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Investigating Upper Limb Movement Classification on Users with Tetraplegia as a Possible Neuroprosthesis Interface

Lucas Fonseca¹, Antônio Bó², David Guiraud³, Benjamin Navarro⁴, Anthony Gélis⁵, Christine Azevedo-Coste³

Abstract—Spinal cord injury (SCI), stroke and other nervous system conditions can result in partial or total paralysis of individual’s limbs. Numerous technologies have been proposed to assist neurorehabilitation or movement restoration, e.g. robotics or neuroprosthesis. However, individuals with tetraplegia often find difficult to pilot these devices. We developed a system based on a single inertial measurement unit located on the upper limb that is able to classify performed movements using principal component analysis. We analyzed three calibration algorithms: unsupervised learning, supervised learning and adaptive learning. Eight participants with tetraplegia (C4-C7) piloted three different postures in a robotic hand. We achieved 89% accuracy using the supervised learning algorithm. Through offline simulation, we found accuracies of 76% on the unsupervised learning, and 88% on the adaptive one.

I. INTRODUCTION

Diseases and lesions of the nervous system can have dramatic consequences for patients. Cases like stroke or spinal cord injury (SCI) can cause partial or complete paralysis of limbs. In the worst cases, individuals lose not only lower limbs motor capabilities, usually relying on a wheelchair for locomotion, but also upper limb motion [7].

Numerous technologies have been proposed as solutions for upper limbs disabilities, such as functional electrical stimulation (FES) [2], and robotic devices [1]. However users with tetraplegia often face challenges on controlling these devices. Relative success has been achieved by either simple interfaces [4] or invasive brain-computer interfaces [12]. Whenever the user still has some controllable upper limb motor capability, it is possible to use that to control a device [6]. The challenge is then to identify the intended movement performed by the user. Electromyography (EMG) has been considered [6], [11], however muscular activity-based control presents some issues like the need for one sensor per muscle. Also, the presence of co-contraction

makes it difficult to contract individual muscles and, when FES is present, the stimulation artifacts in the EMG signal have to be considered. Instead of muscle activity, movements can be used as inputs. In [9], postures performed by healthy subjects were classified using a method based on Linear Discriminant Analysis and 2 9-DOF (degrees of freedom) inertial measurement units (IMUs). Additionally, [5] used multiple IMUs and a radial basis function network based regression algorithm to control an elbow prosthesis with residual upper limb movement on amputees. Recently, on [10], three subjects with tetraplegia controlled a powered wheelchair using residual shoulder movement. The method in [10] is based on Principal Component Analysis (PCA) and 4 IMUs.

In this work we propose a system capable of associating shoulder movements to three commands on a robotic hand. It is based on a single IMU with only accelerometer and gyroscope. For that, we developed three classifiers based on PCA. Eight subjects with tetraplegia piloted the robotic hand postures with one classifier, and the other two were later evaluated through simulation.

II. SUBJECTS AND METHODS

Eight patients with tetraplegia were selected at Propara Neurological Rehabilitation Center in Montpellier, France. They had SCI levels C4-C7, American Spinal Injury Association impairment scale A or B and stable medical condition. They were males between 18 and 65 (39 ± 15) years old, and had lesion chronicity higher than 6 months (14 ± 17 years). The protocol was approved by a national ethical committee (CPP 2016-A00711-50) and subjects provided informed consent prior to their participation. They had limited hand movement, but could perform controlled shoulder movement.

For validation purposes we used the Shadow Dexterous Hand (Shadow Robot Company, London, UK), a robotic hand that can reproduce human movements with great fidelity. We set up two different postures on it: in **opened** position (fingers fully extended); and in **closed** position (fingers fully flexed) in a grasping attitude. We also configured a **rest** position (semi-flexed fingers).

One IMU (Hikob© Fox, Villeurbanne, France) was positioned either on the subject’s upper arm or shoulder depending on their ability to execute two distinct movements in a

¹PhD Candidate at LARA, University of Brasília, Brazil. Invited researcher at INRIA, Université de Montpellier, Montpellier, France. Email: lucasfonseca@lara.unb.br

²LARA, University of Brasília, Brazil.

³INRIA/Université de Montpellier, Montpellier, France.

⁴Université de Montpellier, LIRMM, Montpellier, France.

⁵PROPORA clinical center, Montpellier, France.

