LINarm++

Affordable and Advanced LINear device for ARM rehabilitation

Deliverables D4.2

Final prototype of the sensory system and patient model and verification

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Executive summary

The sensory system, the patient model and the training scenarios are strongly interlinked., however training scenarios are described in deliverable D5.3 in separate document. Both deliverables are public prototypes and this document provides a detailed summary of the prototypes of the sensory system and the patient model and their verification.

This deliverable deals with prototype and final systems for acquisition of physiological data, development and testing of the patient model, and integration of the sensory system with the LINarm++ device.

The sensory system consists of custom-designed components and its performance was compared against the state-of-the-art equipment already available at UL (g.USBamp biosignal amplifier and sensors for measuring physiological and physical parameters).

The patient model was developed as a decision tree with four decision layers. From top to bottom layers the reliability of information for taking the decisions decreases. Therefore, the final layer has the smallest effect on the output of the patient model.

System validation was performed on a HapticMaster robot with a force sensor. Experiments served to a) acquire a set of measurements to test the patient model, b) determine, test and verify the configuration of embedded-and-wearable sensory system and c) develop and verify training scenarios for the LINarm++ system. Healthy subjects were involved in preliminary pilot trials with the proposed setup.

Introduction

Rehabilitation robots are devices that assist the recovery of patients whose motor functions are impaired as a result of stroke, spinal cord injury or other condition. Their benefit is twofold. First, they offer accurate sensors for measurement of forces and positions, thus providing a method of objectively evaluating the patient's motor performance. Second, robots with active motors can help the patient train simple or complex movements, taking some of the strain off therapists. Training with such robots yields long-term results comparable to exercise with a therapist. Frequently, they are combined with virtual environments in order to make rehabilitation more interesting and motivational.

Several rehabilitation systems based on different robots were developed, such as the MIT-Manus, a 2-degree-of-freedom system that supports planar movements using an impedance controller, the GENTLE/s based on the HapticMaster robot or the ARMin. However, while early rehabilitation robots were able to provide active assistance to the patient, they did not adapt their movement to the activity (or passivity) of the patient. Rather, the affected limb was moved along a predefined, fixed trajectory. The patient was also not informed about his or her activity and contribution to the movement. This problem was addressed by patient-cooperative or "assist as needed" control techniques. By recognizing the patient's movement intentions and motor abilities, patient-cooperative techniques adapt the robotic assistance to the activity (or passivity) of the patient. Recently, the concept of patient-cooperative robotics has been extended to biocooperative robotics within the MIMICS EU project, which take into account not only the bidirectional flow of energy between the patient and the robot, but also psychophysiological factors. In a biocooperative rehabilitation task, the parameters of the task are automatically adjusted so that the patient is challenged in a moderate but engaging and motivating way without causing undue stress or harm. The implementation of biocooperative control within the MIMICS project was relatively cumbersome with physiological sensors attached to the patient's body. At the same time psychological state was found challenging to estimate. However, physiological responses still provided an important insight into patient's state during the training.

Within the LINarm++ project the main focus was on the development of unobtrusive sensing technologies for measurement of physiological responses of patients during training with the robot and the use of this information to adapt the training program. Control of a robotic

device relies on high quality measurements. At the same time quality of rehabilitation depends on good assessment of patient's performance and adaptation of the training protocol to the patient's needs. The most relevant physiological parameters to be measured are: 1) heartrate, 2) galvanic skin response (skin conductance), 3) skin temperature (at the finger or similar location), 4) electromyography of arm muscles to provide more insight into the subject's voluntary physical activity.

LINarm robot and sensor integration

The LINarm robot is an assistive device for the rehabilitation of the upper limb, specifically designed to minimize the overall realization costs to enable rehabilitation exercises at home. It features a variable stiffness mechanism, making it possible to adjust the level of assistance by modifying the manipulandum mechanical stiffness on the basis of the actual requirements of the therapy.

The sensor setup was optimized to be low-cost and unobtrusive. Therefore, most of the sensors were embedded directly into the robot mechanism. Sensors embedded in the robot itself already provide information about the arm (hand) position, velocity and interaction force (including grasping force) between the robot and the patient. The acquired information provides an insight into the physical interaction between the robot and the patient (supporting forces, exchange of power).

The interface between the patient and the robot is the handle that provides the most suitable location for integration of physiological sensors (Figure 1). In this way the patient is not disturbed by the measurement procedure.

The robot measurement system can also be augmented with simple wearable sensors attached to the patient to complement information from the embedded sensors in the robot itself. The wearable sensory system consists of magneto-inertial, small, lightweight, wireless and battery powered devices that allow natural human movements. The output of the system completes the kinematic model of the upper limb that includes shoulder and elbow angles (used to properly activate electrical stimulation).

All sensors are interfaced to the control computer. Sensors signals are processed on a low cost hardware meaning that complexity of processing algorithms needs to be limited. The

sensors outputs are used as the input into the patient's model (together with kinetic and kinematic measurements).

Figure 1 LINarm device with the handle as the main interface between the robot and the patient

Technological challenges

The integration of physiological sensors within the handle results in various technological challenges related to non-static measurement conditions. Sensory system and its output are influenced by movement artefacts. Patient's grasping force on the handle changes during training, arm configuration changes due to robot movements and contact area between the hand and the handle is not constant. At the same time the handle must be ergonomically designed and should fit to patients with various hand sizes. Two handle shapes were implemented; a cylindrical and a hemispherical shape were found to be most suitable for majority of applications. Also sterilization of the robot components should be considered. The problem is less critical for home use and more critical for clinical use.

As an alternative to putting physiological sensors into the robot handle several other solutions were considered and validated: 1) bracelet with embedded sensors (battery powered and wireless – certain modern wrist watches use this concept) did not provide reliable information about all physiological parameters, 2) measurements conducted on the resting arm (sensors embedded into a form of handle was considered) was considered and can easily be implemented with the current design of the sensory system, 3) bimanual measurement of physiological signals was considered and partially implemented for measurement of ECG signal.

Embedded-and-wearable sensory system

A low-cost embedded and wearable system for measurement of physiological signals was developed and validated. Three versions of the system were used during the project: 1) state-of-the-art g.USBamp biosignal amplifier and sensors for measuring physiological and physical parameters, 2) a custom designed prototype system and 3) the final version of a custom designed system.

System design

System design included sensor architecture and the design of an ergonomically-shaped handle.

Sensor Architecture

Full sensory system architecture is illustrated in Figure 2. Different analog conditioning circuits are used to acquire person's physiological signals.

Single-lead electrocardiogram (ECG) monitor circuit was designed for measuring heart rate (HR) and heart rate variability (HRV). For the purpose of unobtrusive measurement, we used dry stainless steel electrodes also commonly found in ECG monitors for home use.

For measuring electrodermal activity (EDA) we designed a circuit using a nonlinear feedback automatic bias control with low-power operational amplifiers (TLC274 by Texas Instruments), also utilizing dry Ag/AgCl electrodes.

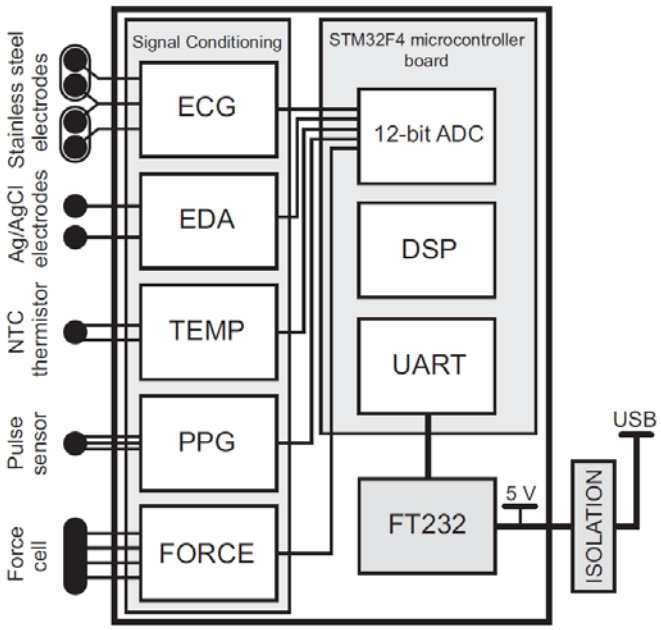


Figure 2 Overview of the system architecture. Separate analog frontends are locally regulated to ensure stable operating voltage. Isolation for this prototype is provided externally, and power is supplied by the USB port.

Conditioning circuit for peripheral skin temperature measurement was designed using a NTC glass thermistor (62S3KF354G by Betatherm), connected in a Wheatstone bridge and amplified using an instrument amplifier (AD8223 by Analog Devices).

Since ECG monitors require bimanual measurement, we upgraded the system with a second heart rate measurement using photoplethysmography (PPG), using an off-the-shelf sensor (Pulse Sensor by World Famous Electronics) in order to test the appropriateness of the PPG signal to see if it can be used as effectively as ECG for measuring HR and HRV in different task conditions. Next possible upside of adding the PPG sensor can be the additional clinical parameters that can be extracted using both ECG and PPG data (e.g. Pulse Transit Time). All signal conditioning is integrated on the PPG sensor printed circuit board that, with the adequate gain, already produces an analog waveform for digital conversion.

Additionally, a force cell conditioning circuit was designed to enable the use of grasping force measurement. A low-power, high-accuracy instrumentation amplifier with a precision reference and differential input amplification (INA125 by Texas Instruments) was used for load cell signal amplification. All conditioning circuits had local voltage references to produce a stable and noise-free analog voltage.

