Deliverable Report

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9.2 Developed a system to monitor prosthesis activities in daily life situations

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WP9, Task 9.2, Develop an activity monitoring system for prosthesis use in daily life tasks, UMCG

1 Description of the task

Activity monitoring is getting more and more important to assess the contribution of assistive technology, such as prosthetic devices, to the patient's quality of life. The current task develops an activity monitoring system to get insight in the use of the prosthesis in daily life (type of grips and motions, number of actuations) and the body movement used to handle the prosthesis during the day. The monitoring of the prosthesis will be done by reading out the on-board microprocessors of the prosthesis. The posture of the arm during the handling of the prosthesis will be measured with body-worn sensors which are at UMCG's disposal. To develop the system, able-bodied participants and prosthetic users will wear these sensors while performing ADL tasks in the lab. Using these data, algorithms will be developed to extract and classify the relevant behaviours and characteristics of the body angles used. In this work package, the analyses will be done always offline. The activity monitoring system developed here is aimed to measure daily life behaviour in a lab situation. Because behaviour in daily life situations shows a lot of variability in behaviour and ranges of body postures usually not used in standardized lab-tasks. This makes that standard movement registration systems (opto-electrical systems like Optotrak or Vicon) cannot be applied here because markers get out of view of the cameras. Therefore, to measure behaviour in daily life situations we need to rely on alternative measurement devices. Note that the activity monitoring system as developed here should provide a basis to devise a system (e.g., downsizing, optimizing computational algorithms) that is capable to measure quality of behaviour in the end-user's operational environment. As such the knowledge and insight developed here will set the stage for the following step to be taken in the future, which is measuring in real daily life. Note however, that although the developed prosthetic control device of INPUT will be used at home in Task 9.3, the activity monitoring device will only be used in the lab.

2 Description of Deliverable

Develop an activity monitoring system for prosthesis use in daily life tasks.

3 Implementation of Work

The work for this deliverable was divided in three parts: (1) We designed criteria for a system capable of measuring performance of activities in daily living with a prosthesis, (2) To get an idea about the conditions in which the activities should be assessed we aimed to gain better understanding of realistic prosthesis use in daily life and (3) we tested the activity monitoring system in an experiment with able bodied participants and a prosthesis user.

3.1 System Requirements

In the field of upper limb (myoelectric) prostheses, the lack of a single accepted and established upper limb outcome measure is a well-known issue[1] while existing tests for prosthesis functionality or "hand dexterity" show several drawbacks: They are often based on abstract tasks (such as picking up wooden blocks), they often force the user to utilize the prosthesis in a pre-defined (unrealistic) manner and most of the tests are limited to evaluating the time it takes to complete a given task. Moreover, some of those tests consist of extremely simple tasks, which could render the outcome measure insensitive to changes introduced by the control paradigm of the prosthesis.

Being aware of these drawbacks, our aim was to develop an activity monitoring system which would allow us to evaluate realistic prosthesis usage while at the same time having a system and test setup that is sensitive to the potential benefits of the new INPUT control device. This will allow us to eventually evaluate the new control system (D9.3).

Therefore, the system needs to fulfil specific key requirements:

1) The hardware needs to be portable and scalable to optionally to measure movements in individual body segments, which is needed in prosthetic research.
2) The hardware should not restrict the movements , so that a variety of activities of daily living (ADLs) can be captured without restrictions.
3) The system should be able to capture body segment orientation, intersegment orientation, rate of orientation change, which are relevant for coordination dynamics.

