A novel immersive augmented reality system for prosthesis training and assessment

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***Abstract*— In recent years, the field of prosthetics developed immensely, along with a variety of control methods and computer interfaces for prosthetic training. In this work, we present an architecture for an augmented reality training system enabling the user to control a virtual prosthetic hand displayed as an extension of the residual limb using EMG pattern recognition in a stereoscopic augmented reality scene. Validated in online experiments with four able-bodied subjects, the novel system provided a more realistic experience compared to the classic 2D implementation and resulted in improved subject performance.**

I. Introduction

After an amputation of a limb, the person loses motor and sensory functions essential for accomplishing the activities of daily living. This has a dramatic impact on the patient's life, both functionally and psychologically. Myoelectric prostheses can be used to restore the lost motor functions to a certain extent. These systems are controlled by decoding the user commands to the prosthesis from the electrical activity of his/her muscles residing in the residual limb. The intention-action mapping can be simple, as in the classic two-channel scheme for the control of single degree-of-freedom (DOF) grippers. In this case, the electrodes are placed on the hand and wrist flexor and extensor muscles, and the activity of these muscles is mapped into prosthesis closing and opening, respectively. For more advanced control of multifunction systems (e.g., Michelangelo and Bebionic hands), the commands can be determined from multichannel electromyography (EMG) using pattern classification [1].

It was recognized already some time ago that computer simulations can be used as instruments for prosthesis training and evaluation. For example, simple computer games can be employed for the training of discrete and proportional myoelectric control, as when using muscle activity to navigate a virtual object avoiding obstacles during a planar animation [2]. Virtual environments integrating a full 3D hand model can be used to simulate standard tests (e.g., virtual clothes pin) [3] or realistic interaction with daily life objects [4]. This technology was also investigated for the treatment of phantom limb pain [5], as it allows the phantom to be materialized through a virtual reconstruction.

In recent years, the field of prosthetics developed immensely. There is a great variety of systems, from single DOF prostheses to dexterous hands with individually controllable fingers, together with many control methods and assessment procedures (e.g., SHAP, box and blocks, clothes pin). A virtual environment can accommodate this flexibility by implementing the aforementioned components as computer simulations, allowing an easy (wide-spread) access to those technologies even when they are not physically available. Previously, computer interfaces for prosthetic training and evaluation were implemented using different levels of immersion. In some implementations, the subject observes the hand in a 3D environment shown on a computer screen [3], or he/she becomes integrated into the virtual scene by wearing virtual reality glasses [4]. Recently, augmented reality (AR) was proposed as a method to create an even more realistic experience. In [6], the authors presented a system in which a web camera records an amputee subject and the video is projected on a computer screen. In addition, a 3D graphical model of the arm is integrated into the scene, extending from the residual limb localized online by tracking a marker. Therefore, the subject observes a video of him/herself in a real environment while his/her limb has been virtually reconstructed.

The main objective of the present work was to implement an AR-based training system for myoelectric control schemes. Our application scenario dictates that a training system must offer a high degree of immersion to the user, be relatively compact and inexpensive in order to be potentially used at home. These characteristics make myoelectric control training systems an appealing application domain for head-mounted displays (HMDs) with stereoscopic cameras and AR. Similarly to [6], the system tracks a marker placed on the residual limb to embed, within the real scene, a 3D graphical model of the prosthesis in the anatomically correct position. The novel contribution of this work is that the system provides an advanced level of immersion, since the user observes the real scene and the prosthesis model from a quasi-orthoscopic view. This is achieved by using a custom-made AR setup combining a HMD and a stereovision camera.

The remainder of this work is structured as follows. In Section II we describe the architecture of our proposed system and the experiments used to preliminary validate the system in able-bodied subjects. Section III contains the experimental results and finally we draw a conclusion in Section IV.