A microcontroller board (STM32F4 Discovery by ST Microelectronics) was used for analog-to-digital conversion, signal processing, and communication. Power is drawn directly from the universal serial bus (USB) port on the local computer, and then locally regulated on the board. A-D conversion was made by an integrated 12-bit ADC. Nyquist frequency set at 100 Hz is sufficient enough for real-time operation, and also to cover most relevant bandwidths of physiological signals (EDA, PPG, skin temperature and force signals reside bellow 35 Hz in the frequency domain, whereas ECG could extend to 50 Hz or higher). We oversampled the analog signals to increase the resolution to 16 bits. After the data has been processed, it is communicated via universal asynchronous receiver/transmitter (UART), through UART to USB data transfer interface (FT232 by Future Technology Devices International), and finally passed to the local computer through the use of external isolation (USB to USB isolator by Baaske Medical). Isolation is needed for safety and for reduction of measurement interference.

Handle Design

To enable an inconspicuous and unobtrusive measurement of physiological parameters, sensors have to be placed at the point of the haptic interaction between the robot and the human, thus the electrodes and sensors were integrated in the robot handle. Two mountable robot handles with different shape were developed for this purpose: one cylindrically-shaped (c-handle) and one hemispherically-shaped (s-handle) handle as presented on Figure 3.

Figure 3 Handle designs with integrated physiological sensors. (a) Cylindrical shape (c-handle). (b) Hemispherical shape (s-handle).

After a preliminary study of comfort in rehabilitation task within the laboratory staff, s-handle showed much better results regarding comfort than the c-handle. However, the cylindrical shape is more universal, and can be easily used in different orientations, for different rehabilitation tasks, enabling grasping force measurements.

Electrodes and sensors were integrated to the handles in a way, to be as intuitive and inconspicuous as possible. The person should be able to grasp the handle with no special care, not needing to focus on the sensors and electrodes during task.

Predicted measurement locations are illustrated on Figure 4. EDA measurement is made through Ag/AgCl electrodes positioned in such a way that distal phalanges of the second and fourth finger cover the entire surface of the electrode. PPG measurement is made by covering the Pulse sensor with the distal phalanges of the third finger. Peripheral skin temperature is measured at the distal phalanges of the fifth finger. Finally, stainless steel electrodes for measuring ECG, are appropriately positioned on the handle, enabling contact with proximal/thenar palmar surface.

A second (static) handle was added to the system, to ensure the bimanual measurement of the ECG was possible, and additionally to provide a bimanual frame of reference for the person, during the physical control task. The second handle, which was designed for the

right hand, is hemispherically-shaped for best ergonomic fit, and includes only the stainless steel electrodes.

C-handle was designed and 3D-printed in the Laboratory of robotics, while s-handle was hand made for best ergonomic fit out of expanded polystyrene.

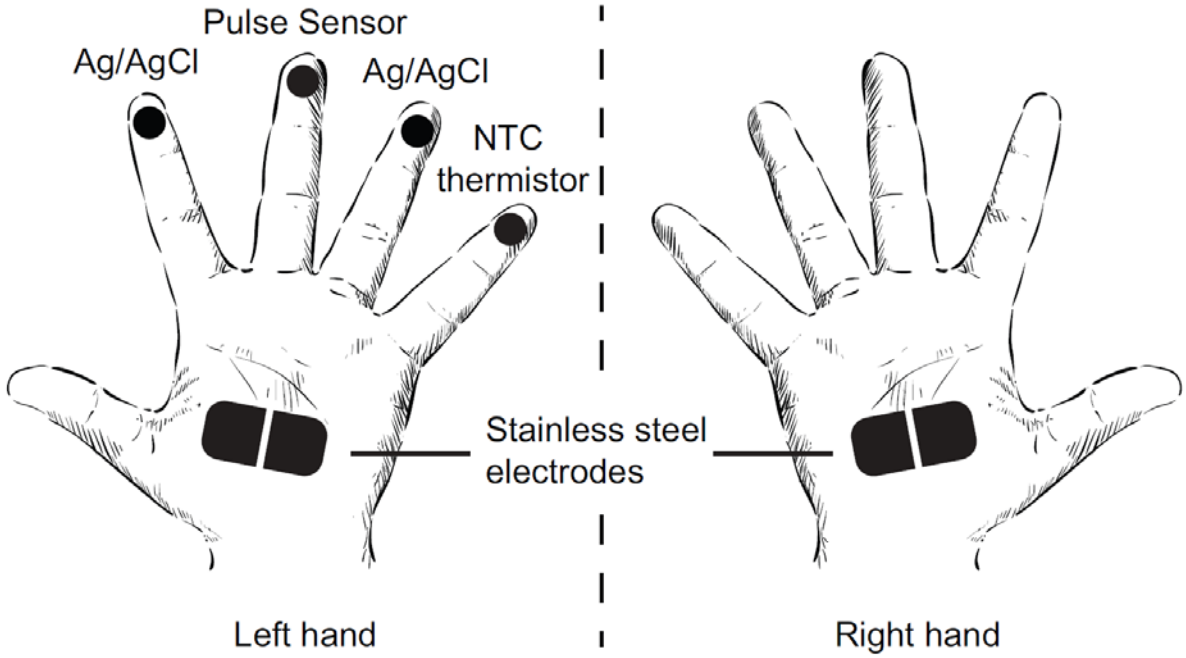


Figure 4 Predicted measurement locations for both left and right palms at time of interaction with the robot. Left (active) hand is interacting with the robot and is simultaneously being measured for physiological response at the handle. Right (passive) hand is resting on the static handle, populated only by the ECG electrodes.

Measurement of arm kinematics during training with the robot

In order to measure arm kinematics during rehabilitation inertial measurement units are placed on the forearm and upper arm of the affected limb as shown in Figure 5. This information can be used for controlling functional electrical stimulation and to estimate quality of upper arm movements.

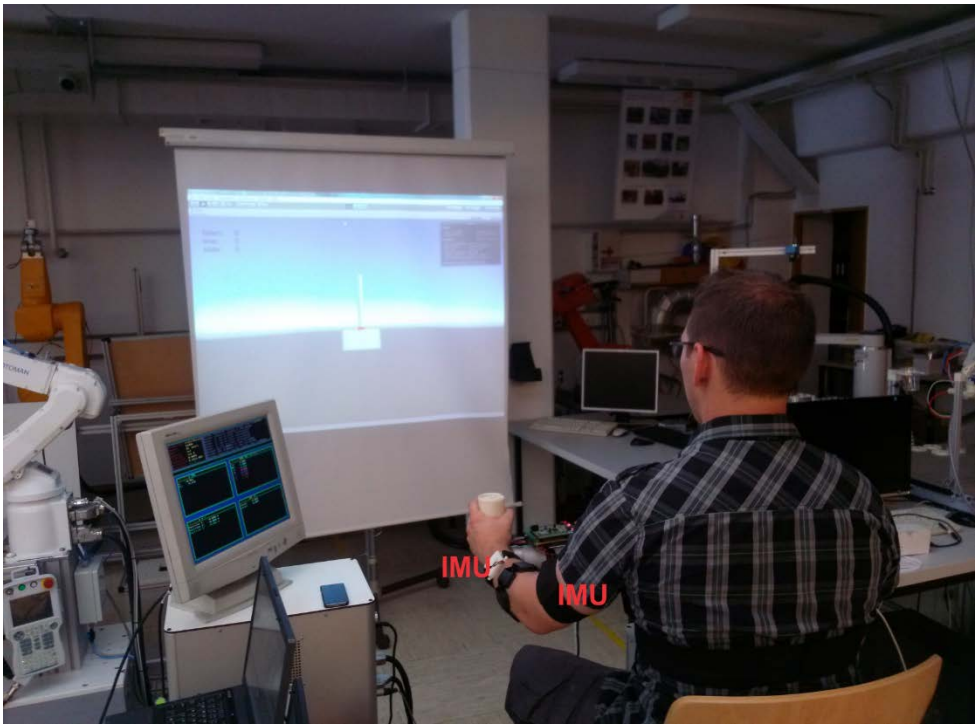


Figure 5 Inertial measurement units (IMU) placed on the forearm and upper arm for measurement of arm kinematics during robot supported training.

Experiments with the prototypes of low-cost and embedded sensory system

Experiments with the proof-of-concept system and two prototypes of low-cost sensory system were conducted on 23 healthy volunteers. The experimental setup is shown in Figure 6. A mathematical model of inverted pendulum was implemented in a virtual environment as the physical control task. The inverted pendulum is an inherently unstable system without control, so the participants had to balance the pendulum by applying a virtual force to the cart (robot end-effector). The amount of force needed and the pendulum dynamics were adjusted through the mathematical model by changing the parameters such as gravity, friction, damping, mass, and pole length. If participants did not manage to stabilize the pole, the pole was reset to the vertical position after the cart was brought back to the middle of the screen. All robot movements and haptics were limited only to the x-axis (horizontal axis) of the robot, to enable a 2-D rehabilitation task and to simplify the experiment.

In order to create different physical conditions in physical control task, mass of the cart was changed between two values (mass at high physical load was set to 5 times higher in comparison to low physical load). Different dynamic conditions were created by changing

the length of the pole between two values (high dynamics were set at one third of the length of the pole at low dynamics). With high physical load the robot produced larger reaction forces at the end-effector for person to move the cart. With high dynamics, the pendulum reacted much faster to the cart movement, also falling much faster. In this condition participants had to react faster in order to balance the pole. This way, two conditions were permuted to create four different tasks:

- Task 1 (T1): low physical load and low dynamics,
- Task 2 (T2): low physical load and high dynamics,
- Task 3 (T3): high physical load and low dynamics, and
- Task 4 (T4): high physical load and high dynamics.

