Megane Pro: myo-electricity, visual and gaze tracking data acquisitions to improve hand prosthetics.*

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Abstract— **During the past 60 years scientific research proposed many techniques to control robotic hand prostheses with surface electromyography (sEMG). Few of them have been implemented in commercial systems also due to limited robustness that may be improved with multimodal data. This paper presents the first acquisition setup, acquisition protocol and dataset including sEMG, eye tracking and computer vision to study robotic hand control. A data analysis on healthy controls gives a first idea of the capabilities and constraints of the acquisition procedure that will be applied to amputees in a next step. Different data sources are not fused together in the analysis. Nevertheless, the results support the use of the proposed multimodal data acquisition approach for prosthesis control. The sEMG movement classification results confirm that it is possible to classify several grasps with sEMG alone. sEMG can detect the grasp type and also small differences in the grasped object (accuracy: 95%). The simultaneous recording of eye tracking and scene camera data shows that these sensors allow performing object detection for grasp selection and that several neurocognitive parameters need to be taken into account for this. In conclusion, this work on intact subjects presents an innovative acquisition setup and protocol. The first results in terms of data analysis are promising and set the basis for future work on amputees, aiming to improve the robustness of prostheses with multimodal data.**

I. INTRODUCTION

Scientific research has proposed several techniques to improve the control of hand prostheses. However, commercial systems include few of them, usually due to limited robustness. Multimodal data acquisition and fusion may contribute to improve robustness of robotic hand prostheses. This paper introduces the first multimodal data acquisitions including surface electromyography (sEMG), eye tracking and computer vision for the control of robotic hand prostheses. The data acquisitions and analyses are performed on intact subjects and show how the setup can provide useful information for prosthesis control.

As described in several review papers (e.g. [1], [2]), during the past 60 years scientific research proposed increasingly sophisticated approaches for the control of hand prostheses via surface electromyography (sEMG). Most of the methods rely on the use of sEMG and pattern recognition or proportional control algorithms. Often, intact subjects are used in the analyses, since they represent a good proxy for amputees [3]. Despite the promising laboratory results, the academic systems usually offer a relatively small functional improvement in daily situations at the expense of a substantial reduction in robustness. Currently available sEMG prostheses are very advanced from a mechanical point of view but they do not correspond to the needs of the amputees: first they do not improve the capabilities in many standard activities; second, they often lead to limited acceptance.

Activities of daily life (ADLs) include categories such as personal needs, eating or use of tools [4]. Several studies highlighted the difficulty that the amputees have in basic ADLs. Lacing shoes, removing a bottle top, using scissors and buttoning a shirt are mentioned as the hardest actions [5]. In general, sEMG prostheses do not strongly improve this situation and they are often not fully accepted by amputees. The main causes are non-intuitive control, limited functionality, absence of feedback, excessive weight and slow motion [6], [7]. Finally, the rehabilitation process is often problematic due to the difficulty to perform and reproduce complex movements. The contribution of all of these factors results in a preference for cosmetic rather than functional prostheses, particularly among unilateral amputees who can compensate the movement capability with the intact limb.

sEMG, visual and gaze data fusion may contribute to improve prosthesis control when performing goal-directed grasps aimed at ADLs. Eye tracking has already been referred to in the literature as a strong point in HCI (Human Computer Interaction) and it was introduced in the control of manual prehension and object identification [8]–[10]. Dosen et al. showed that visual information can be employed efficiently to both select the grasp pre-shape and to adjust dimensions with visual servoing. The authors used a 3D camera and a depth sensor to perform grasp planning [11]. Eye tracking data are complex to analyze, since the users' gaze might be affected by different unpredictable factors. Gaze alternates between fixation pointing (when the user stares at the object for a period of time that exceeds a given threshold), and saccades

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(which are rapid movements of the eyes) [12]. Nevertheless, fixation points can guide object recognition and help to classify the object to be grasped.

This work aims at improving the robustness of prostheses through the integration of sEMG, eye tracking and computer vision in the field of view. The paper introduces the first multimodal data acquisition setup (Section II), protocol (Section III) and data analysis (Section IV) aimed to simultaneously record and evaluate the mentioned techniques. This work confirms that sEMG, eye tracking and computer vision data can provide fundamental information for hand grasping tasks by mixing data regarding the environment with data related to the intentions of the subject. The results are promising for the field and set the basis for future work on data integration, object recognition and robotics and they will guide the future data acquisition and data fusion on amputees.