II. Methods

A. Architecture

As illustrated in Fig. 1, the main tasks of the proposed system are to use a binocular HMD for real-time rendering

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and controlling of a virtual arm displayed as an AR overlay extending from the residual limb of an amputee subject. For this purpose, we use a custom-built parallel binocular stereoscopic camera consisting of two Logitech C610 HD webcams with 115° wide-angle lenses to capture video data. The camera is placed below the HMD to provide a quasi-orthoscopic view. A custom AR marker suitable for SIFT (Scale-Invariant Feature Transform)-based detectors is placed on the residual limb and can be freely moved inside the field of view. In order to achieve an optimal detection quality from various viewing angles resulting from different arm positions, a conical marker shape was chosen. The position detected by the marker tracker is later used to integrate a virtual arm into the stereoscopic video data, which is then projected onto an Oculus Rift DK2 HMD. For EMG data acquisition, we use a wireless MindMedia Nexus 16 DAQ capturing 8 bipolar channels of EMG at a sampling rate of 1024 Hz. The virtual arm is controlled by the amputee using a well-established EMG pattern recognition scheme, as explained later.

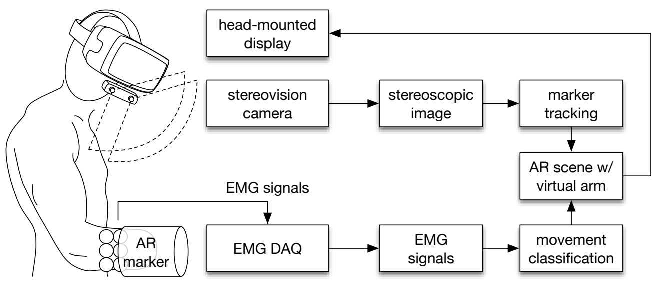


Fig. 1. Top level view of the proposed system. A stereovision camera captures video data of the amputee's field of view where a marker tracking module estimates the position of a marker on the amputee's residual limb. The video data are augmented by a virtual prosthetic hand placed on top of the marker and displayed on the HMD. The virtual prosthesis hand is controlled through EMG pattern recognition.

In Fig. 2, a detailed data flow view of the system architecture is illustrated. The main component of the proposed system is an application developed in Unity 3D (Unity Technologies), a state-of-the-art cross-platform game engine. It is written in C# and comprised of different modules described below.

Before the video stream from the stereovision camera can be used inside the Unity 3D application, it needs to be preprocessed. This step is performed in the stereo rectification module, which receives the video data from the camera driver and modifies the images in two sequential steps using OpenCV library calls. First, the barrel distortion from the wide angle lenses is corrected using a pre-computed calibration matrix and second, the left and right images are rectified for optimal alignment. The resulting rectilinear stereo images are then sent to the Unity 3D application over TCP/IP and used as input for the Unity 3D objects in left and right plane.

For performance reasons, only the left camera image is used as input for the marker tracking module. Here, we rely on PTC Vuforia [7], a state-of-the-art SDK for Unity 3D that offers reliable SIFT-based marker detection. When the marker is detected, its position and orientation are applied to the main arm model, a boned and rigged model of a realistic human arm created in Autodesk 3ds Max. During the Target Achievement Control (TAC) test [8] used for the system's evaluation, as described in the following subsection (II. B), the position and orientation are also applied on the TAC target arm model which is essentially another instance of the main arm model.

For controlling the arm model, our system uses a well-established EMG pattern recognition scheme consisting of extraction of time domain features (mean absolute value, waveform length, slope sign changes and zero crossings) from the raw EMG signals and classification using linear discriminant analysis (LDA) [9]. These steps are performed using BioPatRec [10], an open source framework for EMG pattern recognition control running in MATLAB. The classifier decision along with control commands needed for the TAC test are sent over TCP/IP to the animation controller module inside the Unity 3D application. The window length for feature extraction and command generation through classification was set to 150 ms with an overlap of 50 ms. We have implemented 11 realistic hand animations that can be applied to the main arm and the TAC target arm model using cascaded blend trees. Available animations are: open/lateral grip, wrist pronation/supination, wrist extension/flexion, ulnar/radial deviation, key grip, pinch grip and extension of the index finger. These animations corresponded to the movement classes (prosthesis commands) estimated by LDA. The speed of prosthesis movement was proportional to the average level of muscle activity across the EMG channels normalized to the maximum activation. The calibration and training of the LDA pattern classifier was implemented using BioPatRec.