These experiments served three purposes:

- to test and verify the configuration of embedded-and-wearable sensory,
- to finalize the algorithms for signal processing for analysis of physiological measurements,
- and to collect base for developing the patient model.

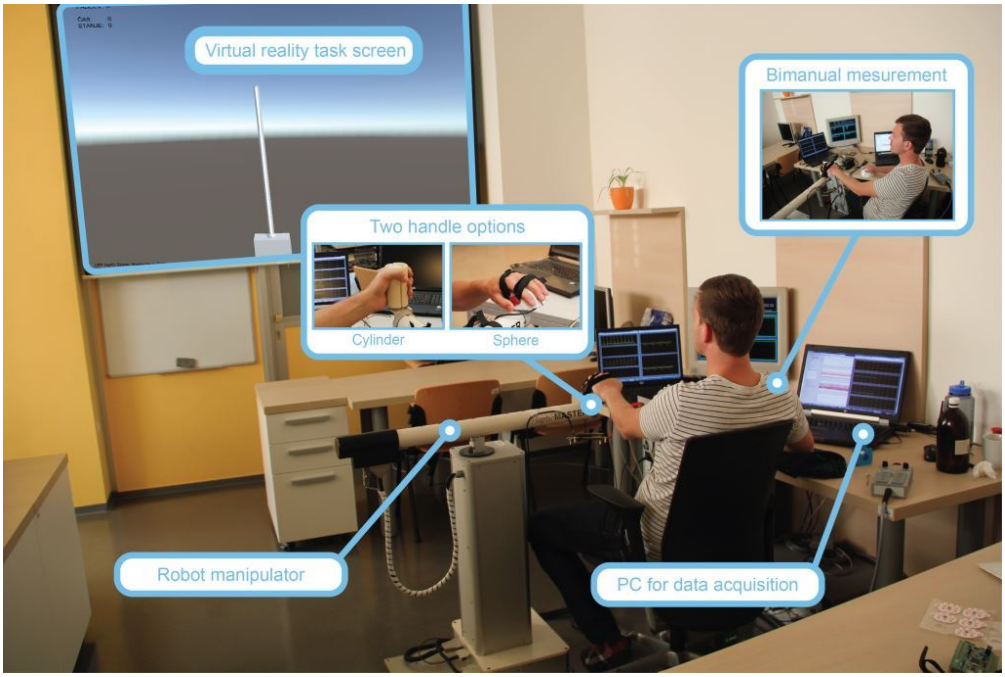


Figure 6 Experimental setup: robot manipulator, virtual reality task screen, PC for data acquisition, along with reference and newly developed physiological measurement systems.

Performance and Biomechanical Measures

Performance was evaluated with parameters, such as success rate, mechanical work, and mean frequency of position signals. Success rate is determined by counting how many times the pendulum has fallen during the task. Subjects with better balancing will have a lower count than others. Also under the task condition with low dynamics, subjects should in general have a lower count than at the high dynamic condition. Total mechanical work is calculated as the sum of all work increments, calculated as a dot product of position and force signals from the robot. Since the task was designed for single degree of motion (horizontal movements), we are calculating forces and work using data only from horizontal movements. In this case, both vectors are always aligned, and both position and force can be either positive or negative and the work increment will always be positive. Total work should increase through the tasks, especially in tasks with greater physical load. Mean frequency of position signals was calculated to confirm the effect of the high dynamic condition, and should increase when high dynamic condition is active. Mean frequency was calculated using Welch's power spectral density estimate.

Physiological Parameters

Physiological recordings were obtained from both handle and reference measurement system for every subject. After the experiment, signals were processed offline for 3-min periods of both baseline and task, from which several standardized parameters were extracted for each period.

From ECG recordings, the mean heart rate was calculated as a mean value of time differences between consecutive RR peaks in the QRS complex. Additionally, two standardized HRV parameters were also extracted: the standard deviation of successive NN intervals (SDNN), and the square root of the mean squared differences of successive NN intervals (RMSSD). ECG processing algorithm is the same for both bi-manual measurement and the reference ECG recording. A HRV signal was produced by cubic spline interpolation of consecutive HR values, for determining the correlation of the HRV information between systems.

Same parameters (mean heart rate, SDNN and RMSSD) and same HR signal were extracted from the first derivative of the PPG signals.

EDA recording can be decomposed into two separate components: a low frequency (tonic) component and a higher frequency (phasic) component. The tonic component describes the overall skin conductance over a longer period of time and is obtained by filtering the raw signal with a low-pass filter with a cut-off frequency of 0.1 Hz. Similarly, the phasic component was obtained by high-pass filtering of the raw signal with a cut-off frequency of 0.05 Hz, to observe the higher frequency fluctuations of skin conductance that are modulated on top of the slower tonic component. From the tonic component mean skin conductance level (SCL) parameter is extracted. Skin conductance responses (SCRs) are a quantitative measure of skin conductance fluctuations in a period of time. SCR frequency was calculated for the duration of baseline and task periods.

Final skin temperature was calculated as an average peripheral skin temperature of the last two seconds of each task period.

Several dedicated graphical user interfaces (GUI) were developed for complete processing and analysis of acquired physiological signals (see Figure 7). GUIs were designed modularly, providing the possibility of separately reviewing raw sensor signals and calculated numerical parameter values. This can provide inter-handle, inter-session, and inter-subject data comparison.

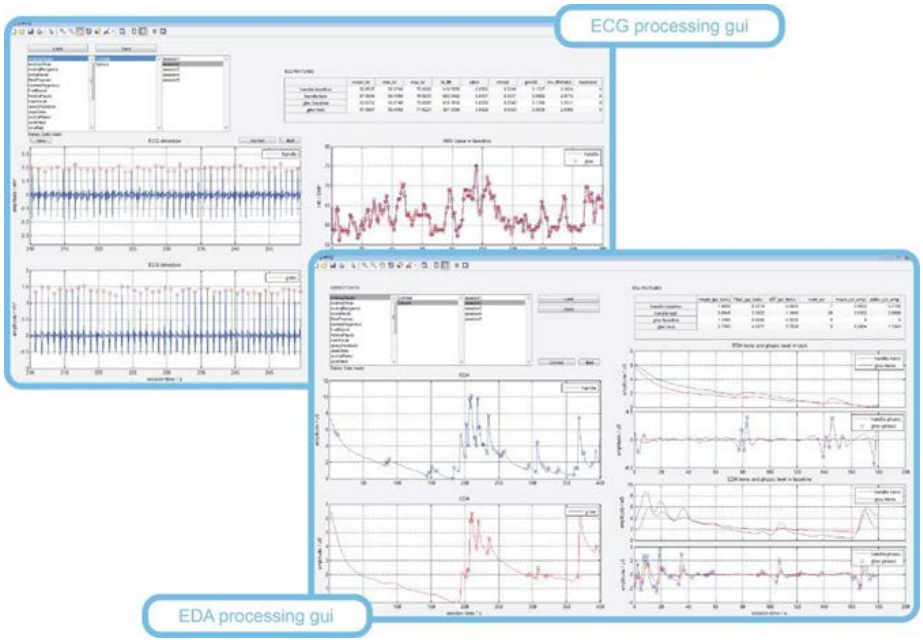


Figure 7 Graphical user interface with acquired signals.

System validation against a reference measurement system

Results for signal similarity can be seen in Figure 8. Pearson' correlation coefficients (PCCs) were calculated between reference system and handle signals for both handles. S-handle showed better correlation for most of the signals through all four tasks, except for PPG HR curve that showed higher correlation for c-handle for all tasks.

For EDA signals (Figure 8 (a)), median values of PCCs in baseline are higher for c-handle and for s-handle than in task. A significant baseline-task correlation reduction $p < 0.05$ was found for tasks T1, T2 and T4 of s-handle results, others were not significant.

For skin temperature (see Figure 8 (b)), median values of PCCs showed a reduction in correlation for T1 and T4 for c-handle and T4 for s-handle. Increase in baseline-task correlation was found for T2 and T3 for both handles. A significant difference of baseline-task correlation ($p < 0.05$) was found for T1 and T4 of c-handle results, others were not significant.

For ECG HR extracted signals (see Figure 8 (c)), median values of PCCs showed high correlation in both baseline and task periods for both handles. For both handles, a significant difference of baseline-task correlation ($p < 0.01$) was found for T2.

For PPG HR extracted signals (see Figure 8 (d)), median values of PCCs showed high correlation in T1, T2 and T3 for all three tasks and both handles. Significant difference of baseline-task correlation ($p < 0.05$) was found for both handles in T4.

