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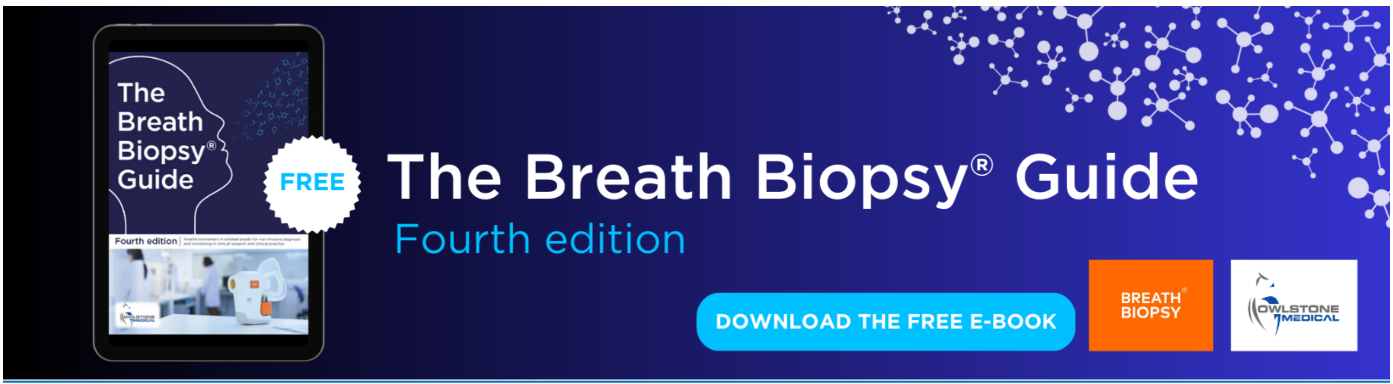

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Sensor fusion and computer vision for context-aware control of a multi degree-of-freedom prosthesis

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Abstract

Objective. Myoelectric activity volitionally generated by the user is often used for controlling hand prostheses in order to replicate the synergistic actions of muscles in healthy humans during grasping. Muscle synergies in healthy humans are based on the integration of visual perception, heuristics and proprioception. Here, we demonstrate how sensor fusion that combines artificial vision and proprioceptive information with the high-level processing characteristics of biological systems can be effectively used in transradial prosthesis control. *Approach.* We developed a novel context- and user-aware prosthesis (CASP) controller integrating computer vision and inertial sensing with myoelectric activity in order to achieve semi-autonomous and reactive control of a prosthetic hand. The presented method semi-automatically provides simultaneous and proportional control of multiple degrees-of-freedom (DOFs), thus decreasing overall physical effort while retaining full user control. The system was compared against the major commercial state-of-the art myoelectric control system in ten able-bodied and one amputee subject. All subjects used transradial prosthesis with an active wrist to grasp objects typically associated with activities of daily living. *Main results.* The CASP significantly outperformed the myoelectric interface when controlling all of the prosthesis DOF. However, when tested with less complex prosthetic system (smaller number of DOF), the CASP was slower but resulted with reaching motions that contained less compensatory movements. Another important finding is that the CASP system required minimal user adaptation and training. *Significance.* The CASP constitutes a substantial improvement for the control of multi-DOF prostheses. The application of the CASP will have a significant impact when translated to real-life scenarious, particularly with respect to improving the usability and acceptance of highly complex systems (e.g., full prosthetic arms) by amputees.

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Keywords: sensor fusion, context awareness, user awareness, reactive control, semi-autonomous, upper limb prosthesis, control of grasping

1. Introduction

Human hands are highly dexterous manipulators that integrate a variety of somatosensory and motor systems with the complex musculoskeletal structure in order to generate reaching and grasping movements [1]. During this motor task, the hand is transported to an appropriate location in the vicinity of the object and then oriented and preshaped conveniently to grasp the object by forming an optimal opposition space for a stable grip [1, 2]. Vision provides critical input for the planning and execution of hand transport and prehension, since it allows the nervous system to estimate the extrinsic properties of the target object. The perception of the object's location, size and shape, and orientation with respect to the environment enables the brain to plan the movement by selecting an appropriate reach and grasp strategy. Vision provides feedback during the execution of the movement [3–5] to allow for corrections, especially in the late phase when the object is approached. This closed-loop operates continuously, providing the flexibility and adaptability that are characteristic of human grasping, where movement planning and execution can be modified at any moment in time to better adapt to the current context. One characteristic example is the change in orientation and preshape during the target approach phase in response to the decision to grasp the object from a different side.

Since we are so heavily dependent on our hands, their loss due to amputation is a traumatic experience with devastating psychophysical effects, dramatically shaping the way affected individuals interact with their environment and others. It has been estimated that in the US alone there are 541 000 people living with the loss of an upper limb [6]. The profound negative impact that amputation has on a person's life can (to some extent) be alleviated through the adoption of a hand prosthesis, acting as a partial morphological and functional substitute for the lost limb.

Prosthetic systems have clearly improved over time, with the first devices being simple cosmetic replacements, later developing into passive body-powered mechanical systems before finally being transformed into actuated, battery-powered devices controlled via myoelectric signals [7] approximately 60 years ago. Nowadays, there is a great variety of active systems offering very different functionality [8]: from simple single-degrees-of-freedom (DOF) grippers (e.g., Sensor Hand Speed developed by Otto Bock [9]) over multi-grasp systems with an active wrist (e.g., Michelangelo Hand by Otto Bock [10]) to highly dexterous multi-DOF devices closely replicating the structure (number of DOFs) and capabilities (grasping patterns) of the human limbs (e.g., i-Limb developed by Touch Bionics, DARPA's prosthetic arm [11, 12]).

Man–machine interfaces for prosthesis control have not advanced as rapidly as robotic technology [13]. Therefore, most commercially available devices still implement classic sequential and proportional control, which is the first concept proposed for myocontrol [13]. This is partially due to the fact that most transradial prostheses have a small number of DOFs. In these SOA systems the user has to switch between the DOFs, adjusting them one by one, which is a tedious and non-intuitive process [14]. In research, pattern recognition has been extensively tested as a method to improve prosthesis control by allowing the user to select from a predefined set of prosthesis commands through generating an appropriate pattern of muscle activity or other biosignals (e.g., EEG [15, 16], voice [17], foot pressure [18]). Despite the promising laboratory results, pattern recognition has so far had only limited translation into clinical applications, mainly due to a lack of robustness. There is only one recently presented, commercially available system advocating this approach (COAPT [19]). Contrary to pattern recognition, in which the user still needs to switch between a limited set of classes, biologically-inspired invasive [20, 21] and non-invasive [22–24] methods for direct simultaneous and proportional control of multiple DOFs are being developed with increasing effort.

The current approaches for myocontrol share the same overall structure. As explained above, human grasping proceeds through a sequence of phases, from planning to execution, and involves the integration of sensory information from different sources (e.g., vision and proprioception). In the classic control scheme, the user is responsible for most of the steps, including context assessment, grasp planning, and the generation of control biosignals, while the artificial controller is at the end of the chain, i.e., it acquires the signals and translates them into prosthesis actions. Our research, presented in this paper, advocates an alternative approach that can be classified as symbiotic. Namely, in natural settings, decisions are made on the basis of multisensory information. In the context of movement control the sensors used are vision, muscle spindles, Golgi tendon organs, joint receptors, skin receptors, and the overall neural network at several levels of the central nervous system. This is to say that, apart from capturing myoelectric signals, there are many other sensors that can be used to assist in the control of grasping, as demonstrated in robotics research [25, 26]. If equipped with such sensors, the prosthesis controller can emulate the high-level processes traditionally considered the responsibility of the user. By fusing information from different sources, the controller is also able to detect and analyze the current context, plan the grasping action, and simultaneously and proportionally control multiple DOFs available in the prosthesis.

