User-Prosthesis Interface for Upper Limb Prosthesis Based on Object Classification

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***Abstract*—The complexity of User-Prosthesis Interfaces (UPIs) to control and select different grip modes and gestures of active upper-limb prostheses, as well as the issues presented by the use of electromyography (EMG), along with the long periods of training and adaptation influence amputees on stopping using the device. Moreover, development cost and challenging research makes the final product too expensive for the vast majority of transradial amputees and often leaves the amputee with an interface that does not satisfy his needs. Usually, EMG controlled multi grasping prosthesis are mapping the challenging detection of a specific contraction of a group of muscle to one type of grasping, limiting the number of possible grasps to the number of distinguishable muscular contraction. To reduce costs and to facilitate the interaction between the user and the system in a customized way, we propose a hybrid UPI based on object classification from images and EMG, integrated with a 3D printed upper-limb prosthesis, controlled by a smartphone application developed in Android. This approach allows easy updates of the system and lower cognitive effort required from the user, satisfying a trade-off between functionality and low cost. Therefore, the user can achieve endless predefined types of grips, gestures, and sequence of actions by taking pictures of the object to interact with, only using four muscle contractions to validate and actuate a suggested type of interaction. Experimental results showed great mechanical performances of the prosthesis when interacting with everyday life objects, and high accuracy and responsiveness of the controller and classifier.**

I. Introduction

The main difficulty that both high-end and affordable 3D printed multi-grasp prosthetic hands present to the end user is the way that they interpret the user intent. Some prostheses control the motion of the fingers through an on-off or proportional controller based only on electromyography (EMG) pattern recognition, which has issues towards clinical robustness such as electrode shifting, force variation, the position of the limb and transient changes in the signals [1]. Also, the required cognitive effort and the time spent on training to control EMG based prostheses do not guarantee that the amputees will reach full control of the device. This fact combined with the reduced functionality of low-cost solutions brings frustration to users and lead them to stop wearing the devices rapidly [1,2]. Furthermore, according to the last world reports on disabilities, there is a significant number of people with amputations that resides in developing countries without any possibility to acquire prosthetic care provided by public health entities. Not to mention the problematic acquisition of leading commercial upper-limb prostheses or even conventional ones because of their elevated prices [3,4]. Thereby, solutions based on 3D-printed technology are growing since they address problems of availability, high cost and offer an extended set of grasps and gestures [5]–[8]. Moreover, to better interpret the user's intent, some research projects had focused on developing multi-modal approaches to control upper-limb prosthetic hands [9]–[11].

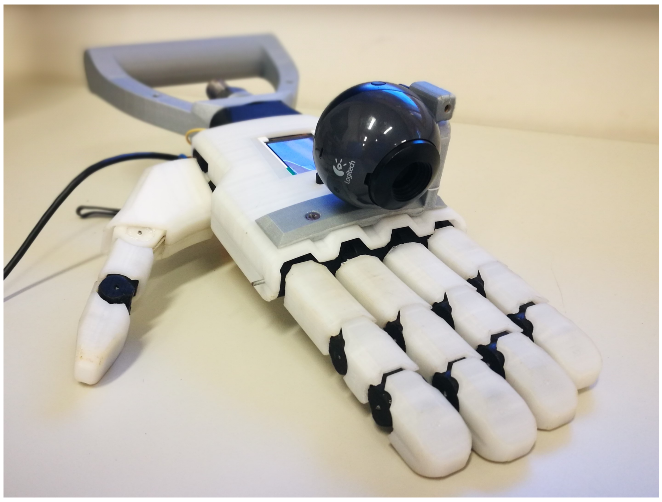

Fig. 1. Galileo Hand, 15 DOF under-actuated 3D-printed bionic version mounted with a webcam.

Based on this scenario, we integrated an original User-Prosthesis Interface (UPI) based on object classification from images with the Galileo Hand, which is an open-source, multi-grasping and anthropomorphic upper-limb prosthesis [7,12]. This integration not only increases the range of target users and allows a widespread distribution, but also reduces the cognitive load required from the users due its multi-modal approach. The UPI takes advantage of the EMG pattern recognition of the MYO Armband from Thalmic Labs – a well-known device developed to be used in gaming that has proven its viability as a replacement of the expensive EMG devices [13,14]. This way, the user can interact consciously with the system by using a predefined set of muscle contractions interpreted by a smartphone through an Android application. This application uses a pre-trained Convolution Neural Network (CNN) model implemented with TensorFlow. This network classifies images of everyday life objects and returns a label from pictures taken by a webcam, where this label serves as an entry to a database that suggests a predefined set of actions for the prosthesis.