To meet these requirements we choose to use wearable inertia-magnetic sensors (Xsens Technologies, Enschede, The Netherlands) to capture upper body kinematics. The sensors have an internal sampling rate of 1000Hz, latency of 30ms, buffer time of 10s and a battery which allows for continuous measurements up to six hours. The sensors are relatively small (47 x 30 x 13mm) and can be easily attached to body segments with velcro straps or tape. They communicate wirelessly with a station which needs to be connected to a laptop, the official operating range is 50 meters.
The system we used for this deliverable report consists of four such sensors. Each sensor consisted of a tri-axial accelerometer, gyroscope and magnetometer with a wireless update rate of 100 Hz. The sensors were attached to the sternum, the upper arm, the lower arm, and the hand (the latter three on the affected side of the prosthesis user). The setup is illustrated in figure 1. For the three sensors on the participant's hand and arm, the sensors' axes were oriented so that the X axis pointed upwards, the Y axis pointed sideward and the Z axis pointed to the front when the participant was standing in a neutral position (standing upright, arms aligned with upper body, hand pointing down, thumb pointing to the front). The sensor at the sternum was oriented so that the X axis pointed upwards, the Y axis pointed forwards and the Z axis pointed sideward when the participant was standing in a neutral position. Zero degrees corresponded to the participant standing in this neutral position.
The sensor 3D orientation angles, i.e. their attitude, were calculated in a separate customized MATLAB script. This choice allows us to avoid well-known problems inherent in attitude calculations of human movement, where Euler angles are preferred for easy interpretation. An open-source,

commonly-used, gradient descent algorithm[6] was used to compute the attitude of each sensor. The angles between sensors were then calculated using quaternion multiplication and successively converted into Euler angles[7]. This procedure allows customization of the algorithm in case of gimbal lock related problems, which is not possible if the sensor orientation output from Xsens is used directly, since access to the internal sensor fusion algorithm is not possible.

3.2 Realistic Prosthesis Usage

As a first step we decided to contact prosthesis users to increase our knowledge about realistic daily life usage of state of the art multifunction myoelectric prostheses and to better understand the shortcomings of conventional control and the potential benefits of a machine learning based myoeletric control.

We decided to conduct face-to-face interviews with the participants because such a qualitative approach is known to gain deeper knowledge of a given subject, compared to quantitative approaches, (e.g. questionnaire studies). We interviewed 16 users and 7 therapists who were experienced with state-of-the-art multi-function myoelectric prostheses. Four of those users and one therapist were moreover experienced with machine learning based control (standard LDA classifier, for details of the system see Amsuess et al. (2015)[2] due to earlier study participation). Contact to those participants was facilitated through collaboration with WP1 (OBHP). The interviews with those participants were carried out in collaboration with OSS in Austria (WP7), the remaining interviews were carried out in the Netherlands. Interview questions concerned activities for which the prosthesis is needed as well as (dis-) satisfaction with conventional control (and pattern recognition control, whenever applicable). All interviews were transcribed and analyzed using an established 5-step framework approach.[3]

3.3.1 Activity Monitoring System

The development of an activity monitoring system builds on earlier work carried out at UMCG. Deijs et al. (2016)[4] also used Xsens to capture upper body kinematics in prosthesis users who performed activities of daily living (ADL) in the lab. This system has been validated in the past for measuring upper body kinematics based on experiments where kinematics where measured with an additional optoelectric system, which is the golden standard in the field[5]. For the study of Deijs this validation was repeated in the labs of the UMCG. In the study of Deijs, compensatory movements could be successfully captured with the system, as the maximum range of motion in the shoulder showed significant differences between able bodied and prosthesis users.

We compared the kinematic data of the able-bodied individual to the data of the individual with an amputation, who actively uses a state of the art myoelectric prosthesis (iLimb quantum, Touch Bionics, UK) on a daily basis.

We evaluated the data on three ‘levels’: (1) Compensation Strategies (2) Coordination between body segments, and (3) Time to complete task.