The concept of semi-autonomous control of upper limb prostheses was developed long ago [27–29]. In the prosthesis presented in [28], one of the two available grasp types (pinch or lateral) could be selected automatically depending on the point of first contact with the object as detected by touch sensors. Similarly, in [29] a conceptual solution for triggering the automatic wrist pronation/supination by monitoring the forearm inclination was presented. The idea was to detect the intent of the user to rotate the hand by detecting the start of the compensatory movement (e.g., forearm rotation, shoulder abduction/adduction) and then complete the motion automatically, implementing essentially a pronation/supination amplifier [30]. In [31] a full arm prosthesis was envisioned to be operated as a state machine triggering different autonomous functions, such as maintaining constant orientation of the object during transport using inertial sensing (e.g., to prevent spilling of liquid from a glass). Some aspects of the semi-autonomous control concept have also been demonstrated in several subsequent developments [32–35]. In these systems, the user delivered high-level commands (e.g., grasp, squeeze, hold), which the prosthesis would implement automatically based on input provided by the embedded prosthesis sensors (e.g., position, touch). Finally, a simplified form of semi-autonomous control has been translated into a commercially available system with automatic slip prevention [9].

More recently, the control methods were presented based on the fusion of signals from multiple sources. For example, gaze direction was assessed using electrooculography or eye tracking and combined with a brain–computer interface (BCI) or computer vision in order to guide an orthosis [36] or a robotic exoskeleton [37, 38] towards the target. Electrooculography was also employed [39] to communicate the object size to the prosthesis controller as the user scanned the object perimeter using his/her gaze. The controller would then automatically select the grasp type and size suitable for grasping the object. Sensor fusion using electrophysiological signals as well as pressure sensors and inertial units was applied to improve intention detection in the classic pattern-recognition- and regression-based manual control systems [40]. One recently presented system [41] combined a BCI with gaze tracking and computer vision in order to trigger and automatically guide the reach-grasp-drop motion of the modular upper limb prosthesis which is mounted next to the user. Models of shared control are being addressed extensively in robotics literature [42] from a somewhat different perspective with the aim to improve the collaboration between humans and external robotics systems, but the concepts are relevant also in the context of robotic rehabilitation.

These developments imply that the semi-autonomous sensor-fusion approach to the control of assistive systems will likely continue to gain in momentum, especially as these systems are becoming increasingly complex (dexterous hands, full-arm prostheses). This is also clearly emphasized in the relevant strategic documents, such as the Multi-Annual Roadmap for Robotics in Europe [43].

In this study, we demonstrate how the sensor-fusion approach can be exploited to improve the control of a multifunction prosthetic system. More specifically, we present a novel controller equipped with artificial vision and proprioception to perceive the state of the user, the prosthesis and the environment. Based on this information, the controller makes autonomous decisions and automatically configures the prosthesis parameters, simultaneously and proportionally adjusting multiple DOFs according to the task demands and reactively to the user's intentions. Therefore, the method presented here exploits a unique and comprehensive combination of sensing units, comprising myoelectric recording, computer vision, inertial measurements and embedded prosthesis sensors (position and force), to develop a controller endowing a multi-DOF prosthesis with the abilities characteristic for advanced robotic systems. The method is based on sensor fusion which allows for the continuous and simultaneous perception of the user (proprioception), the environment (exteroception) and their interaction, leading to online simultaneous and proportional control of multiple DOFs through context-dependent behavior (e.g., reactive response). To the best of our knowledge, this is the first prosthetic system with such a level of autonomy and component integration. Importantly, this approach should not be considered as a substitute for the existing prosthesis control methods. The aim is to integrate the new ideas and solutions with those methods and enhance them with the new functionality. In the current study, we specifically, demonstrated and evaluated how user and context awareness can enrich the classic myocontrol system, leading to autonomous operation using sensor fusion.

2. Material and methods

2.1. Sensor fusion for context-aware semi-autonomous prosthesis control

The novel concept is depicted in figure 1. The context-aware sensor-fusion controller (CASP) integrates automatic (ACU, figure 1(1)) and myoelectric (MCU, figure 1(2)) control units. The user employs the MCU for manual control (e.g., a classic sequential multi-DOF scheme [44]) and for triggering of the automatic operation. The ACU comprises the artificial exteroception (AEM, figure 1(3)), artificial proprioception (APM, figure 1(4)), and sensor-fusion (SFM, figure 1(5)) modules, providing for the automatic simultaneous and proportional control of multiple DOFs (e.g., a multi-grasp prosthesis with an active wrist).

The AEM (figure 1(3)) uses computer vision to acquire information about the 3D structure of the scene. It analyzes the scene, segments out the object that is closest to the center of the camera's field-of-view, and estimates its shape, size, and orientation. To accommodate arbitrary objects, the AEM does not rely on the predefined database, but analyzes the extracted cloud of points and approximates the target object using common geometrical models.

The APM (figure 1(4)) receives data from the position sensors embedded into the prosthesis providing the size of the hand aperture and wrist rotation relative to the socket. In addition, an inertial unit is used to track the absolute orientation of the prosthesis with respect to an external coordinate system. Therefore, the APM determines the current state of the hand on the basis of commands sent to the prosthesis (hand to socket angles and aperture) as well as volitional user movements (hand to external reference).

The SFM (figure 1(5)) integrates the outputs of the sensing modules (i.e., the hand and object state) and

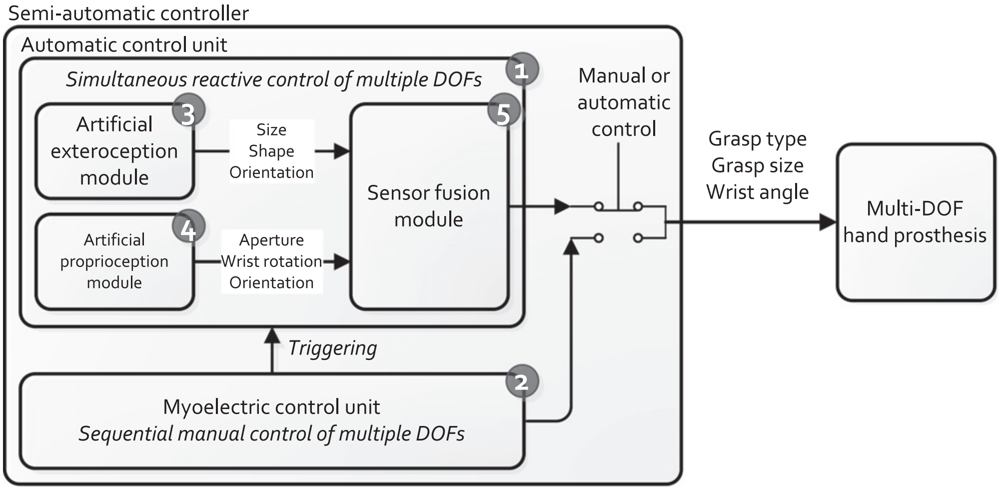

Figure 1. Conceptual scheme of the novel control approach. The semi-automatic controller integrates the myoelectric interface and automatic control unit. The latter provides simultaneous, proportional and reactive control of multiple DOFs (grasp type, size, and wrist rotation) based on the fusion of computer vision (exteroception) and position/orientation measurements (proprioception). The user employs the myoelectric interface for manual control and triggering of the automatic operation.