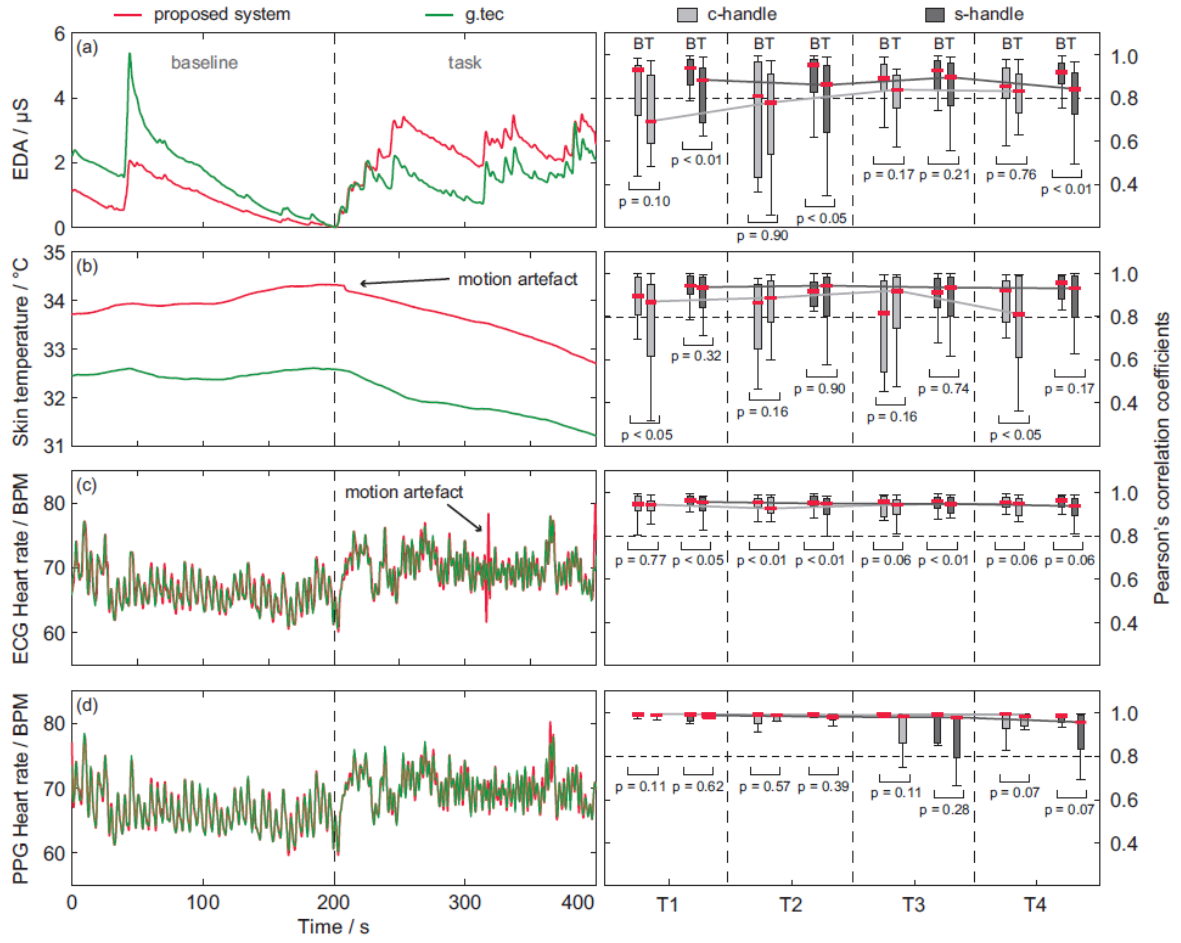


Figure 8 Raw physiological waveforms (left) and Pearson's correlation coefficients for all tasks are represented as box plots (right): Electrodermal activity (a), Peripheral skin temperature (b), ECG HR signal (c), and PPG HR signal (d). Gray lines are connecting the median values of Pearson's correlation coefficients in tasks to better illustrate the correlation trend between different tasks. B and T are marking baseline and task period for each of the four tasks respectively.

Final version of the embedded-and-wearable sensory system

The knowledge and experiences obtained from the ptototype sensory system for measurement of physiological signals were used for the design of the final version of the system. The final design takes into account the system performance, size limits for the electronics and most importantly safety aspects required for medical grade devices.

The aim is to measure physiological parameters: heart rate and its variability (using electrocardiography and photoplethysmography), electrodermal activity, and peripheral skin temperature. Full sensory system architecture is illustrated in Figure 9. Different analog conditioning circuits are used to acquire person's physiological signals. All circuits in contact with the human are isolated in two stages in order to guarantee safety and to enable medical device certification. A microcontroller board (STM32F4 Discovery by ST

Microelectronics) was used for analog-to-digital conversion, signal processing, and communication. Power is drawn directly from the universal serial bus (USB) port on the local computer, and then locally regulated on the board. A-D conversion was made by an integrated 12-bit ADC. With Nyquist frequency set at 100 Hz will be sufficient for real-time operation and also to cover most relevant bandwidths of physiological signals (EDA, PPG, skin temperature and force signals reside bellow 35 Hz in the frequency domain, whereas ECG could extend to 50 Hz or higher).

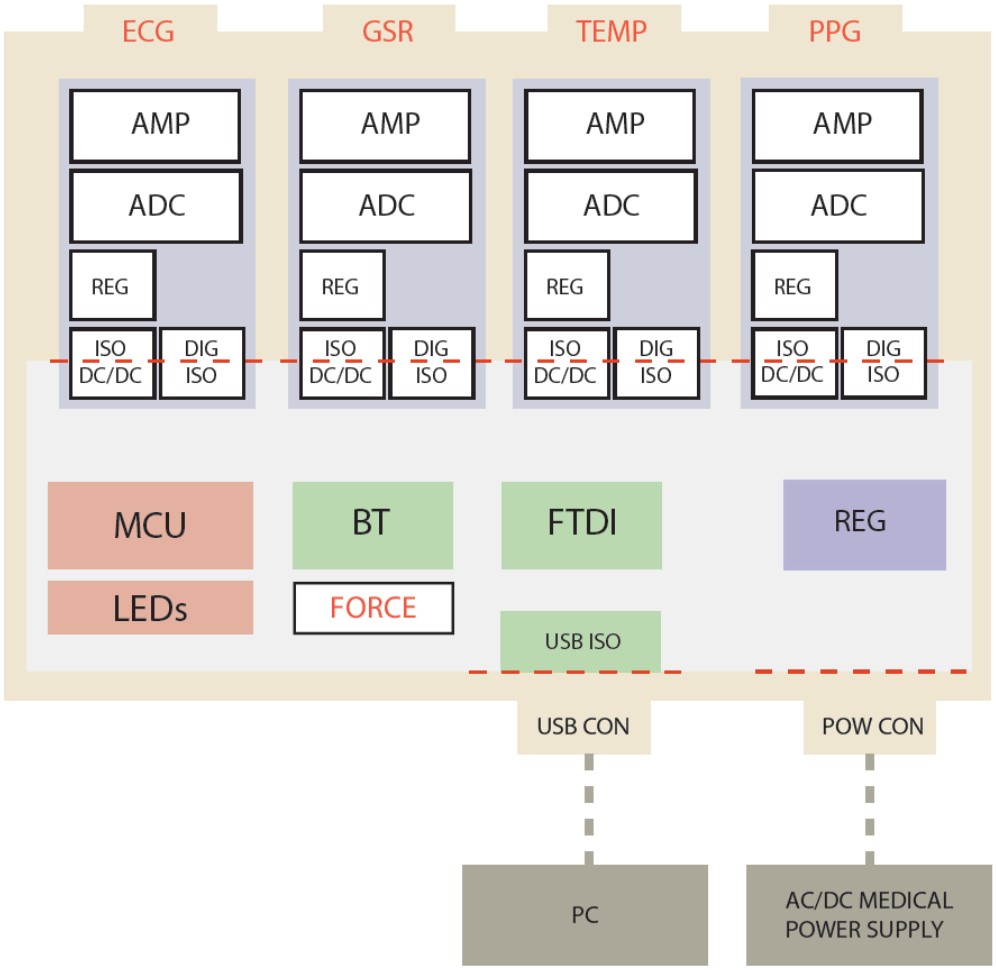


Figure 9 Block diagram of the final version of low-cost measurement system for measurement of physiological signals

In order to fit into both types of handles, the electronics is designed in a circular shape. Figure 10 shows the printed circuit board of the final version of the electronics system for acquisition of physiological signals. Figure 11 shows 3D models of bottom and top layer of the board. Figure 12 shows combined cad models of the handle and the electronics.

Figure 10 Printed circuit board of the final electronics.

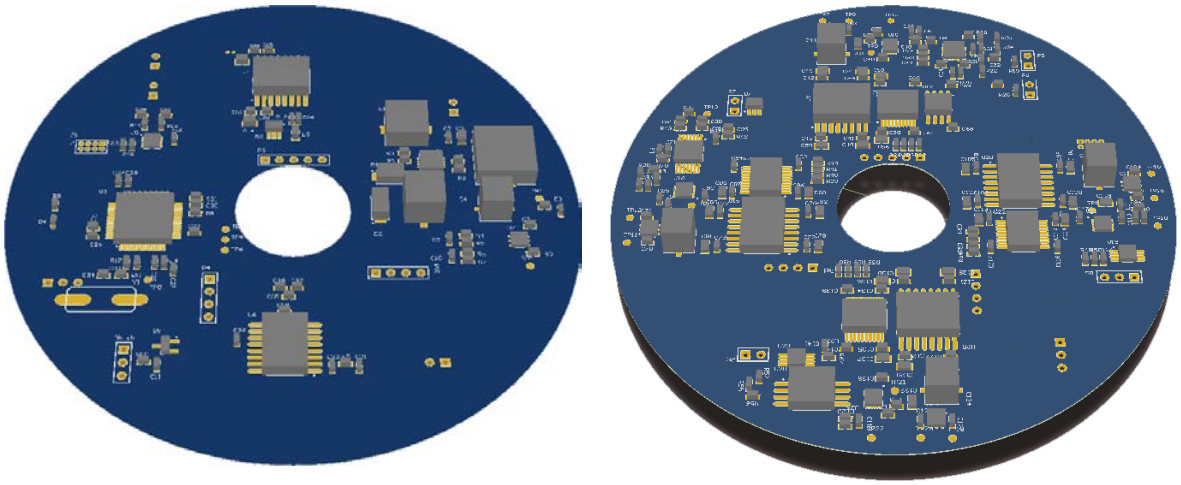


Figure 11 Bottom and top 3D model of the printed circuit board.

