Clinical, anatomical and external factors to improve dexterous robotic hand prostheses.

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Summary

1. Hand prostheses can be controlled in many movements with surface electromyography (sEMG).
2. The natural & robust control of robotic prosthetic hands with sEMG techniques is still a challenge.
3. Recently, a publicly available database database for sEMG analysis was released.
4. The studies on the Ninapro data base show that:
   - Several subject characteristics can influence sEMG control with machine learning methods.
   - External factors and additional data sources can influence myoelectric prosthesis control.
5. A proper integration between medical procedures (finalized to better exploit clinical subject characteristics) and multimodal data analysis can improve current prosthesis performance, leading to better performing naturally controlled robotic hands.

Introduction

sEMG hand prosthetics state of the art

Pros:
- Mechanically advanced hands
- Rotating thumb and wrist
- Up to 36 programmed movements

Cons:
- Rudimentary control systems
- 2 sEMG electrodes (open/close)
- Sequential control strategies
- Long training times

First commercial pattern recognition system in 2014 *(http://www.coaptengineering.com/)*

Figure 1: Example of a modern prosthesis with high mechanical functionalities. The Touch-Bionics i-limb ultra

sEMG scientific research state of the art

Many advancements have been achieved in recent years:
- Multi-electrode sEMG and machine learning can be used to understand the movements that amputees are aiming to do.
- Regression-based techniques allow a more flexible and fluid proportional control of movements.
- Targeted muscle reinnervation (TMR) redirects the nerves that used to control the muscles to innervate accessory muscles from which surface sEMG can be recorded.

However, several steps are required to obtain robust, naturally controlled robotic hand prostheses.

Subject characteristics that can influence sEMG prosthesis control

Analyzed in very few studies. They include:
- Anatomical characteristics
- Use of myoelectric prosthesis
- Fatigue
- Sweating

Other factors that can influence sEMG prosthesis control

- Electrode positioning
- Arm positioning
- Additional data sources (e.g. accelerometers, computer vision, data)