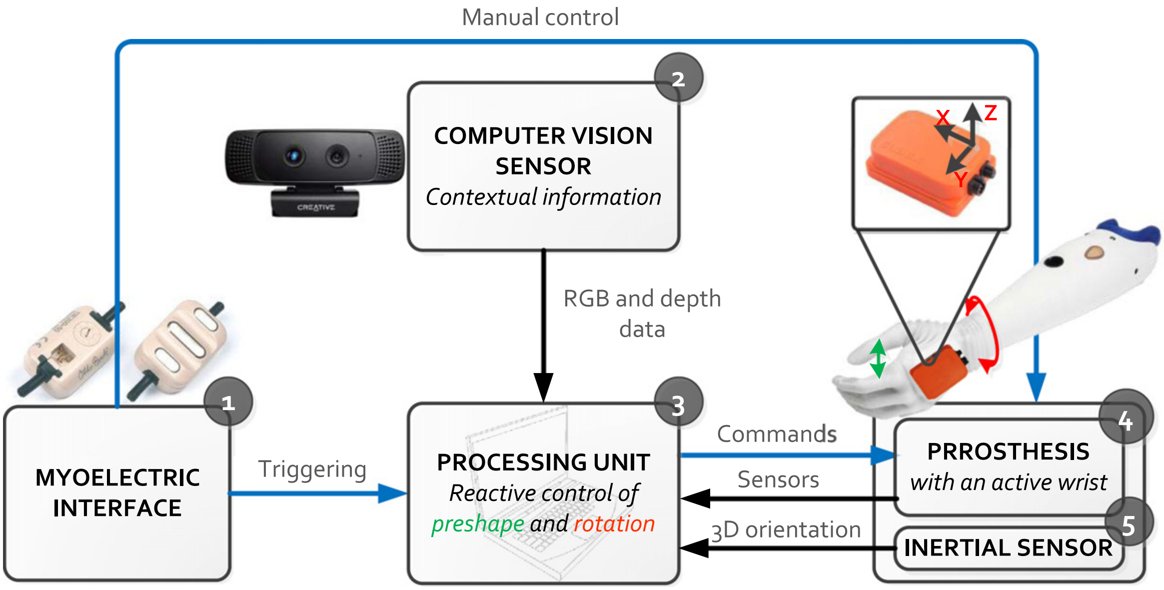

Figure 2. CASP system prototype. When the user generates the trigger command, the processing unit fuses the data acquired from the sensors (i.e., prosthesis aperture, grasp type, orientation, and depth image) in order to perform automatic and real-time updates of the prosthesis parameters. Based on the current state of the prosthesis and the estimated properties of the target object (shape, size, orientation), the prosthesis posture (i.e., grasp type, size, and wrist angle) is configured so that the hand is prepared for grasping the target object. Additionally, the user also has full manual control of the prosthesis through the myoelectric interface, thus being able to correct or fine-tune the autonomous decisions (semi-automatic control).

chooses the grasping strategy. Specifically, the SFM selects the optimal preshape (grasp type and size) and orientation (wrist rotation) for the prosthesis in order to ensure that the prosthesis is suitably configured for grasping the target object.

The semi-automatic controller is continuously active, acquiring and processing the sensor data, and is thus able to reconfigure the prosthesis when necessary (reactive operation). For example, the controller selects a different grasp type and/or readjusts the aperture size if the user decides to change the side from which he/she intends to grasp the object. Importantly, in this control scheme, the system and the user share the responsibility (semi-automatic control). The system automatically controls (e.g., preshapes and rotates) the prosthesis in order to accommodate different objects and situations, as described above, while the user triggers, supervises, corrects and fine-tunes the system decisions through manual control via the MCU. He/she can intervene at any time to manually readjust any of the prosthesis parameters.

2.2. System prototype

The CASP prototype comprises the following components (figure 2): (1) two 13E200 dry EMG electrodes with integrated amplifiers (Otto Bock Healthcare GmbH, Vienna, AT) (2) Creative Senz3D camera (Creative Technology Ltd, SG) (3) a processing unit (i.e., standard PC with 16GB RAM and four-core i7@2.9 GHz CPU), (4) Michelangelo left-hand prosthesis with a wrist rotator (Otto Bock Healthcare GmbH, Vienna, AT) and (5) an MTx inertial measurement unit (IMU) (Xsens Technologies B.V., Enschede, NL).

The Michelangelo Hand provides simultaneous opening and closing of all fingers with two grasp types (palmar and lateral), as well as and wrist pronation and supination (i.e., three DOFs in total) [10]. The hand was instrumented with three position encoders (thumb, fingers, and wrist) and a single force transducer positioned at the base of the thumb, measuring the hand aperture, grasping force, and hand orientation relative to the socket. The prosthesis was connected to the host PC via a Bluetooth (BT) interface implementing a bidirectional communication protocol running at 100 Hz. This communication channel was used to receive the sensor data from the prosthesis and to send the control commands to the prosthesis.

The IMU was externally attached to the prosthesis (figure 2). The IMU measured the absolute orientation of the prosthetic hand with respect to the laboratory coordinate system, i.e., yaw, roll and pitch angles. The IMU was connected to the battery-powered acquisition and wireless transmission unit (XBus, Xsens Technologies B.V., Enschede, NL) sending data to the host PC at a sampling rate of 20 Hz.

A Creative Senz3D camera simultaneously acquired color and depth images (RGB-D) [45] and was mounted on the custom-designed support glasses worn by the subject, thus ensuring that the camera was always directed towards the same scene at which the user was currently looking. The acquired image streams were transmitted to the host PC via a USB port at a 30 Hz refresh rate and a resolution of 640×480 pixels for RGB and 320×240 pixels for depth images, respectively.

The myoelectric interface comprised two active electrodes placed on the forearm over the wrist and hand flexor and extensor muscles. The electrodes with adjustable gain acquired the EMG data at 1 kHz and directly provided the smoothed signals (linear envelopes), as in a commercial system developed by Otto Bock. The linear envelopes were sampled at 100 Hz and transferred to the host PC via the Bluetooth connection.

The data from the prosthesis, inertial unit, and camera were received by the host PC, where data processing, sensor fusion, and control algorithms were performed. The host PC also provided a user interface for high-level control (e.g., starting and stopping) and system monitoring and setup. The control algorithm was implemented using object-oriented programming in MATLAB 2013a (MathWorks, Natick, US-MA).

The control flow in the prototype was implemented as a finite-state machine in which the state-transitions were triggered manually by the user via the myoelectrical control interface or automatically by external events (i.e., object contact). The operation of the system is depicted in figure 3. The system is ready and waits for the user input (figure 3(1)). The prosthesis is in the neutral position/preshape, i.e., relative rotation (hand to socket) and absolute rotation (hand to laboratory coordinate system) are close to zero and aperture is 100%. The user directs his head towards the target object resting on the table surface in front of him and indicates his intention to grasp the object by generating a short burst of extensor muscle activity. The system responds by automatically rotating and preshaping the hand conveniently for grasping the object (figure 3(2)). In this particular example, the hand rotated counterclockwise by 90°, preparing to grasp the object from the left side, and simultaneously preshaped into the palmar grasp with an aperture of 30%, thereby adapting to the size of the object. Once the automatic hand preshaping is accomplished, the user assumes full manual control. He/she can employ the myoelectric interface to fine-tune and/or correct the automatic decisions or to close the hand and grip the object, via classic sequential and proportional control. Co-contractions are used to switch between the DOFs, while the currently active DOF is operated proportionally, i.e., the velocity of closing/opening, wrist pronation/supination, and grasping force are proportional to the muscle activation level. In addition, the system continues to track the absolute prosthesis orientation in order to be able to assist grasping by reacting to the user's movements. In the current example (figure 3(3)), instead of approaching the object from the side as initially expected, the user decided to grasp the object from the top. Consequently, the user started pronating the prosthesis (compensatory action) and this was detected by the system, which reacted by readjusting the prosthesis, i.e., the hand was automatically rotated so that the palm was in a horizontal (absolute orientation 0°); the system thus completed the pronating movement on behalf of the user. Simultaneously, the grasp type was changed to lateral and aperture was set to 20%. Due to this reactive action, there is a theoretical possibility for the user and a prosthesis to enter into a race condition, i.e., the situation in which the CASP and the user would continuously compete to correct each other. This has been prevented through a fundamental design assumption of the CASP system, which is that the user always has priority over automatic control. Therefore, the system stops the automatic adjustment of the prosthesis' posture immediately upon detecting that the user employs the myoelectric interface to manually steer the prosthesis. To grip the object, the user manually closed the prosthesis (figure 3(4)) by activating the flexor muscles (proportional myoelectric control). When the object is contacted, the automatic control is switched off. The operation loop restarts immediately upon the object release.

