FRIEDRICH-ALEXANDER UNIVERSITÄT ERLANGEN-NÜRNBERG

FACULTY OF ENGINEERING

Intent detection and somatosensory feedback

#05: Pressure sensing (FMG, TMG)

Claudio CASTELLINI, Sabine THÜRAUF

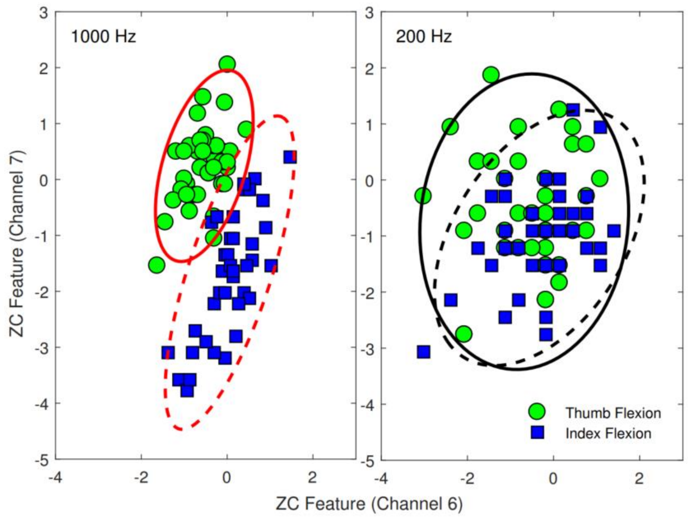

Figure 2. Differences in EMG patterns between using: (**left**) a 1000 Hz sampling rate; and (**right**) a 200 Hz sampling rate. ZC features are extracted from two different EMG channels (6 and 7) during thumb flexion (green circle markers and solid lines) and index flexion (blue square markers and dashed lines). Samples are from Subject 1 of Database 3.

EMG patterns related to two actions. Reproduced from Angkoon Phinyomark, Rami N. Khushaba and Erik Scheme, *Feature Extraction and Selection for Myoelectric Control Based on Wearable EMG Sensors*, MDPI Sensors 2018, 18, 1615

The *rubber hand illusion.* See Botvinick M, Cohen J., *Rubber hands 'feel' touch that eyes see.* Nature. 1998 Feb 19;391(6669):756. doi: 10.1038/35784. PMID: 9486643.

Lecture #05:

Pressure sensing (FMG, TMG)

- Forcemyography (FMG)
- Tactile myography (TMG)
- Summary

1. Sampling refers to the process of converting a continuous signal (analog) into a discrete signal (digital) by capturing its value at specific points in time.
2. Here's how it relates to bandwidth:
3. Bandwidth: This represents the range of frequencies a signal can carry. It's typically measured in Hertz (Hz) and indicates the highest frequency component present in the signal.
4. Sampling rate: This refers to the number of times the signal's value is captured per second. It's also measured in Hz.

Force Myography

- so here‘s a further way to detect muscle activity:
  - activation of muscles causes their *deformation*
  - deformation of muscles causes *changes in the shape of the body*
  - which can be detected and *measured*.

- the simplest way: using pressure sensors
  - located inside a semi-rigid structure (socket / housing / bracelet / exoskeleton)
  - which detect pressure generated by the „bulges“ of the muscles against the structure

- potential advantages over EMG:
  - not influenced by fatigue - EMG signals are affected by muscle fatigue because they measure the electrical activity of muscle fibers, which changes with fatigue. Amplitude Changes: As muscles fatigue, the amplitude of the EMG signal can decrease because the muscle fibers are less able to generate strong contractions.
  - possibly also not by sweat – changes the electrical properties of the skin, conductance increase (saline) – so EMG signal changes. Here the sensors are sealed – sweat wont affect
  - cheaper, simpler electronics

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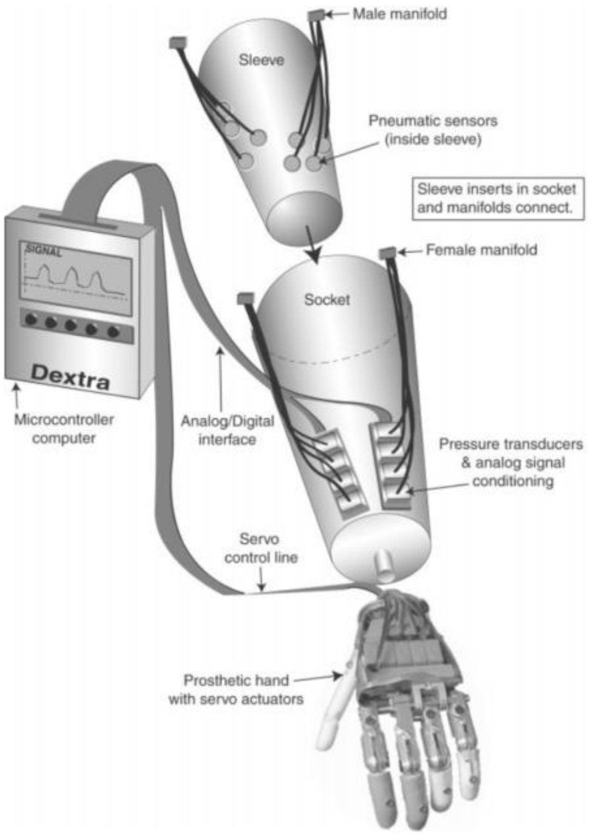

Fig. 2. Biomimetic *Dextra* hand prosthesis. The silicone "smart sleeve" fits snugly over the residual limb and registers 3D forces produced by muscle activity within the hard socket. The pocket computer allows the user to retrain the robotic hand for optimal performance. The hand can flex and extend all five digits in response to commands from the natural motor pathways of the user. [Figure provided by D. Curcie]

William Craelius, The Bionic Man: Restoring Mobility, Science 295, 1018 (2002)

Sam L. Phillips and William Craelius, Residual kinetic imaging: a versatile interface for prosthetic control, Robotica 23, pp. 277–282, 2005.

Force Myography

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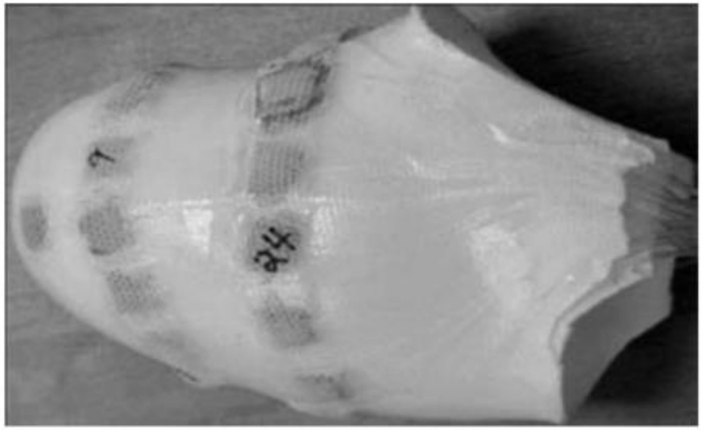

Fig. 1. A *Smart-Sleeve*. The final product is a custom-formed silicone sleeve with sensors (black squares) embedded inside in predetermined locations. Sensor hoses exit the sleeve at right. Total Length from the distal end to the olecrenon posteriorly, and to the fold of the elbow anteriorly, for subject A ~ 15 cm, for Subject B ~ 23 cm.

Table I: Clinical Characteristics of Subjects.

Subject	Age	Age of Amputation	Level and cause of Amputation	Tissue Condition
A	27	12	Trans Radial, Upper third, electrical burn	Soft, scarred, fatty
B	69	33	Trans Radial, Distal third, sharp trauma	Firm, unscarred, Lean

Sam L. Phillips and William Craelius, Residual kinetic imaging: a versatile interface for prosthetic control, Robotica 23, pp. 277–282, 2005.

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  - The residual limb movements (pinky,middle and thumb) produced different heatmap from pressure sensors.

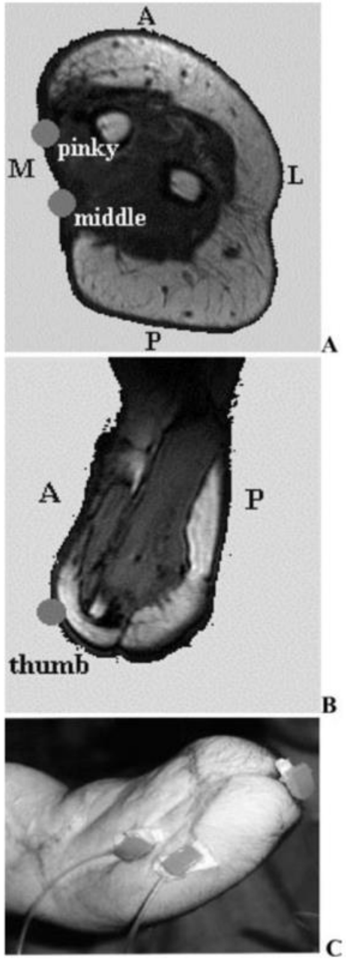

Fig. 5. MRI photographic images and of subject one's residual limb. Panel A shows a transverse slice near the distal end. Panel B is a longitudinal slice. Areas of movement have been superimposed as discs on the image. 5C is a photograph of Subject A's residual limb for comparison. M-P sensors are attached at three sites.

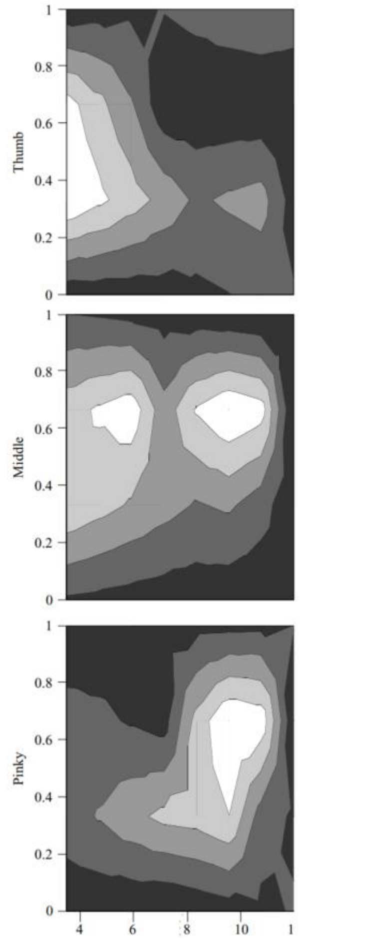

Fig. 2. RKI of residual limb movements for subject A during requested finger tapping. Each requested movement is identified by a unique image of pressure energies. Maximum pressures were approximately 3 kPa with white being the greatest and black being no change.

