REHABILITATION MONITORING AND BIOSIGNAL IDENTIFICATION USING IOT-MODULES

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ABSTRACT

Microelectronics and high level integration provide in combination with simulation and modeling of embedded systems new approaches in biotechnology and medical therapy. The integration of intelligent systems as well as sensors and actors in an adaptive hardware/software-platform increases flexibility and provides a scalable measurement and identification platform. Based on modeling and simulation methods, different applications, like biosignal identification, prosthesis control and rehabilitation monitoring, offer completely new treatment and therapy options. In this paper we focus on the platform extensions of the modular biosignal acquisition and identification platform by using Internet-of-Things modules and introduce new applications for rehabilitation monitoring and evaluation of motion sequences.

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

1. INTRODUCTION

Embedded systems provide new approaches in biotechnology and medical therapy. Based on modeling and simulation methods, biological, physical and technical relationships can be described and verified (Kandel, Schwartz, and Jessell 2000), (Law and Kelton 2000), (Zeigler, Praehofer, and Kim 2000), (Klinger 2014).

The integration of hardware- and software-components provides an intelligent, smart and application-specific system. Using a platform paradigm, the partitioning between hardware- and software-components is adaptable concerning project-specific requirements. Furthermore the platform characteristic enables a modular architecture with high-level flexibility. The integration of sensors and actors in this adaptive hardware/software-platform increases flexibility and provides a measurement and identification platform for lots of applications.

In (Klinger and Klauke 2013), (Klinger 2014) and (Klinger 2015) we have presented a modular platform focused on the acquisition of electromyogram (EMG) and electroneurogram (ENG)-signals and a data-based identification approach.

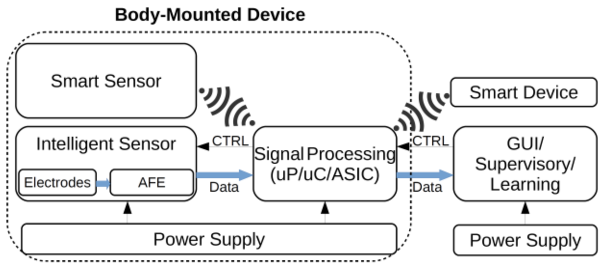

Figure 1: Block diagram of SMoBAICS

In addition to a continuous improvement of the system core features (in particular the identification), we are working on new fields of application and an enhancement concerning flexibility. In
Figure 1 a block diagram of ram of the smart modular biosignal acquisition, identification and control system (SMoBAICS) is shown.

The SMoBAICS-platform consists of several stages and modules, described in the following overview:

A Data acquisition and stimulation
The ENG or EMG (ExG) data or further sensor data have to be acquired and sampled according their signal characteristics. The number of channels has to be determined by the application. In particular applications a stimulation is necessary, for example to trigger movements by activating muscle groups.

B Data processing
Data processing focuses on two key priorities: Data conditioning and identification.

B.1 Data Conditioning
The acquired data have to be processed to improve the signal conditioning. Besides the programmable filters and amplifiers are resampling functions available to provide periodic samples. The acquired data (action potentials) are disturbed by intrinsic and a substantial extrinsic noise, originated for example by EMG from surrounding muscles. Therefore we have to condition the recorded data with integrated analogue filters and additional digital filters. Several filters like specific high-pass, low-pass, band-pass and notch

filters are available. A further data processing is necessary to generate events from the action potentials like the activity level of a muscle group or the detection of an exposure scenario.

B.2 Identification

The identification feature is required for prosthesis control or any type of high level signal evaluation, like gait analysis. The identification is based on machine learning and recognizes different information sources: The action potentials from brain to muscle, the action potentials from the proprioceptors and additional sensor data from microelectromechanical system (MEMS) of force sensors. The identification method and the corresponding verification scenario have been introduced in (Klinger and Klauke 2013), (Klinger and Klauke 2015) based on results in (Bohlmann, Klinger, and Szczerbicka 2009), Bohlmann, Klinger, and Szczerbicka 2010), (Bohlmann, Klinger, and Szczerbicka 2011), (Bohlmann, Klinger, and Szczerbicka 2012). 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 (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 the camera-system or the MEMS, using inverse kinematic algorithms.

C Data archiving

A local data archive is necessary due to two scenarios, online and offline operation.