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This approach allows achieving common types of grasping based on the Cutkosky grasp taxonomy and the Be-bionic hand [15,16] and more complex customized actions such as time-based actions. This user-friendly system allows flexibility when it is integrated into activities of daily living (ADLs), reducing the period of training, adaptation and cognitive effort required from the user [17].

This work is divided into V sections. This first section presented an introduction to the problems faced by amputees towards upper-limb prosthetic devices. An overview of the state of the art about the control of upper-limb prostheses is described in Section II. Methods involved in the design and integration of the UPI with the Galileo Hand are described in Section III. Experimental results and conclusions about the classification and functionality of the system are presented in Sections IV and V.

II. Related Work

Traditionally, research on upper-limb prosthesis control was focused on different techniques based on the preprocessing of EMG signals to analyze the user intent and to activate the prosthesis with a specific activation profile. Typical commercial hands use state machines activated by a single feature of a predefined subset of muscle activity, while the majority of sophisticated research hands are based on pattern recognition in a multi-modal approach. The multi-modal approach uses a set of EMG features combined with information from other types of sensors. This approach is used to address some of the well-known issues of EMG techniques, such as the limb position effect, that is solved using Inertial Measurement Units (IMUs) to improve the classification process associated with this issue [9,18]. Additionally, some multi-modal approaches implement combination of EMG and mechanomyography (MMG) features captured by a microphone (mMMG) and an accelerometer (aMMG) showing an increase in the classification accuracy [19]. Also, a new approach are taking advantage of the Optical Fiber Force Myography (FMG), as an affordable and more accurate alternative to the EMG [20].

Hybrid or multi-modal systems were also introduced to improve the user control of prosthetic devices. As an example, an EMG and Radio Frequency Identification (RFID) hybrid system uses RFID tags on specific objects to reduce the cognitive effort to operate a prosthesis [21]. In the same way, other systems have been experimented with the use of EMG hybrid control in different manners, such as voice-controlled approaches in a combination of graphical visual feedback through a touchscreen LCD, allowing the users to decide between different modalities to control their prosthetic device in a more flexible and friendly way [11]. Besides, there are several approaches for the use of Brain-Machine Interfaces (BMIs) as a means to control upper limb prostheses. The most recent work is based on high-density electrocorticography (ECoG), which allows the user to individually control the fingers naturally. Leaving aside its excellent and promising results, the use of ECoG is an invasive and expensive method that requires the implant of an ECoG array in the brain and a targeted muscle re-innervation (TMR) on a specific set of muscles. Both the implant of ECoG and TMR are challenging procedures to get for most of the amputees [14].

Other studies implemented a combination of BMI with other technologies, taking advantage of voice recognition, eye tracking, and some computer vision techniques. Nevertheless, the mentioned systems required high levels of concentration and training, entailing a massive cognitive effort from the user [22,23]. Computer vision approaches have also been proposed to control prosthetic devices, such as the one-shot learning method implemented to generate specific grasps for unknown objects. This method generalizes a single kinesthetically demonstrated grasp to generate many grasps of other objects of different and unfamiliar shapes" [24]. Meanwhile, another work proposed a hybrid control using augmented reality (AR) glasses with an integrated stereo-camera pair and an EMG interface for activation by detecting muscle activity. This system can automatically select the type of grasp using stereo-vision techniques while the users are allowed to adjust the grasp selection using the AR feedback, obtaining low effort control and significantly better results [25].

Finally, to increase the functionality of multi-grasping upper-limb prosthesis, some studies developed hybrid deep-learning artificial vision systems combined with EMG. Aiming to improve the way that the system interprets the user intent, the system associates a subset of objects to a specific kind of grasp based on the geometric properties of the object. The classification task is done through an object classifier implemented with a CNN in [26,27]. Following the line of artificial vision-based systems, the next section presents the details of the implementation of this work proposed interface.