II. Acquisition Setup

The acquisition setup was designed to record data from several sensors providing information of different nature: hand kinematics, gaze direction, and dynamics and muscular activity of the forearm. It can be subdivided into a hardware part (including the laptop and the sensors used to perform the data acquisitions, section II.A) and a software part (including the software to manage the simultaneous recording from the sensors (synchronization) and the user interface to guide the subjects during the data acquisitions, section II.B).

A. *Hardware*

The hardware acquisition setup extends the acquisition setup of [13]. It includes the laptop used to perform the data acquisitions, the eye tracking device with scene camera, the sEMG sensors and a CyberGlove.

The laptop used for the data acquisitions is a DELL Latitude E5520. The laptop was used to record the data from the devices while also guiding the subject through the acquisition protocol. The gaze was recorded using the Tobii Pro Glasses II (Tobii AB[1]), a wearable eye tracking system. The device is composed of a lightweight head unit with eyeglass design and a recording unit (to record and save data to an SD card). The device was connected to the acquisition laptop via a wireless connection. This device is capable to estimate where the subject is looking in its field of view. The eyes of the subjects are recorded with four infrared cameras embedded in the frame of the glasses. The movement of the eyes is tracked by applying black pupil and corneal reflection methods. An embedded full HD camera allows to record the scene in front of the subject in first person perspective [14]. The reported accuracy of the gaze direction estimation is 0.5 degrees with a root mean square (RMS) precision of 0.3 degrees. The eye tracking data are sampled at 100 Hz while the scene camera video is recorded at 25 fps (frames per second). The parallax and slippage are automatically compensated for by the device. A Software Development Kit (SDK) with Application Programming Interfaces (APIs) is provided with the device.

The muscular forearm activity was measured using 14 Delsys Trigno double differential sEMG Wireless electrodes (Delsys, Inc.[2]) that include 3-axes accelerometers. The electrodes were connected via a proprietary wireless protocol to their base station. The base station was connected to the acquisition laptop via USB. sEMG data are sampled at 2 kHz and the 3-axes accelerometer data at 148 Hz. The electrodes are placed equally spaced around the forearm with a dense sampling approach. Eight electrodes are placed in proximal position, with the first electrode at the height of the radio-humeral joint. The remaining six are placed just below the first set in a more distal position. The electrodes were attached to the forearm using a specific adhesive tape. A latex-free band was placed around them to reduce movement artifacts and to keep good contact between the electrodes and the skin (Figure 1).

Hand kinematics was measured using a 22-sensor CyberGlove II dataglove (CyberGlove Systems LLC[3]). Thanks to a proprietary resistive bend-sensing technology, the CyberGlove can accurately measure the joint angles of the hand and fingers. The CyberGlove was connected via Bluetooth to the acquisition laptop and sampled at 25 Hz.

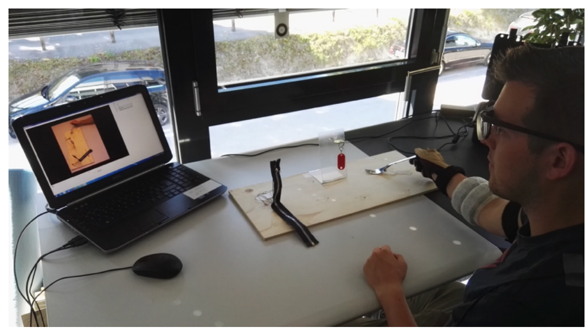


Figure 1. Acquisition setup. In particular, acquisition of the lateral grasp.

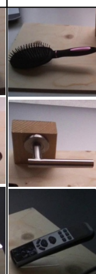
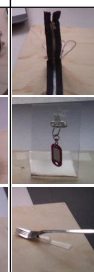
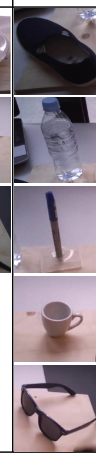
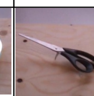
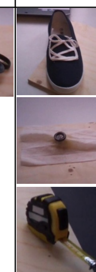
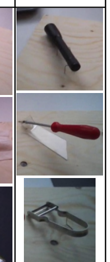
B. *Software*

The software acquisition setup is subdivided into two parts that cooperate in order to accomplish the data acquisitions: the first part consists of the software that manages the simultaneous data recording from all the sensors; the second part is the user interface to guide the subjects during the data acquisitions.