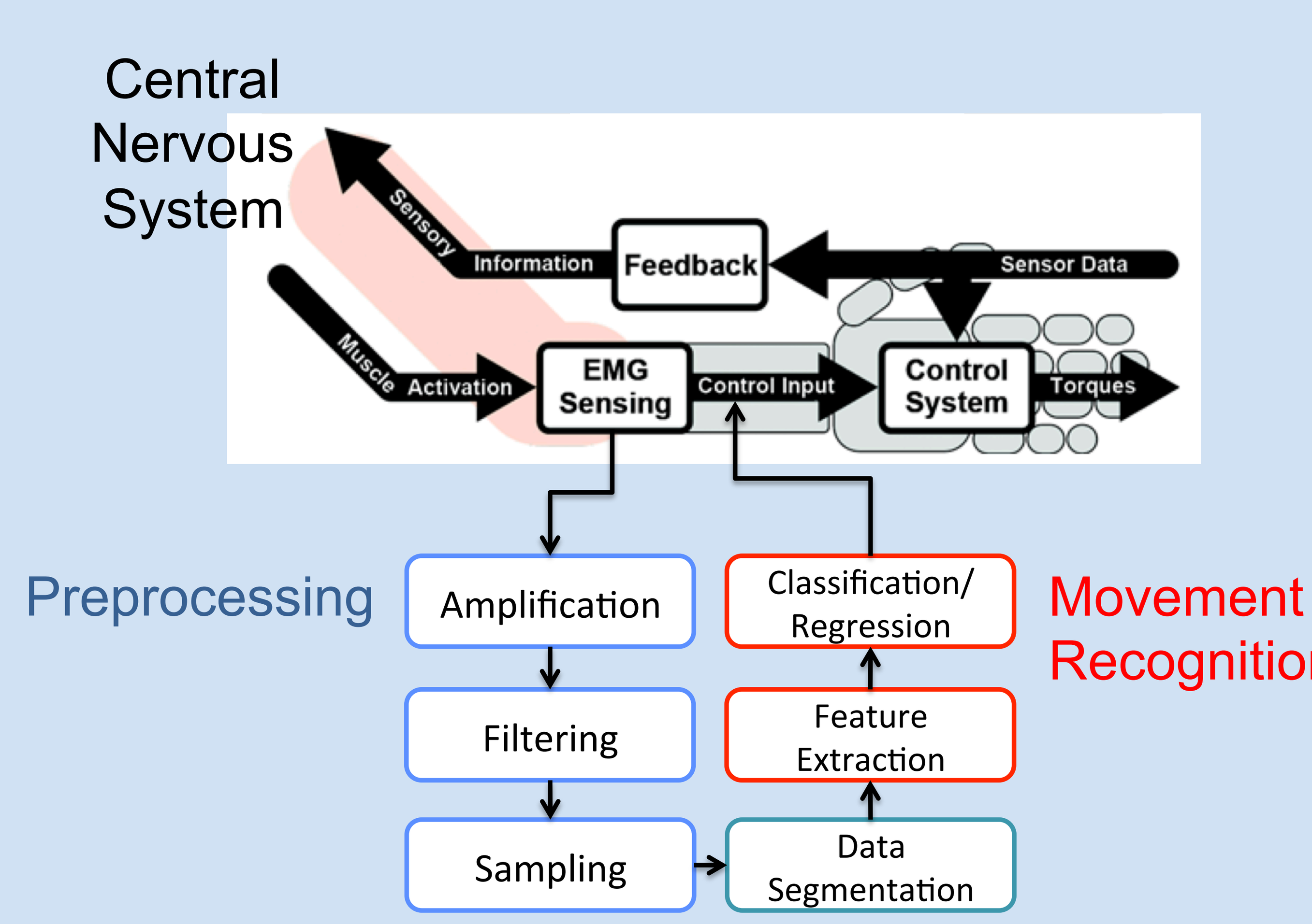


Figure 2: Scheme of a common pipeline for hand prosthetis control with artificial intelligence methods. *(Peerdeman, 2011)*

Methods

Data

Ninapro benchmark database for sEMG control of robotic prosthetic hands

- 3 datasets
- 67 intact subjects
- 11 trans radial amputated subjects
- publicly available (http://ninapro.hevs.ch)

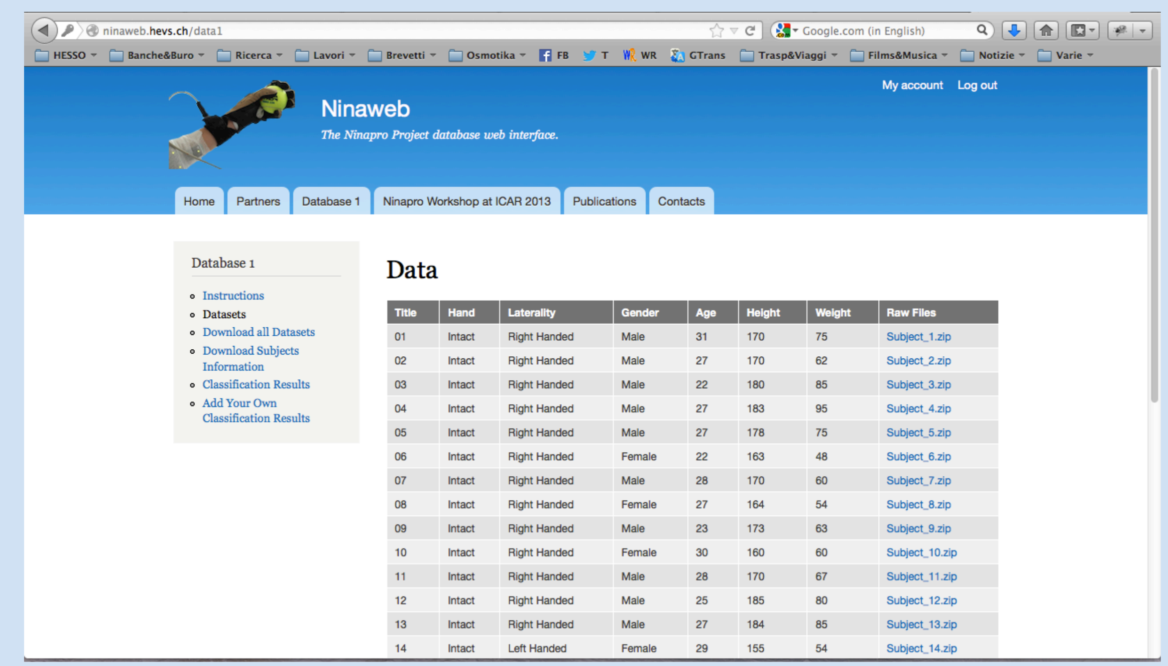


Figure 3: Screenshot of the Ninapro website.