David J. Curcie, James A. Flint, and William Craelius,
Biomimetic Finger Control by Filtering of Distributed Forelimb Pressures,
IEEE Transactions On Neural Systems And Rehabilitation Engineering, 9(1), 2001

Force Myography

- so here‘s a further way to detect muscle activity:
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  - **Time vs amplitude**

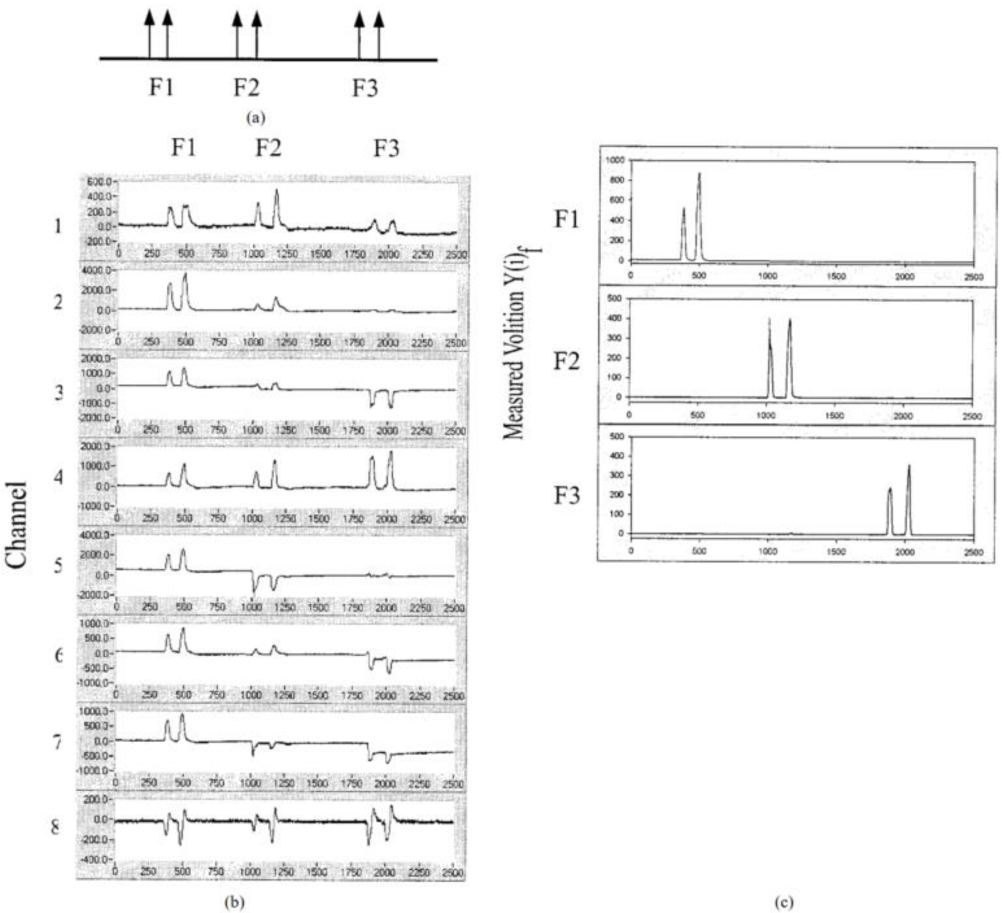

Fig. 5. Pressure vector decoding of M-P data. (a) Intended volition. The test set was two taps on each of three fingers, sequentially, sampled on 8 channels. (b) Test input data. Shown are 12.5 s of data at a sampling rate of 200 Hz. Axes are the same as Fig. 4. Note: amplitude scale varies among channels, and differs from Fig. 4. (c) Output signal response matrix. Traces represent 12.5 s of data, calculated from (1), including squaring and full-wave rectification. Rows represent the finger control output, and columns represent the intended volitional command.

Force Myography

- is easy and cheap to detect.

C. Castellini and V. Ravindra, ‘A wearable low-cost device based upon Force-Sensing Resistors to detect single-finger forces’, in *Proceedings of BioRob - IEEE International Conference on Biomedical Robotics and Biomechatronics*, 2014, pp. 199–203.

Force Myography

- is easy and cheap to detect.

***Abstract*—In rehabilitation robotics it is highly desirable to find novel human-machine interfaces for the disabled, in particular to substitute or augment surface electromyography (sEMG), trying to keep at the same time its easiness of use, precision and non-invasiveness. In this paper we design and demonstrate one such device, based upon Force-Sensing Resistors (FSRs). An array of 10 FSRs was wrapped around the proximal section of the forearm of ten intact subjects engaged in pressing on an accurate force sensor with their fingers (this includes the rotation of the thumb). The FSRs would detect the forearm surface deformations induced by muscle activity; the signals provided by the FSRs were then matched to the recorded forces. The experimental results show that finger forces can be predicted using this device with the same accuracy obtained in literature using sEMG. The device, even as an academic prototype, weighs about 65 grams and costs around 50 EUR. Thus, it is remarkably light and cheap in comparison to standard sEMG electrode arrays.**

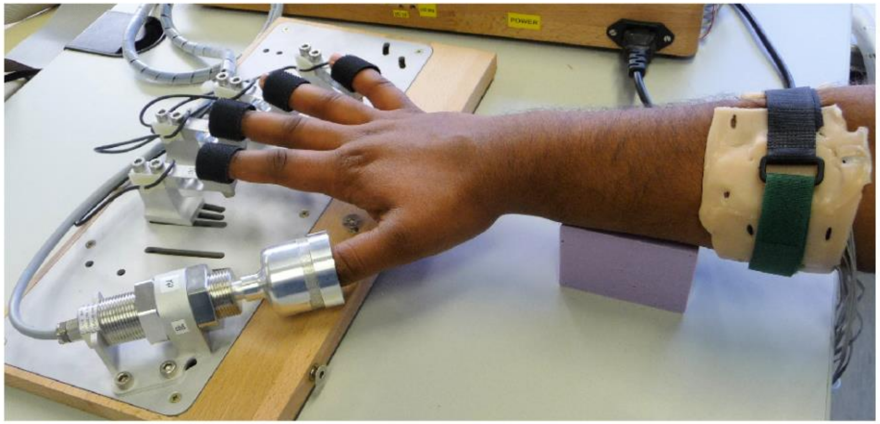

Fig. 1. A bird’s eye view of the experimental setup: the subject’s finger forces are measured by a strain-gauge-based high-precision force sensor (FFLS), while a bracelet fitted with Force-Sensing Resistors is wrapped around the forearm.

C. Castellini and V. Ravindra, 'A wearable low-cost device based upon Force-Sensing Resistors to detect single-finger forces', in *Proceedings of BioRob - IEEE International Conference on Biomedical Robotics and Biomechatronics*, 2014, pp. 199–203.

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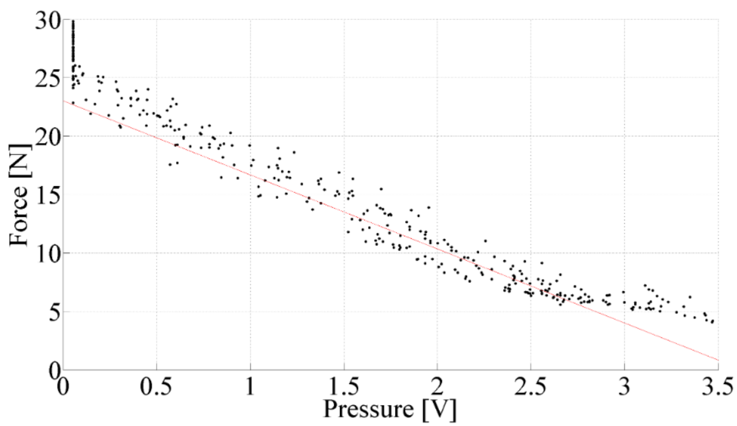

Fig. 3. Typical data obtained during the calibration of a FSR and a linear fit *limited to the region of interest*, that is, for output values larger than 0.1 Volts. The R-squared coefficient is 0.97.

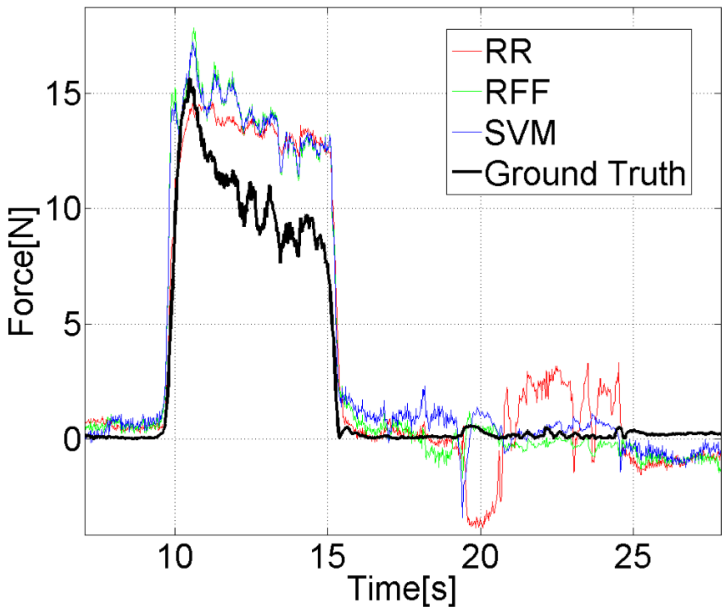

Fig. 5. Ground truth and predictions obtained by RR, RFF and SVM during a typical repetition in scenario 3.