The software that manages the simultaneous data recording from all the sensors is a custom-made acquisition software based on the producer-consumer pattern implemented by Pizzolato et al. [15]. The software was written in C++ using the Boost 1.60.0 libraries. It consists of a multithreaded application, in which each producer and consumer runs in an individual thread. The producers acquire the data from the connected devices and the data are queued in dedicated queues. The queued data are extracted by consumers and stored on the hard drive of the laptop. As soon as the data are acquired, a high resolution time stamp (Windows High Performance Counter, resolution < 1 μs) is assigned to them.

[1] http://www.tobiipro.com/
[2] http://www.delsys.com/
[3] http://www.cyberglovesystems.com/

TABLE I. GRASPS AND OBJECTS INCLUDED IN THE ACQUISITION PROTOCOL

Grasp	1	2	3	4	5&6	7	8	9	10	11	12	13	14	15
Description	large diameter	small diameter	index finger extension	medium wrap	prismatic 4 fingers & writing tripod	power sphere	precision sphere	lateral	parallel extension	tripod grasp	power disk	using scissors	palmar pinch	adducted thumb
Objects														

This time stamp is used to synchronize the data recorded from the different devices.

The user interface that guides the subjects during the data acquisitions was developed to correspond to the acquisition protocol. In the initial phase the signals provided by the acquisition devices are recorded but not stored. Afterwards, the signals were stored in the stimulus file with a timestamp, the grasp label and the object label. During the entire acquisition procedure, automated vocal instructions are employed in order to guide the user to perform the movements. In particular, one command informed the user when to begin the movement, while a second one triggered the return to the rest position. The audio instructions are available in four languages (French, German, English, Italian), depending on the native language of the subjects involved.

III. ACQUISITION PROTOCOL

The acquisition protocol consists of the repetition of 15 grasps performed on a set of 30 objects while the subject sits with the forearm comfortably leaning on a desk (Figure 1). The subject was asked to watch two videos on the screen of a laptop showing how to reproduce each set of grasps from two different points of view (in third person and in first person respectively). The user had the possibility to try the grasps on the objects while the videos were playing in order to get confident with them. Afterwards, the subject performed the grasps while a fixed image of the grasp was shown. The image can provide a level of distraction for the subject. However, preliminary experiments showed that it was a helpful reminder for the subjects, as otherwise they may forget the grasp to be performed. Vocal commands guided the user throughout the acquisition. Each grasp was repeated on several objects. The items were presented to the subject in a specific sequence leaning on wooden boards, which were interchanged by an assistant. The 15 considered grasps are reported in Table 1 together with the objects used to perform them. The majority of the objects were considered in the repetition of more than one grasp. Both the movements and the objects were selected according to the needs of amputees. In particular, the objects and the movements were chosen to correspond to ADLs that the scientific literature mentions as most complex and useful for the amputees [4], [5]. Each grasp was repeated 12 times. The repetitions were equally distributed among the objects used for the grasp. In other words, the number of repetitions for each object was chosen in such a way that the total number of repetitions for each grasp was 12. For example, the large diameter grasp was repeated 3 times on 4 different objects (namely a bottle, a can, a mug and a glass), for a total of 12 repetitions. The variable number of iterations for each object allowed to include the most important ADL movements into the acquisition protocol, including the most difficult actions for amputees (such as lacing shoes, removing a bottle top, using scissors and buttoning a shirt) [5]. In every repetition, the movement lasted for approximately 8 seconds, including 4 seconds of grasping and 4 seconds of rest.

IV. DATA ACQUISITION & ANALYSIS

The acquisition setup and protocol were tested on 7 subjects (5 males, 2 females, average age 27 ± 5, all right handed). The number of subjects is chosen in order to provide a sufficient test-set to validate the acquisition protocol and setup (that will be applied to amputees) and not to infer more general results. This section describes the results of sEMG (IV.A) and eye tracking analysis (IV.B) for movement classification and object detection.