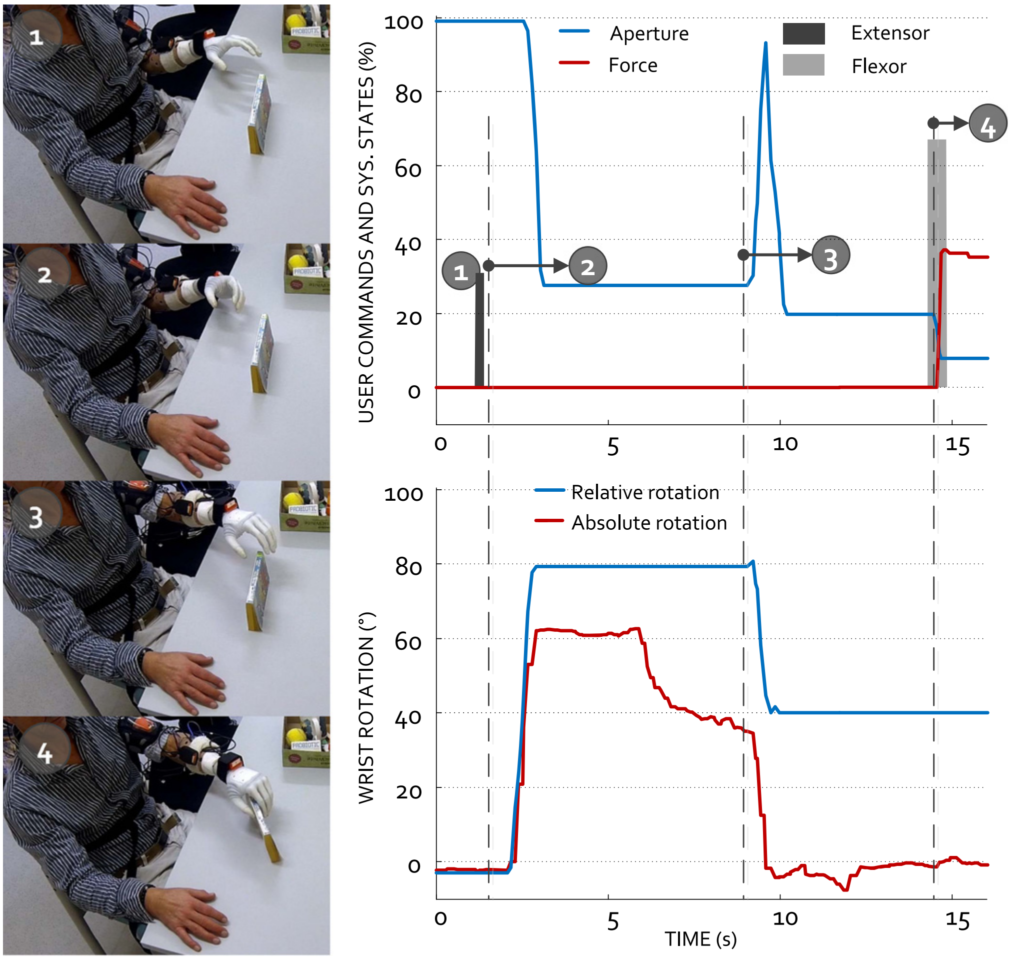

Figure 3. An example of the system workflow. The plot depicts the system states (i.e., absolute/relative rotation, aperture and force of the prosthetic hand) and user commands (i.e., activity of the flexor and extensor muscles). Each number on the snapshot and plot indicates an event triggering a state transition. For the explanation, see the text.

2.3. Experimental protocol and setup

The overall goal of the experiment was to test the performance of the proposed CASP system with respect to the SOA manual myoelectric control (MAN).

Subjects. Experimental tests were performed in ten able-bodied subjects (26 ± 3 yrs, six with prior experience in myoelectric prosthesis control) and one amputee (55 years, 35 years since amputation, active 1-DOF prosthesis user). The local ethics committee approved the study and the subjects signed an informed consent form before starting the experiment.

Procedure. The subjects were seated comfortably in an adjustable chair in front of a table and the system was mounted (figure 4). For able-bodied subjects, the hand was attached to a custom-made ergonomic splint and strapped firmly using Velcro straps to the subjects' left forearm, so that it was positioned directly beneath and perpendicular to the subjects' hand. Due to the space constraints, two EMG electrodes were placed on the contra-lateral arm (figure 4(1)), over the finger and wrist flexor and extensor muscles, which is a common placement for the myocontrol of transradial prostheses. The position was determined by palpating the contracted muscles. For the amputee subject, the prosthesis was mounted using a custom-made socket with integrated electrode placement. Therefore, the myoelectric interface was positioned on the ipsilateral side, as in a real-life application (figure 4(2)). The subjects wore the glasses with the attached depth sensor and the XSens acquisition unit was strapped around the waist and placed on the back.

In addition to the components comprising the CASP system, two extra inertial sensors were placed on the left forearm and upper arm to measure the orientation of the subject's arm. These data were used only for offline analysis to evaluate the employed reach and grasp strategies. In order to simplify the data interpretation the subject's trunk was immobilized using two set of straps to fix the trunk to the chair thus providing a stationary reference for the measurements of arm orientation using inertial sensors. The sensors were positioned so that the local coordinate systems were aligned, with the *X*- and *Y*-axis pointing in the proximal-distal and median-lateral directions, respectively. The present experimental setup imposes specific constraints (fixed trunk, seating position, prosthetic splint) that likely influence the resulting limb kinematics. Nevertheless, the aim of the present

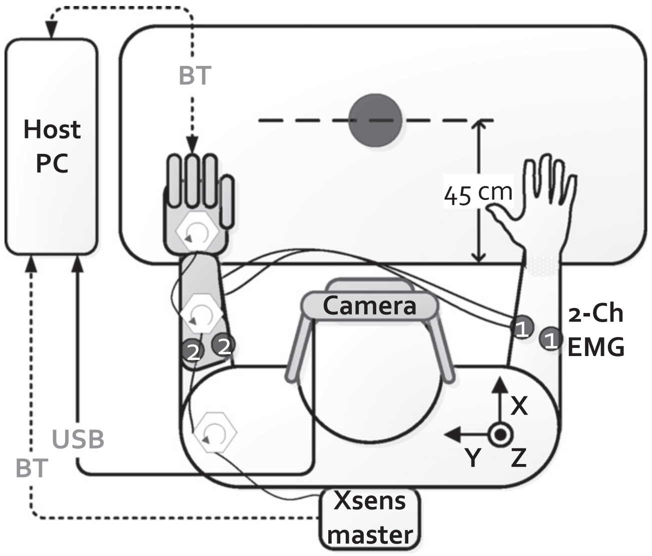

Figure 4. Experimental setup. The user was comfortably seated in front of a table where different objects were presented to him, at the indicated distance. Note that only one inertial sensor, mounted on the prosthetic hand, was used by the sensor-fusion system (other two were used for offline data analysis). Due to the specific prosthesis mounting and space constraints, placement of the EMG electrodes differed for able-bodied (1) and amputee (2) subjects.

study was to capture the kinematic trajectories characteristic for the employed control systems in the given conditions as an additional measure for a more thorough comparison between different solutions.

The outcome of the study is the comparison of the performance between CASP and three, progressively more complex, manual control scenarios MANn ($n = 1$, 2, and 3 denotes the number of manually controllable DOFs):

(1) MAN1: proportional control of the prosthesis velocity of closing and opening and grasping force, hand in palmar grasp, wrist orientation fixed in the neutral position.
(2) MAN2: as in MAN1 plus the subjects selected between the palmar or lateral grasps using co-contractions.
(3) MAN3: as in MAN2 plus the subjects proportionally controlled the velocity of wrist rotation (pronation and supination), co-contractions were used to switch between the DOFs in the following order: palmar grasp, lateral grasp, and wrist rotation.
(4) CASP: prosthesis operated as described in section 2.2.