C.1 Offline Operation

For offline operation the identification needs sets of model parameters, data from the learning outcomes and RAM for algorithm execution. Furthermore all data can be logged on the system for a later offline analysis. During event recognition all data are logged, only event data, for example an exceeding of a maximal force, are sent to the host system.

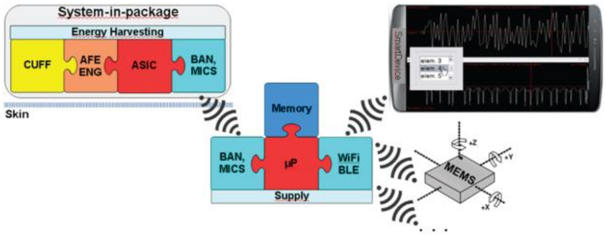

Figure 2: System Architecture

C.2 Online Operation

During online operation all local algorithms need memory for an efficient execution. This local memory reduces the requirements for data bandwidth to the host system.

D Data exchange / Connectivity

With regard to

Figure 1, the processing of data goes in two different directions, either the local signal processing (operating phase (Klinger and Klauke 2013)) or the host processing (learning phase (Klinger and Klauke 2013)). Furthermore the data can be saved locally or on the host, transferred using the communication link (cable or wireless).

E User interface

The graphical user interface (GUI) allows access to the different system functions and presents either a configuration or a data display.

F Configuration

The system functions can be configured for different use cases and specific GUI.

F.1 Learning

The control application helps to adapt parameters and to initiate different learning phases.

F.2 Operating

The operating GUI allows to start and stop the application and to load specific parameters.

F.3 Logging

The logging collects not only events but all system data for a later offline analysis.

F.4 Event

The different events and their corresponding limits have to be defined and selected.

In Figure 2 the block diagram is transformed in the platform layer, where the architecture and the functional system components are visualized. This figure shows the future design roadmap, where the key component is integrated into a system-in-package (SIP) to provide an implantable device.

Furthermore this figure shows the wireless integration of the MEMS-device, which is a smart sensor providing the required connectivity shown in the block diagram (Figure 1). This wireless connection improves the flexibility and simplifies the system integration. With regard

Table 1: Comparison of selected connection opportunities and ranking from the wireless point of view

Issue	Ranking	Comment
The device has to provide an own power supply	-	Cable linked, the device can be powered by the main system.
Wireless connection flexibility	+	No number of inputs have to be specified)
The device has higher complexity	-	Design effort
Local intelligence	+	Local intelligence provides more features
No cable link	+	Cable link makes trouble due to the mobile system

to the platform, the advantages (+) and disadvantages (-) of this wireless connection type are opposed in Table 1. Based on this comparison and with regard to platform paradigm, system flexibility and mobility, the wireless connection has been chosen for the integration of all external sensors into SMoBAICS. This decision opens the perspective of using Internet of Things (IoT)-modules which have the added benefit of the future availability of legio of IoT-sensors and actors. The internal sensors, like the cable wired cuff-electrode (Klinger and Klauke 2013), cannot be connected using wireless techniques according to the current state of the art.

2. IOT-BASED EXTENDED MODULAR SYSTEM ARCHITECTURE

The Internet of Things creates new opportunities to link sensors, actuators or intelligent decentralized systems either with each other or with other systems (Bassi et al 2013). The IoT-Roadmap promotes new technologies and, therefore, new challenges. Based thereon the availability of technologies and components offers good conditions for a platform-based system such as SMoBAICS. The extension or adaptation of the system may then, depending on the application, benefit from existing developments and/or modules.

The SMoBAICS platform is used to acquire EMG- and ENG-signals and to provide a data-based identification of movements and trajectories. The identification method is model-based and uses simulation for the continuous model improvement and for verification purposes. The data of the external sensors, here especially of the 9-axis tracking device, are essential for the model- and simulation-based identification method. First we introduce in the following with the general properties of these systems. Then we focus on a first own IoT-module for SMoBAICS that already uses components developed based on this new technology.