A. Hand movement recognitions based on sEMG

The data analysis shows that hand grasp classification and grasped object classification (using the same grasp) can be both performed with the recorded sEMG data after pre-processing and feature extraction.

Pre-processing includes synchronization, filtering and relabeling. First, the number of repetitions for each grasp is computed. Second, the accelerometers and the Tobii camera data are super-sampled to the highest sampling frequency (2 kHz) and synchronized with the sEMG signals through the interpolation of the timestamps. Third, the sEMG data are filtered using a low-pass Hampel filter at 50Hz. Fourth, the sEMG data are relabeled following the Hodges approach and the Lidierth rule [16], [17]. All the blocks of rest are used as reference for the rest value, while in the Lidierth rule the parameters t1 and t2 are set respectively to 2200 and 1000.

The feature extraction and classification procedure is the same as the one used in previous acquisitions [13], following Englehart et al. [18]. Each movement repetition ss subdivided in time windows of 200 ms (400 samples), overlapping for 10 ms (20 samples). The RMS and the time domain statistics described by Hudgins et al. [19] (TD) are computed for each time window. These features were applied successfully to myoelectric signals in previous work [7], [13], [19]. 30% of the repetitions of each grasp is used for the test dataset (repetitions 2, 5, 8, 11), while the remaining repetitions were used to create the training set. Finally, classification was performed using Random Forests [20] (number of trees = 100). In particular, the classification accuracy was computed before and after relabeling (Table II).

The sEMG data analysis confirms that the data can be used for the classification of hand movements. The average accuracy is approximately 75% for the relabeled data and 63% for the original data with both features. Thus, the relabeling step appears to significantly increase the overall outcome. The analysis highlights lower accuracy for the datasets recorded from the female subjects (subjects 1 and 5), for whom the classification performance is always below 60% before the relabeling. However, the accuracy is always above 50% and it reaches 81.18 % in one subject after relabeling. The majority of the datasets provides an accuracy that is rarely lower than 70%, and even slightly exceeding 80% in one case. The novelty of the acquisition protocol is one of the possible reasons for the difference in classification accuracy from previous work. The confusion matrix of the movement classification (Figure 2) shows that movement 2, 3 and 4 are often misclassified. This can be explained by the similarity of the grasps (Table I). Visualizing the signal shapes for each grasp, it was possible to notice common patterns among the repetitions of the same grasp on the same objects. Thus, the successive part of the analysis was aimed to examine the sEMG classification of specific objects for a set specific movements (3, 4, 5, 6, 7) using the RMS feature extraction and classification pipeline previously described in this paragraph. The average classification accuracy results are also in this case high (Table III), highlighting the fact that it is possible to classify different objects grasped with the same movement with an accuracy of up to 95.49%. This contributes to motivate the grasp classification accuracy reported in Table II and it suggests that object recognition methods can help to improve the accuracy over different grasps and objects.

In conclusion, the analysis to perform hand movement recognition based on sEMG data shows that both hand grasp and grasped object classification can be performed. Both tasks are fulfilled with accuracy much higher than the chance level for the considered number of movements and grasp classification seems to be strongly influenced by movement similarity and by the object used to perform the grasp.

TABLE II. GRASP CLASSIFICATION ACCURACY RESULTS

SUBJECT	ACCURACY			
	RMS		Time Domain	
	Non relabeled	*Relabele d*	*Non relabeled*	*Relabele d*
1	55,08 %	80,75 %	55,54 %	81,18 %
2	73,90 %	69,65 %	72,66 %	71,5 %
3	69,10 %	72,90 %	69,17 %	73,51 %
4	68,38 %	73,48 %	68,6 %	73,97 %
5	50,93 %	73,99 %	51,69 %	75,09 %
6	63,00 %	77,90 %	59,59 %	78,17 %
7	62,13 %	72,65 %	64,15 %	74,18 %
Average	63,22 %	74,47 %	63,20 %	75,37 %
Standard Deviation	8,10	3,69	7,87	3,25

TABLE III. OBJECT CLASSIFICATION ACCURACY RESULTS

Movement	3	4	5	6	7
Accuracy (%)	78.74	69.34	73.22	78.43	95.49
Standard Deviation	10.42	20.06	24.78	14.38	1.26

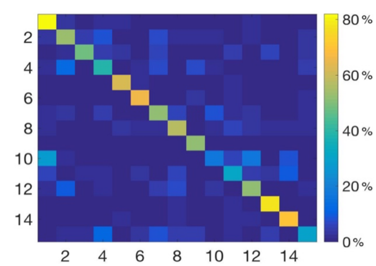


Figure 2. Movement classification confusion matrix.