The test comprised training and evaluation session conducted in two consecutive days. In both sessions, the subjects followed the same protocol, i.e., they grasped, lifted, transported and released a set of common daily objects (see table 1) using the four control conditions. The initial (resting) position for the hand and the initial position for the target object were marked on the table surface. A box container to which the objects had to be transported and released after being grasped was also placed on the table, as depicted in figure 4. The four conditions were performed in a random order and each comprised 17 grasping trials.

The myocontrol parameters were adjusted at the beginning of the sessions. The maximum command to the prosthesis was generated with the muscle activity at approximately 70% of the maximum voluntary contraction. The attached inertial sensors were calibrated while the subject was holding his arm fully extended, in front of the body and parallel to the table surface.

The aim of the training session was to familiarize the subject with the setup, protocol and tasks to be performed during the experiment. The subjects were explained how to operate the prosthesis using the commercial SOA myocontrol interface and then practiced switching between the active DOFs by generating co-contractions as well as the proportional control of the selected DOF by modulating the level of muscle activity. The subjects were also trained in using CASP system as a whole, including triggering, reactive operation, and the use of manual control to fine-tune/override the system decisions. For each control scenario, the subjects had a short introduction 5–10 min, after which they continued the training by performing the grasping trials.

In each grasping trial, the subjects were presented with a single object and instructed to adjust the prosthesis so that the hand was configured appropriately for grasping the object, as specified in table 1. There was no time limit for performing the trial. The subjects were instructed to perform the task correctly and as fast as possible. In MAN conditions, this was accomplished by manually operating the available DOFs. In MAN1 and 2, the wrist was inactive and the subjects had to use the proximal arm joints to orient the hand properly for grasping. The grasp type in table 1 was ignored in MAN1 (i.e., all objects grasped using palmar grasp). With CASP, the subjects triggered the system, assessed the outcome of the automatic decisions and corrected the system using manual control when necessary (wrong decision). After the hand was preshaped, the subjects used manual control to close it, lift, transport the object, release it into the container and finally return the prosthesis back to the initial position. The experimenter observed the task execution and the trial was repeated if the gross error has been made and hand has not assumed the correct posture (i.e., the subject or the system employed wrong grasp type or orientation). Concerning the orientation, the absolute precision was not of interest, similar to the real life application where there is a reasonable margin of error under which the task can be successfully accomplished. For example, the user can fine-tune the alignment between the hand and the object using other degrees of freedom (e.g., shoulder joint). Therefore, we deemed that asking the user to control precisely the orientation would be highly artificial (and likely worse in the manual control scenario, where it is done using a naked eye). Instead, the subjects were instructed in general terms to adjust the orientation to complement that of the object, and only if it was completely wrong (e.g., hand vertical and the object horizontal), the experimenter decided to repeat the task. Importantly, the prosthesis posture (grasp type, orientation) was not altered in-between the trials, i.e., the initial posture in the current trial was the posture used to grasp the object in the previous trial. This has been done in order to simulate the real-life usage of the prosthesis, as when

Table 1. Overview of the test trials, objects used and grasping instructions given.

Trial tag	Object description and dimension (cm)	Object placement on the table surface	Grasp type	Hand orientation in respect to table surface
P1_0_P	Tennis ball (6.5)	Horizontal	Palmar	Parallel
P2_90_P	Mug (9 × 8)	Vertical	Palmar	90° supination
P3_0_P	Juice-bottle (169 × 7.5)	Horizontal	Palmar	Parallel
P3_45_P	—	Leaning 45°	Palmar	45° supination
P3_90_P	—	Vertical	Palmar	90° supination
P4_0_P	Tea-box (139 × 7.59 × 6.5)	Horizontal	Palmar	Parallel
P4_45_P	—	Leaning 45°	Palmar	45° supination
P4_90_P	—	Vertical	Palmar	90° supination
P5_90_P	Espresso cup (59 × 5)	Vertical	Palmar	90° supination
L1_0_L	Thin pen (149 × 1.5)	Vertical	Lateral	Parallel
L1_45_L	—	Leaning 45°	Lateral	45° pronation
L2_45_L	Fork (189 × 1)	Leaning 45°	Lateral	45° pronation
L3_0_L	Thick pen (129 × 2.5)	Vertical	Lateral	Parallel
B1_0_L	Medicine-box (9 × 7 × 1.5)	Vertical	Lateral	Parallel
B1_90_P	—	Vertical	Palmar	90° supination
B2_0_L	Book (15 × 9 × 2)	Vertical	Lateral	Parallel
B2_90_P	—	Vertical	Palmar	90° supination

the user grasps objects in succession readjusting the hand from the configuration attained in the last grasp to the one convenient for the next target object. Therefore, even though the task was divided in trials for convenience (e.g., data logging), it could be regarded as an uninterrupted sequence of actions in which the task of the user was to pick up and transport a set of objects. The only exception was if the trial had to be repeated, in which case the posture was reset to the one the hand assumed at the beginning of the trial.

2.4. Data analysis

The primary outcome measure was the time to grasp (TTG) an object using a specific control scheme, assessing the efficacy in operating the prosthesis employing that particular control. The TTG was also used to compare the performance between the training and evaluation sessions for the same control scheme to assess if there was an improvement due to the training. The TTG was measured from the start of the trial until the hand contacted the object (force > threshold).

Secondary outcome measures were the shoulder joint angles computed from the inertial data, recorded during the evaluation session only, assessing the arm configuration just before the hand grasped the object (0.5 s before contact). They were calculated as the Euler angles of the upper arm with respect to the immobilized trunk.

To assess the system responsiveness, the reaction time (RT) of the CASP to user trigger and reactive response was monitored during the experiment. The former was measured as the time from the detection of the user's trigger until the commands have been sent to the hand and it therefore includes sensor-fusion processing. The RT for the reactive responses comprises the time between the detection of the movement (compensatory rotation) and command transmission. It is important to note that this time is actually already integrated in the TTG performance metric. The trial failure rate was also determined. This index indicated the number of repeated trials, when either the user (MAN1-3) or the system (CASP) made a gross error in adjusting the prosthesis' posture. The gross error referred to an incorrect grasp type or completely wrong orientation (as explained above).

Friedman test was used to assess the statistically significant difference within the group of conditions in the evaluation session, since the data did not pass the test of normality (Liliefor test). For the pairwise comparison, Tukey's honestly significant difference criterion was applied. Finally, to compare the same condition between the training and testing, a Wilcoxon signed-rank test was employed. A p-value of 0.05 was selected as the threshold for the statistical significance.

3. Results

In total, 1496 trials (11 subjects × 2 days × 4 series × 17 trials) were performed. They were allocated evenly between the four control conditions. The results are reported as mean ± standard deviation and are presented separately for able-bodied and the amputee subject.