sEMG acquisition setup *(Figure 4)*

1. 8 equally spaced sEMG electrodes (Otto Bock, Delsys Trigno including accelerometers)
2. 4 main activity spots sEMG electrodes (Flexor and Extensor Digitorum, Biceps, Triceps)
3. two axes Inclinometer
4. data glove (Cyberglove II)

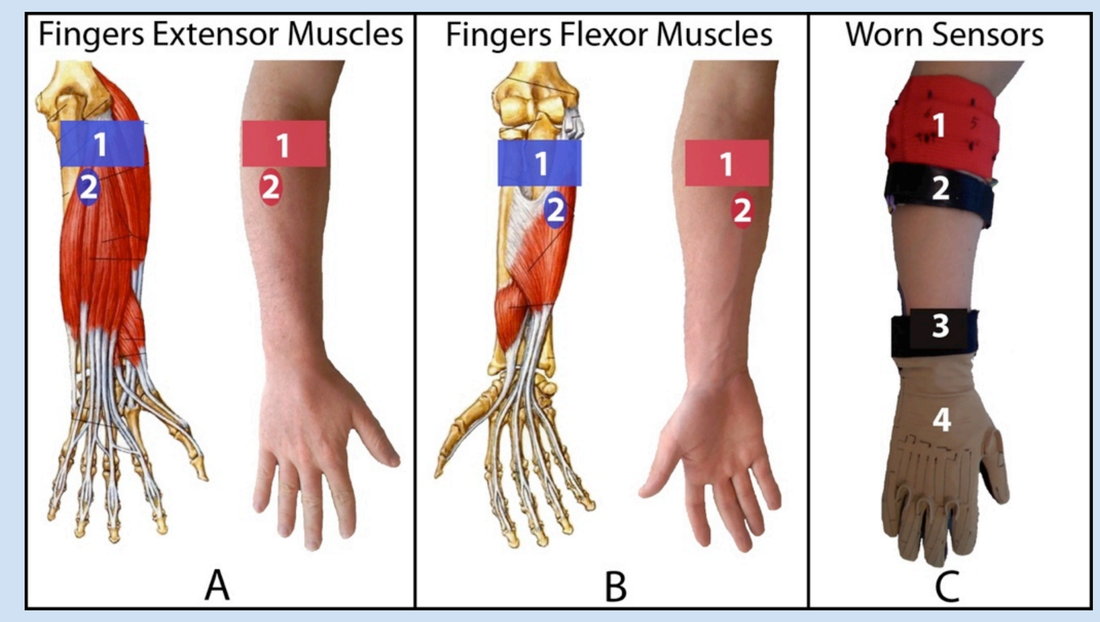


Figure 4: Ninapro acquisition setup.

sEMG acquisition protocol

- 6 repetitions of ~50 movements *(Figure 6)*
- *intact subjects:* repeat movement movies with the right hand *(Figure 5)*
- *amputees:* mentally repeat movement movies with the missing hand *(Figure 5)*