B. *Object detection based on gaze tracking*

Most of our daily actions do not require high levels of conscious involvement. However, Land et al. [8] pointed out that also in routine activities every step is monitored by the eyes. This section describes the first set of analyses to estimate if gaze tracking and computer vision can be used to improve the robustness of robotic hand prostheses.

Multi-sensor integration of the sEMG signals with methods based on computer vision can effectively be used for prosthetics control [11], [21]. However, many objects may appear in the human field of view. Thus, detection of the object (and of the part of the object) to be grasped is fundamental before object recognition is useful. According to the scientific literature, many neurocognitive parameters influence gaze direction, with different timings and dynamics [22]. The visualization of the gaze direction according to neurocognitive parameters allows to verify that the data can effectively be used to improve the robustness of sEMG hand prostheses with object detection and recognition algorithms in future work.

Eye-hand coordination during grasping is related to several neurocognitive parameters that have been analyzed, but not yet integrated into robotic devices. It was shown that humans look

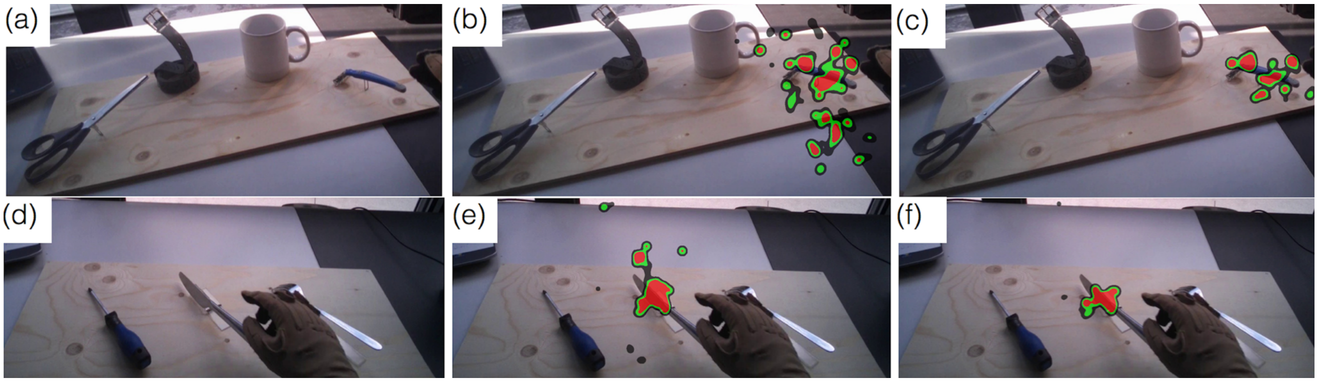


Figure 3. Heat maps for two grasps on different objects. The first column shows the snapshots automatically selected. The second shows heat maps computed on the entire stimulus (~4 s). The third shows heat maps computed on the first 200 samples after the specific reaction delay for each subject.

at an object 40-100 ms before initiating a movement towards it. The fixation points are related to where the subject aims to grasp the object (for example, where they place their index finger during a precision grasp), to the shape of the object and to forthcoming actions (e.g. landing sites, and obstacles) [22]. Castellini et al. [23] showed that the fixations directed towards the object to grasp have a different duration for each user, ranging around [350-450] ms [24]. However, how fixations change throughout a reach-to-grasp movement and exactly what object properties are fixated has yet to be fully explored, as well as how to consider all the mentioned parameters to improve gaze-guided object detection for grasping.