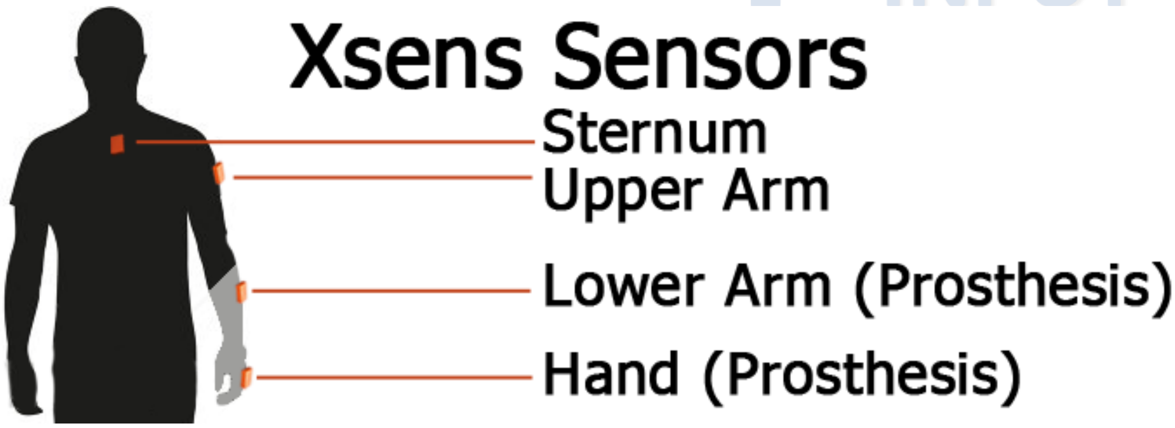

Figure 1: Xsens Sensor Setup

3.3.2 ADL TASKS USED TO VALIDATE THE SYSTEM

In the study of Deijs et al. simplified ADLs were used where prosthesis users made relatively simple movements and only one grip type had to be performed within one task. Hence, these ADLs were insufficient for our purposes since INPUT focuses on a fluent and smooth production of sequential and simultaneous grip types. This implies an adaptation of the tasks to use as well as a check as to whether the system captures these more complex movements in an appropriate way. To validate the activity monitoring system for D9.2 we conducted experiments with a prosthesis user and a reference able bodied individual. The participants carried out an ADL task ("*Lifting a tray & Grasping objects*") which we chose from the interview data and the ADL tasks deliverable of OSS (D7.2). This tasks consists of two phases: (1) Standing upright, the participant first grasps an object (in our case: a wooden cylinder representing a round object such as a bottle) which is positioned at shoulder level on a shelf. He then places this object on a tray which is positioned at hip level on a table in front of him. (2) In the second phase he grasps the tray bimanually and places the tray (with the object standing on it) back to a position on shoulder height. He then returns to the neutral starting position.

4.1 INTERVIEWS

The interview study revealed important aspects of prosthesis use which we integrated in D9.2 and which will be used to finally evaluate the new INPUT control system (D9.3). We found that in contrast to most existing functional upper limb tests, prosthesis users state that they mostly need their prosthetic device in bimanual tasks, which cannot be carried out with one hand only. Moreover, while most users claim to be satisfied with their prosthesis while performing simple tasks such as grasping, fixating or holding objects, more complex tasks reveal the limitation of the current state-of-the-art technology: Even though modern myoelectric prostheses offer several movement/grip modes, users hardly exploit these functions because switching between those functions is perceived as unreliable, non-intuitive, and mentally exhausting. Users therefore hardly benefit from additional movement/grip modes under conventional control. Some users even literally explained to rather use compensation movements in the shoulder, trunk or leg level to complete a task than switching between movement/grip mode. Furthermore, users experienced with pattern recognition stated that this type of control becomes unreliable in real life scenarios, when forces are acting on the socket (e.g. due to lifting objects) or when arm orientation changes.

Given these results and in agreement with OSS and their deliverable D7.2, we formulated requirements for ADL tasks to thoroughly test the new INPUT control:

- Complex movements which require exploiting several degrees of freedom at wrist level and/or change of grip mode
- Change of arm orientation
- Weight applied to the prosthetic device
- Unimanual and bimanual manipulation of objects

4.2 Testing Activity Monitoring System

In our validation experiment for the activity monitoring system we therefore chose the task "*Lifting a tray and grasping objects*" since it fully satisfies the requirements we formulated above. This bimanual task includes a change of arm orientation, it requires (in a natural situation) rotation of the wrist and a re-orientation of the thumb to either grasp the tray or the bottle. Moreover, (moderate) weight is applied to the prosthetic device since the tray has to be moved when loaded with weight.