2.1. IoT Characteristics

An analysis of different use cases shows the need of an integration of additional sensors in the acquisition and identification platform. This includes the MEMS-device, which is needed to provide motion data of the prosthesis. The connectivity is here one key factor. Lots of smart devices, like smart phones or tablets, provide a communication- and computing- infrastructure. Based on this the flexibility and scalability of the platform can be increased significantly. In addition the number of intelligent components rises within the scope of the IoT rapidly (Bassi et al. 2013). Thus intelligent sensors can be integrated to the platform. This decentralized periphery extends the application spectrum of the platform considerably. Nevertheless, some key aspects have to be taken into consideration:

- The core platform is an essential part. It enables an efficient and performant integration of different modules and provides smart services.
- The modular character of hardware and software and their platform characteristics is of particular relevance. The platform paradigm provides a flexible partitioning and relocation of functions and services on specific hardware and software modules. Especially the open system gateway initiative (OSGI) is one of the key features realizing the software platform.
- Connecting more than one or two devices, the Smart- Device and/or the CPU-module of SMoBAICS has to provide gateway functionality. Based on new Bluetooth- (mesh) or WiFi- (802-11ah) standards, the communication environment with these characteristics can be realized.
- The service orientation of the interface is an essential aspect due to the integration of IoT components. An efficient linking and communication require a defined quality-of-service level to realize a seamless integration of services and modules.
- Using IoT-modules security aspects are a further key point. Without secure data transfer and a secure module interconnection an IoT-based system is applicable in a limited way. Every connection has to be secured using pairing-based or certificate-based strategies.

In Figure 3 the essential features of an IoT-device are depicted. The base functionality of an IoT-module contains an actor/sensor element, and processing, memory and connectivity features, adapted to the specific application. For example, the connectivity may be based upon a wireless or wired connection. Moreover, all modules are designed regarding low-power strategies providing an autonomously operation. Here, energy harvesting is one of the main future topics for IoT-systems.

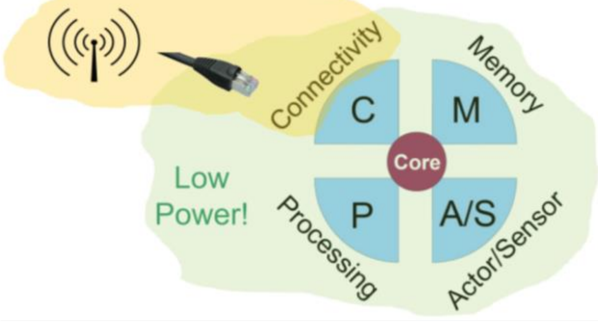

Figure 3: Platform circle, covering the major system features

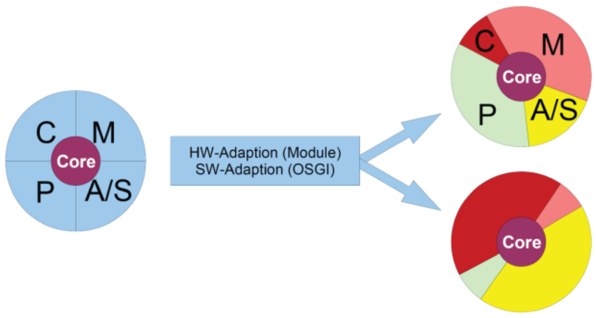

Figure 4: IoT instances based on an IoT-platform

Figure 4 shows different specifications of IoT-systems designed for specific applications. For example processing features (above) or connectivity (below) are more pronounced than other features. Based on the platform paradigm every IoT-system can be designed according its specific project requirements.

2.2. SMoBAICS IoT-Modul

As described in (Klinger and Klauke 2013) and (Klinger 2014) the SMoBAICS is a modular system for identification and prosthesis control. Based on the acquisition of action potentials via ENG, the information of the peripheral nervous system is used to identify movement patterns. A MEMS (mobile phase (Klinger and Klauke 2013) and/or camera system (learning phase (Klinger and Klauke 2013)) is necessary to get information about the movement trajectories. To integrate the MEMS, an IoT-module was designed to improve flexibility and to simplify the integration of the sensor using wireless connection. Figure 5 shows the block diagram of the SMoBAICS IoT-module. The first prototype with a rectangular base has the system dimensions shown in this figure. The design can be shrinked massively, due to design for test considerations we did not shrink the prototype further. It is realized according to the platform paradigm and consists of a modular design. According to the platform circle, shown in Figure 3, all essential features are realized:

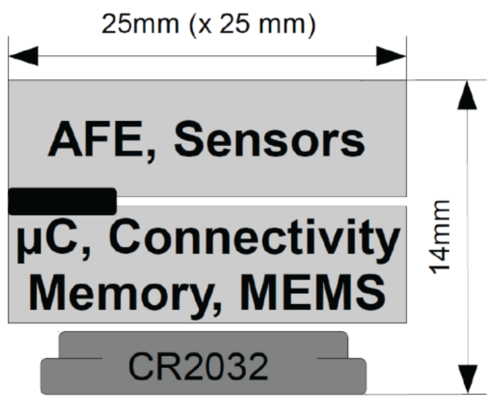

Figure 5: SMoBAICS IoT system: Base System (Lower Board); Sensor Extension (Upper Board)

- µController
  ARM-based controller for data and event processing, system control and analog-digital conversion.
- Connectivity
  In the current version Bluetooth is supported to provide a communication link to the body area network (BAN), connecting all devices of the platform.
- Memory
  For logging and data buffering a SD-card is integrated.
- Sensor
  The MEMS is an integral part of this IoT-module because the acceleration and gyro data are for all relevant applications around this project important. To provide further sensor support an interface is designed to connect additional sensors to the IoT-system. This additional sensor system can be connected to the base system as shown in Figure 5. In subsection 3.2 we show a corresponding application scenario using additional sensor support.

The prototype attached button-cell battery provides enough energy to independently operate the IoT-device for several days. The intelligent power management helps to reduce power consumption according to the activity cycles. In Figure 6 activity cycles for different use cases are shown, ranging from training applications to different rehabilitation scenarios. The four operation modi are characterized by power consumption and wake-up capability:

- Off
  The device is powered off, no power consumption.
- Standby
  The device is in the lowest power consumption mode, waking up by interrupt of the MEMS-device.
- Activity
  Data acquisition is activated automatically from standby; depending on the communication status (logging, event mode, transmit continuously, transmit periodically) the power consumption differs considerably.
- Training
  Data acquisition is activated manually and the communication mode is selectable according the activity mode.

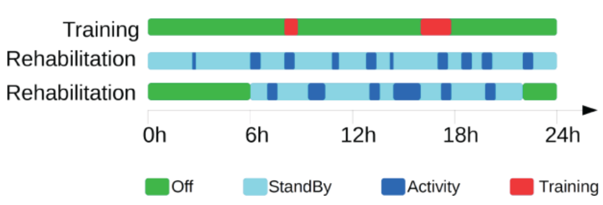

Figure 6: Application specific time-of-use: Day Schedule

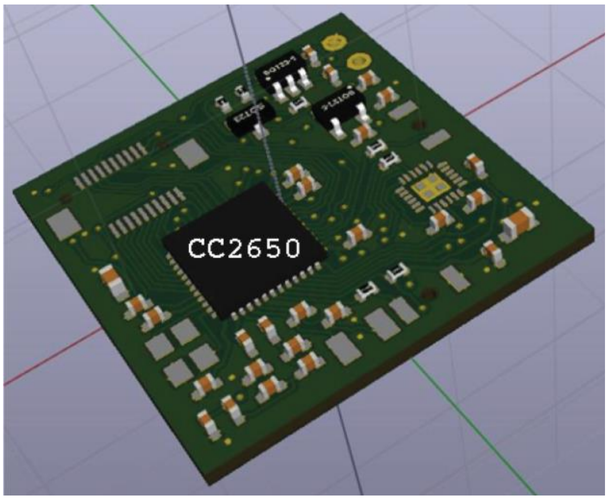

Figure 7: Design overview of the current CPU-module

In Figure 7 the current design of the CPU-module is shown. To realize the IoT-system according platform paradigm we have chosen the large CC2650-package providing more I/Os. Realizing a product-based design, the IoT-system can be shrinked considerably.

3. APPLICATIONS

A wide range of applications in the field of biosignal measurement, signal processing and biosignal monitoring are existing. We focus on two specific examples, demonstrating the further development of the known platform (Klinger and Klauke 2015) and the flexibility of the platform paradigm.

3.1. Prosthesis Control System and Gait Identification

Based on the idea of an ENG-based arm prosthesis control we are still working on the identification to improve the identification algorithms and to make it more robust. Using signals from the peripheral nervous system, the objective of a prosthesis control is adaptable to leg prosthesis, too. In Figure 8 the application schematic is shown, consisting on the same elements like the system for the arm prosthesis control (Klinger and Klauke 2013).