Finally, the animations are applied to one or both arm models which are then passed along with the left and right plane objects as input to the Oculus SDK. Here, the specific Oculus Rift lens distortion is applied to the resulting image, which is then displayed inside the Oculus Rift. Fig. 3(a) shows the complete system used by an able-bodied test subject while he controlled the virtual arm in an AR scene.

B. Experimental validation

To validate our system, we conducted TAC tests with four able-bodied subjects (30±4 yrs.). The experimental protocol was approved by a local ethical committee, and the subjects signed an informed consent form before commencing with the tests. The TAC test is a widely used method to evaluate the online performance of multifunction pattern recognition-based myoelectric control systems [8]. It was originally designed to investigate how well classification accuracies measured in offline experiments translate to online control of a virtual hand. Compared to previous tests (e.g., [11]), the TAC test uses combinations of multiple DOFs. Fig. 3(b)-(d) shows the different stages of one TAC test trial from the subject's quasi-orthoscopic view.

The classic test protocol, as implemented in [10], can be summarized as follows: the test person is presented

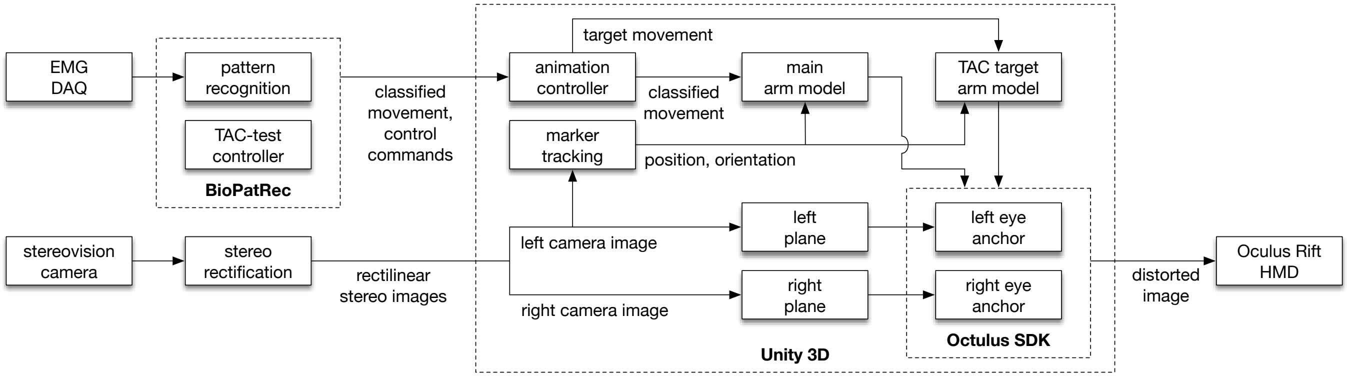
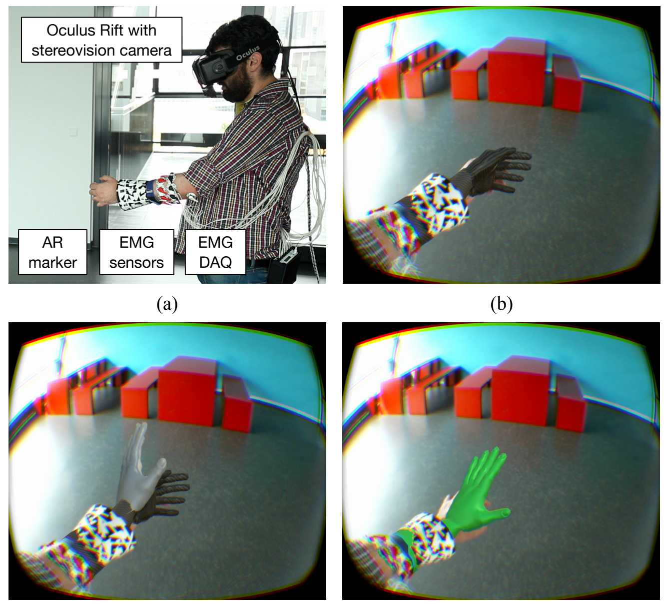