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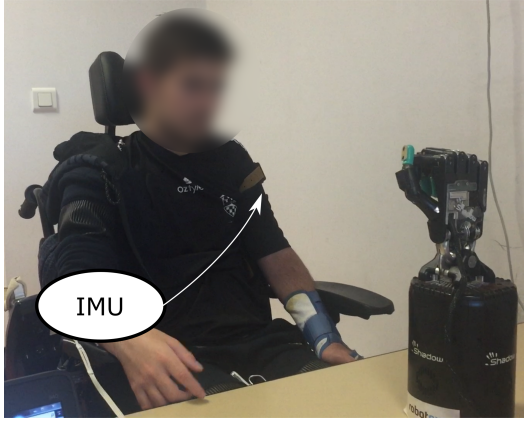


Figure 1. Experimental set-up.

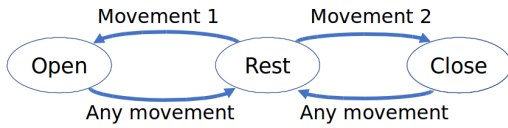


Figure 2. Finite state machine used to control the robotic hand depending on the classified movement performed.

reproducible manner. The IMU communicated wirelessly with a computer at approximately 50 Hz. It sent 3-axis accelerometer and 3-axis gyroscope data. No magnetometer was used in order to simulate a scenario where low processing power and power consumption are issues, e.g. if it were implanted.

Subjects faced the robotic hand so they could see it react to their movements. The set-up is illustrated on Fig. 1, where the robotic hand is in the closed position.

Two movements were calibrated and associated to two commands to control the robotic hand. Since there are three different positions to be controlled by two movements, the finite state machine depicted on Fig. 2 was employed. Each command had to correctly classify the user's movement to activate the desired posture - robotic hand opened or closed - from the rest position. When in one of these two postures, any movement triggered the rest position.

The experimental protocol consisted of a calibration and a validation phase. On the calibration phase, we asked users to repeatedly perform up to four movements during 10 seconds each. These could be any repeatable and distinct movement, like moving the shoulder up or forward, and returning it to the initial position. On the validation phase we asked them to pilot the robotic hand. Each posture was comprised of two movements: one starting on the rest position, which had to be correctly classified by the system, and one back to the rest position, which had only to be detected, but not classified (see Fig. 2). Each of the two postures (open/close) was executed 5 times in a random order following our instructions.

We developed three algorithms: unsupervised learning, supervised learning, and unsupervised adaptive learning. The **unsupervised learning** algorithm collected data from the IMU during the calibration phase and derived it to remove

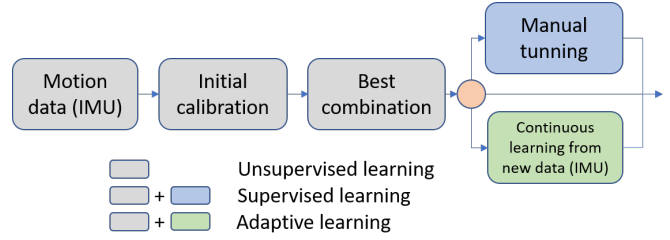


Figure 3. Learning processes block diagram.

the steady state component and to ignore initial angular positions. Thresholds were then calculated according to Eq. 1.

$$T = \frac{\max\left(\frac{dX}{dt}\right)}{2} \quad (1)$$

where vector X features the raw sensor measurements and vector T is the threshold vector. An overlaying moving window of 1 second was defined. Whenever its center value was greater than a threshold, a movement was detected and characterized as a 6-dimension point based on the Root Mean Square (RMS) of each of the 6 axis. A PCA is then applied to these points and the two first principal components are used to find two movement centroids based on the mean 2-dimensions coordinates of all points. After that the system calculates the centroids and points on all possible combination of two movements. It then proposes the best combination based on the highest score s , defined by Eq. 2.

$$s = \frac{d_{1,2}}{\sigma_1 + \sigma_2} \quad (2)$$

where $d_{1,2}$ is the distance between the two centroids, and σ_i is the standard deviation of the distance of all points of movement i to that movement centroid.

After calibration, the system could start classifying new movements associating the new PCA calculated 2-dimensional point to the closest centroid, and activating the appropriate robotic hand command.

