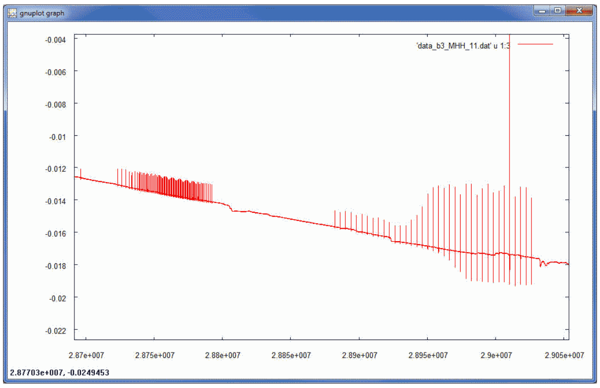

Figure 11: Measurement of the nerve activities due to stimulations with varying frequency

In Figure 11 the nerve activities on stimulation with different frequency are shown. On the left there is a faster stimulation (20 Hz) with an uniform electrical stimulation. On the right there is a slower stimulation (3 Hz) where the electrical stimulation is increased by scaling the stimulation current. The measured signals agree with the relative stimulation voltage and stimulation frequency. In the amplitude certain changes are recognizable; these changes appear on the basis of superposition of action impulses generated by a number of axons. The spatial resolution within the fascicle is up to now not possible because the used Cuff provides only 2 sensors which are used to check different amplifier configurations and reference potential configurations. On the reason for the increase in activity can be speculated here, meaning the certain fascicle activity of the whole nerve fiber. According the expectations, the total number of axons which are active is increased. The superposition of axon activities inside one nerve fiber related to a complex sequence of muscle contractions is due to a simple correlation. Thus, for example, the overall muscle contraction is controlled according the force required for a movement. Two different mechanisms are well known: To get more overall moving force

- the frequency of axon impulses controlling some muscle fibers has to be increased, and
- the number of active axons has to be increased to control more and more muscle fibers.

This effect can be also observed in Figure 12. There a sequence of action potentials is shown on account of a more complicated stimulation, triggered through a real leg movement during the animal experiment. Here a number of axons within the taken nerve bundle are firing action potentials according the triggered muscle activity. The different amplitudes are composed by the superposition of the sequences of action potentials formed by All-or-None single impulses. The superposition of several All-or-None action potentials can be measured outside the nerve bundle by the Cuff electrode.

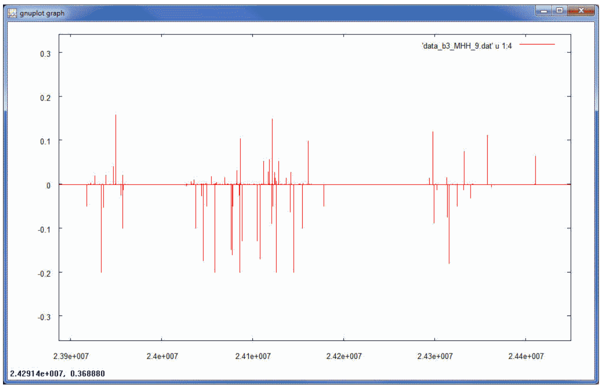

Figure 12: Measurement of the superposition of action potentials from the taken nerve bundle by the Cuff-electrode

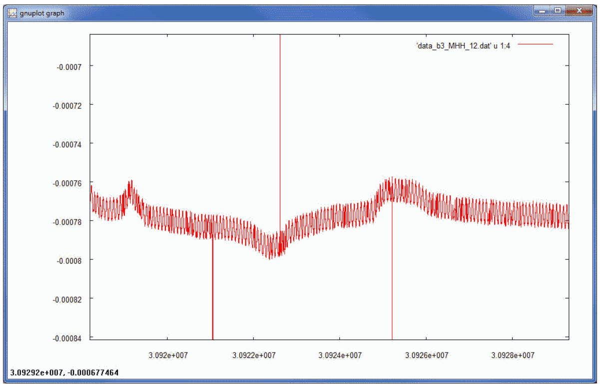

Figure 13: Resolution and noise amplitude

These results are important to receive data from the possible amplitude area and to get information about the whole signal path and its proper configuration parameters. For the improvement of the signal-to-noise ratio the analog front-end module has been optimized, especially for the measurement of ENG data. In Figure 13 there is the noise on an input signal shown. The noise amplitude is less than 20 nV. Compared to the action potentials measured by the Cuff-electrode the signal to noise ration fulfils the requirements. On account of the very good low-noise specification and large amplitude range, the sensor signal can be used at a very high-resolution. Its properties for extracellular recording measurements could be confirmed. The three outliers in the measured signal are uncritical; the software bug has been tracked for fixing.

5. SUMMARY AND FURTHER WORK

The presented approach for a platform-based embedded biosignal acquisition and identification system offers a wide range of medical applications. The modular system character provides adaptability to different diagnostic, rehabilitation monitoring and control scenarios with regard to computing power, connectivity and analog frontend characteristics. To emphasize this key feature beyond the presented application scenarios in section 3, in Figure 14 a possible next system generation for the prosthesis control application based on an integrated system-in-package (SIP)-solution is shown. The communication between SIP-based implant and the body-mounted system is connected for example via medical-implant- communication-service (MICS).

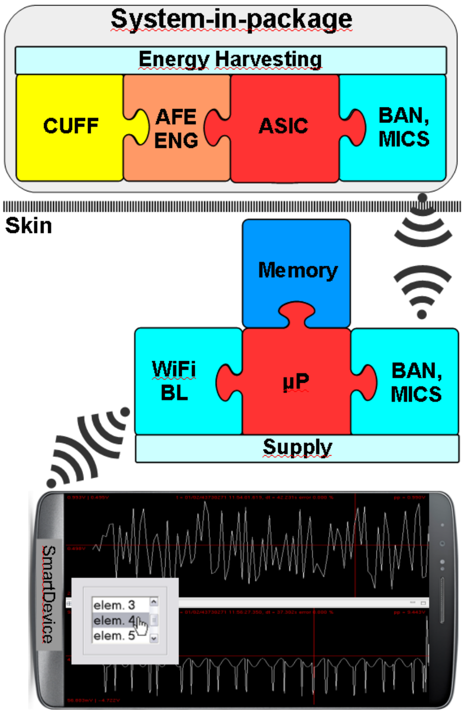

Figure 14: Verification architecture of SMoBAICS

The simulation-based closed-loop verification, presented in subsection IV-A, provides an efficient and transparent verification. Using the NEURON simulator and forward/inverse kinematic it allows a large test depth including anatomical and physiological parameters, like nerve bundle configuration and electrical parameters of peripheral nerves. The identification method helps to understand and to evaluate the correlation between movement and peripheral nerve information, including the actoric and the related sensoric feedback information flow. The results related to the ENG-based data acquisition system, introduced in subsection 4.2, show the technical feasibility and establishes the basis for the data-based identification. All results help to reduce the number of animal experiments using simulation and closed-loop verification methods.

The embedded EMG- and ENG-based biosignal data acquisition and identification system using a flexible hardware and software-platform offers considerable potential. Additional tests and clinical applications will follow to improve the system characteristics and the identification further.

6. ACKNOWLEDGEMENT

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