Fig. 2. Data flow view of the proposed system architecture with the focus on building the stereoscopic augmented reality scene with a virtual arm overlay in Unity 3D for display inside the Oculus Rift.

with a virtual arm displayed on a computer screen that can be controlled along multiple DOFs using an EMG pattern recognition control scheme (Fig. 3(b)). Additionally, a second, usually semi-transparent virtual arm with a target posture is displayed on the same screen (Fig. 3(c)). When the trial starts, the user is given a certain amount of time to position the virtual arm into the desired posture by generating proper inputs (myoelectric patterns) into the classifier. If the user succeeds in reaching the target posture in time with a predefined tolerance (e.g. ±5 degrees), the virtual arm turns green, and the task is deemed successfully accomplished (Fig. 3(d)). The main measures of the TAC test are mean task completion rate and mean task completion time.

Integrating the TAC test into our system was straightforward. As discussed in the previous subsection, an additional virtual arm model, the TAC target arm model was included into the Unity 3D application. The control commands are sent by the TAC test controller already included in BioPatRec. Importantly, in our implementation of the TAC test, the subject observed the target and controlled virtual model from the quasi-orthoscopic view in full 3D (compared to 2D projections on the computer screen, as in [10]). In addition, the virtual models were embedded into the real scene (augmented reality).

We chose the TAC test as a means to validate our system for three reasons. First, it is a widely used real-time evaluation method with several available implementations. Second, we wanted to evaluate whether there is a training effect noticeable in the test subject's performance across trials when using the standard 2D implementation and the AR system. Even though the TAC test is not primarily intended to validate upper limb prosthesis usability, the authors assume that it captures significant information about the algorithms being tested and that systems with a higher score will ultimately be more controllable and more usable [8]. Third, we wanted to investigate whether test subjects can benefit from the AR system in comparison to a 2D screen-based implementation. Standard 2D visualizations of a virtual arm typically used in TAC test implementations might have a common problem: they offer only a fixed viewing angle on the virtual arm, making some combinations of DOFs hard to interpret for the user. Therefore, our goal was to investigate whether test subjects can benefit from the ability to choose their view angle on the virtual arm, when using a novel 3D AR system.



(a) (b) (c) (d)

Fig. 3. Experimental setup (a) and different stages of one TAC test trial from the patient's quasi-orthoscopic view (b)-(d).

Each of the four able-bodied subjects conducted four independent TAC test runs: the first and the third run with a 2D-based visual feedback as in [10], the second and fourth run using our proposed AR system with 30 minute breaks between the runs. In each run, a subject had to perform 4 trials with 8 possible combinations of the following DOFs in random order: open/lateral grip, extension/flexion, pronation/supination. Each trial was conducted with a time-out of 45 seconds where a subject tried to reach a target position with a tolerance of ±5 degrees.

III. Results

Fig. 4 shows the individual task completion rates of the four subjects and the mean and standard deviation over all subjects. The first and second runs with the standard 2D system (runs 1 and 3) are depicted in light and dark blue,