On the **supervised learning** algorithm the user performed the previously calibrated movements and watched the robotic hand reaction. We then observed the PCA graphical representations of these points in real time. If the new points seemed to appear far from the initially calibrated ones, we recalibrated the system with them, and without the old ones. It was also possible to arbitrarily choose each centroid location on the 2-dimensional space. With these tools we were able to manually tune the learning process until the users felt they had good control over the robotic hand.

On the **adaptive learning** algorithm, this process of improving the calibration is automated. After every new movement during the validation phase, the system is recalibrated using the new point, removing the oldest one.

Note that, differently from the supervised learning system, the other two are completely automatic. The three systems are summarized in Fig. 3. Users performed the experiments with the supervised learning algorithm. All data was recorded to later simulate the two other algorithms.

Table I
MEAN PERFORMANCE RESULT ON THE RANDOM 10 MOVEMENTS SEQUENCE TEST. THE SUPERVISED LEARNING SYSTEM SCORES WERE OBTAINED FROM TESTS WITH THE SUBJECTS, WHILE THE OTHER TWO WERE SIMULATED.

Subject	Performance [%]		
	Supervised	Unsupervised	Adaptive
p1	90	70	60
p2	100	100	100
p3	90	50	90
p4	70	70	70
p5	100	60	100
p6	70	70	80
p7	90	90	100
p8	100	100	100
Average	89	76	88

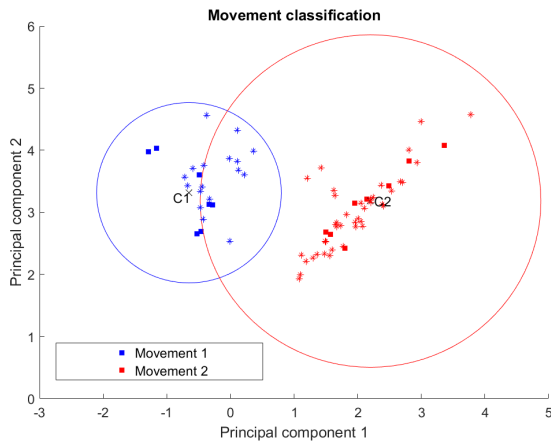


Figure 4. Supervised learning and classification for subject p8. The two axis represent the two principal components. Squares represent the movements used for learning and the asterisks the movements classified by the system. C1 and C2 are the centroids for movements 1 and 2, respectively. The circles, for visualization purposes only, represent three standard deviations of the euclidean distance of the squares to their centroids.

III. RESULTS

The average performance achieved experimentally with the supervised algorithm and through simulation with the other two is shown on Table I. Results were calculated as the percentage of correctly classified commands. Note how the unsupervised had inferior results (76%) when compared to the supervised (89%) and adaptive (88%). Additionally, the adaptive learning algorithm would have the best performance were it not for patient p1.

After the initial calibration phase, it was possible to analyze its results on a graphic that represents the two main components of the PCA. Fig. 4 shows an example of one experiment.

The adaptive learning algorithm was simulated with points from the validation phase. Fig 5 shows the performance obtained along all steps of the learning process. Note how the performance seems to further improve after the seventh point.

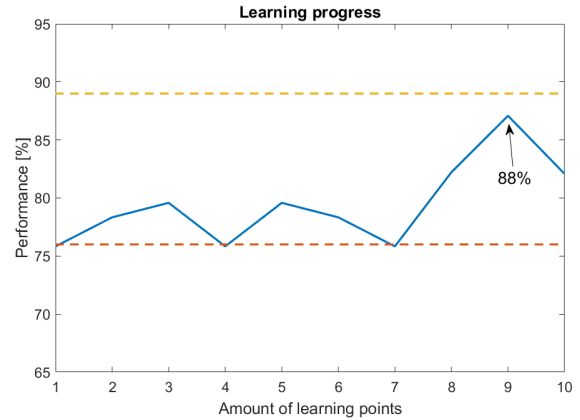


Figure 5. Adaptive learning algorithm process. The average best result was achieved when learning from 9 points. For comparison purposes, the red dashed line indicate the unsupervised learning system performance, and the yellow dashed line represent the supervised learning system performance.