Intent detection and somatosensory feedback

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Force Myography

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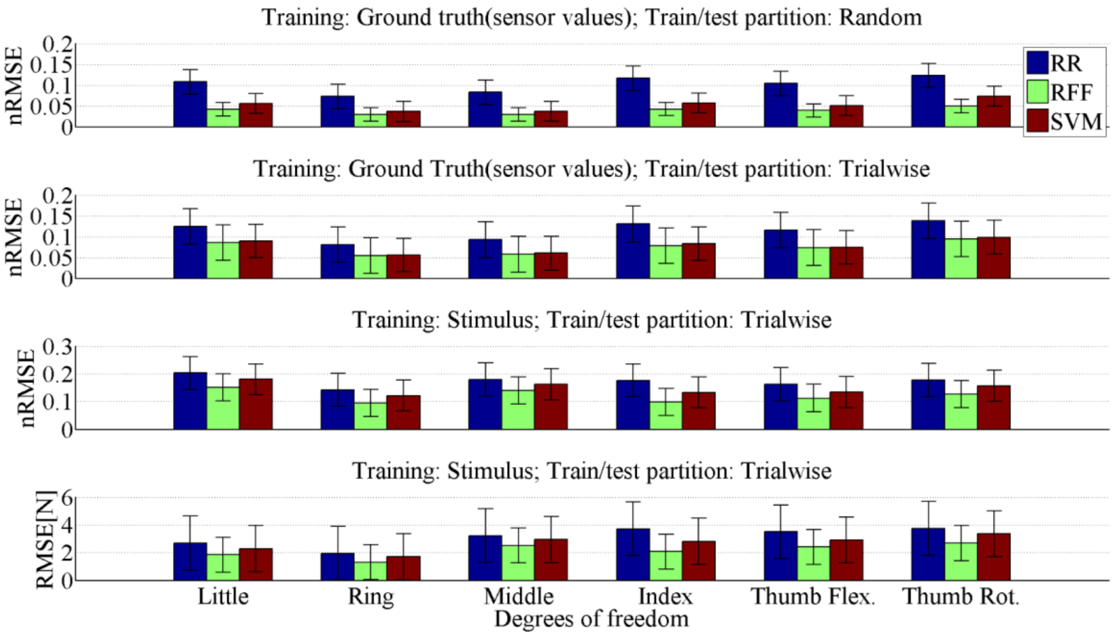

IV. Conclusion and Future Work

In this paper we have described and demonstrated a wearable, low-cost device to detect fingertip forces. The device consists of a plastic bracelet fitted with ten Force-Sensing Resistors; these sensors, whose characteristic curve is highly non-linear for high forces, are shown in this case to be working in the linear section of their operating range. Three machine learning methods have been applied to their signal in order to predict finger forces, namely Ridge Regression, Support Vector Regression and Ridge Regression with Random Fourier Features. The error obtained is less than one Newton, and is in the worst case of about 4 Newtons, making the accuracy comparable to that obtained by surface electromyography [7]. The best accuracy is about 1.5 Newtons.

The experimental results shown in this paper are to some extent surprising. They show that this device, weighing only about 65 grams, and whose total price (for a prototype) is about 50 EUR, can be used to predict finger forces to a remarkable accuracy by employing Random Fourier Features, a method already employed for sEMG [7]. The

Force Myography

- is easy and cheap to detect.

*Ravindra V and Castellini C (2014) A comparative analysis of three noninvasive human-machine interfaces for the disabled. Front. Neurorobot. **8**:24.*

Force Myography

- is easy and cheap to detect…
- …but how does it compare to, e.g., sEMG?

In the framework of rehabilitation robotics, a major role is played by the human–machine interface (HMI) used to gather the patient's intent from biological signals, and convert them into control signals for the robotic artifact. Surprisingly, decades of research have not yet declared what the optimal HMI is in this context; in particular, the traditional approach based upon surface electromyography (sEMG) still yields unreliable results due to the inherent variability of the signal. To overcome this problem, the scientific community has recently been advocating the discovery, analysis, and usage of novel HMIs to supersede or augment sEMG; a comparative analysis of such HMIs is therefore a very desirable investigation. In this paper, we compare three such HMIs employed in the detection of finger forces, namely sEMG, ultrasound imaging, and pressure sensing. The comparison is performed along four main lines: the accuracy in the prediction, the stability over time, the wearability, and the cost. A psychophysical experiment involving ten intact subjects engaged in a simple finger-flexion task was set up. Our results show that, at least in this experiment, pressure sensing and sEMG yield comparably good prediction accuracies as opposed to ultrasound imaging; and that pressure sensing enjoys a much better stability than sEMG. Given that pressure sensors are as wearable as sEMG electrodes but way cheaper, we claim that this HMI could represent a valid alternative/augmentation to sEMG to control a multi-fingered hand prosthesis.

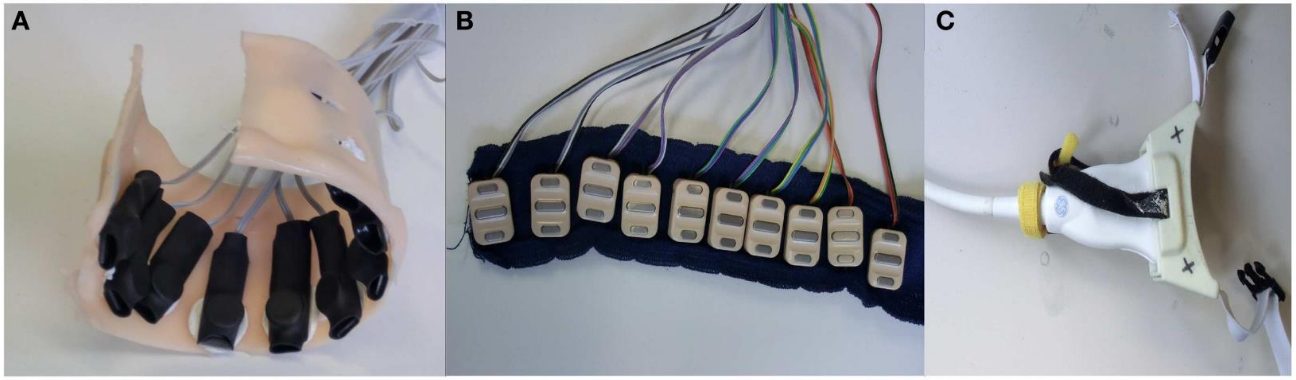

FIGURE 1 | HMI devices used: (A) customized arrangement of FSR housed in a semi-rigid bracelet; (B) ten sEMG electrodes arranged on a strip of bio-compatible self-adhesive tape; (C) ultrasound transducer fixed to a custom-made cradle.

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Force Myography

- is easy and cheap to detect.
- result #1: larger errors for smaller forces (worse SNR)
- result #2: larger errors when using the stimulus as ground truth rather than the FFLS
- result #3: sEMG and FMG are comparable to each other
- result #4: FMG is more stable over time

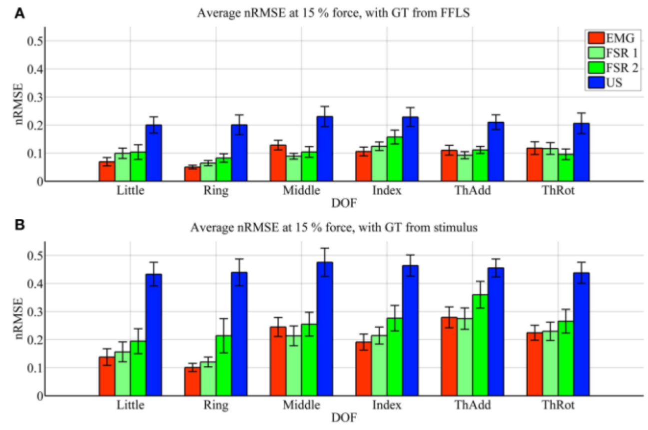

FIGURE 3 | Prediction accuracy (nRMSE) obtained by each HMI for each degree of freedom considered, during the high-forces experiment (stimulus at 80% of the maximum voluntary contractions). (A) Error obtained when the FFLS data are used as ground truth; **(B)** error obtained when the stimulus is used as ground truth. The legend denotes, in turn, sEMG (EMG), the two FSR sessions (FSR1, FSR2) and ultrasound imaging (US). Bars and stems denote average nRMSE values across ten subjects, plus/minus one standard error of the mean.

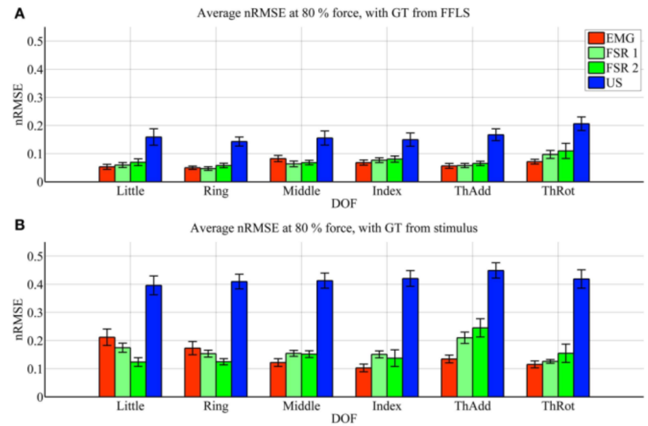

FIGURE 4 | Prediction accuracy (nRMSE) obtained by each HMI for each degree of freedom considered, during the low-forces experiment (stimulus at 15% of the maximum voluntary contractions). (A) Error obtained when the FFLS data are used as ground truth; **(B)** error obtained when the stimulus is used as ground truth. The legend denotes, in turn, sEMG (EMG), the two FSR sessions (FSR1, FSR2) and ultrasound imaging (US). Bars and stems denote average nRMSE values across ten subjects, plus/minus one standard error of the mean.