We could successfully capture relevant kinematic data from the able bodied individual and the prosthesis user. Problems with gimbal lock or integration drift were not evident in our data. Illustrative examples of the data are shown in the next paragraph for the three evaluation 'levels': (1) Compensation Strategies (2) Coordination between body segments, and (3) Time to complete task.

4.2.1 Compensation Strategies

We found a significant difference in the range of motion of the upper body between able bodied and the prosthesis user. Data of the sensor placed at the sternum shows that the prosthesis user moved his trunk almost twice as far in the sagittal plane, compared to the mean of able bodied. The prosthesis user moreover moves his trunks backwards to complete the task while the able body leans forward. The prosthesis user possibly choses this strategy to compensate for a long prosthesis and an inactive wrist.

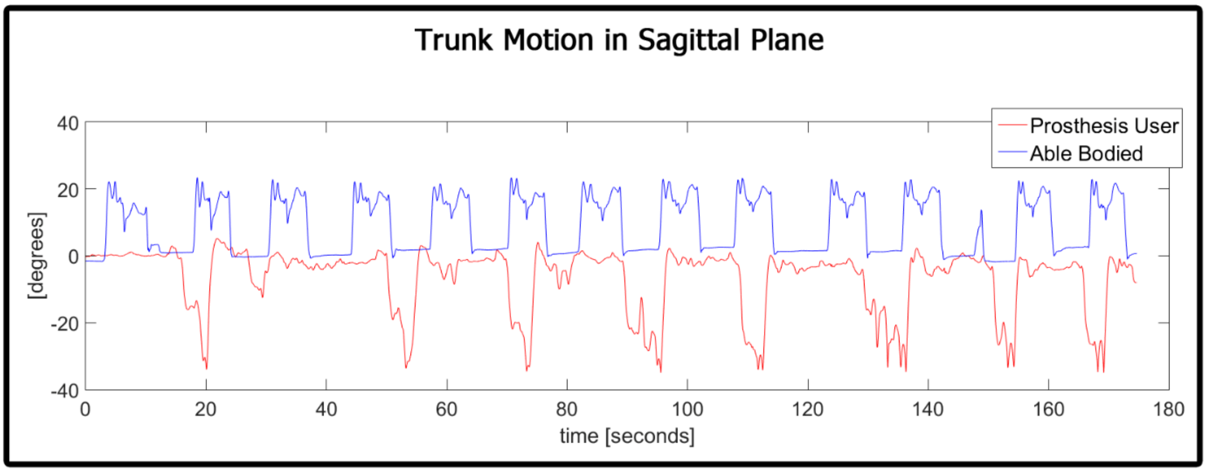

Figure 2: Trunk motion in sagittal plane

4.2.1 Intersegmental Coordination

To depict differences between the able bodied and the prosthesis user on the level of inter-limb coordination during the task, we constructed angle-angle relative motion plots. The result is shown in figure 3, where upper arm elevation is plotted against trunk motion in the sagittal plane. The data of the able bodied individual suggests a stable coupling of the two motions; In the upper panel of figure 3 time series of trunk motion (forward/backward) and upper arm motion (elevation) are shown. It is clearly visible that when the trunk is bent forward, the arm is elevated, and vice versa. This can also be seen in the angle-angle plot in the lower panel, which shows smooth trajectories, suggesting that both motions are ‘activated’ in parallel without major disruptions. Moreover, the participant’s ‘strategy’ can be visualized based on this this angle-angle plot: First, the arm is elevated and the trunk is moved forward to grasp the bottle. The arm is then lowered and the trunk moved backwards to put the bottle on the tray. A similar pattern can be observed in the second phase of the task: The arm is elevated again while the trunk moves forward to place the tray on the higher position. After that, the participant moves back into the starting position.