Figure 5 shows the average TTG for each of the four test conditions during training and evaluation. During the evaluation session, the TTG in the manual control scenarios (MAN1-3) increased consistently with the number of controllable DOFs, i.e., it was 3.7 ± 1 s for MAN1, 4.3 ± 1.7 s for MAN2, and then it increased substantially to 11.2 ± 4.1 s in MAN3. The differences were statistically significant between all MAN conditions. The TTG with CASP was 5.9 ± 1.9 s, which was slower than in MAN1 and MAN2 but substantially faster than in MAN3. Using CASP, the subjects could grasp an object in approximately twice less time compared to MAN3. There was virtually no improvement between the training and evaluation sessions with CASP,

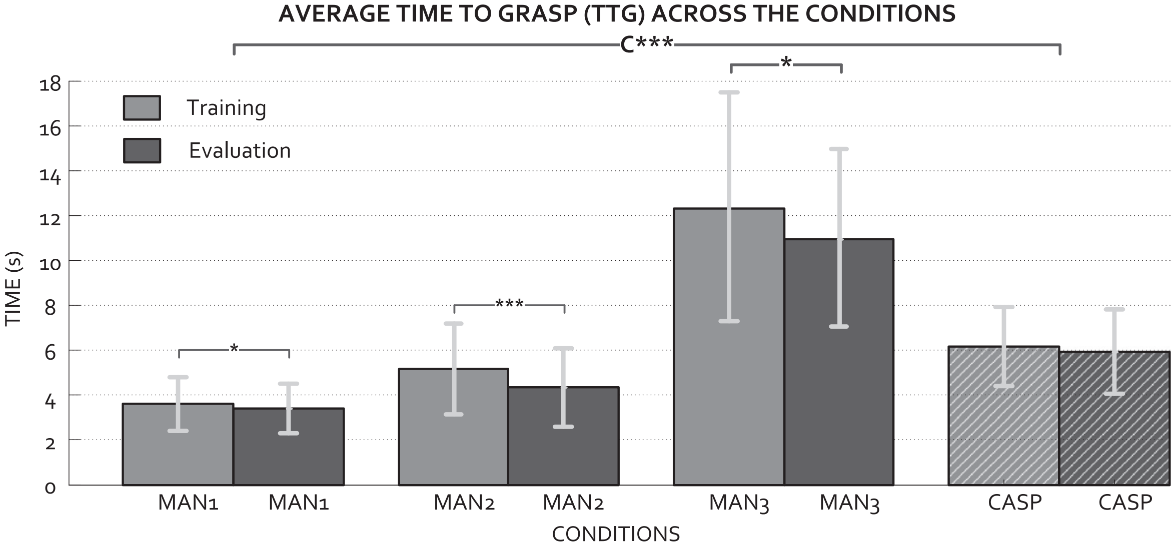

Figure 5. Summary results (mean ± standard deviation) for average time to grasp (TTG) an object. The statistically significant differences are denoted by a star (*, $p < 0.05$; **, $p < 0.01$; ***, $p < 0.001$) while the symbol 'C' indicates that the difference exists across all conditions that were performed within the same session. Notations: MANn—manual control of n DOFs; CASP—context-aware sensor-fusion prosthesis (3 DOFs).

contrary to MAN conditions, which all improved with training.

The RT of the CASP system for user trigger and reactive response were less than 0.75 and 0.1 s, respectively. The cumulative trial failure rate, overall all subjects and trials, was consistently small across all control scenarios: four in MAN2, five in MAN3, and seven in CASP condition, which accounts for less than 1% of the total number of performed trials.

Similar trends were also observed in the amputee subject where the average TTG was 2.5 ± 1 s, 4.7 ± 1.8 s, 10 ± 2.2 s, and 5.5 ± 1.8 s for MAN1-3 and CASP conditions respectively. The subject successfully learned how to use the CASP system and, although he was an experienced user of a classic myoelectric prosthesis, the results were similar to the ones obtained for the able-bodied subjects. The CASP system was approximately twice as fast as the manual control for the same number of DOFs (MAN3). The subject reported that the CASP was easy to use and that he liked the approach, especially the fact that the system reactively readjusted the wrist-hand configuration, which added to the overall easiness of the grasp execution.

The summary results for the recorded shoulder-joint angles are given in figure 6(A). The conditions in which there was no wrist rotation control (i.e., MAN1, MAN2) differed significantly in shoulder abduction and external rotation compared to the conditions with manual (MAN3) or automatic (CASP) rotation control. Between MAN1 and 2, the angles were similar, which also held for MAN3 versus CASP.

Figures 6(B) and (C) depicts graphically the arm configurations when the cup positioned horizontally (figure 6(B)) and vertically (figure 6(C)) was grasped using MAN1 (figures 6(B), (C-1)) and CASP (figures 6(B), (C-2)). In MAN1, the user had to perform extensive compensatory movements consisting of either shoulder abduction and external rotation (figure 6(B)) or adduction and internal rotation (figure 6(C)) in order to orient the hand appropriately for grasping the object. The shoulder joint movements were employed in order to compensate for the lack of pronation/supination at the wrist, and the exact strategy was dependent on object orientation (horizontal versus vertical). On the other side, there were no such over-extensive movements when using CASP and the shoulder angles remained virtually unaffected by the object orientations, since the automatic control adjusted the hand orientation accordingly, using the active wrist joint.

4. Discussion

In this study, we have presented a novel concept for the semi-autonomous, simultaneous and proportional control of a multi-DOF prosthesis, which is based on fusion of information from a variety of sensing technologies, including computer vision, inertial sensing, position and force sensors, embedded into the prosthesis and myoelectric signal acquisition. These inputs equip the artificial controller with the artificial vision and proprioception for context estimation and autonomous operation, and implement the integration of the biological and artificial control. By exploiting the sensor fusion, the artificial controller is able to emulate the high-level functions that are traditionally regarded as the responsibility of the biological control, such as, grasp planning and execution, and online reactivity to dynamically changing user intentions. At the same time, the status of the user is not compromised, since he/she still has a supreme control over the system.

The system presented here should be considered as an early stage prototype (lab-based device) which is used to demonstrate and evaluate the novel concepts for prosthesis control on able-bodied and amputee subjects. This is an