1. Results

2. Smaller forces produce smaller deformations in the muscle, which might not be as easily detected by the pressure sensors used in FMG. This makes it challenging to differentiate between the actual signal and noise.
3. The FFLS(Feed-Forward Linear System (FFLS)) likely provides a more precise and direct measurement of the muscle activity and force, whereas the stimulus can have variability and may not perfectly represent the actual muscle activity. The FFLS might account for dynamic changes and system characteristics that the raw stimulus does not.
4. Despite measuring different types of signals (electrical for sEMG and mechanical for FMG), the overall performance in terms of detecting and interpreting muscle activity is comparable. This suggests that FMG is a viable alternative to sEMG, especially in situations where sEMG's direct skin contact requirement is a limitation. Both sEMG and FMG provide similar levels of accuracy and reliability in detecting muscle activity.
5. FMG signals remain consistent and reliable over extended periods, showing less drift or variation compared to sEMG.**Reason**: FMG measures mechanical deformations, which are less susceptible to factors like skin impedance changes, sweat, or electrode displacement that can affect sEMG signals. This stability makes FMG particularly useful for long-term monitoring and applications where consistent signal quality is crucial.

Ravindra V and Castellini C (2014) A comparative analysis of three noninvasive human-machine interfaces for the disabled. Front. Neurorobot. ***8****:24.*

Force Myography

- is easy and cheap to detect.
- result #4: FMG is more stable over time

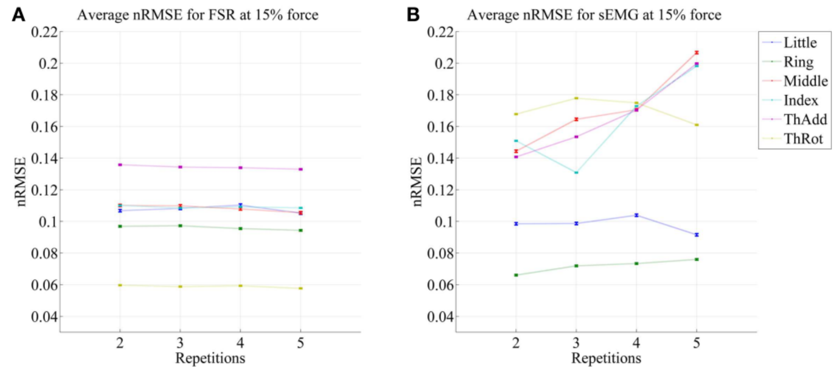

FIGURE 5 | Prediction accuracy (nRMSE) obtained by FSR (A) and sEMG (B) for each degree of freedom considered, during the high-forces experiment (stimulus at 80% of the maximum voluntary contractions); the system was trained on the first repetition; the graph shows the error obtained while testing on repetitions #2, #3, #4, and #5. The FFLS data are used as ground truth.

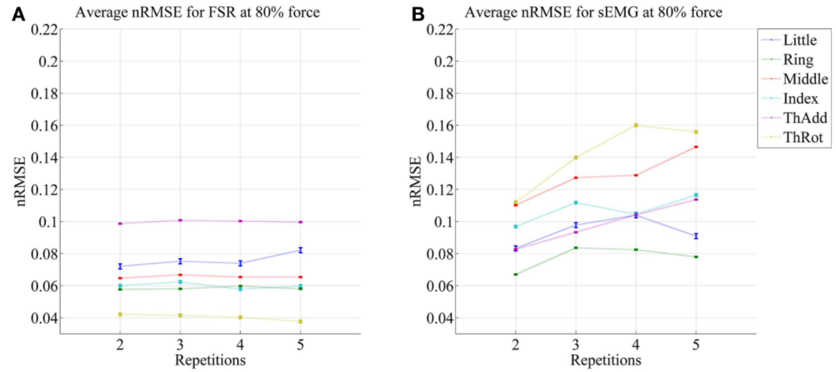

FIGURE 6 | Prediction accuracy (nRMSE) obtained by FSR (A) and sEMG (B) for each degree of freedom considered, during the low-forces experiment (stimulus at 15% of the maximum voluntary contractions); the system was trained on the first repetition; the graph shows the error obtained while testing on repetitions #2, #3, #4, and #5. FFLS data are used as ground truth.

Force Myography

- so, is it better/worse than sEMG?
- still controversial.

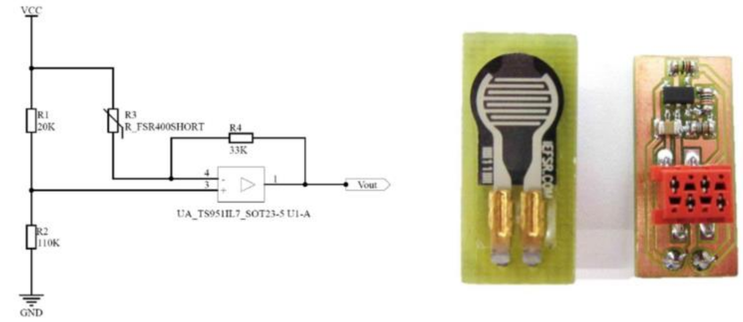

FIGURE 2 | (Left) The amplification circuit for the FSR. (Right) The FSR sensor's PCB.

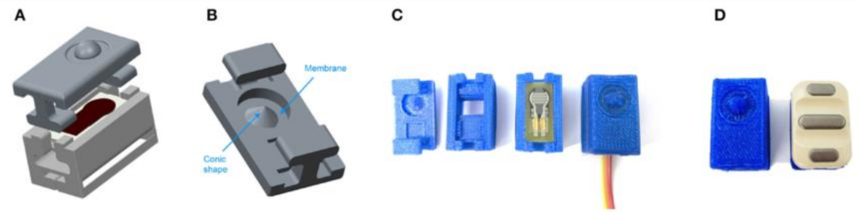

FIGURE 3 | (A) Exploded view of the 3D-model of the FSR housing. (B) 3D-model of the top part of the FSR housing, where the membrane and the conic shape are identified. (C) Assembly process of the housing and the FSR sensor. (D) Comparison between the final FSR sensor and the EMG sensor.

FIGURE 1 | (Left) Overview of the experimental setup. The subject is wearing th
FMG sensors, the other one with sEMG sensors. The Bluetooth data acquisition
system; an i-LIMB prosthetic hand by Touch Bionics (not used in this experiment

Connan M, Ruiz Ramírez E, Vodermayer B and Castellini C (2016), Assessment of a Wearable Force- and Electromyography Device and Comparison of the Related Signals for Myocontrol. Front. Neurorobot. 10:17

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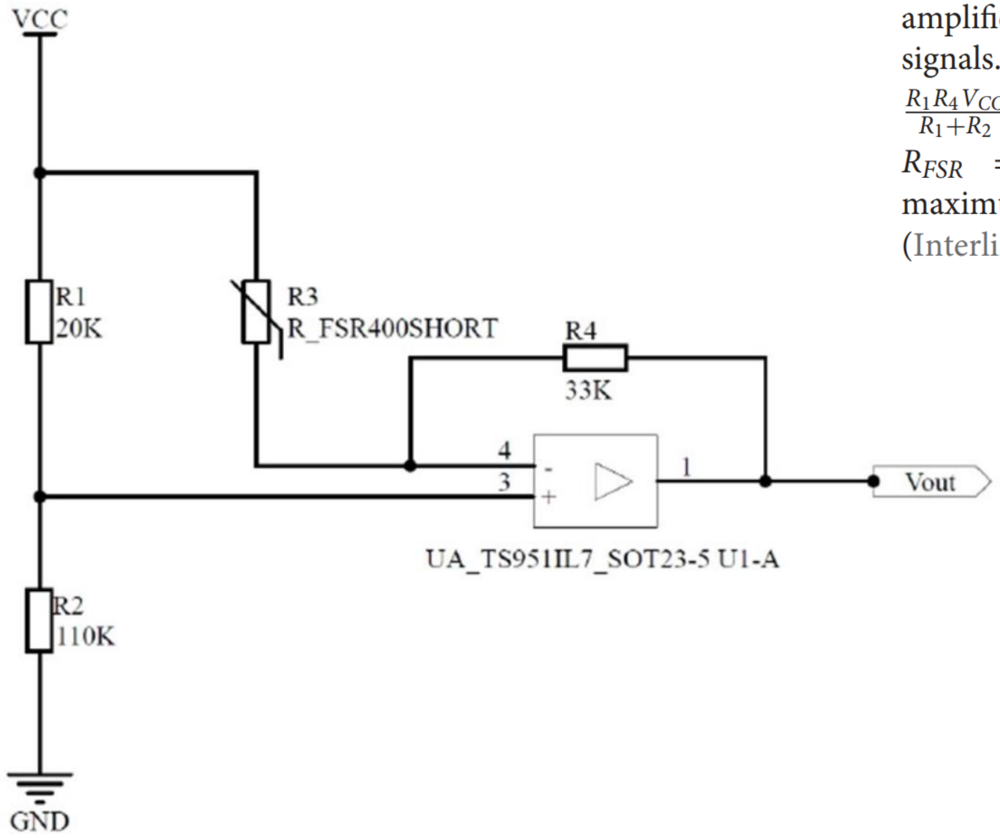

In our setup, a small printed circuit board with a voltage amplifier (see **Figure 2**) provides the amplification of the FMG signals. The output of the sensor circuit is $V_{out} = \frac{R_2 V_{CC}}{R_1+R_2} - \frac{R_1 R_4 V_{CC}}{R_1+R_2} \times \frac{1}{R_{FSR}}$, yielding a lowest admissible resistance of $R_{FSR} = \frac{R_1 R_4}{R_2} = 6k\Omega$, which corresponds to a theoretical maximum force observed on the FSR's surface of $3.33\,N$ (InterlinkElectronics, 2014).