III. System Architecture

The system is based on the interaction of four different devices: a smartphone, a webcam, the MYO armband and the Galileo Hand showed in Fig. 1. It interprets the user intent and controls a prosthetic device in a friendly way, allowing the user to associate an expendable list of 14 indexed predefined interactions (i.e., grasping and hand motion) with a vast list of objects in a customized way. The predefined interaction hand motions are described in [12]. The diagram showed in Fig. 2 proposes a flexible prosthesis controller, with the capability to provide customized hand postures that best suit the users lifestyle using commercial easy-to-acquire devices with a 3D-printed and open-source prosthesis.

Fig. 2. Block diagram showing the integration and interaction between the different devices of the system.

A. User-Prosthesis Interface

Because of the limitations of traditional activation profiles for upper limb prosthesis, the implementation of the UPI relies upon a hybrid methodology based on our previous work tested and validated with a prosthetic simulation using the V-REP robotic framework [12,28,29]. In this work, the EMG signals to interact with the prosthesis are the subset of muscular contractions $Q = \{q_0, q_1, q_2, q_3\}$ performed by the user, where q_0 to q_3 are defined as the contractions classified as fist, open hand, wave in (hand flexion) and wave out (hand extension) respectively. These contractions are classified directly from the residual limb of transradial amputees by the default EMG pattern recognition system from the MYO armband's firmware. The aim is to interact consciously with the system through a Finite State Machine (FSM) implemented on a smartphone through an Android App.

Therefore, the smartphone acts as a central device that interacts with the other devices in a transparently way, using the muscular contraction as the transition to navigate through the state machine, to take a picture and initiate, invalidate or cancel the proposed interaction suggestion. In the initial state S_0, the prosthesis stays in a natural rest posture while the UPI stays on idle until the user points the mounted camera towards the specific object with which he wishes to interact. Then the user performs the contraction q_0 to trigger a transition to the state S_1. In this state, the system takes pictures of the object that are classified by a CNN, until a valid label l is defined. A label's validity is obtained with the classification certainty reaching a heuristic threshold that consequently triggers the transition to change to the state S_2. If the process does not return a valid label, the UPI returns to the state S_0, upon a predefined timeout t. The FSM diagram of the implementation is shown in Fig. 3.

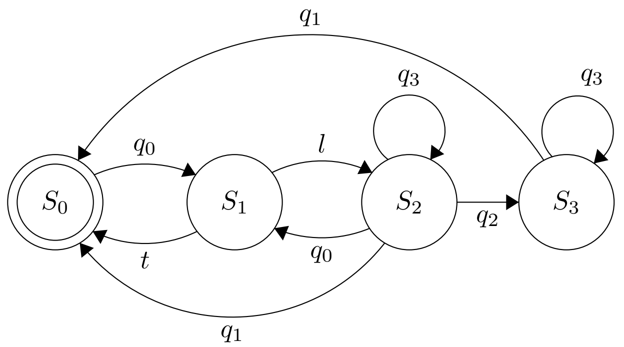

Fig. 3. Finite State Machine implementation of the User-Prosthesis Interface using the hybrid EMG Controller based on object classification.

A list of one thousand objects associated to labels is implemented as a dictionary where the most used type of grasp is linked with the highest probability value to be suggested to the user. Hence, in the state S_2 the result of the classification is presented by audio played on the smartphone with the name of the object, while the LCD mounted on the Galileo Hand presents an animation associated to the suggested type of grasp. The user can either accept the suggestion of the dictionary by performing the contraction q_2 and triggers the transition to the state or state S_3 or reject it by performing the contraction q_3. In this case, the system stays on state S_2 and suggests the next most appropriate grip. This way, the UPI adapts to the ADLs of the user in a customized way presenting flexibility to the user due to the successive proposals of the system that modifies the probability values on the dictionary. In case an object in the dictionary has never been detected, all the interaction suggestion are equiprobable, and their increasing interaction index will display the suggestion sequence. Then, in the state S_3, the prosthesis performs the accepted grip and release it by performing the contraction q_1. In exceptional cases such as in the mouse grip or the active index grip, secondary actions are triggered by performing the contraction q_3 [12,16].