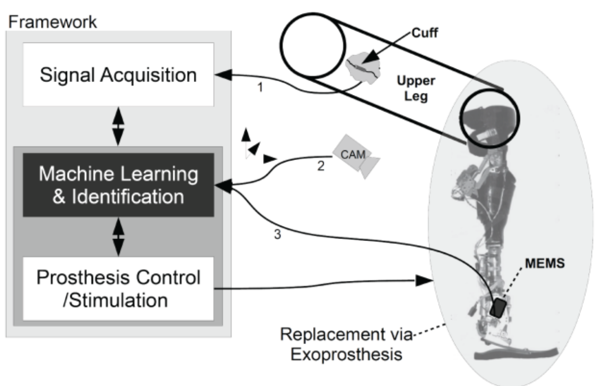

Figure 8: System overview

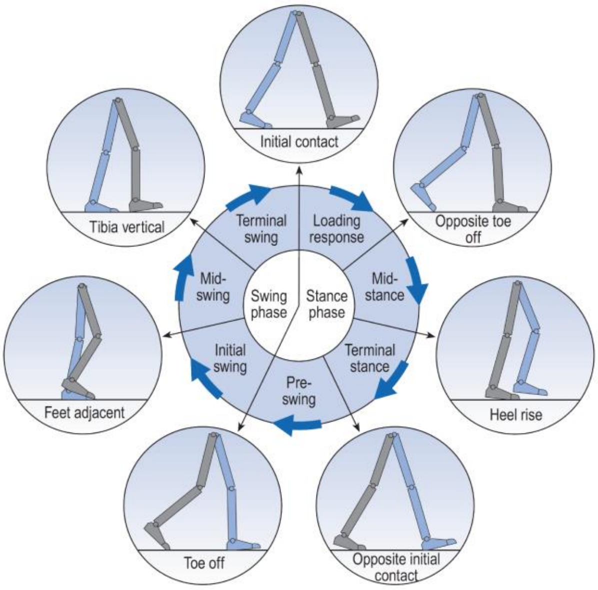

Figure 9: Positions of the legs during a single gait cycle by the right leg (gray) (Levine, Richards, and Whittle 2012)

According to this scenario we need to integrate a MEMS to get information about zero space movements during the operating phase (Klinger and Klauke 2013). This MEMS contains a 9-axis motion tracking device (gyro + accelerometer + compass). During the first identification runs it turned out, that the MEMS-signals are not sufficient to correlate with the information from the nervous system due to signal drift. So it was not possible to realize a gait identification which is necessary to provide a leg prosthesis control. Therefore we add force sensors to the MEMS, called now MEMS+F. The design was made according to the description in section 2; the wireless integration of this so called smart sensor was realized according Figure 1 and Figure 2. Using force sensors, it is possible to get more precise information about the force progression over time and therefore about the gait cycle, shown in Figure 9. The gait cycle information and the force sensors are essential requirements for an identification process (Aziz, Park, Mori, and Robinovitch 2014), (Ito 2008), (Kugler et al. 2012), (Tao, Liu, Zheng, and Feng 2012). Furthermore, the gait cycle information triggers another application, shown in the following subsection.

3.2. Rehabilitation Monitoring System and Gait Evaluation

Deploying the MEMS with additional force sensors (MEMS+F) there are a lot of rehabilitation monitoring systems and gait evaluation systems possible.

- Rehabilitation Monitoring
  Using the MEMS+F device it is possible to measure, evaluate and archive all forces acting on the foot vertically (z). With additional sensors, adaptable to the MEMS+F-device, it is possible to take the other forces (xy) and tor-

ques into account. During a rehabilitation phase after a fracture, dislocation, etc. the physical stress can be observed continuously. Therefore a correlation between stress type, stress duration and recovery progress is possible. In addition the accumulated load per time period can be taken into account. Furthermore the monitoring can be used to optimize the gait during rehabilitation to realize a normal gait. If the specific permitted limits are exceeded, an event can be triggered, informing the patient or the treating physician to take the situation into consideration.