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Force Myography

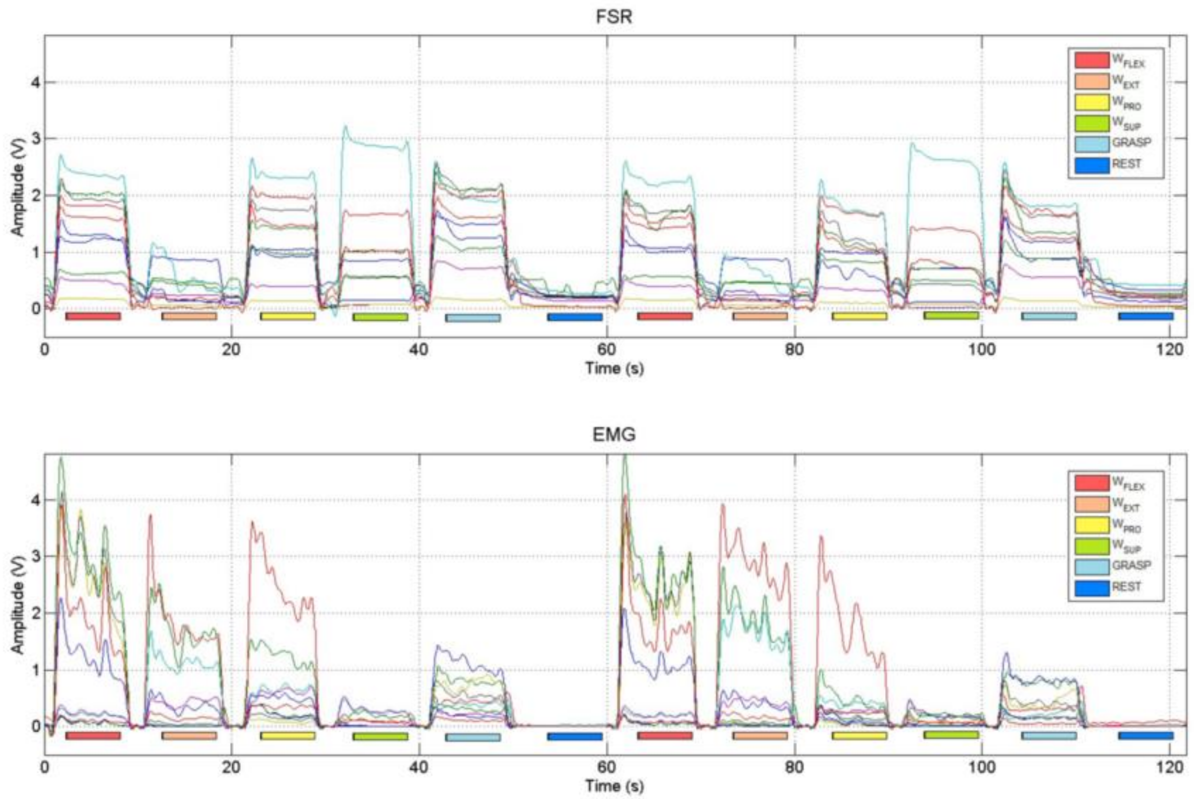

FIGURE 6 | Typical FSR and sEMG signals obtained from two repetitions of the instructed hand and wrist movements (wrist flexion, wrist extension, wrist pronation, wrist supination, power grasp and rest). Colored bars denote the activation phases, during which data were collected to represent the maximal activation of the stimulated movement.

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Force Myography

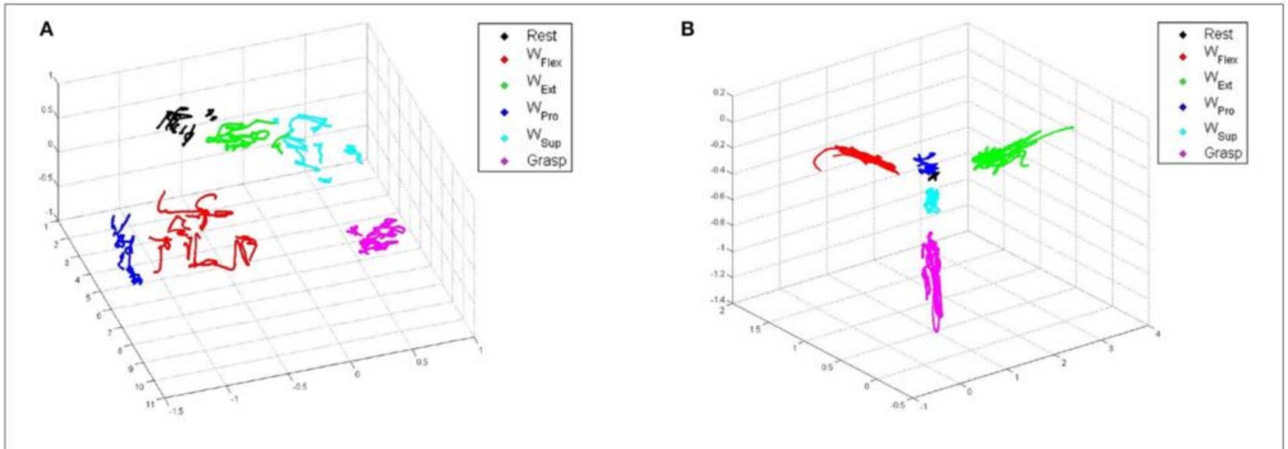


FIGURE 7 | 3D-reduced PCA projections of typical data for each type of sensor, colored according to the stimulated movements. (A) FMG. **(B)** sEMG.

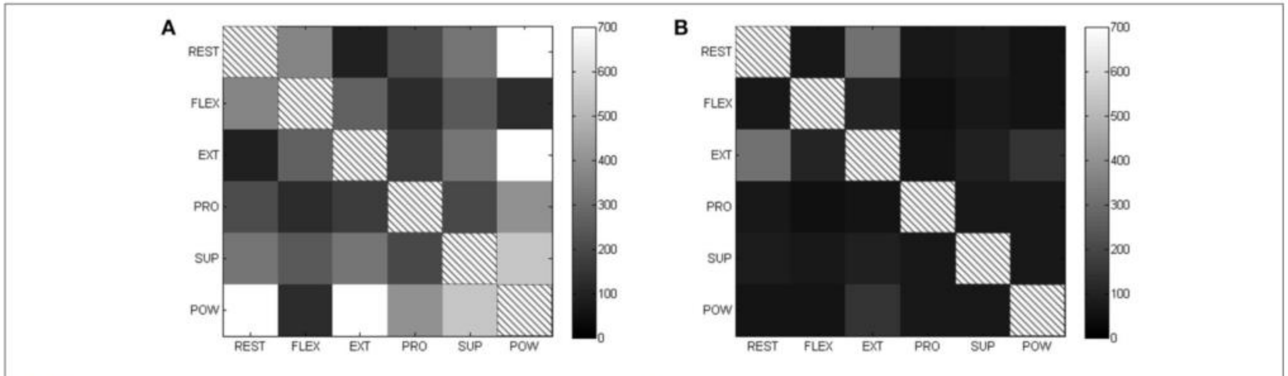
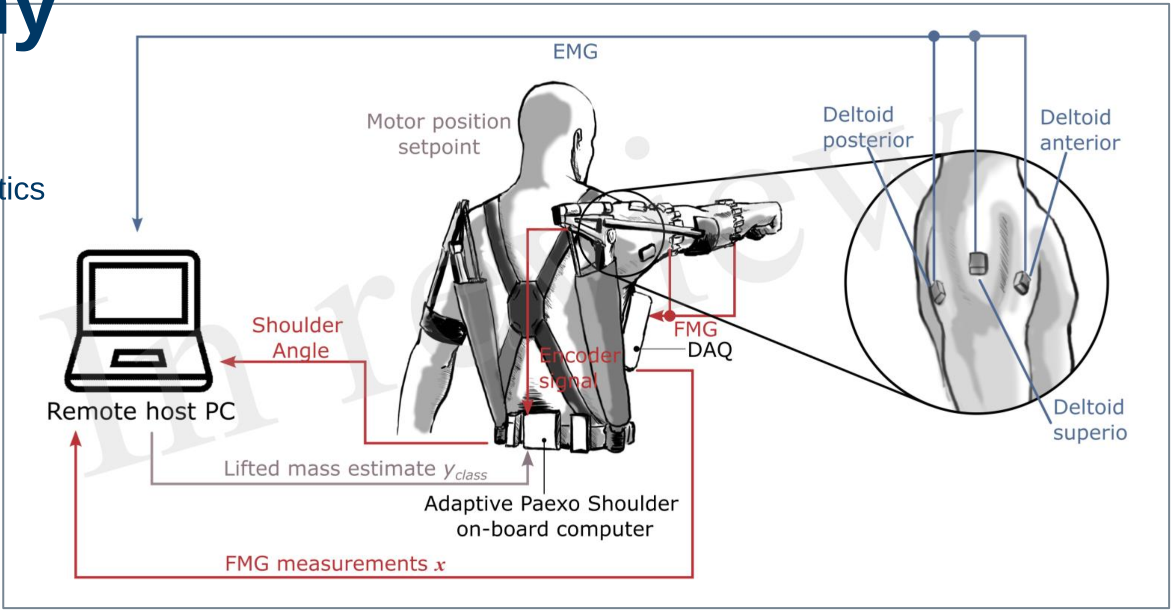


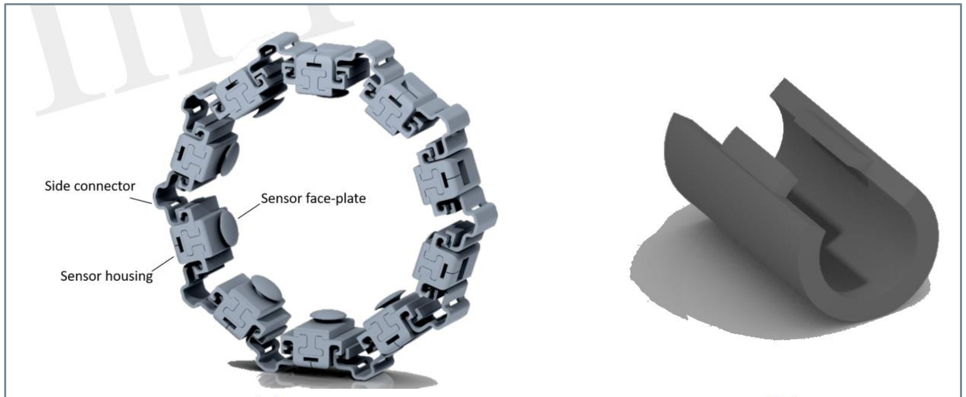
FIGURE 8 | Fisher's Index matrices for each type of sensor (higher is better). (A) FSR Fisher's index. **(B)** EMG Fisher's index.

