The Ninapro Database: a Resource for sEMG Naturally Controlled Robotic Hand Prosthetics*

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Abstract— **The dexterous natural control of robotic prosthetic hands with non-invasive techniques is still a challenge: surface electromyography gives some control capabilities but these are limited, often not natural and require long training times; the application of pattern recognition techniques recently started to be applied in practice. While results in the scientific literature are promising they have to be improved to reach the real needs. The Ninapro database aims to improve the field of naturally controlled robotic hand prosthetics by permitting to worldwide research groups to develop and test movement recognition and force control algorithms on a benchmark database. Currently, the Ninapro database includes data from 67 intact subjects and 11 amputated subject performing approximately 50 different movements. The data are aimed at permitting the study of the relationships between surface electromyography, kinematics and dynamics. The Ninapro acquisition protocol was created in order to be easy to be reproduced. Currently, the number of datasets included in the database is increasing thanks to the collaboration of several research groups.**

I. Introduction

The dexterous natural control of robotic prosthetic hands with non-invasive techniques is a challenge that can strongly increase the quality of life of amputated people.

Nowadays hand amputated subjects can rely on surface electromyography (sEMG) prostheses. In most cases the movements that the prosthesis can perform are limited to opening and closing but in recent years the top-level commercial offers started to include mechanically advanced prostheses that can perform several programmable movements relying on specific control strategies (e.g. sequential control strategies).

The use of pattern recognition techniques recently started to be applied in practice[1]. This kind of approach has been described several times in the scientific literature (e.g. [1]–[4]). Usually several electrodes record sEMG activity on the remaining arm of the subject while pattern recognition algorithms are used to classify the movement that the subject aims to perform. The average classification accuracy results are usually below 80-90% [1], while the highest ones can reach up to 90% on approximately 10 movements [2], [3].

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[1]http://www.coaptengineering.com/

Despite the excellent results described in literature, this field can still be improved in several ways. First, most of the studies include few subjects (according to our knowledge up to 11 intact and 6 hand amputated subjects [5]) and few movements (according to our knowledge up to 12 [6]), that make it difficult to obtain statistically relevant results. Second, it is not clear how clinical and experimental parameters related to the amputation and physiological phenomena can affect the natural control capability of the prosthesis. Finally, the movement recognition accuracy is never high enough to avoid misclassification on a high number of movements, which is the ideal result for real-life applications. Moreover, usually the data collections are not publicly available, thus different analysis methods cannot be compared quantitatively. In contrast with this situation, the usefulness of publicly available databases and benchmarking protocols was demonstrated repeatedly in several fields [7], [8], where it permitted to compare different methods and to push scientific progress.

In this work we describe the Ninapro (Non Invasive Adaptive Prosthetics) database, which includes data acquired from 67 intact subjects and 11 hand amputated subjects while repeating several times approximately 50 hand movements. The data are aimed to study the relationships between sEMG, hand kinematics, dynamics and clinical parameters. The data are publicly available to worldwide research groups, with the final goal of fostering the creation of non-invasive, naturally controlled, robotic hand prostheses for trans-radial hand amputated subjects. The number of subjects is high in comparison to other datasets described in the field, especially considering the difficulty of recruiting trans-radial amputated subjects and considering that intact subjects can be used as a "proxy" measure for amputated subjects [9]. In this work we also summarize the results of several analyses and technical validations that have been performed on it and the ongoing improvements of the Ninapro project.

II. Methods

A. Acquisition Setup

The Ninapro acquisition setup includes several sensors, aimed to record hand kinematics, dynamics and correspondent muscular activity. These sensors are connected to the laptop responsible for data acquisition.

The data are divided into three databases with slightly different sensor combinations.

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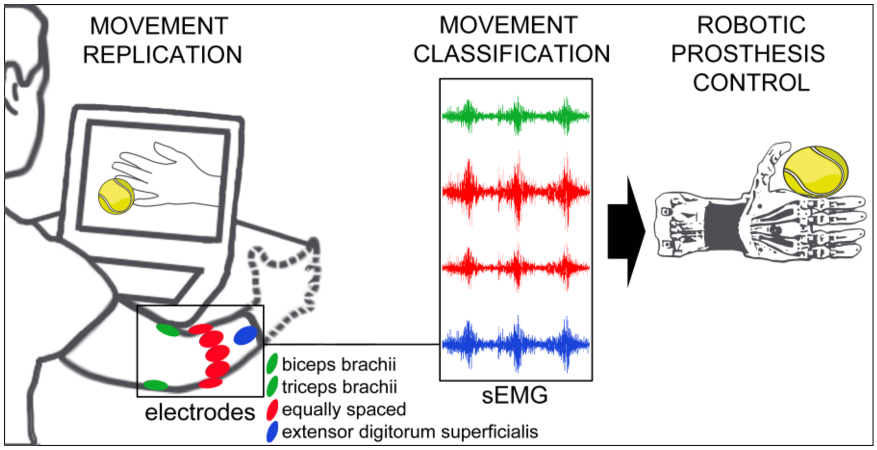
Figure 1 The Ninapro acquisition protocol [22].