- Gait Monitoring
  The evaluation of gait of apparently healthy persons is an important method to analyze an imbalance or dysfunction which can result in health problems. These problems can be evaluated using a continuous gait monitoring to identify pathological or abnormal gaits. Paying attention to how you walk and run reduces unnecessary muscle strain. In addition this gait monitoring can be used to monitor and optimize movement sequences within the sports segment.

4. RESULTS

In this section we focus on the first measurements taken by the new SMoBAICS IoT-device. This device is necessary for all applications and use cases with identification to provide a positioning information. Both applications in section 3 are using this device as MEMS+F-device. Focusing on the second use case in subsection 3.2, the whole system can be downsized with regard to the platform paradigm. In Figure 10 a small cutout of the block diagram in Figure 1 is shown, emphasizing an additional direct connection between the smart sensor MEMS+F and the smart device used in this class of application. In addition to the 9-axis motion tracking device, the prototype is using currently three force sensors to provide a mobile measurement of forces as well of accelerations and gyro data according a gait evaluation. The current resolution of the analog digital converter (ADC) is 12 bit at a sampling rate of 10 kHz for all force, acceleration and gyro data. These parameters are adequate to detect all effects with sufficiently accuracy.

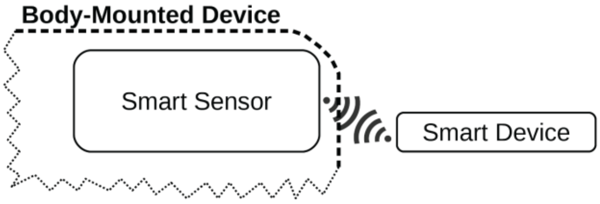

Figure 10: Direct connection from the MEMS+F-device to the smart device

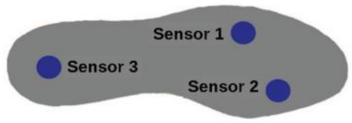

Figure 11: Sole configuration with 3 sensors for vertical force

The position of the three force sensors, used by the current prototype, are depicted in Figure 11. The force sensors extend the information from acceleration and gyro data to identify the center of gravity and to determine the different phases of the gait cycle (see Figure 9). In contrast to fixed installed measurement plate (Heidenfelder 2011), providing a one dimensional data stream for the vertical force, the mobile MEMS+F-device supports in the current version three force sensors as shown in Figure 11. Figure 12 shows this one dimensional data stream for the vertical force during two steps (Fzl: Left leg; Fzr: Right leg). Using three force sensors a far more detailed force level and force progression can be detected. In Figure 13 to Figure 16 the load distribution for the sensors 1 (red), 2 (green) to 3 (blue) (see Figure 11) for different scenarios, like step, run, jump and changes in balance are shown.

- Figure 13: Normal gait
  According the gait cycle the different force levels and the force progression for all force sensors over time are shown with regard to one step. From the initial contact on the heel up to the push off, the force levels for all ensors are available over time.
- Figure 14: Running
  In comparison to the gait, here the shorter and more intensive force level, dependent on the way of running, is shown over time.
- Figure 15: Jumping
  All phases of the jump including the short flight (forces=0) between 930 ms and 1110 ms are evident.
- Figure 16: Standing with changes in balance
  At first the posture is inclined slightly to the front moving to posture which is inclined slightly to the back.

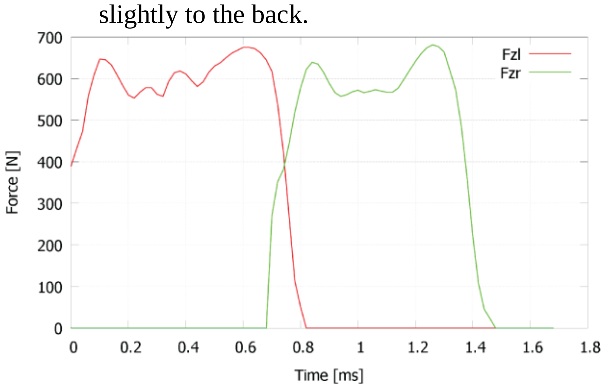

Figure 12: Normal gait: Vertical Force plotted over time on a fixed installed measurement plate (Fzl: Left leg; Fzr: Right leg)