Donato Brusamento, Marek Sierotowicz, Benjamin Schirrmeister, Mathilde Connan, Jonas Bornmann, Jose Gonzalez-Vargas and Claudio Castellini, Unobtrusive, natural support control of an adaptive industrial exoskeleton using force-myography, under review

Force Myography

- application to non-reha, non-medical robotics





(a) (b)

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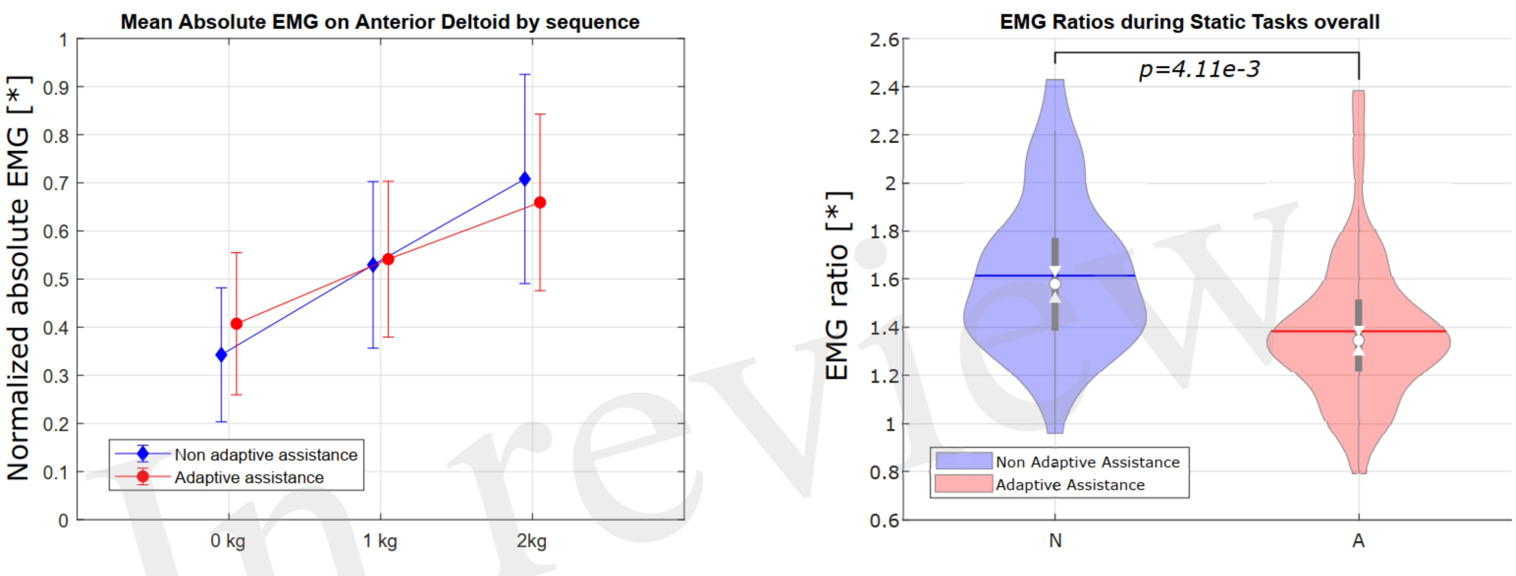

(a) (b)

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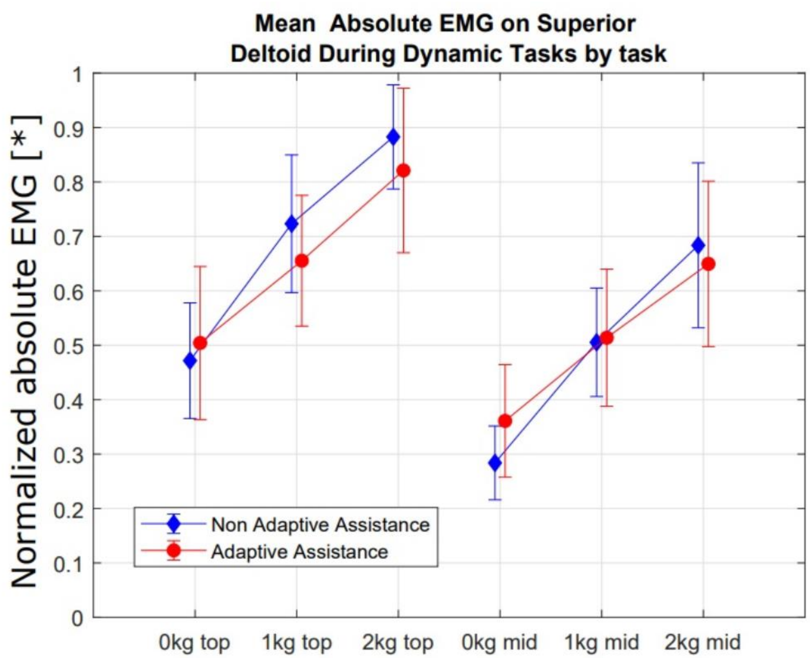
Force Myography

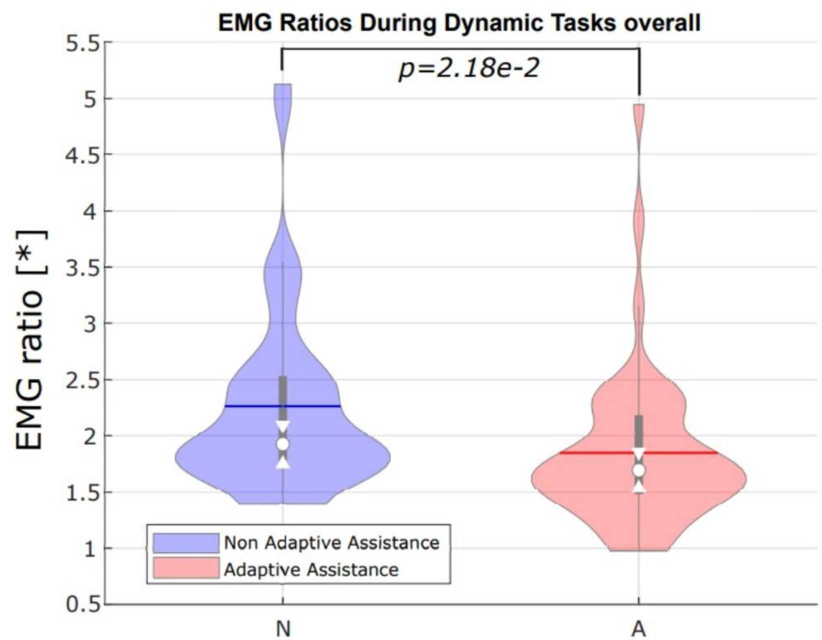
5 CONCLUSION

The Paexo has been conceived since its early design stage with non-obtrusiveness and simplicity in mind: it can be donned and doffed easily and quickly and guarantees the full range of motion of the user's shoulders while worn. The Adaptive Paexo Shoulder follows the same design philosophy, in addition to enforcing adaptive control of support thanks to a lightweight servo-motor. Still, the question remains: *how* to let the user control it transparently, effectively, in real-time? Taking inspiration from previous work in the field of upper-limb prosthetics, in this work we have assessed the effectiveness of FMG to determine in real time the amount of support required by the user, and consequently, to control the motor of the Adaptive Paexo Shoulder, thereby determining the support offered by the device.

A substantial advantage provided by FMG is that it can be worn on the worker's clothing, as opposed to sEMG sensors, which is an unavoidable constraint in most industrial and commercial settings.

- application to non-reha, non-medical robotics
- The p-value (2.18e-2) suggests a statistically significant
- difference between the EMG ratios for non-adaptive and
- adaptive assistance. As weight increase, the force exerted by individuals is less.





Tactile Myography

a.k.a. high-density FMG

- what if we use *many* such sensors instead of 10?
- obtained extremely good results in controlled conditions
- A tactile pixel or tixel is the
- smallest measuring/transmitting
- element of a tactile matrix.
- Collecting data from 8 different arm positions. The data collected for one position should be able give predictions for other positions as well – should be able to generalize what we are trying to do

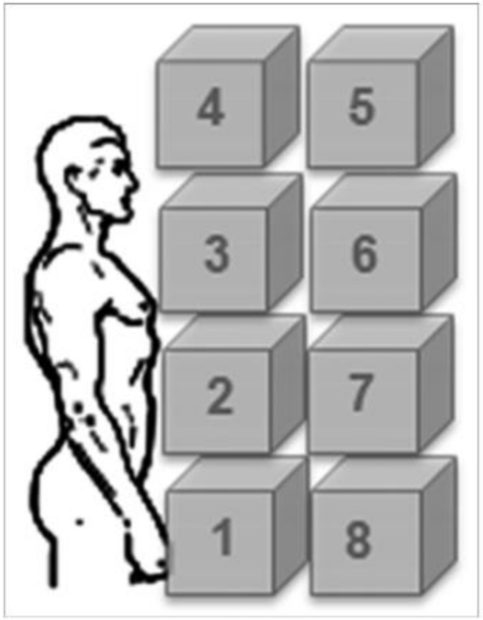


Figure 2.
Subjects were asked to perform four sets of contractions corresponding to eight classes of motion while holding their arm such that the hand was located in each of the eight static positions represented by the boxes numbered 1 through 8. Reprinted with permission from Radmand et al. [28].