B. Galileo Hand Prosthesis

Galileo Hand is an anthropomorphic and underactuated prosthetic hand intended to be released as an open-source project. The weight below $360g$ allows an affordable and highly functional prosthesis with a price about \$350, where mechanical parts (except for the motors) were designed to be manufactured using 3D printing technologies. The prosthesis is intrinsically-actuated, providing more flexibility and reaching a broader audience. Besides, the design has fifteen Degrees of Freedom (DOF) and six Degrees of Actuation (DOA). As the prosthesis is an under-actuated design, it performs the grasps with six miniature brushed DC gearmotors with an output torque around 60 oz-in. The Galileo Hand has one motor for the flexion and extension for each finger, plus one motor dedicated to the rotation of the thumb. However, it can achieve adaptive grasping to hold objects in the ADLs [7,30].

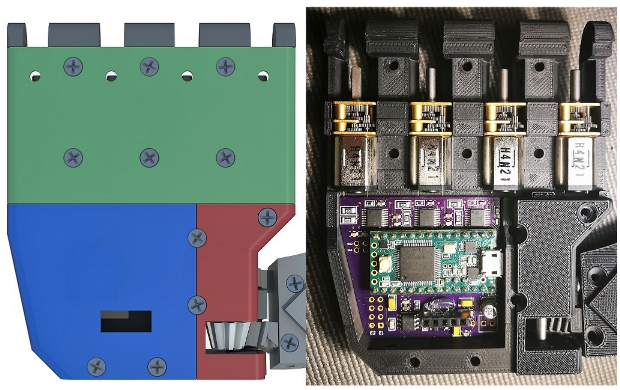

Fig. 4. Top view of modular palm sections, embedded controller and DC motors of the Galileo Hand.

The thumb was designed with 2 DOAs aiming to resemble the six movements of the thumb [31] while doing a trade-off between performance, space, and ease of printing. It has one actuator inside the thumb metacarpal phalanx an the other inside the palm at the base of the metacarpophalangeal joint. The later using an interesting beveloid gear pair shifting the axis of rotation 15 degrees, allowing it to perform a larger prismatic grasp [15]. A custom PCB board was designed to achieve a self-contained embedded controller to actuate the fingers that allow flexibility to be fitted in subjects with different amputation degrees, as shown in Fig. 4.

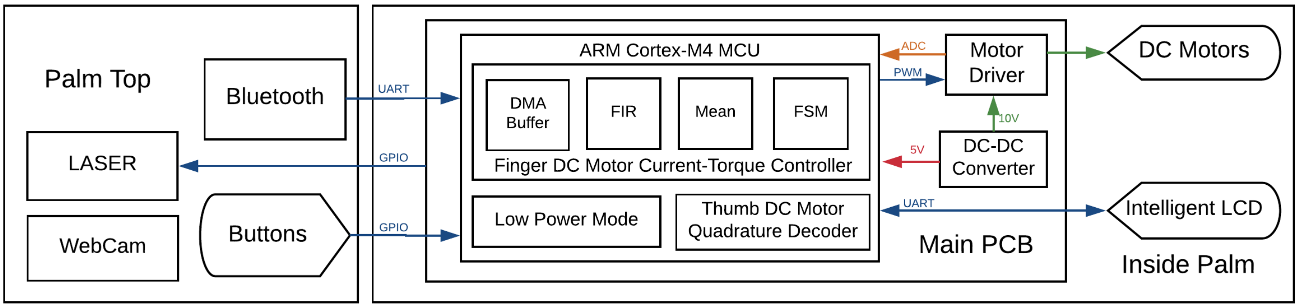

Fig. 5. System block diagram showing the embedded controller architecture of the Galileo Hand with its respective interfaces.

C. System Integration

Aiming to interact with the smartphone and fulfilling the requirements presented by the system shown in Fig. 2, the embedded controller of the Galileo Hand was slightly modified, and it is shown in Fig. 5. The addition of a Bluetooth v2.0 module was performed to establish a full-duplex communication between the devices by the use of messages under the JSON format. Hence, the processes implemented on the smartphone and the embedded system run in a concurrently way, allowing modularity and distributing the computational load in the UPI. This way, the embedded controller can administrate and execute the commands received from the smartphone easily and transparently. Also, a small low power laser was placed strategically, aiming to choose a proper pose to take a picture of the object that the user wishes to interact. Moreover, an intelligent LCD module (1.44" TFT LCD screen) from 4D systems is used to provide modularity through a simple communication protocol between the LCD and the embedded controller. The LCD screen allows visual feedback to the user by showing text and animations of the suggested grip as shown in the Fig. 6.