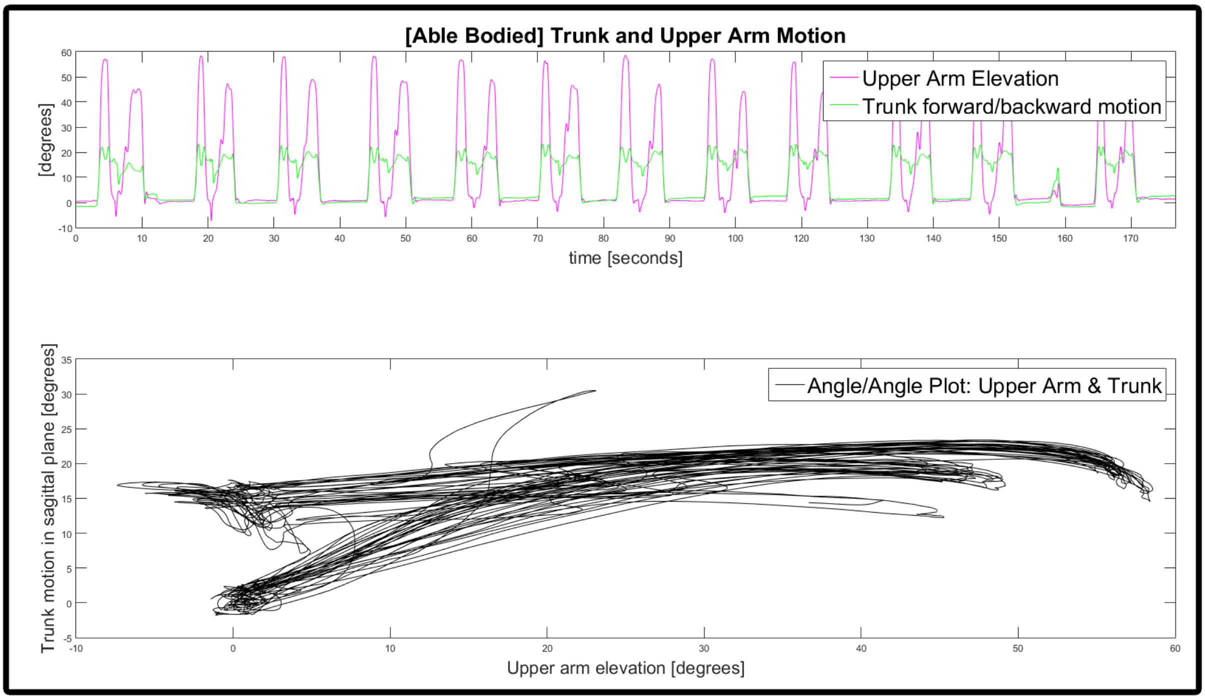

Figure 3: Angle-Angle plot illustrating coordination between upper arm and trunk (a) able bodied

In contrast, the data from the prosthesis user show less smooth trajectories with abrupt changes in the angles and without a clear coupling (figure 4).