Hand kinematics is measured using a 22-sensor CyberGlove II data-glove[2], which detects hand movements through high-accuracy angle measurements.

A 2-axis Kübler IS40 inclinometer[3] is fixed on the wrist of the subject to measure the orientation of the wrist with a range of 120° and a resolution of less than 0.15°.

Hand dynamics is measured using a Finger-Force Linear Sensor (FFLS) [10], which uses strain gage force sensors to measure forces exerted by the fingers, including the adduction and abduction forces of the thumb.

Muscular activity is measured using two configurations of double differential sEMG electrodes. The first one consists of ten OttoBock MyoBock 13E200-50[4], which provide a pre-processed, rectified version of the raw sEMG signal. These electrodes are already widely used in prosthetics, and they use frequency shielding and filtering technologies in order to avoid low and high frequency interferences.

The second combination of electrodes is a Delsys Trigno Wireless System[5], which is made of a base station and 12 wireless sEMG electrodes. These electrodes sample the raw sEMG signal at a rate of 2 kHz with a baseline noise of less than 750 nV RMS and integrate a 3-axes accelerometer sampled at 148 Hz.

The electrodes are positioned combining two methods which are common in the field, i.e. a dense sampling approach[6], [11], [12] and a precise anatomical positioning strategy [13], [14]. As shown in Figure 1: eight electrodes are equally spaced around the forearm at the height of the radio humeral joint; two electrodes are placed on the main activity spots of the flexor digitorum superficialis and of the extensor digitorum superficialis [15]; for the Delsys electrodes only, two electrodes are placed on the main activity spots of the biceps brachii and of the triceps brachii.

[2] CyberGlove Systems LLC; http://www.cyberglovesystems.com/
[3] Fritz Kübler GmbH, http://www.kuebler.com/
[4] Otto Bock HealthCare GmbH, http://www.ottobock.com/
[5] Delsys Inc., http://www.delsys.com/products/wireless-emg/

B. Acquisition Protocol

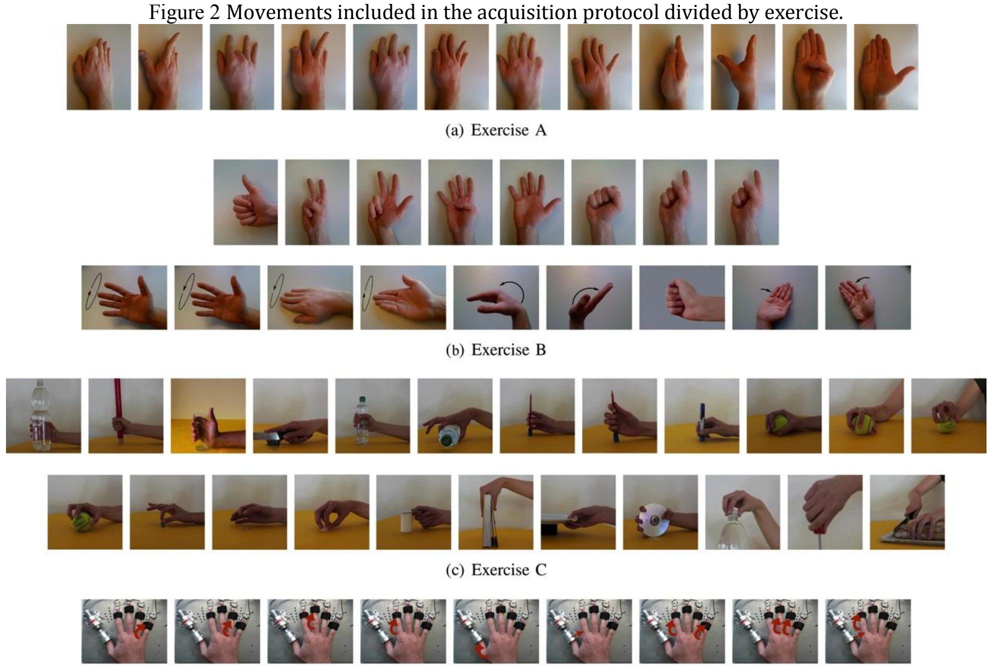
The subjects give informed consent and clinical information also regarding the amputation [16]. The experiment is divided into one training part and three exercises addressing different types of movements (Figure 2), interrupted by rest time in order to avoid muscular fatigue. During the acquisitions, subjects sit at a desk resting their arm comfortably on the desktop. A laptop in front of the subject provides visual stimuli for each movement while at the same time recording data from the measurement devices. The details of the acquisition procedure depend on the nature of the acquisition (kinematic or dynamic). During kinematic acquisitions (Figure 2, exercise A, B, C), the intact subjects are asked to mimic movies of movement shown on the screen of the laptop with their right hand, while amputated subjects are asked to mimic the same movements with the missing limb as naturally as possible (Figure 1). The set of movements is selected from the hand taxonomy, robotics, and rehabilitation literature [17]–[20]. Each movement repetition lasts 5s, and it is alternated with a rest posture lasting 3s. The sequence of movements is not randomized in order to encourage the subjects to perform the movements as naturally as possible.