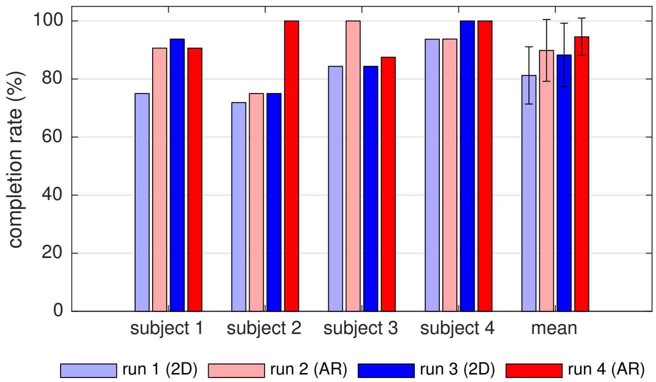


Fig. 4. TAC test task completion rate over subjects

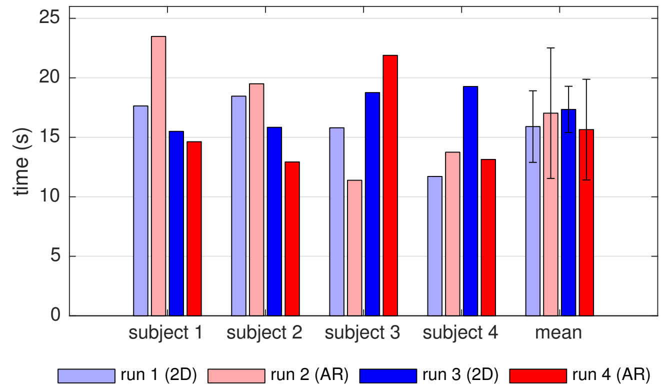


Fig. 5. TAC test task completion time over subjects

while the first and second runs with the AR system (runs 2 and 4) are shown in light and dark red. In average, the second run of both systems resulted in a higher task completion rate than the first run, indicating an obvious training effect in both systems. It can also be seen that the subjects were in average able to perform more correct tasks with the AR system in both runs, i.e., 89.8% vs. 81.2% for the first run and 94.5% vs. 88.2% for the second. Furthermore, with the AR system, there were three runs in which the subjects successfully accomplished all the tasks (100%), whereas in the case of the classic 2D TAC there was only a single run with the performance of 100%.

In Fig. 5, the task completion times of the four subjects and the mean and standard deviation over all subjects are shown. The results are variable between trials and subjects, ranging from 11.7 to 19.2 s for 2D TAC and from 11.4 to 23.5 s for 3D TAC. The mean values ($\sim$16.6 s for 2D and $\sim$16.3 s for 3D) do not indicate a clear trend for the difference in performance between the two systems.

IV. Discussion and Conclusion

In this work, we have presented an architecture for an AR training system that enables the user to control a virtual arm displayed as an extension of the residual limb using EMG pattern recognition in a stereoscopic AR scene. The system was implemented in Unity 3D and validated in online experiments with four able-bodied subjects using a standard test (TAC). The novel system provided a more realistic experience, including quasi-orthoscopic view of an AR scene, compared to the classic 2D implementation. This resulted in improved subject performance, increasing the rate of task accomplishment. This outcome is promising but the present evaluation was preliminary and conducted in a small number of able-bodied subjects. The future tests will consider larger pool of subjects, also including amputees.

The next step in the system development is to add other virtual objects in the scene together with a realistic physics engine, so that the system can simulate the interaction of the prosthesis with the environment. This will be used to implement standard and novel tests for the assessment of the prosthesis control, e.g., virtual box and blocks, clothes pin, book turn test, grasping objects with different compliance properties, grasping static and dynamic (moving) objects etc. The resulting framework is envisioned as a general and flexible test bench in which the prosthesis as well as the tests will be easily configurable, allowing fast setup and comprehensive assessment of different configurations. For example, the same test (clothes pin) can be performed using a prosthesis with different number of DOFs (from a simple gripper to a dexterous hand) and/or clothes pins with a range of spring stiffness levels. We also think that the developed framework can be relevant for the treatment of phantom limb pain, offering a realistic experience with a high level of immersion through the 3D AR setup. Finally, in the future, we plan to port the system to a wearable see-through AR glasses (e.g., Google Glass, Meta Glass) for an even better portability and user experience.

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