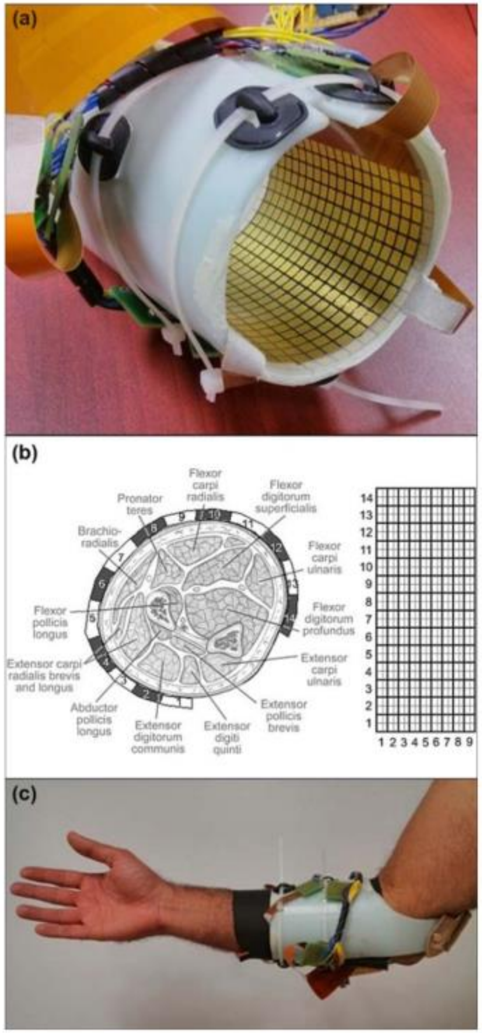


Figure 1.
(a) Adjustable pressure-sensing socket. Each 2 × 2 array of cells forms a single pressure sensor. **(b)** Sensor grid with its corresponding location on the muscles. **(c)** Placement of the socket with zip ties used to adjust socket size.

Ashkan Radmand, PhD; Erik Scheme, PhD; Kevin Englehart, High-density force myography: A possible alternative for upper-limb prosthetic control, JRRD 53(4), 2016

Intent detection and somatosensory feedback

1. **Limb Position Effect** refers to the phenomenon where the position of a limb can significantly influence the measurement and characteristics of muscle signals. This effect can impact both EMG (electromyography) and FMG (force myography) readings, leading to variations in the data based on the limb's orientation, angle, or position during measurement.
2. In the next slide – signals produced by 14*9 sensors (in total) for same arm position are quite distinguishable
3. Compactness: This refers to the reduction in size or the number of data points, sensors, or features in a dataset
4. Gradient – vector with x,y,z values – high force – high absolute vector values
5. Combination of action – making a fist and wrist pronation
6. An ideal model is trained for single actions, but it should be able to predict combination of actions
7. RR- all 320 features
8. RR-ROIG – 60 features
9. Success rate for RR is slightly higher than the less feature extraction one – so we are forced to use all the features, just like how we use in CNN’s
10. In both we were able to predict combined actions even though they were trained for only single actions

Tactile Myography

a.k.a. high-density FMG

- what if we use *many* such sensors instead of 10?

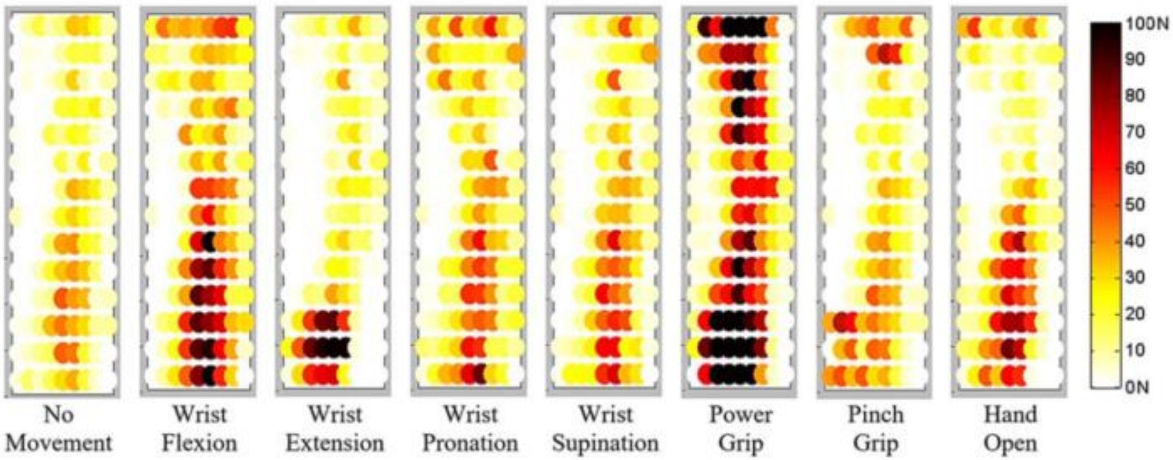


Figure 6.
Examples of acquired pressure map images for the motion classes performed in a fixed static position (darker areas correspond to higher pressure).

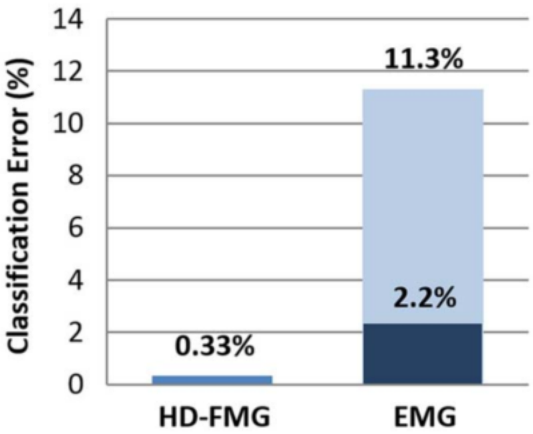


Figure 7.
Average classification errors of high-density force myography (HD-FMG) and electromyography (EMG) control methods for eight hand motion classes with arm in a fixed static position.

Ashkan Radmand, PhD; Erik Scheme, PhD; Kevin Englehart,
High-density force myography: A possible alternative for
upper-limb prosthetic control, JRRD 53(4), 2016

Tactile Myography

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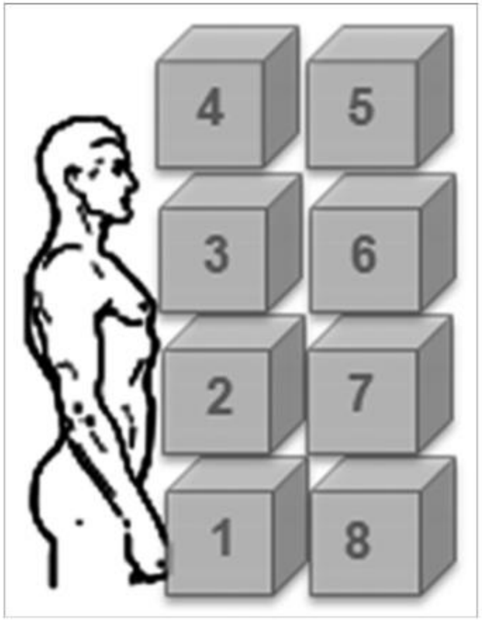
- generalisation problem: the *limb position effect*
- TMG – solves the limb position effect to some extent as the error is around only 10%, should have been high with an EMG



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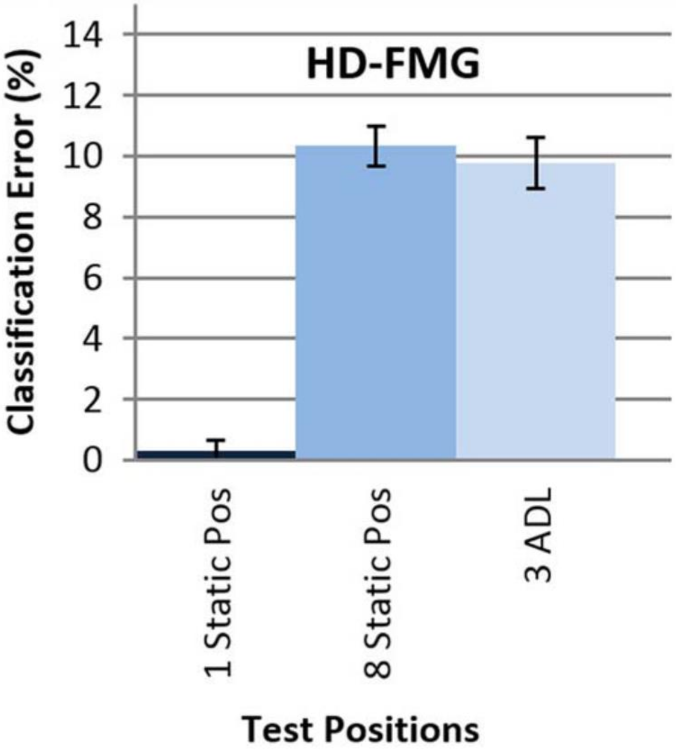

Figure 9.
Illustration of increase in classification error when a classifier that has been trained in only a fixed position (Pos) is tested during dynamic limb movements. Error bars indicate standard error across all subjects. ADL = activity of daily living, HD-FMG = high-density force myography.