IV. DISCUSSION

We developed a system capable of classifying two shoulder movements performed by persons with tetraplegia with 89% accuracy. Even though the performance achieved by [9] (96%) was greater, tests were done only on able-bodied subjects. Both [8] and [3] used multiple IMUs and EMG, with many more features than this work, to classify upper limb movement with LDA, the latter achieving results close to 80% on a 6 classes scenario. It is expected users with tetraplegia to have lower dexterity than healthy subjects, but our results indicate that, given more training for both users and system, better results are achievable. Furthermore, in comparison to the EMG approach, our system is capable of classifying multiple movements with a single IMU.

During the calibration phase, graphical visualizations as presented on Fig. 4 helped to assess the supervision process and manually tune the calibration. This, therefore, was a subjective process. Still, we were able to tune the system so the supervised learning algorithm presented the best results, while the unsupervised learning method presented the worst, highlighting the importance of the supervision on learning tasks with low informations level.

It was clear the difference in subject attitude and performance between the calibration (no feedback) and the validation (visual feedback from the robotic hand) phases. It was not unusual for them to change the movements then. When that happened, if no supervision was allowed, we would see results as the one shown on Fig. 6. That explains some of the bad performances, as subject p5's on the unsupervised algorithm. Nevertheless, these are also the cases when the adaptive learning performs best because it is capable of forgetting those initial trials and “focus” only on the recent ones. Note how p5's performance improves both on the supervised and adaptive algorithms. Were the adaptive algorithm working on real time, we expect its performance would improve in a similar manner as depicted on Fig. 5. Still, visual feedback representing a deeper functioning of

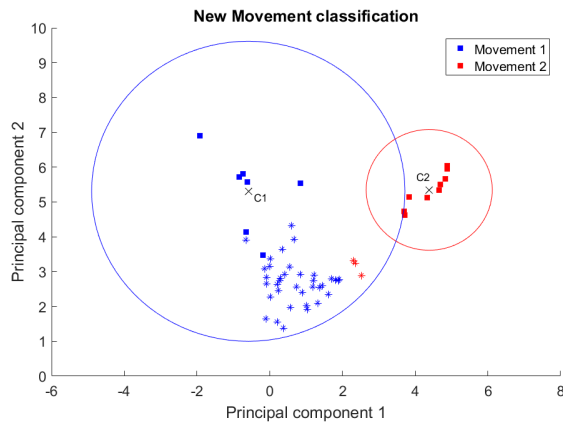


Figure 6. Unsupervised learning system test for subject p5. Note how almost all movements were classified as Movement 1, and they were significantly different than those initially calibrated (square points).

the system and user's performance may be beneficial [10].

Observing Fig. 5, we can see the performance only improves after many new points are considered for learning. It possibly happens because the system still recalls the original, outdated points. As soon as the new points become a majority, their cumulative weight overcomes the old ones. It is also important to note that the adaptive learning system is fully automated, which can be an advantage on real world scenarios, when a user would possibly calibrate and operate it without specialized assistance. Since only the supervised learning system was tested by the subjects, and not the adaptive, such scenarios are yet to be evaluated.

Although no subject had cognitive impairments, some of them presented difficulties on operating the system. Most of them had never seen a robotic hand, and none was ever able to control one. In deed, novel technologies and control interfaces may initially be hard to use [10]. As a result, sometimes they lost focus on the task, and performed careless movements. That was particularly true for subject p6. Once again, in this case, we can see a slight improvement when using the adaptive learning system, highlighting the importance of the algorithm adaptability, either supervised or not.

In a larger clinical trial, our system should be adapted to control a more functional neuroprosthesis, e.g. FES on forearm to control grasping. The current finite state machine requires every posture to return to the rest position before performing a new one, which was useful for the algorithm evaluation, but is not practical. In addition, triggering the predefined movements works well for complex tasks as grasping, but lacks fine control like proportional force or hand opening range. This, too, could be addressed with residual shoulder movement [10], and could even be integrated in a larger finite state machine. Nevertheless, the simple setup of a single commercial IMU and flexible, quick learning algorithm provide easy adaptation and scalability.

V. CONCLUSION

Complex neuroprosthesis can be controlled by residual movement in users with tetraplegia. We developed a system capable of classifying different shoulder movements using a single wireless IMU with only accelerometer and gyroscope. We found that results close to 90% could be achieved either by a supervised system or by an unsupervised adaptive system with minimum user training. Regardless of the approach, the calibration process is simple and fast. To the extend of our knowledge, this is the first work to perform movement classification experiments where subjects with tetraplegia controlled a robotic hand. Future works include longer training and sessions with functional daily life activities.

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