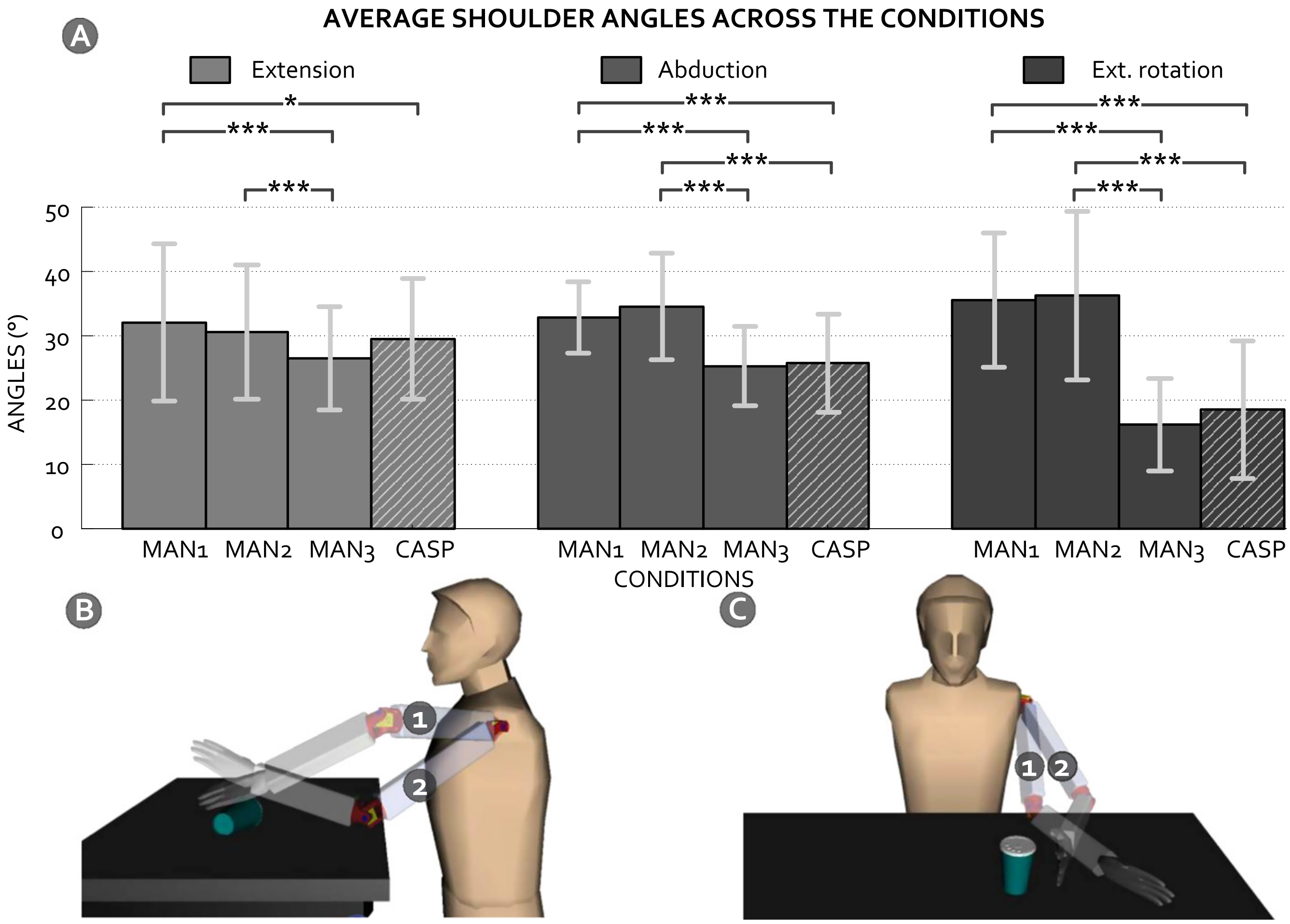

Figure 6. Summary results (mean ± standard deviation) for average shoulder joint angles (A) across different conditions and 3D model showing the arm positions recorded shortly before the object was grasped (B), and (C). Object placed horizontally (B) and vertically (C) was grasped using MAN1 ((B1) and (C1)) and CASP ((B2) and (C2)) control schemes. Note that the subject employed compensatory maneuvers at the shoulder joint when there was no active wrist rotation ((B) and (C), MAN1), and these movements depended on the orientation of the given object.

important step since the semi-autonomous sensor-fusion approach to prosthesis control opens up a number of possibilities for enhancing the device with automatic functions characteristic for context-aware robotic systems [43]. However, determining which of these functions is feasible and most useful still needs testing. This assessment should identify those functions that deserve to be translated into the future practical version of the system. Even though the current state-of-the-art technologies (e.g., the sensor size [45] and computational requirements) prevent its full integration, the practical relevance of the proposed approach is indicated by *the industrial interest in this technology* (joint patent application with Otto Bock Healthcare GmbH, Vienna, AT) [46]. Moreover, the wearable technology trends set by the IT industry leaders, i.e., ergonomic glasses integrating inertial units, depth sensors, and augmented reality, are becoming available on the market from a variety of vendors (e.g., Microsoft HoloLens [47], Meta glasses [48]).

The prototype described in the present study is based on our previous work [49–51]. Its performance in correctly estimating the prosthesis aperture and orientation is in the range of 0.75 ± 1.1 cm and 9 ± 5°, respectively, as reported in [49, 52]. Importantly, it represents a substantial step ahead with respect to the earlier developments, demonstrating for the first time several important concepts realized thanks to the fusion of information from multiple sensors. First, the system integrates the control of an active wrist by combining computer vision (environment analysis) and the measurement of the prosthesis orientation. Second, in addition to assessing the environment, the artificial controller monitors the behavior of the user (his/her movements) via inertial sensing. By integrating this information and the user's voluntary commands, the controller is capable of generating context-dependent decisions, reacting to the dynamically changing state of both the user and the environment. Importantly, the sensor-fusion in the present prototype lays down the basis for a powerful approach, allowing the prosthesis to incorporate many additional intelligent behaviors, which will be tested in the future (see section 4.4). In addition to demonstrating the approach, the present study compares for the first time the performance of this semi-autonomous sensor-fusion prototype to that of the classic manual control (commercial benchmark). The tests were conducted for several configurations of the manual interface, determining the pros and cons of the semi-automatic control through a range of functionally relevant assessments.

The fusion of information from multiple sources has been used for decades for grasp planning and execution in industrial and humanoid robotics [53, 54]. However, the control of prostheses is a unique context, since the artificial controller has only a partial control of the system. For example, in the case of a hand prosthesis, the user transports the hand and orients it in space through elbow and shoulder actions, whereas the prosthesis controller operates the wrist and hand closing/opening. This specific scenario on one side relaxes some performance requirements, i.e., the user can compensate for the mistakes of the autonomous controller. On the other hand, it also imposes some specific constraints with respect to typical robotics applications. For example, to properly implement the autonomous actions, the prosthetic controller needs to consider both the prosthesis and the user.

4.1. Comparison with a commercial myoelectric control

Single DOF control in MAN1 (hand open/close) was a simple scenario, in which the subjects only had to reach for the object and close the hand, resulting in the smallest TTG overall. However, the subjects had to employ compensatory strategies characterized with the excessive shoulder movements in order to accommodate for the lack of active DOFs (figure 6). In MAN2, the subjects could additionally select between the two grasp types and the control scheme has increased in complexity, as the subjects had to perform the co-contractions to switch between the grasps. This had a statistically significant impact on the overall performance, which slightly deteriorated. However, the addition of a novel grasp-function did not change the reaching strategy, and the same compensatory movements were still present, i.e., the shoulder angles employed in MAN1 and MAN2 were not statistically different. Only in MAN3, in which the wrist was also actively controllable, the overall shoulder angles displayed a significant reduction, especially in abduction and external rotation. This was also obtained during the CASP control condition, meaning that the reaching movements employed in MAN3 and CASP were kinematically similar, i.e., there was no statistical difference between the respective angles. However, although the increased flexibility eliminated the compensatory movements, it also substantially increased the complexity of control since the subjects had to perform tiresome co-contractions several times in a single grasping trial. Consequently, the TTG increased dramatically with respect to MAN1 and 2.

The TTG with the CASP was higher when compared to the MAN1 and 2, but also substantially lower when compared to the MAN3. Therefore, the CASP system is somewhat slower than MAN1 and 2 but results in grasping strategies and arm configurations that are similar to those employed in MAN3, with the benefit that it is substantially faster than the latter. Therefore, when using the full potential of the prosthetic system, the CASP outperforms the myoelectric control significantly. Furthermore, the CASP system was easy to adopt and use, which is demonstrated by the fact that there was no significant improvement in performance between the two experimental sessions (training versus evaluation), which is contrary to MAN conditions.

4.2. Integration with other methods

As stated before, the CASP was not designed to compete with the myoelectric interfaces but rather to encapsulate those methods within the semi-autonomous framework and thus enhance their functionality and performance. The present study, for example, demonstrated how adding the CASP on the top of the classic control scheme (commercial benchmark) influenced time efficiency as well as the grasp kinematics. The currently implemented two-channel proportional myocontrol is just one of the many system components that will be improved in the next developments. Future studies will investigate how beneficial would be to integrate the CASP system with advanced myoelectric control schemes, such as methods for simultaneous and proportional myocontrol of multiple DOFs [22, 55]. The concept of the experiment would be similar as in the present study, i.e., the subject performance with an advanced myoelectric interface would be compared to the performance when using the same myoelectric interface integrated within the CASP framework. However, it could be also relevant to compare the CASP against manual control even when the myoelectric interfaces are not the same. In this case, the CASP could allow similar performance as the sophisticated manual control, such as, the multichannel simultaneous and proportional multiple DOF control, but by using a substantially simpler human–machine interfacing, e.g., a two-channel EMG interface triggering automatic simultaneous and proportional control of multiple DOFs. However, these assumptions still need to be confirmed through dedicated experiments.

Similar approach could be also applied in the patients that underwent targeted muscle reinnervation [21] and therefore need to control a full prosthetic arm. Semi-autonomous control could be used to assist direct control through independent signal sources available in these patients. For example, CASP controller could operate the shoulder and elbow joints transporting the hand near the target object, which is a challenging task to perform manually, and then the user could take over and perform the grasp by operating the hand and wrist using direct approach.