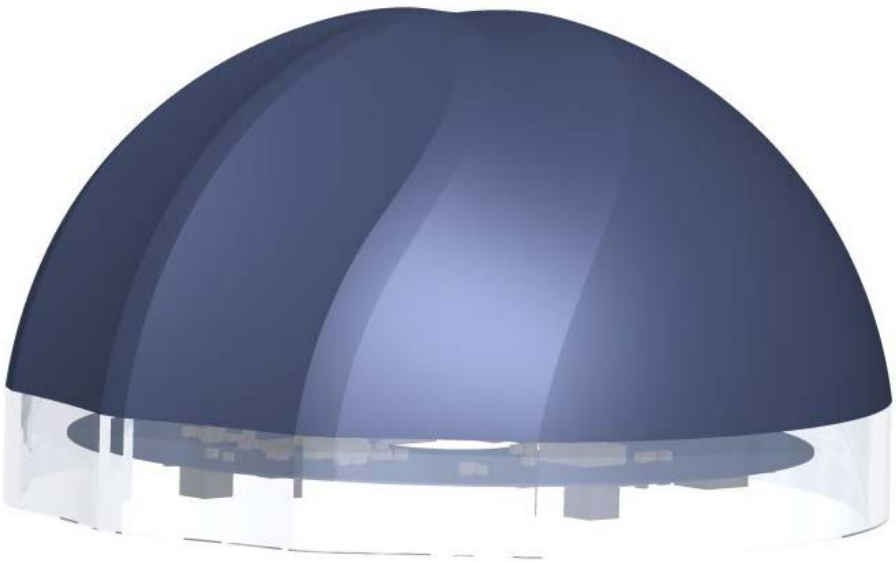


Figure 12 CAD model of the handle and the electronics.

Patient model

Patient model provides the core functionality for adaptation of training to individual patient's needs. The task can be adapted in terms of motor and cognitive challenges. Motor challenge influences the required patient's motor activity. Cognitive challenge is adjusted using questions or cognitive tasks (such as mathematical tasks) that are divided into two distinctive levels by difficulty. Cognitive tasks are taken from established psychological test used to test the cognitive load. The level of cognitive challenge is adjusted based on user's score. A fixed threshold is used to change the difficulty of the cognitive task. If user answers correctly a series of cognitive tasks (usually three in a row) the difficulty is increased and vice versa if user answers a series of tasks wrongly the difficulty is decreased.

The model integrates clinical information about the patient with the automatic observations of patient's activities during the training with the LINarm++ device. The model is divided into two sub-models:

- Patient performance model estimates various parameters related to physical activity and task performance.

- Physiological model fuses data from sensors (embedded into the handle), which measure physiological signals. Outputs are parameters summarizing the information about the physiological state of the user. The main focus is on observation of trends of physiological parameters in order to optimize training activity.

Outputs of patient model are not analyzed only in terms of absolute parameter values, but more importantly they are analyzed in terms of trends of signals. Based on that training settings should be optimized in order to keep the parameter values within the adequate boundaries.

Patient model algorithm

During this period the patient model was developed and evaluated with data collected with healthy subjects. Patient model is organized in a structure of the decision tree (see Figure 13) with four distinctive layers of nodes:

- Clinical Observation layer is based on computation of Clinical Observation Index (COI).

  COI is set by clinician prior to training. This observation is very reliable and meaningful to clinical staff. Therefore, it has the highest priority in the model. Based on the criterion patients are grouped in three slightly overlapping categories (those that need high robot support with assistance value $a>0$, those that do not need support at all with the assistance value $a<0$, and the intermediate group).
- Task Performance layer is based on computation of Task Performance Index (TPI).

  TPI is calculated from various parameters related to performance in the particular game (score, time to complete the task, number of errors). It provides a very reliable and objective measure of general patient's performance. Therefore, the second layer of decisions is based on the TPI. Patients are further divided into two subgroups based on the TPI.
- Motor Performance layer is based on computation of Motor Performance Index (MPI).

  MPI is calculated from various parameters related to movement and force. Values such as power, velocity, interaction force, grasp force, movement smoothness, deviation from ideal trajectory, and robot support are calculated in real time from

the force and position sensors mounted on the robot. The values provide an objective measure of patient's motor performance. These values are used in the third layer of the decision tree in order to further differentiate between individual patients. MPI is reliable as TPI. However, patients with lower MPI can still accomplish training tasks. Therefore, MPI was placed lower in the decision tree. Patients are divided into additional two subgroups based on the MPI.

- Physiological layer is based on the computation of the Physiological Trend Index (PTI).

  PTI is calculated from various parameters measured by physiological sensors (heart rate, heart rate variability, temperature, skin conductance response, skin conductance level – all the parameters are differences between baseline levels and levels measured during the task). These values provide a good insight into the patient physiology and potentially also psychology that is not considered here. In terms of motor rehabilitation, they are the least reliable. Therefore, the decision based on physiological parameters is placed in the lowest level on the decision tree. Patients are divided into the final subgroups based on the PTI.

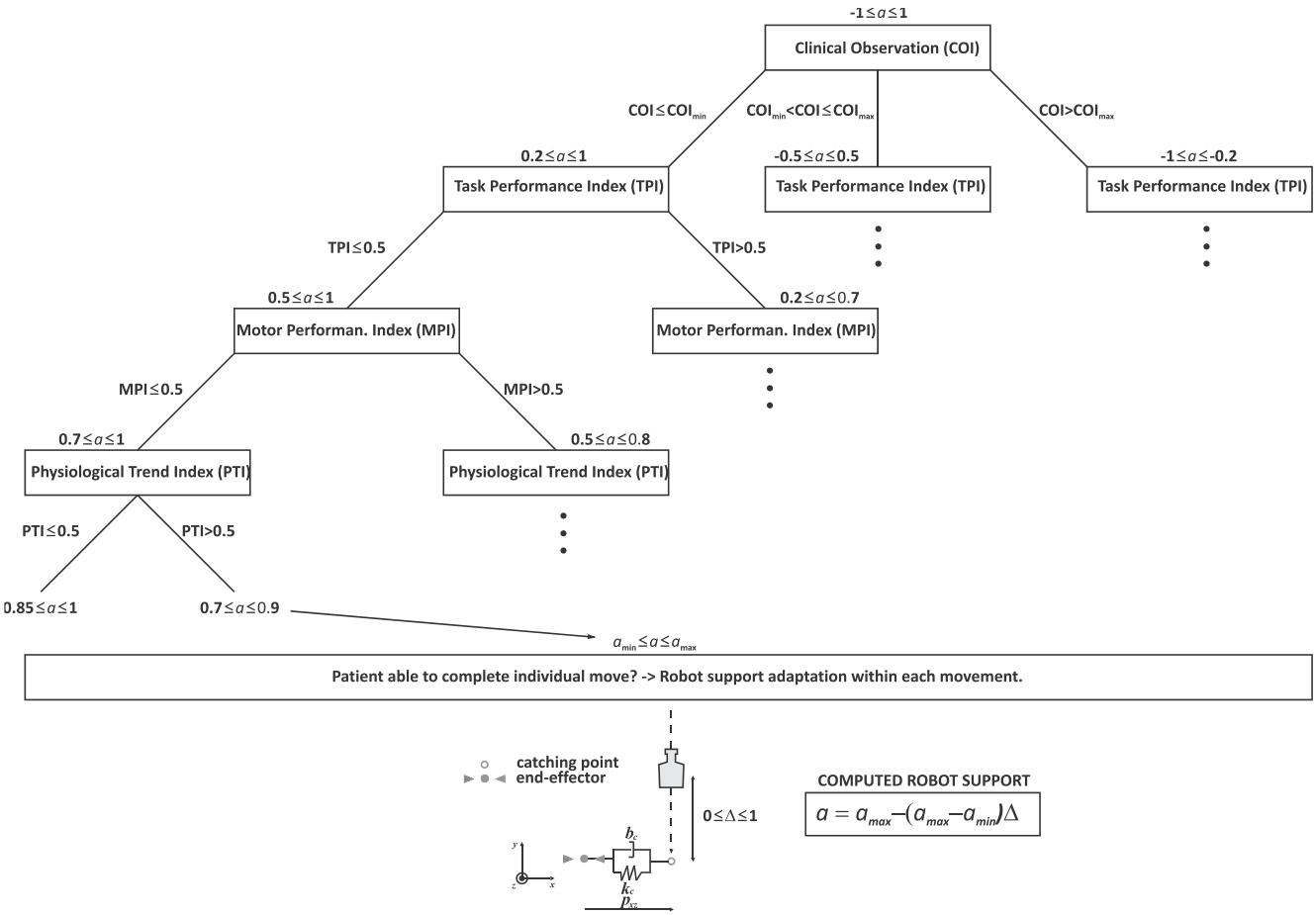


Figure 13 Part of the decision tree of the patient model.

Each Index is linear combination of the parameters used to calculate the index. Index is limited to values between 0 and 1. The weights for parameters included into calculation of the particular index are determined algorithmically by using linear classifiers (e.g. Linear discriminant analysis, Naïve Bayes classifier). This requires learning set which is gathered using preliminary experiments with fixed values of difficulties.

Example for PTI is given with the following equation

$$PTI=s\cdot\Delta HR+t\cdot\Delta HRV+u\cdot\Delta T+v\cdot\Delta SCR+w\cdot\Delta SCL,$$

where *s, t, u, v, and w* are weights determined using linear classifier, *ΔHR* is difference in heart rate between baseline measurements and measurements during the execution task, *ΔHRV* is difference between heart rate variability during the baseline measurement and measurement during the execution of the task, *ΔT* is difference between temperature during the baseline measurement and measurement during the execution of the task, *ΔSCR*

is difference between skin conductance response during the baseline measurement and measurement during the execution of the task and finally the *ΔSCL* is difference between skin conductance level during the baseline measurement and measurement during the execution of the task.