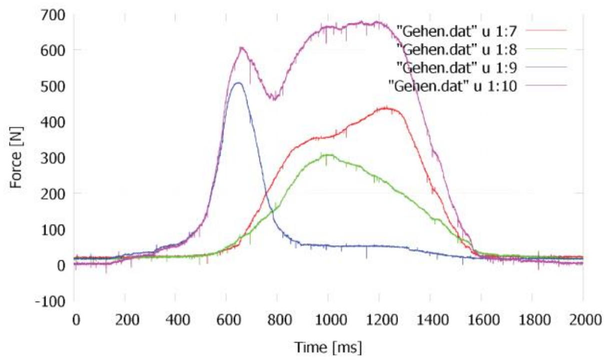

Figure 13: Normal gait: Vertical Force plotted over time on a fixed installed measurement plate (Fzl: Left leg; Fzr: Right leg)

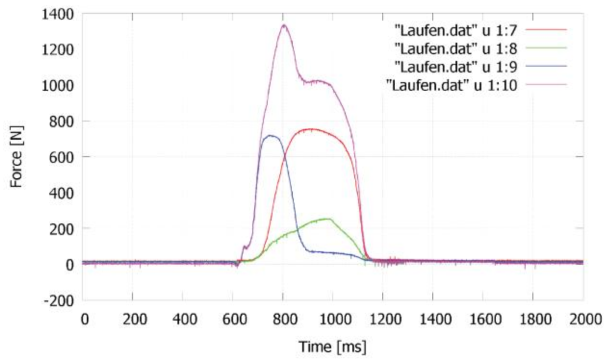

Figure 14: Normal gait: Vertical Force plotted over time on a fixed installed measurement plate (Fzl: Left leg; Fzr: Right leg)

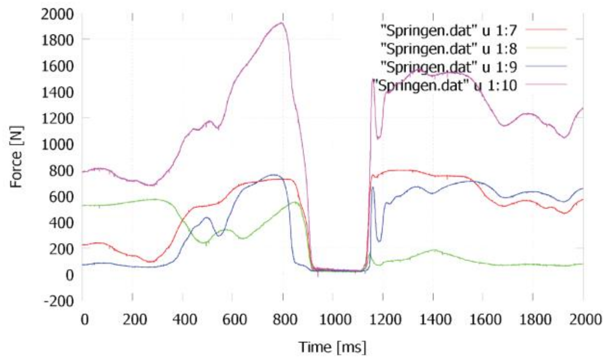

Figure 15: Normal gait: Vertical Force plotted over time on a fixed installed measurement plate (Fzl: Left leg; Fzr: Right leg)

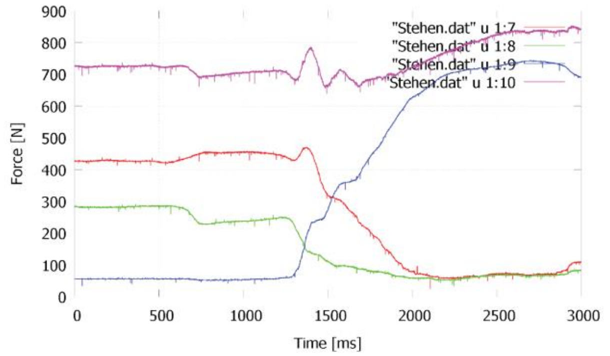

Figure 16: Standing with changes in balance, right leg: Vertical Force plotted over time for 3 sensors (1 (red), 2 (green), 3 (blue), sum(1,2,3) (magenta), see Figure 11)

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 based on the platform paradigm provides adaptability to different diagnostic, rehabilitation monitoring and control scenarios with regard to computing power, connectivity and analog frontend characteristics.
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 are ongoing to improve the system characteristics and the identification method further.
The use of monitoring platforms based on platform architectures allows flexibly tuning the system to different application scenarios. The additional integration of IoT systems further expands the range of applications and allows the correlation of data and thus the sensor fusion and context recognition. The new IoT-device, also designed according the platform paradigm, helps to acquire missing data, like MEMS- and force data for identification, and provides a smart integration into the platform using wireless links. Based on the developed IoT-device new applications are constantly emerging, like rehabilitation monitoring, gait evaluation and training-based motion sequence optimization.

The current research and development activities have a dual focus: On the one hand the further development and verification of identification algorithms and the integration of MEMS- and force data, on the other hand the deployment of a software framework for monitoring applications.

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