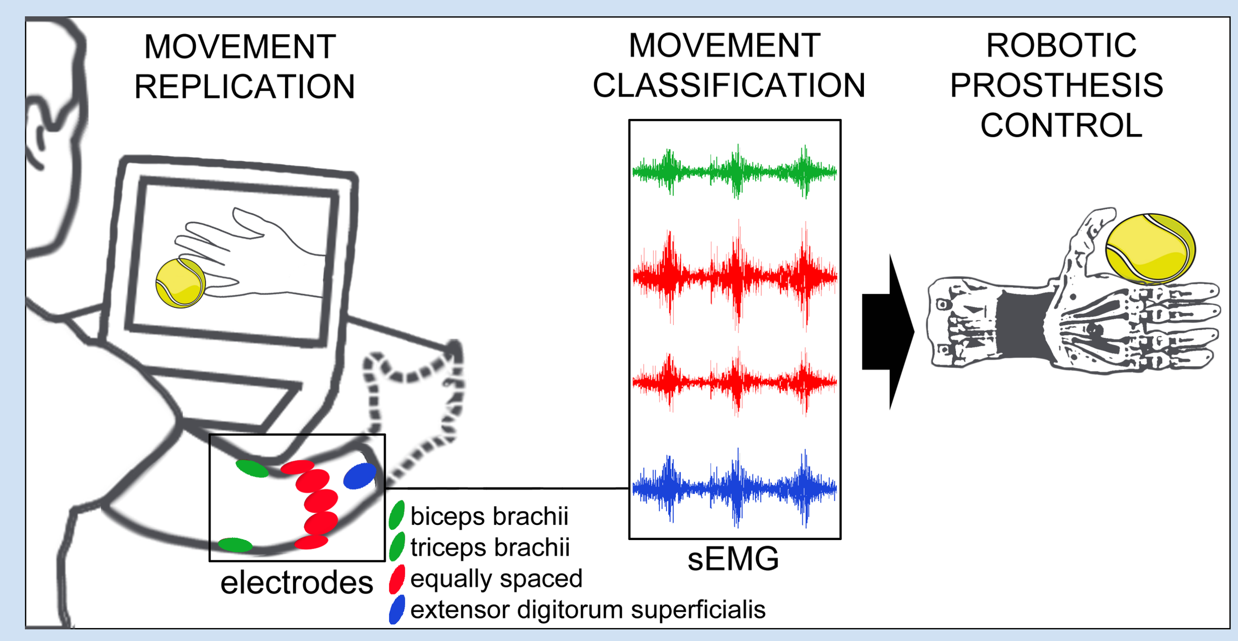


Figure 5: Ninapro acquisition protocol.

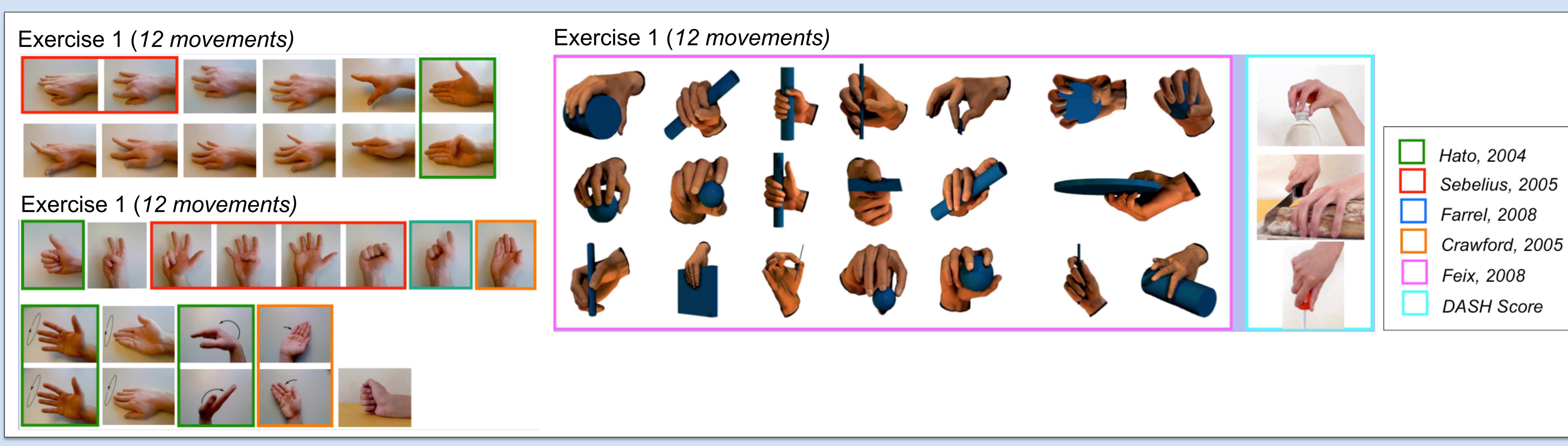


Figure 6: Ninapro movements.