A useful way to evaluate gaze usability for prosthetic control is to localize the areas on the objects where the gaze has a fixation via heat maps [12]. The eye tracking device records gaze as raw data. Gaze coordinates can be directly projected on the video recording to have a simultaneous visualization. The direct dependency between the camera frame and the gaze data at a specific instant was removed by mapping an interval of gaze data on a single video snapshot. In order to automate the snapshot for the heat maps in such a way that all the objects (used for each grasp) were included in the frame, the psychophysical parameters related to gaze fixation in hand-eye coordination were considered. To automate the selection, the gaze allocation parameters in correspondence to grasping tasks were studied. As suggested by Desanghere [22], eye movements typically precede hands in both pointing and object manipulation. Thus, the snapshots were automatically captured after the start of the stimulus. The length of the gaze data time window to be plotted on the video snapshot is 200 ms or the length of the entire stimulus. This is in line with the expected fixation onset and duration according to the literature [24]. Moreover, this allows to avoid selecting too little information about the ongoing movement and useless information about the resting period. The procedure for the creation of the heat maps is divided in the following four main steps: synchronization, snapshot extraction, gaze mapping and heat map drawing. First, the eye tracking signal that is recorded at 100 Hz is synchronized with the video recording. Second, a video frame is captured as a reference snapshot. Depending on the subject, a delay between 0 and 150 ms is introduced to take into account different reactivity to the vocal stimulus. Third, for each 200 samples in the gaze time window, the corresponding frame is captured. Then, the 10 best matches between the two pictures are computed using ORB (Oriented FAST and Rotated BRIEF) features [25]. Afterwards, the homography matrix is computed through random sample consensus (RANSAC) and the coordinate system is changed accordingly. Last, the heat maps for the the new set of coordinates are computed with the Python library Heatmappy[4].

The results (Figure 3) highlight the usefulness of gaze tracking for object detection and they show that several neurocognitive parameters are fundamental for the detection of the proper object (and the part of it) to be grasped. First, the results on the 200ms time windows (determined via neurocognitive parameters, 3rd column) show that in most cases the gaze is focused on the object to be grasped, and in particular on the part of the object aimed to the specific movement. Gaze tracking is expected to be a useful parameter to improve the autonomy of prosthetic hands with object recognition. Second, the gaze time windows determined via neurocognitive parameters (3rd column) are more localized on the object to be grasped than the time windows covering the entire stimulus (2nd column). This highlights the importance of the gaze time window length as neurocognitive parameter for grasping. Third, it is possible to detect changes in the heat maps depending on the target object. For example, when the subjects were asked to grasp a mug or a bottle, the size and location of the red areas changed among subjects. Conversely, when they were asked to do a precision grasp (such as picking up the button, or the zip) the areas with the highest number of fixations (red areas) were always on the points where the subjects intended to put the fingers. Finally, gaze heat maps allow to extract the information concerning the areas in the environment that mostly captured the user attention during the ongoing grasp.

V. Conclusion

This article introduces a novel acquisition setup and acquisition protocol aimed at performing multimodal data recordings and fusion for robotic hand prosthesis control. A first set of data acquisitions is done and the data are analyzed. For testing such a setup it is better to use non-amputees, as for amputees there is an additional stress in doing such repetitive

[4] https://pypi.python.org/pypi/heatmappy/

movements and data from non-amputated persons is a good proxy for amputees, even though absolute results can differ.

The results highlight the usefulness of the novel acquisition setup and protocol and they motivate future analysis to integrate the proposed multimodal sensors into prosthesis control. The results show that sEMG, eye tracking and computer vision data provide information regarding the environment and regarding the intentions of the subject, laying the foundations for multimodal prostheses involving the three techniques.

sEMG movement classification confirms that it is possible to classify movements with sEMG data alone. sEMG object classification shows that not only the grasp type, but also small differences in the object to be grasped can be recognized via sEMG. This factor, together with the variety of items employed in the experiments and physiological factors, may influence the average classification accuracy in subjects. However, despite the low accuracy gained for a few of the subjects, the analyzed data are perfectly usable and the overall outcome is satisfactory.

The integration of eye tracking and scene camera data suggests that these sources of information can result in a significant aid for improving the robustness of current prosthetic hands. Moreover, the results highlight that several neurocognitive parameters must be considered for a proper sensor integration and data fusion.

In conclusion, the acquisition setup, protocol and analysis proposed in this paper are highly promising and encouraging for future work in order to improve the robustness of robotic hand prosthesis control. They will guide future data acquisition and data fusion on amputees.

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