Assistance level is then calculated with the following equation

$$a=a_{max} - (a_{max} - a_{min})\Delta,$$

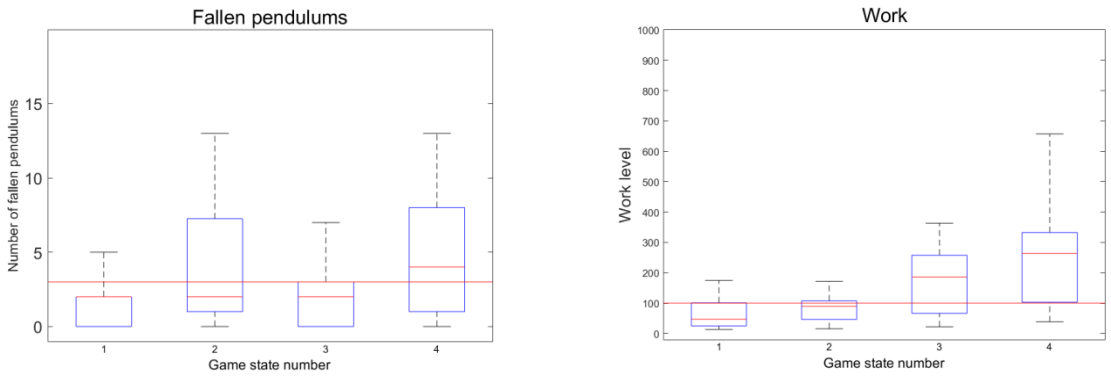
where a is assistance level, a_{max} and a_{min} are upper and lower bound of assistance level for particular case and Δ is the normalized distance of the object from the target. Since parameter Δ changes from value 1 when the object starts to fall down to 0 when object reaches the target, assistance level a changes linearly from assistance level a_{min} to a_{max}. The rationale for this is that the assistance level needs to change depending on the distance of the object from the target. If the patient is not able to move the object to the target using the assistance level a_{min} in time the robot will increase the assistance level to level a_{max}. Parameters a_{max} and a_{min} are outputs from the decision tree structure of the patient model. At each level both parameters are outputted from the model.

This section explains the basics of the patient model on an example of one healthy subject. Each node branches based on values of individual parameters (see Figure 14). Output of the Patient model is minimal and maximal value of assistance parameter a which determines the level of assistance.

COI = 3	a_{min} = -1, a_{max} = -0.2
TPI = 1	a_{min} = -1, a_{max} = - 0.5
MPI = 0.35	a_{min} = -0.8, a_{max} = -0.5
PTI = 0.33	a_{min} = -0.7, a_{max} = -0.5

The subject was assigned with Clinical Observation Index 3, which branches for assistance range between -1 and -0.2. Subject achieved Task Performance Index 1, which branches into assistance range from -1 to -0.5. In the next layer the Motor Performance Index equals 0.35. The resulting a range is -0.8 to -0.5. In the last layer the Physiological Trend Index is 0.33, which outputs the final range of a parameter. For this subject the PTI is 0.33 and the

resulting *a* range is -0.7 to -0.5. The assistance index is negative. This means that the robot does not need to provide support to the healthy subject. However, this subject did not perform very well. Therefore, the task challenge remained moderate.



(a) Number of fallen pendulums

(b) Level of work during the task

Figure 14 Figure shows examples of two parameters for the task. Figures show median value and dispersion for 22 healthy subjects that played the inverted pendulum balancing task. Parameter of Number of fallen pendulums was used to calculate Task Performance Index, while parameter Work was used to calculate Motor Performance Index. Red horizontal line over all four boxplots is the threshold for branching in next level of the patient model.

Validation of patient model

Validation of the patient model was done using the Stroop game. Experiments were performed on 10 healthy subjects and were divided into two parts: 1) Increasing difficulty and 2) Adaptive difficulty using a simplified patient model.

Each part started with 2 minutes of baseline measurements when subject needed to rest. During the baseline measurements a baseline values of physiological signals were collected.

Figure 15 shows normalized velocity of the falling words during both experiments.

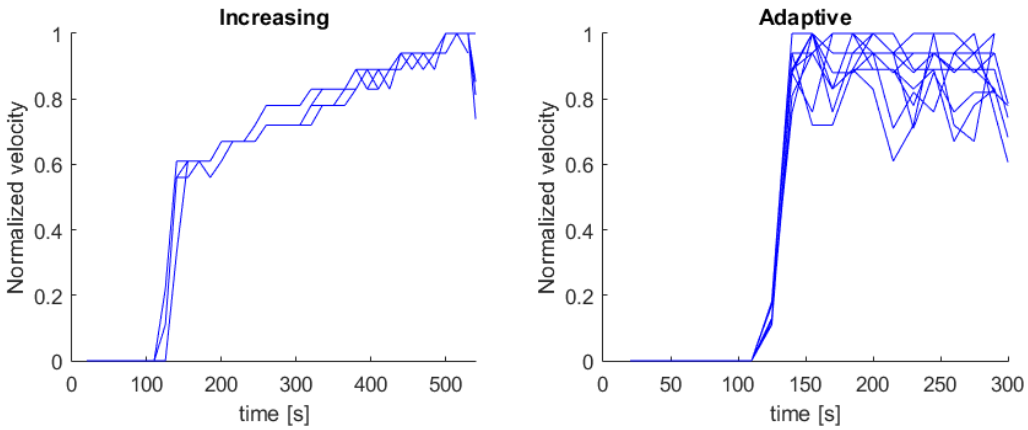


Figure 15 Figure shows velocity of the falling words during the experiments.

Increasing the difficulty

The aim of this experiment was to determine how various parameters which are included into calculation of indices used in patient model change in relation to different levels of difficulty. Based on the results of this experiments all parameters in patient model will be updated to create a final version of the patient model.

Difficulty level of the game was changed by increasing the speed of words that were falling from upper edge towards the colored clouds in steps from lowest speed to highest speed. Seven different speed values were used for seven difficulty levels. Each difficulty level lasted 1 minute; therefore, the whole experiments for rising difficulty lasted 9 minutes (2 minutes for baseline + 7 minutes for 7 levels). Figure 15, left subfigure, shows the normalized velocities of the falling words during the experiment which was increased in steps from 0.6 to 1.

Adaptive difficulty using a simplified patient model

In this experiment the aim was to test the patient model. The patient model was simplified as Clinical Observation Layer and Physiological layer were excluded from the model. Since all the subjects were healthy subjects they would all receive same Clinical Observation Index. The Physiological layer is lowest layer of the patient model and therefore does not change the assistance parameter significantly. The aim of the patient model was to change the

difficulty in such a manner that the performance of the user remains relatively constant throughout the whole experiment.

Experiments with adaptive difficulty lasted 5 minutes (2 minutes for baseline measurements and 3 minutes for adaptive part of the experiment).

Results

Several parameters were tested and the results will be explained in this section. Figure 16 shows the parameters measured during the experiments for ten subjects. First column designated Increasing shows results for experiments where difficulty was increased in from lowest difficulty level to highest difficulty level. Work is calculated from speed of movement and applied force by the user in fixed time window. The second column designated Adaptive shows results for experiment with adaptive difficulty using a simplified patient model. First row shows success parameter and shows number of correctly placed words in correct clouds. Second row shows work performed by the user. Third row shows parameter *Pmnf*, which is position mean frequency. *Pmnf* is the average frequency of the signal, and is calculated by dividing the sum of frequency bin and power spectrum products by the sum of the whole power spectrum (total power) of the signal:

$$MNF = \sum_{j=1}^{M} f_j P_j \Big/ \sum_{j=1}^{M} P_j \ .$$

Parameter *Pmnf* is related to speed with which the user moves the robot. Higher value means higher activity of the subject.

Fourth row shows parameter *Ftpf*, which is total power of force signal. Total power is calculated by summation of the entire power spectrum, in our case by summation of the Welch's power spectral density estimate.

$$TTP = \sum_{j=1}^{M} P_j = SM0 \ .$$

Vertical red lines indicate the end of baseline measurement and the start of the game. Horizontal red lines show the thresholds for various parameters which were used in patient model.