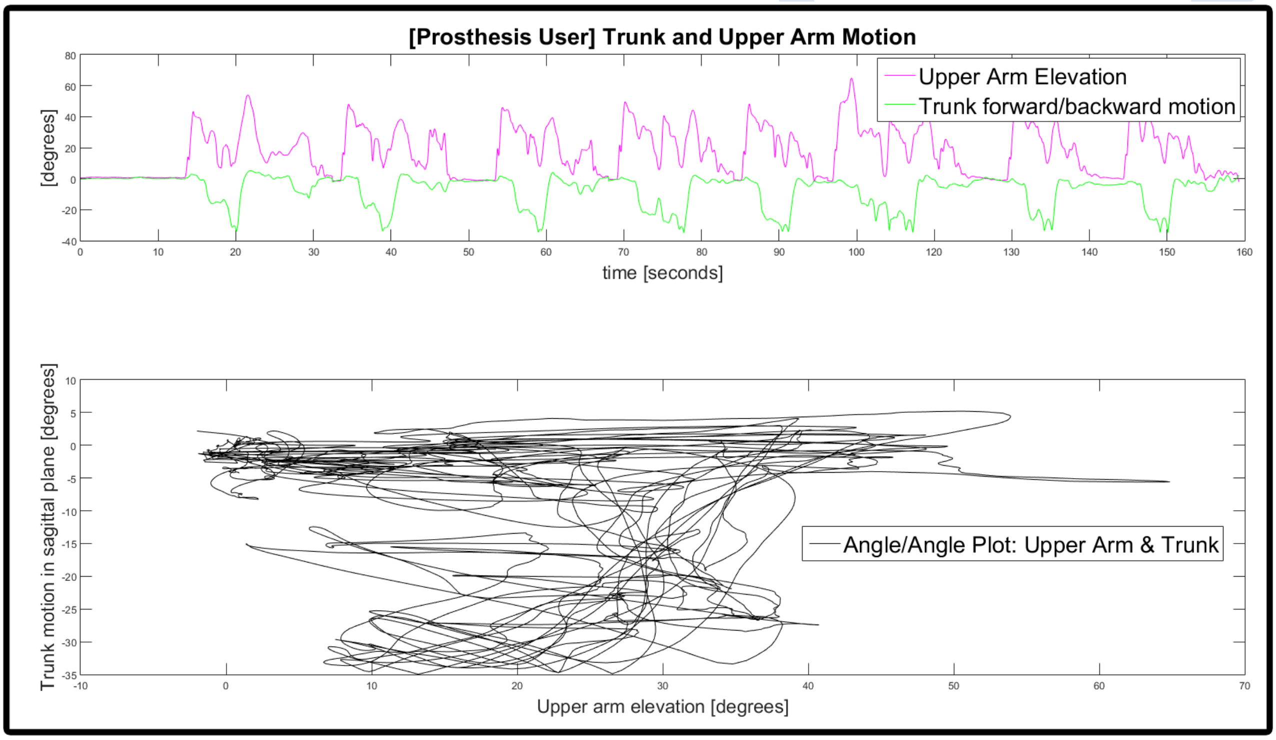

Figure 4: Angle-Angle plot illustrating coordination between upper arm and trunk (b) prosthesis user

Instead of smooth lines which would indicate strongly coupled motion, the angle-angle plot of the prosthesis users suggests that trunk and arm move independent of each other; The nearly horizontal lines in the upper part of the angle-angle plot suggest that motion of the trunk is disconnected from arm elevation. Furthermore, while the “strategy” was readily visible in the plot of the able bodied, data from the prosthesis user suggests that he is not relying on a fixed/stable strategy, but rather constantly adjusting.

4.2.1 Time to complete task

Furthermore, kinematic data from the activity monitoring system allowed for measuring the time that the user needs to complete the tasks. Beginning and completion of one repetition of the given task was determined by a peak detection algorithm and visually inspected for correctness. It can be readily seen in figure 5 that the able bodied completed more repetitions of the task within the time (3 minutes). More precisely, the data shows that the prosthesis user needed nearly twice as long for the completion of one repetition compared to the able bodied participants (13.3 seconds and 7.4 seconds, respectively).