Data Analysis

Artificial Intelligence

Machine learning procedures have been applied to the datasets in order to recognize the hand movements that the subjects aimed to do. The analysis included the following phases.

- *Data pre-processing:* procedures to level out the data and prepare them for the analysis (e.g. relabeling, windowing, normalization).
- *Signal feature extraction:* procedures to identify the signal features useful for movement recognition (e.g. Root Mean Square (RMS), Waveform Length (WL), Marginal Discrete Wavelet Transform (mDWT)).
- *Signal feature classification:* artificial intelligence methods are trained on 4 movement repetitions and tested on 2 repetitions to evaluate their capability to distinguish different movements. The tested classifiers include Support Vector Machines (SVM).

Statistical Analysis

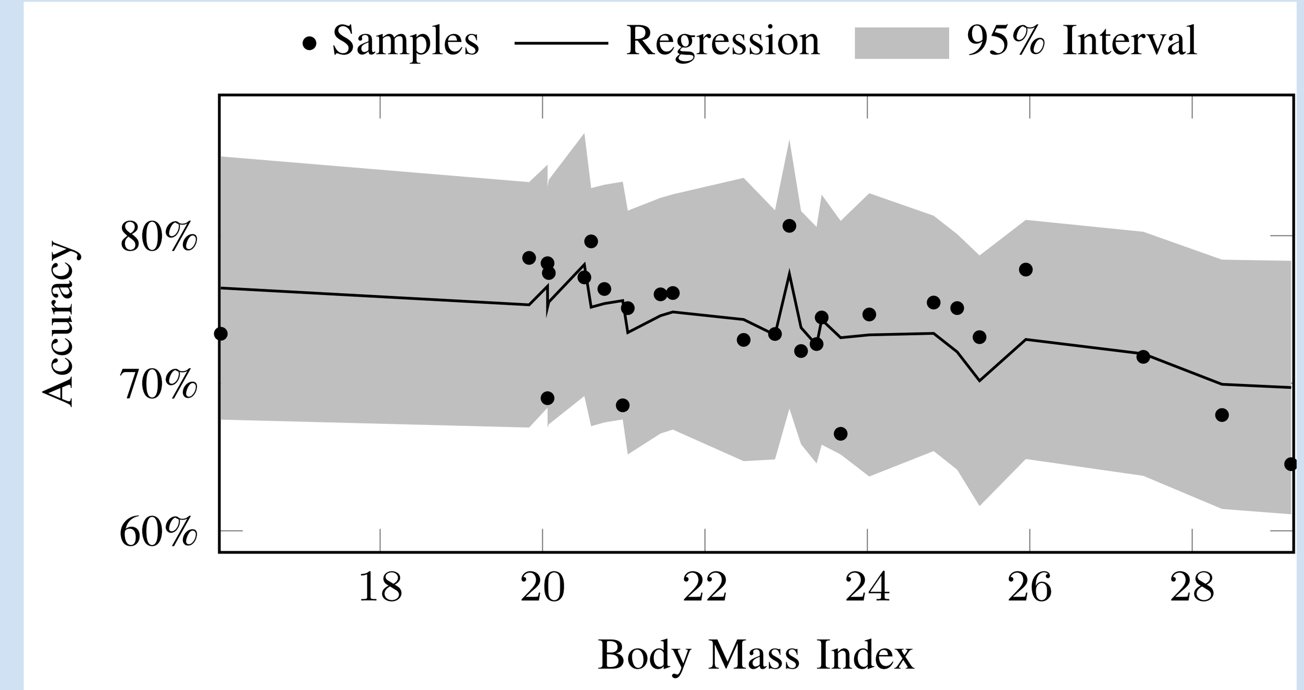
Standard statistical methods have been used to quantify the results from the artificial intelligence data analysis:

- Average classification accuracy & standard deviation have been used to measure how well movements can be recognized in different settings.
- F-test have been used to assess the influence of subject characteristics on movement classification acccuracy.