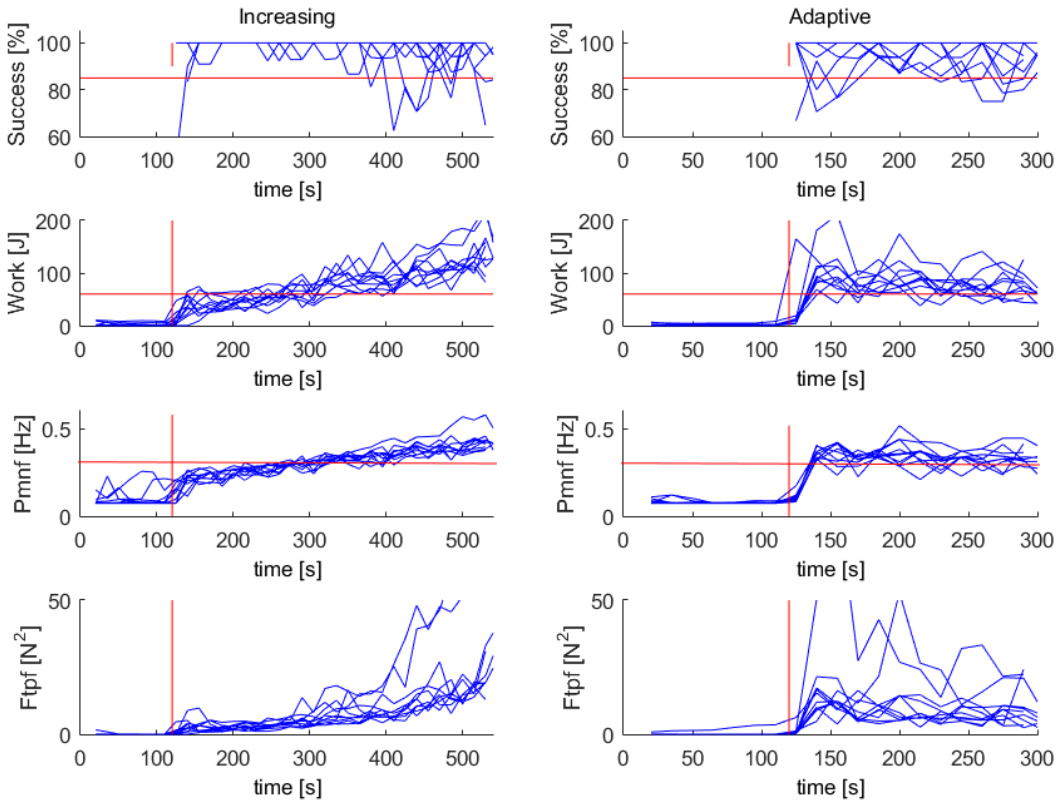


Figure 16 Figure shows various parameters for patient model validation experiments.

Task performance index

Task performance index is calculated from the success rate. Success rate is calculated as percentage of correctly placed words into correct clouds. Figure 16, top row, shows values for success rate. For increasing difficulty experiments it can be seen that success rate decreases when difficulty increases. In the beginning of the experiment when difficulty level is low more or less all the subjects were above 90% of success rate. After 400 s the success rate drops, although some subjects did perform very good also at highest difficulty level. At adaptive experiment it can be seen that success rate is constant and is in general at level typical for higher difficulty levels from beginning of the experiment to the end of the experiment. The threshold for success rate was set to 85%.

Motor performance index

Results show that the most important parameters are: (1) *Work*, (2) *Pmnf* and (3) *Ftpf*. Figure 16, second row, shows the work during the experiment of increasing the difficulty. From the figure it is clearly seen that work performed by the user increases with the

increased level of difficulty. Figure 16 shows the work during the experiment where the difficulty was adapted using the patient model. From the figure it can be seen that the work fluctuates around constant value, which was the aim of the experiment. The fluctuation is expected since the parameters need to change so that the patient model can either increase or decrease the difficulty based on results in last time window. Similar observations can be made for *Pmnf* and *Ftpf* parameters.

Figure 15, right subfigure, shows the velocities of the falling words during the adaptive difficulty experiment. Typically, the velocity was high at the beginning of the experiment. If the velocity and therefore the difficulty level was too high, patient model decreased the difficulty level, which corresponds to lower velocity. This usually resulted in slight increase of the success rate, but more importantly the Motor performance index decreased since subject was less active because the words were falling slowly. In next time interval patient model typically increased the difficulty. Since success rate was high most of the time Motor Performance Index had the most impact on the chosen difficulty level.

Physiological trend signals

First inspection of the results showed that the subjects that participated in the experiments can be divided into two groups based on how their temperature changed during the increasing difficulty experiment:

- group 1 – subjects with positive trend of temperature and
- group 2 – subjects with negative trend of temperature.

Coincidently both groups were the same size of 5 subjects.

Figure 18 shows the result for group 1 and Figure 17 shows the results for group 2. Each figure has two columns (left is for increasing difficulty experiment and right column is for adaptive difficulty experiment).

While for group 1 in increasing difficulty experiment we can hardly notice any trends of change in physiological signals group 2 shows distinctive trends which can be correlated with the increased difficulty of the task.

Increasing difficulty experiment

Heartrate in group 2 is increasing proportionally with the increased difficulty: higher the difficulty higher is the heart rate. Since also work performed by the user is increasing with the difficulty it can be expected that heart rate will increase and results support that for group 2. Temperature is decreasing (see Figure 17 first column second row). Parameters of skin conductance (SCL, SCR frequency and SCR amplitude – see Figure 17 first column rows 3 to 5) are all increasing from the baseline values. SCL changes significantly in the beginning of the experiment when the difficulty is still low, and then only slightly with increasing difficulty. SCL seems also to be the only parameter that increases in group 1. Other parameters remain relatively unchanged compared to baseline values in group 1. This parameter is therefore suitable to detect early changes in difficulty. In contrast SCR parameters change significantly during the highest difficulty and are therefore suitable to detect higher difficulties.

Adaptive difficulty experiment

Second column in Figure 17 and Figure 18 shows the results of the adaptive difficulty adaptation for physiological parameters. In group 2 heart rate increases (see Figure 17, second column, first row) after the beginning of the experiment and it stabilizes in the second half of the experiment. In group 1 heart rate does not change during the experiment compared to baseline values. Again groups react differently when it comes to temperature parameter. In groups 2 temperature slightly, but not significantly increases during the first half of the experiment, but remains mostly constant compared to baseline values. Compared to group 2 the temperature parameter in group 1 increases significantly in the second part of the experiment. Skin conductance parameters for group 1 and group 2 behave similarly. After the beginning of the experiment the parameters values increase compared to baseline values and after the second half of the experiment they remain relatively constant. This shows that the difficulty settings determined by the patient model were set appropriately.

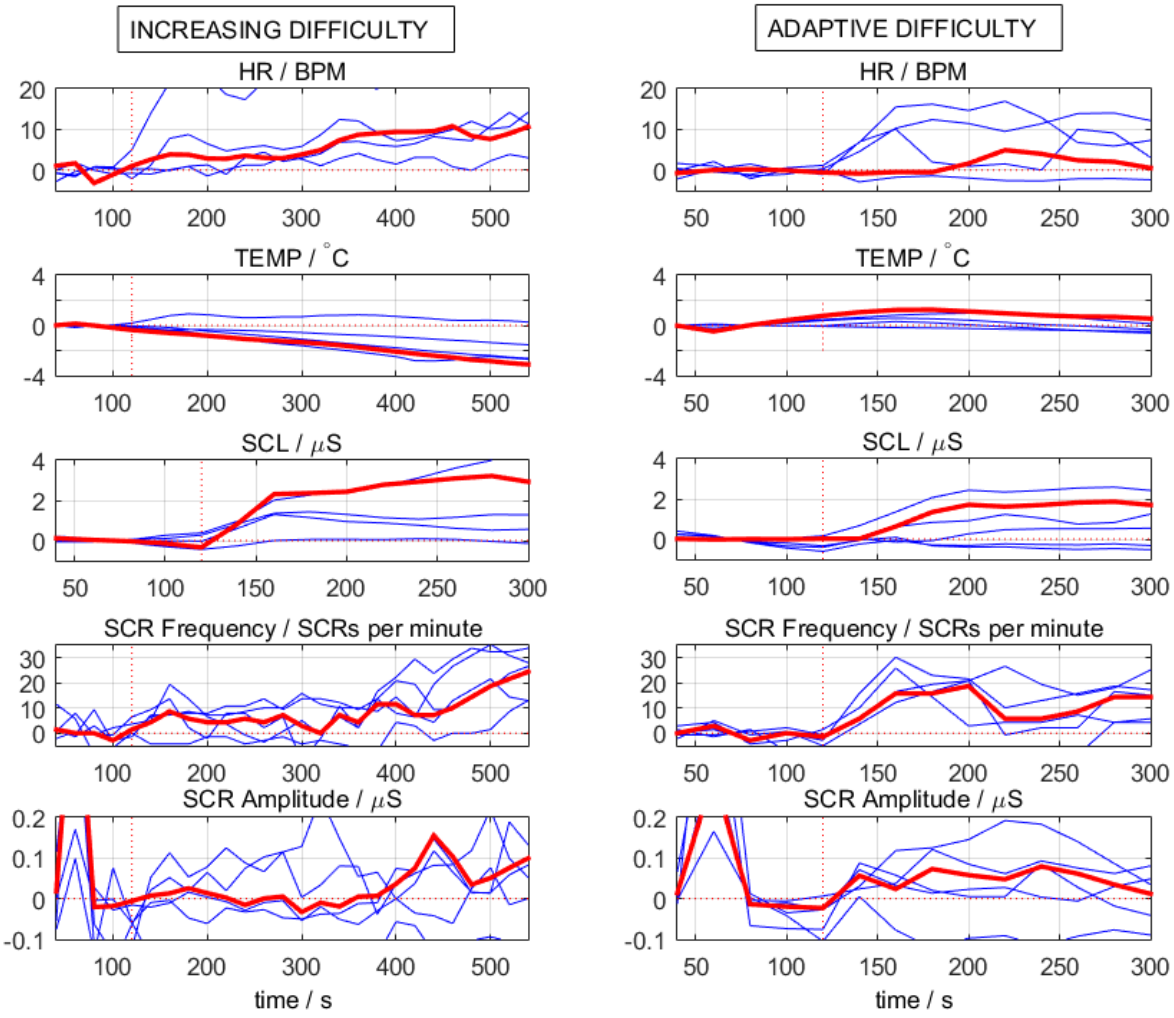


Figure 17 Physiological parameters for subjects of group 2.