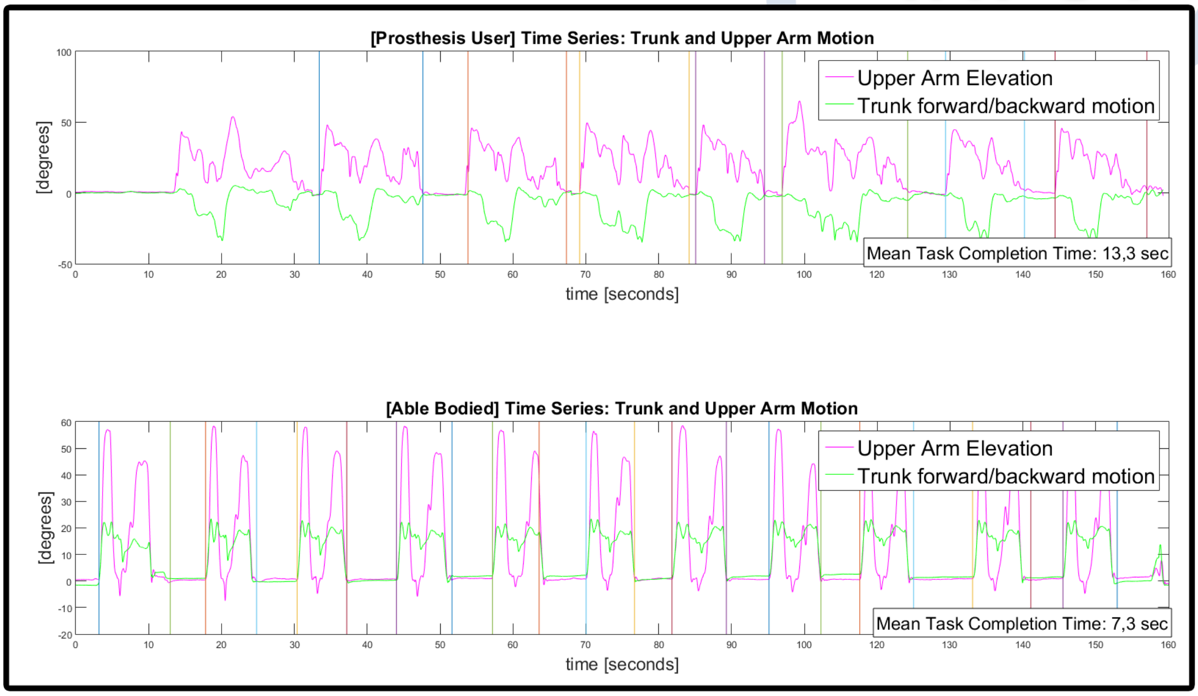

Figure 5: Detection of beginning and completion of task

4 Conclusion

For this deliverable we first investigated realistic prosthesis use in daily life of individuals with an amputation. The results suggested that simple tasks such as used in most functional outcome tests are ill-suited to assess the functionality of the prosthesis, since the prosthetic device would hardly be used for those. Moreover, these tasks might be insensitive to the possible benefits of advanced, machine learning based myocontrol. In close collaboration with OSS we therefore proposed to use a set of more realistic ADLs. We then tested and validated an activity monitoring system that is capable of measuring aspects of motor behaviour when prosthesis users perform such ADL tasks. We found that indeed the system is able to evaluate the motor behaviour of prosthesis users with respect to able bodied data on levels of compensation strategies, intersegment coordination and time. As the system is highly flexible and can be set up in short time, it also allows us to measure prosthesis users in their home environment, which is a major advantage over lab-based camera systems. This means that with this system, we can eventually evaluate the INPUT control system on a kinematic level in a nearly realistic-use setting, when prosthesis users perform ADL tasks in their natural environment, which supports the high TRL level of the project.

5.1 Outlook

Based on this system, we plan to eventually evaluate the new INPUT control system in a longitudinal experiment we are currently preparing. After obtaining approval from our medical ethical committee and receiving the necessary hardware (liner, electrodes, sockets) we will train prosthesis users with the new control system (which we already received from IDSIA) and use the activity monitoring system and the functional ADL tasks to evaluate the advancement of the new control (D9.3) by comparing kinematic data to those of prosthesis users with conventional control. We will specifically test three hypotheses: With machine learning control, users will (1) exploit more grip/movement modes of the prosthesis and therefore avoid compensation movements. (For this purpose, additional data will be gathered from the main drive of the prosthetic hand and synchronized with the Xsens activity monitoring system, as soon as we obtain the final hard- and software components). (2) With more intuitive and reliable control, prosthesis users will show improved inter-limb coordination. (3) With seamless, simultaneous control, ADLs will be completed faster.

5 Subcontracting

All of the work was done within the consortium, mainly by UMCG and in collaboration with OSS and OBHP. No subcontracting occurred.

6 References

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