Importantly, there are many other possibilities for integration of various manual control methods with the CASP approach, and the aim is to investigate this in the future studies. In addition to controlling a multi-DOoF prosthesis, the presented approach can be extended to other similar applications, e.g., improving the control of an upper-limb rehabilitation robot or functional electrical stimulation. Importantly, the semi-autonomous sensor-fusion control in both prosthetics and rehabilitation robotics can benefit substantially from a large body of work regarding the grasp planning and execution already available in the robotics literature (e.g., visual servoing [53, 54, 56]). However, these methods need to be integrated into the context of shared control with its specific constraints and challenges, as explained in section 4.

4.3. Sensor fusion and reactive control

Control based on sensor fusion is a central feature of the proposed system. By integrating the artificial proprioception and vision estimating the orientation of the prosthesis and the object, respectively, we could implement the control of wrist rotation (grasp planning) and an automatic response (artificial reflex) triggered by the change in the approach to the object during hand transport (automatic prosthesis readjustment). The main principle when implementing the autonomously controlled readjustment was that it was synchronized with the users' intentions. In the present prototype, this action was integrated as a reflex, i.e., an automatic response triggered by a discrete sensor input. More specifically, the system monitored the hand orientation (pro/supination axis) and when it detected that the user started rotating, crossing a predefined angular threshold, the system would complete the rotation on behalf of the user as well as readjust the preshape parameters. The threshold was set in the pilot tests to guarantee robust triggering. The system therefore 'amplified' an ongoing movement of the subject, performing the action only when the certainty about the user intention was high. Hence, the reactive behavior was regarded as intuitive for the subjects (verbal report), the subjects easily learned the function, and it did not lead to overshooting of the target or race conditions in any of the trials.

These can be considered as basic actions demonstrating the potential of the sensor fusion for prosthesis control, which can be used to implement many other functional high-level behaviors. For example, by adding inertial sensors to the able hand, in the form of a miniature bracelet or clip attached to clothing, the CASP could adjust the posture of the prosthesis automatically when it detects that the able hand approaches the prosthesis in order to hand over an object. This activity belongs to the class of symmetric bimanual tasks, during which one hand essentially mirrors the orientation of the other. To achieve this, the CASP would read the momentary orientation of the able hand and adjust the prosthesis accordingly. Importantly, this configuration (inertial units placed bilaterally) would open up possibilities for other, more sophisticated scenarios, including automatic intention detection from hand/prosthesis motion as well as automatic support to the other types of bimanual activities. This functionality would be of interest for unilateral amputees, who often use the prosthesis to support the dexterous activities performed by the contralateral (unaffected) side [57].

We hypothesize that the CASP could yield two additional important advantages. First, the automatic functions (e.g., grasp planning) could potentially decrease the cognitive effort of the user. The sensor fusion could allow the user to focus on the task rather than on how to steer the prosthesis. In the current implementation, for example, the user needed to issue only a single, simple command (extensor contraction) and the automatic control would adjust all the prosthesis DOFs on his/her behalf. In MAN3, on the contrary the muscles had to be activated several times, including multiple co-contractions, to achieve the same task. Second, the autonomous operation could facilitate the integration of the prosthesis into the body scheme, since the sensor fusion could improve the coordination between the prosthesis and rest of the body. For example, with automatic control, the user could issue the trigger command and immediately start transporting the hand towards the target. The controller would automatically adjust prosthesis' DOFs during reaching, which resembles a simultaneous evolution of reaching and grasping characteristic for able-bodied subjects [1]. In addition, the artificial reflexes such as reactive readjustment (present study) or future work in bimanual tasks represent the prosthesis actions that are triggered by and synchronized to the volitional movements of the user. However, the decrease in the cognitive effort and the improvement in coordination with CASP are currently only the hypotheses that need to be evaluated objectively via a set of psychometrically validated tools such as NASA Task Load Index [58, 59].

4.4. Study limitations and future developments

The CASP approach can be developed in several directions. First, other sensors can be used to monitor the state of the prosthesis and the user and estimate the features of the environment (e.g., laser scanners, ultrasound rangers, time-of-flight cameras, RFID tags etc) These sensing elements can be considered and evaluated as the potential information sources for the sensor fusion. For example, RFID tags, or a similar technology such as Bluetooth equipped miniature chips [60], could be used to tag objects in a known environment (e.g., at home). The prosthesis equipped with an integrated RFID reader [61] could detect the tag when approaching the object, read the programmed grip pattern, and preshape automatically [62]. As demonstrated in [63], the tags can be placed also on the user to trigger prosthesis functions each time the user approaches the tag. This approach fits well with the concept proposed in the present study, where additional sensors are placed on the user (e.g., miniature inertial sensing bracelet) to monitor his/her behavior for context-dependent control. Moreover, as shown in [64], RFID tags could be used not only to identify the object and associated grasp, but also to determine its orientation, providing an additional exteroceptive input for the semi-autonomous control. Second, methods for estimating the contextual features from the sensory modalities have to be developed. Inertial units, for example, can be used to detect the movement phases (e.g., start and end of reaching) as well as other features (e.g., movement speed, direction). The present evaluation considered a simple scene including one object at a time. However, even at this early phase of development, the system would be able to handle more complex and cluttered environments, as partly demonstrated with the previous prototype (see figure 10 in [49]). The overall system robustness and performance in a realistic environment is the main scope of these developments. For example, a depth sensor was selected rather than a stereo-camera, the computer vision module assumes that the objects are unknown rather than using a predetermined database (limited object set), etc. The scene and user analysis is being continuously improved. We are currently developing the sophisticated SLAM-based [65] approaches in conjunction with advanced clusterization algorithms [66]. This would ultimately result in advanced object modeling schemes capable of simultaneously handling and identifying multiple objects of interest together with their respective features (e.g., object affordances, multiple objects stacked together, etc). Yet another improvement can be implemented in the algorithm for object selection, which is certainly sub-optimal since the user first needs to turn his head towards the object and then trigger the system. Namely, it has been shown that during grasping the subjects mostly move the eyes rather than the head [67]. Therefore, the object selection could be improved by using a practical eye tracking system, embedded into the glasses [68], but such systems are still rather expensive. Another, more feasible and cost effective, solution would be to perform hand tracking algorithm using fusing vision [69, 70] and advanced inertial sensing [71]. This would allow the CASP system to infer the object that is likely to be grasped by the user (e.g., the one towards which the hand moves) thus eliminating the need for explicit head movement.

In the present study, the grasp kinematics was influenced by the specific experimental setup. Therefore, the joint angles were not measured in order to identify normal versus abnormal movements in real life conditions, but mainly to compare how different control systems influence the kinematics in an identical setup. When the CASP system reaches the stage of development in which the components are properly integrated and ergonomically attached to the subjects (e.g., prosthesis on the socket, sensors miniaturized), the kinematics will be acquired and compared to those of able-bodied subjects to assess the naturalness of the movement.

The experimental evaluation performed in this study was designed to test the novel system prototype for its potential transferability and overall applicability in the prosthesis control, and especially how the semi-autonomous control at this stage of development compares to the classic manual operation (commercial and clinical benchmark). Therefore, the study focus was set primarily on performing a set of functionally relevant ad-hoc experiments (e.g., grasping and lifting differently oriented objects) designed for heavy-duty multi-DOF prosthesis usage, taking into account also the constraints of the setup (e.g., vision sensor worn by the users, prosthesis mounted on the splint). The ad-hoc test used in the present study was therefore the result of a compromise and was not psychometrically validated. However, such tests are not unusual in the scientific literature, even when evaluating ready-to-use systems [22, 72]. We are fully aware of the importance of standardized evaluations and of the current efforts in the scientific community towards establishing such benchmarks [73, 74]. Therefore, in the more mature development phase, as the system approaches its clinical applicability, and amputees are able to utilize it in a practical setup (integrated components), the current test will be substituted by the psychometrically relevant measures (e.g., SHAP [75]).

Acknowledgments

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