Results

Intact subjects:

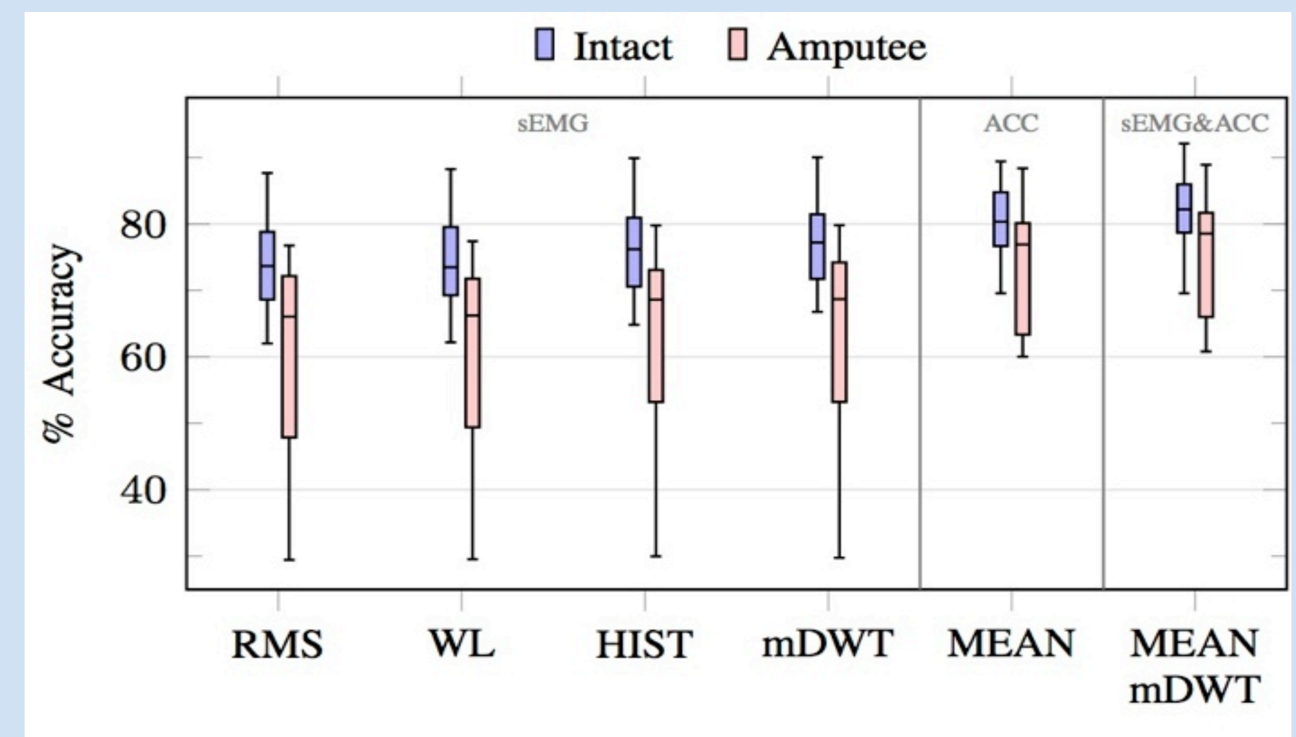
- Fat layers can act as insulant for the muscles, since classification accuracy decreases with Body Mass Index ($p<0.05$)



Atzori et al., Transactions on Neural Systems and Rehabilitation Engineering, 2014

Figure 7: Movement classification accuracy vs BMI.