In addition, the finger motion controller implements the movement of flexion and extension through the measurement of the current, which is proportional to the torque generated by the DC motor, achieving adapting grasping when executing the flexion of each finger. However, to reach and perform more complex gestures and grips, a position controller implemented with a quadrature encoder was added for precise thumb rotation movements [7].

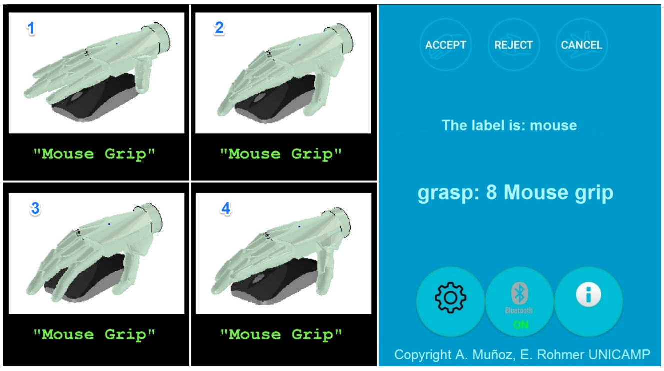

Fig. 6. Visual feedback presented to the user. Galileo Hand LCD on the left and smartphone screen on the right.

D. Object Classification

This module was implemented using TensorFlow under CNN techniques and integrated with the Android App to detect and classify objects from the pictures taken with the webcam. The model used in this work is based on the Inception architecture that improves the utilization of computing resources inside the network, such as power and memory use, ideal for mobile and embedded computing due to its efficiency, high accuracy, and responsiveness. The main idea of this architecture is to consider how readily available dense components can approximate a sparse structure [32]. Thereby, the implementation of the classification system is divided into two stages:

1) Off-line learning: The module was trained with millions of images taken from the ImageNet database, which comprises 100,000 images and about 1000 categories of objects. This database had to be adapted to the requirements of the system to reduce the ambiguity given from specific labels. Thus the size was reduced to 400 frequently used categories. The dataset was divided into: training (80 %), validation (10 %) and test (10 %). The module was trained and tested using different convolutional filters and stripe sizes to determine the best network configuration.

2) On-line learning: The object classifier is embedded in the Android App, which also takes a picture, sorts the objects recognized and then generates a score for each one. This score is the probability that the object is present in the image. Therefore, the system generates a label associated with the object that has the highest score of probability. Once a valid label is obtained from the module, the system suggests a specific grip according to its probability of use, as mentioned in the subsection A.

IV. Results

To validate and test the functionality of the proposed UPI integrated with the prosthetic hand, six classes of everyday life objects were chosen as follows: mouse, banana, coffee mug, wallet, bottle, and ballpoint. A healthy subject tested the system. He interacted with the objects by performing four basic grips defined in the Cutkosky's taxonomy: Power, hook, precision and lateral grasps [15]. Examples of the satisfactory performing of these prehensile are shown in Fig. 7. However, some of the objects need to be placed in a specific place to be grabbed by the prosthesis.

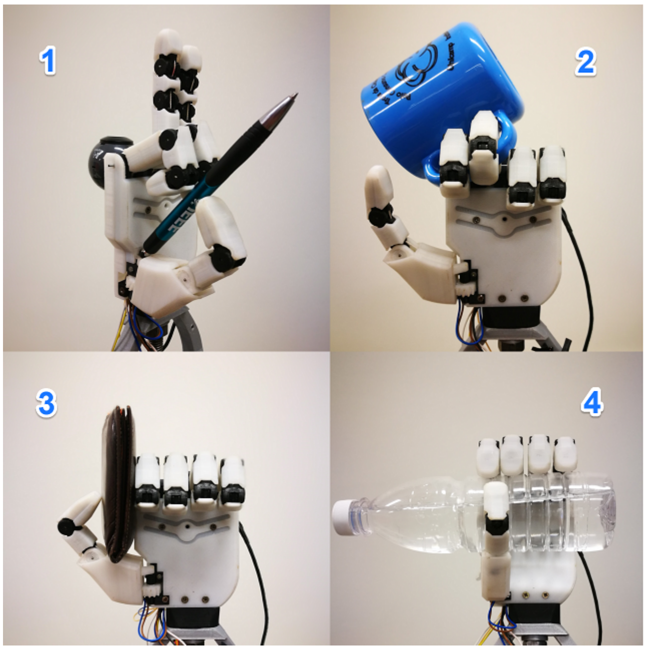

Fig. 7. Grips performed on the test. (1) Precision grasp. (2) Hook grasp. (3) Lateral grasp. (4) Power grasp.