During dynamic acquisitions, the subjects repeat several times nine force patterns (Figure 2, exercise D) by pressing with one or more hand digits on the device. An initial calibration phase is performed to establish the rest and maximal voluntary contraction force levels for all fingers and training is performed before each force pattern. The force levels requested for each finger are represented as coloured bars on the screen.

C. Signal Processing

Signal processing steps include synchronization, relabeling (to realign the movement label with the real movement boundaries [21]) and (for the Delsys electrodes) filtering from power-line interference (using a 50 Hz and harmonics Hampel filter [21]). Original labels are included in the released files, while raw data are available upon request.

Figure 2 Movements included in the acquisition protocol divided by exercise.



(a) Exercise A

(b) Exercise B

(c) Exercise C

(d) Exercise D

III. RESULTS

Ninapro is currently the repository with the highest number of intact and hand amputated subjects in the field. It includes data from 78 subjects (67 intact subjects, 11 trans radial amputated subjects) divided into three databases. The first database contains data acquisitions from 27 intact subjects (20 males, 7 females; 25 right handed, 2 left handed; age 28 ± 3.4 years). The second database contains data acquisitions from 40 intact subjects (28 males, 12 females; 34 right handed, 6 left handed; age 29.9 ± 3.9 years). The third database contains data acquisitions from 11 trans-radial amputated subjects (11 males; 10 right handed, 1 left handed; age 42.36 ± 11.96 years). The experiment was conducted according to the principles expressed in the Declaration of Helsinki. It was approved by the Ethics Commission of the state of Valais (Switzerland), and all participants signed an informed consent form.

The evaluation of the effect of experimental conditions on the amplitude of the signals [22] shows that there are not significant differences considering movement repetitions, while there are significant differences considering different subjects and movements. This makes sense because different subjects are characterized by different anatomical characteristics and because different movements involve the use of different muscles, thus leading to different sEMG and kinematic amplitudes. In previous papers [15], [22], [23], we evaluated the database using several state of the art classification methods and signal features using pattern recognition-based methods [24]. These results enforce the possibility to use the Ninapro data for movement recognition analysis in hand amputated subjects, in order to improve the field of robotic hand prostheses, and they can also offer a baseline for future studies on the Ninapro repository.

The Ninapro acquisition protocol was planned in order to be easy to be reproduced, thus in order to foster new data acquisitions by other research groups. Currently, the number and the variety of datasets in the database is increasing thanks to the collaboration of several research groups.

IV. CONCLUSIONS

This paper describes the NINAPRO database, which aims at forming a standard benchmarking resource for the biorobotics community. At the moment of writing it is the only publicly available database relating sEMG to hand movements, it contains a much larger number of subjects and of hand movements in comparison to related work. The dataset consists of muscular activity gathered in controlled conditions using double differential sEMG electrodes, kinematic and dynamic data. So far data are available for 67 intact subjects and 11 amputated subjects performing several repetitions of approximately 50 hand, wrist, and forearm movements. The database showed low dependence on experimental conditions and movement classification capabilities comparable to previous literature, proving to be a proper resource for the scientific community. The Ninapro acquisition protocol was created in order to be easy to be reproduced. Currently, the number of datasets in the database is increasing thanks to the collaboration of several research groups. Hopefully, this will continue and will help to improve the knowledge of the effect of different clinical and experimental parameters too.

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