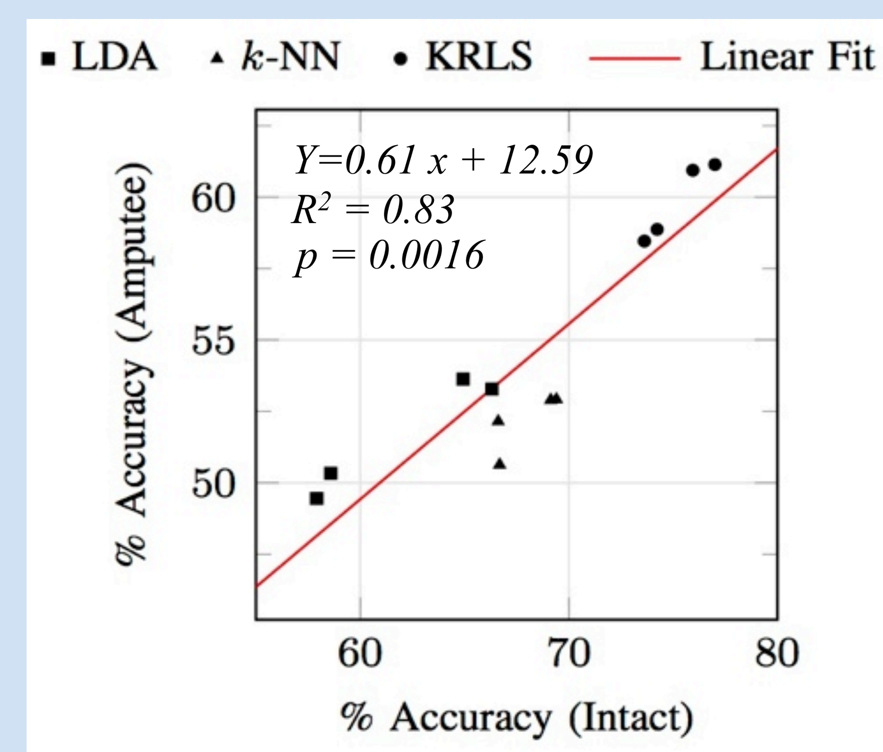
- Multimodal data recorded with sEMG and accelerometers can outperform the accuracy obtained solely with sEMG data.



Atzori et al., EMBC 2014

Figure 8: Ninapro movements.

- The performance obtained by artificial intelligence methods on intact subjects can be used as representative for the performance obtained on amputees ($p<0.05$)



Atzori et al., EMBC 2014

Figure 9: Ninapro movements.

Amputees:

Preliminary studies on the Ninapro database show that movement classification accuracy can be related to several subject anatomical characteristics, including phantom limb sensation ($p<0.01$), forearm length ($p<0.01$) and years by the amputation ($p<0.01$).

These relationships should be studied in more detail in future works with more patients and more detailed data analysis procedures.

The proposed results have the potential to improve quality of life and prognosis for amputees:

- the prostheses can be improved and adapted to the clinical characteristics of the subjects.
- "functional amputation" procedures, can be developed to optimize prosthesis integration with patient characteristics in order to improve its rehabilitative capabilities.

Table 1: Clinical characteristics of the amputated subjects.

Subject	Handedness	Amputated Hand(s)	Amputation Cause	Remaining Forearm (%)	Years since Amputation	Phantom Limb Sensation (0-5)	DASH Score	Prosthesis Use
1	Right	Right	Accident	50	13	2	1.67	myoelectric
2	Right	Left	Accident	70	6	5	15.18	cosmetic
3	Right	Right	Accident	30	5	2	22.50	myoelectric
4	Right	Right & Left	Accident	40	1	1	86.67	No
5	Left	Left	Accident	90	1	2	11.67	kinematic
6	Right	Left	Accident	40	13	4	37.50	kinematic
7	Right	Right	Accident	0	7	0	31.67	No
8	Right	Right	Accident	50	5	2	33.33	myoelectric
9	Right	Right	Accident	90	14	5	3.33	myoelectric
10	Right	Right	Accident	50	2	5	11.67	myoelectric
11	Right	Right	Cancer	90	5	4	12.50	myoelectric

Conclusions

- Several subject characteristics can be related to sEMG control with advanced methods, including, use of myoelectric prosthesis, fatigue, sweating but also body mass index (BMI), forearm percentage and phantom limb sensation intensity.
- Additional data sources can strongly improve myoelectric prosthesis.
- A proper integration between medical procedures (finalized to better exploit clinical and anatomical data) and multimodal data analysis can improve current prosthesis performance, leading to better performing naturally controlled robotic hands.

Future Works

- Currently we are studying the relationship between classification accuracy, subject characteristics and multimodal data in order to improve the knowledge in the field and to increase the robustness of sEMG prostheses.