The object classifier was trained up to 4000 epochs obtaining 92.66% of accuracy with the training dataset. It was validated with 400 epochs and obtained an accuracy of 89.60% with the validation dataset. Fig. 8 shows the cross-entropy loss of the training and validation processes. The blue data represents the training process, and the red data represents the validation process. This measure gives feedback about the performance of our classification model before being tested in a real scenario. The results showed in Fig. 9 were obtained from the classification of the everyday life objects. During the tests, five different objects from the same class were chosen and presented to the user randomly. The weight of the prosthesis terminal end device has remained below $450\ g$, not taking into account the socket and the battery. The estimated cost is around \$450, including 3D printing materials, electronic components, mechanical materials and the webcam.

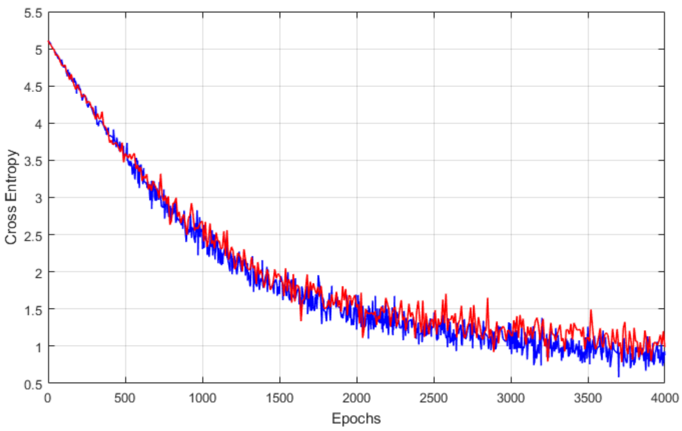

Fig. 8. The cross-entropy error of the training and validation set in blue and red respectively.

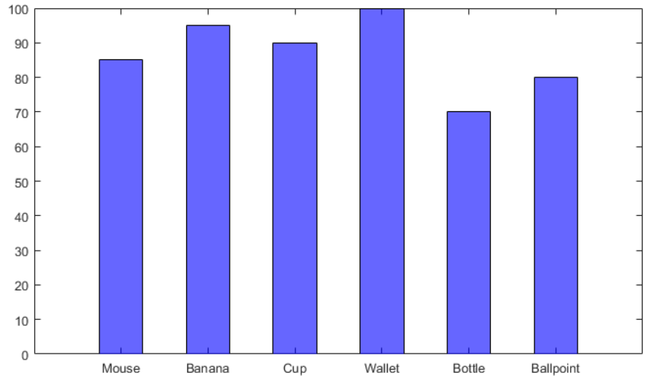

Fig. 9. Classification accuracy rating of a subset of everyday life objects.

V. Conclusions

This work showed that the UPI proposed has advantages over traditional systems since its flexible and user-friendly interface increases the number of customized hand postures that can be performed. The results obtained testing the different hand prehensile were successful and experimentally validated as shown in Fig. 7 and in our previous work [7]. The user did not present any problems to interact with the objects chosen for the test, except for the ballpoint where the object had to be placed on a specific place and in a specific pose in order to be grabbed. Also, it is challenging to keep that particular object in hand due to the slipping present in this type of objects. These results are very satisfactory compared with the results research and commercial prosthesis presented in [5,7,33]–[35].

However, a user with transradial disarticulation does not need to perform complex tasks with his prosthetic device since he will use his healthy hand to develop this kind of tasks. Regarding the everyday life object classification, the lowest rate was obtained by the interaction with the bottle achieving 70%, while the highest one was obtained by the interaction with the wallet that reached 100%. This result is explained by the ambiguity created by the vast amount of object classes used to train the model, which usually helps to achieve a better generalization about the classification process. Finally, we achieved a flexible UPI were the user can associate the grasp for every classified object in a customized way, allowing to grab the objects in different ways because of its ability to update the scores of the most used prehensile through the implementation of the dictionary. Detailed experimentation of the performance and the cognitive effort that the user has to perform will be validated on future work.

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