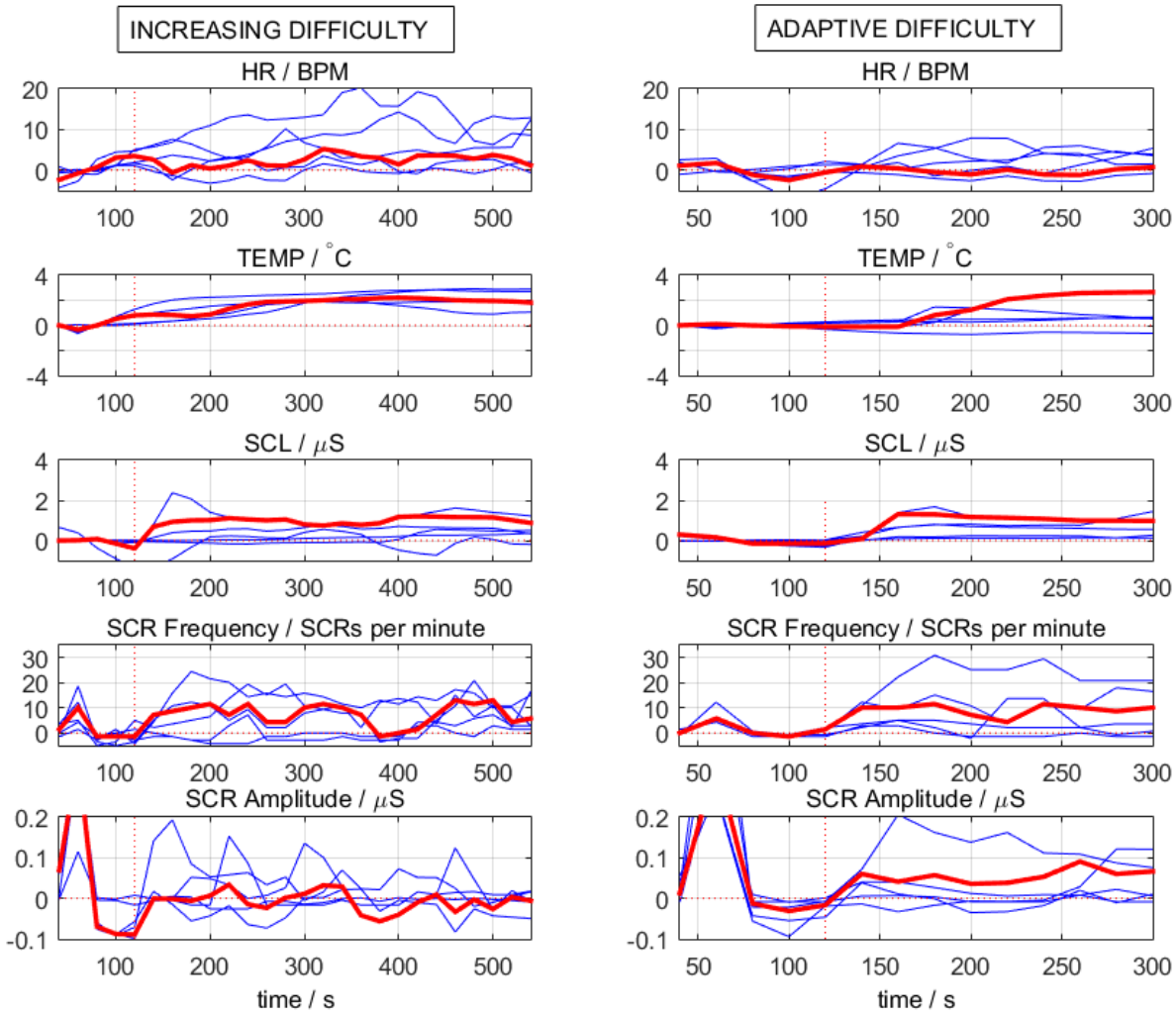


Figure 18 Physiological parameters for subjects of group 1.

Integration with the LINarm device

The sensory system for measurement of physiological signals was successfully integrated with the LINarm++ device. The integration was accomplished on the level of mechanical interfaces, electrical connections as well as communication protocols. The main device controller has access to all sensor data that are included in the control of the device. With the integration of the sensory system also the patient model was transferred from the prototype system based on the HapticMaster robot to the LINarm++ system. The two versions of the integrated system are shown in Figure 19.

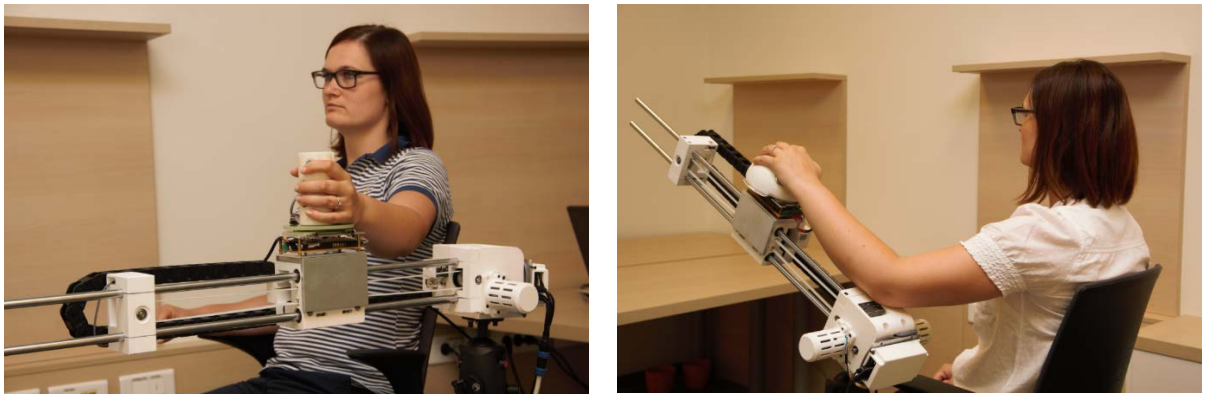


Figure 19 Integration of the sensory system with the LINarm++ device. The left figure shows the integration of the cylindrical handle; the right figure shows the integration of the hemispherical handle.

The integrated system was validated with the training scenarios presented above (see Figure 20). All functionalities were transferred from the prototype system that was based on HapticMaster robot. The only difference between the two robots is a slightly lower dynamic bandwidth of the LINarm++ device due to the variable impedance actuator.

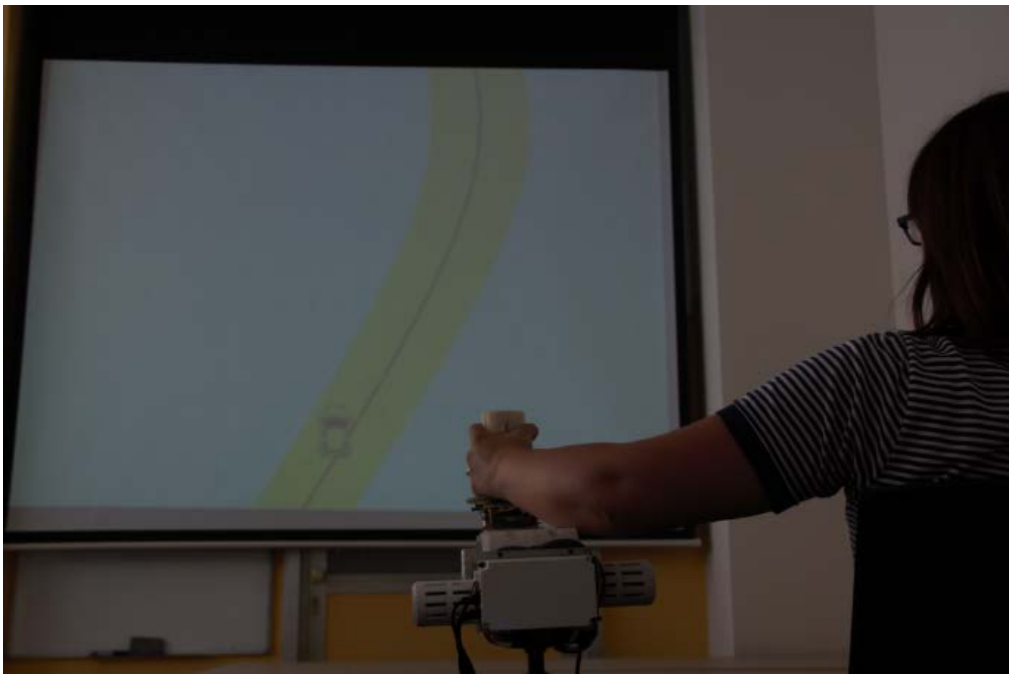


Figure 20 Validation of the integrated system with the tracking game scenario.

Conclusions

The sensory system for measurement of physiological signals was developed, validated and integrated with the LINarm++ device. Already the first prototype included custom designed electronics for data acquisition and processing. The final system builds on that experience and takes into account other factors, such as ergonomics and patient safety. The final system will be integrated with the LINarm++ device together with the integration of the functional-electrical stimulation system and will be validated with patients in RIF.

In parallel with the sensory system also the training scenarios were developed which are described in deliverable D5.3. Five different training scenarios were developed and tested. The scenarios differ in required motor performance. The more advanced training scenarios include also adaptive cognitive challenges to make the training more intensive and efficient. At least part of training scenarios will be validated with patients after the final integration of the system. The training is adapted to individual user needs with the assistance of the patient model. Since all system validations until now were performed with healthy subjects, the parameters of the patient model are tuned to healthy subjects. These values will be adapted to patients' needs for the final validation of the system. The structure of the patient model will be kept as it is now, since it was optimized for patients' characteristics.

The designed system provides a low-cost and nonintrusive solution for acquisition of physiological signals during a robot-supported motor rehabilitation. The system output provides reliable information in most of the training conditions. However, movement artifacts can disturb measurement occasionally. This will have no major effect on training. The patient model structure is designed in such a way to put more emphasis on the reliably collected information about the patient's performance.