Ashkan Radmand, PhD; Erik Scheme, PhD; Kevin
High-density force myography: A possible alternati
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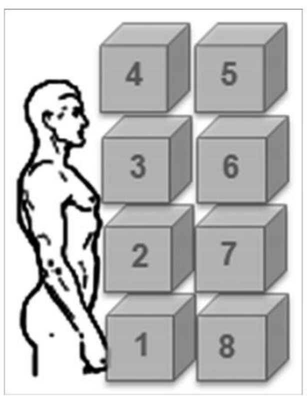

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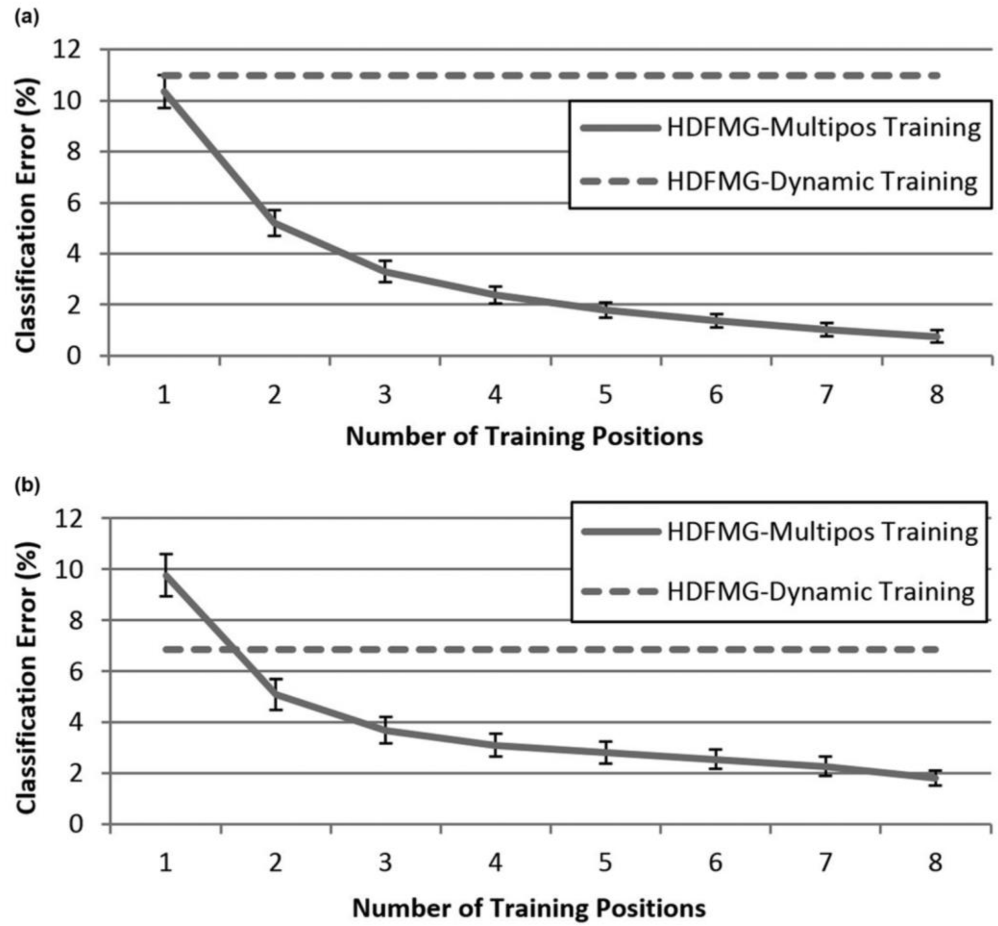

Connan M, Kõiva R and Castellini C, (2020) Online Natural Myocontrol of Combined Hand and Wrist Actions Using Tactile Myography and the Biomechanics of Grasping. Front. Neurorobot. 14:11

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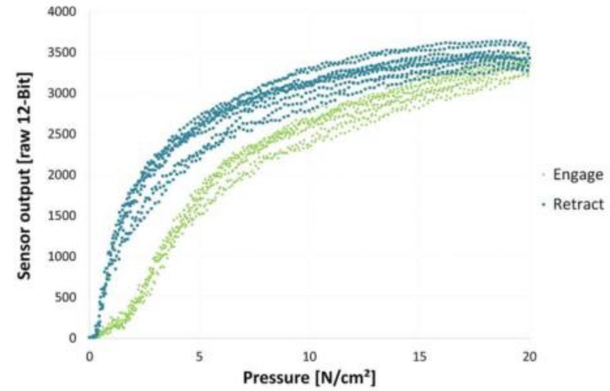

FIGURE 2 | Sensor characteristics measured over 10 trials from no contact to 20 N/cm^2 and back to no contact using the new 3 mm thick PANA Foamtec GmbH PE-K45EVAELS. The green samples are collected while pressure onto the sensor was increased whereas the blue ones are sampled during the retraction phase.

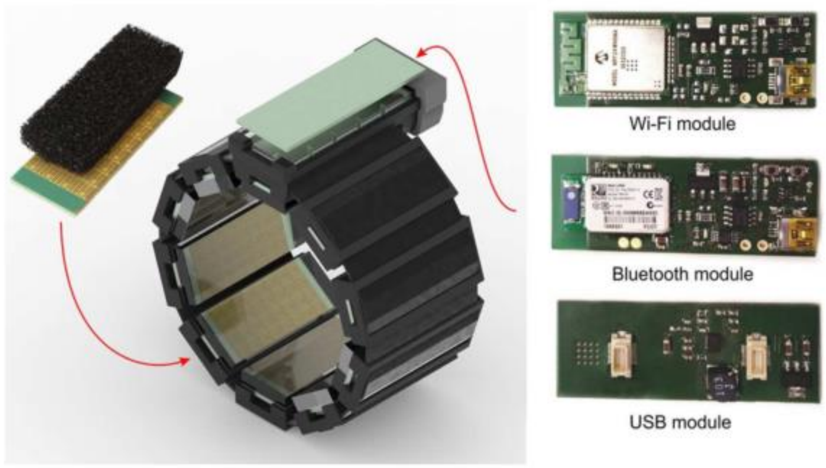

FIGURE 1 | The second generation tactile bracelet: **(left)** the bracelet and a single sensor module in the upper left; **(right)** three communication modules — USB, Bluetooth and Wi-Fi. The wireless modules include the circuitry for battery charging, powered through a dedicated USB connection.

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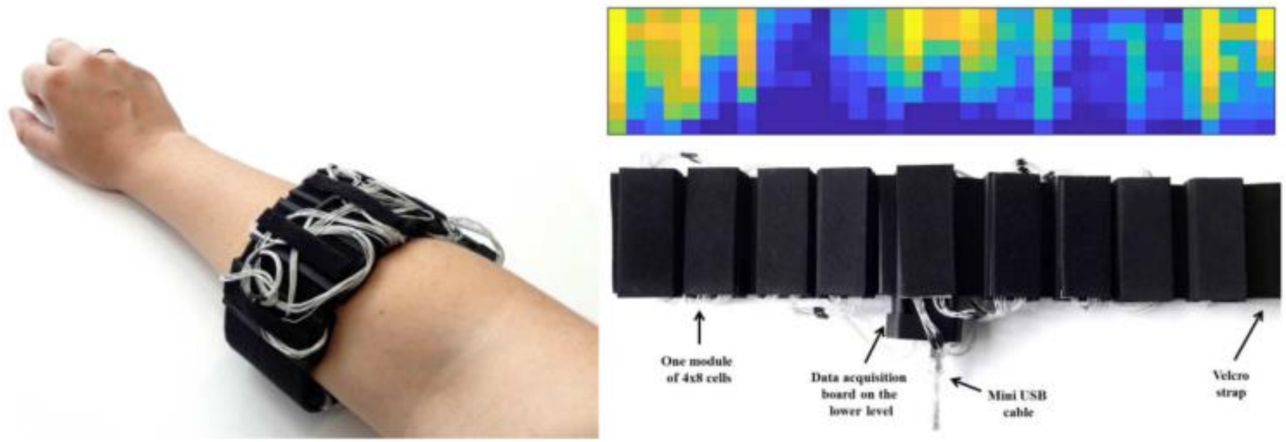

FIGURE 3 | Picture of the tactile bracelet, consisting of 9 boards of 32 cells each (8 vertical and 4 horizontal), and visual representation of the data.

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Tactile Myography

a.k.a. high-density FMG

- what if we use *many* such sensors instead of 10?

- in this case:
  - having so many sensors could „make the problem linear": - problem can be solved using simple ML algorithms
  - if each action independently excites one single region of the sensor,
  - chances are that combined actions would be automatically detected.

- use linear regression on two different sets of features:
  - the taxel values *per se:* $d = 32 \cdot 10 = 320$, or
  - consider two „regions of interest" (RoI) per board,
    - extract three values from each region: $d = 3 \cdot 2 \cdot 10 = 60$
    - representing the „gradient" of the values in the RoI

- one set is more compact, but will it retain all useful information?

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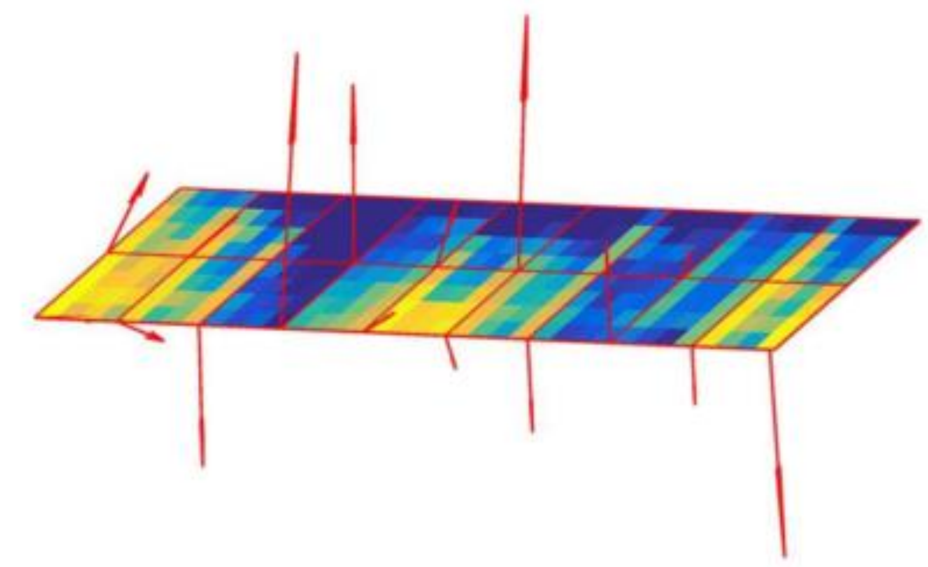

FIGURE 5 | A schematic representation of ROIs and their gradient, obtained from real data.

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Tactile Myography

a.k.a. high-density FMG

- what if we use *many* such sensors instead of 10?

- involve participants in a TAC (Target Achievement Control) test:
  - show a target (limb in a specific configuration),
  - ask participant to reach it (drive tactile-controlled hand to same configuration)
  - and stay close (tolerance threshold) for 2 seconds
  - timeout: 20 seconds

Intent detection and somatosensory feedback

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Tactile Myography

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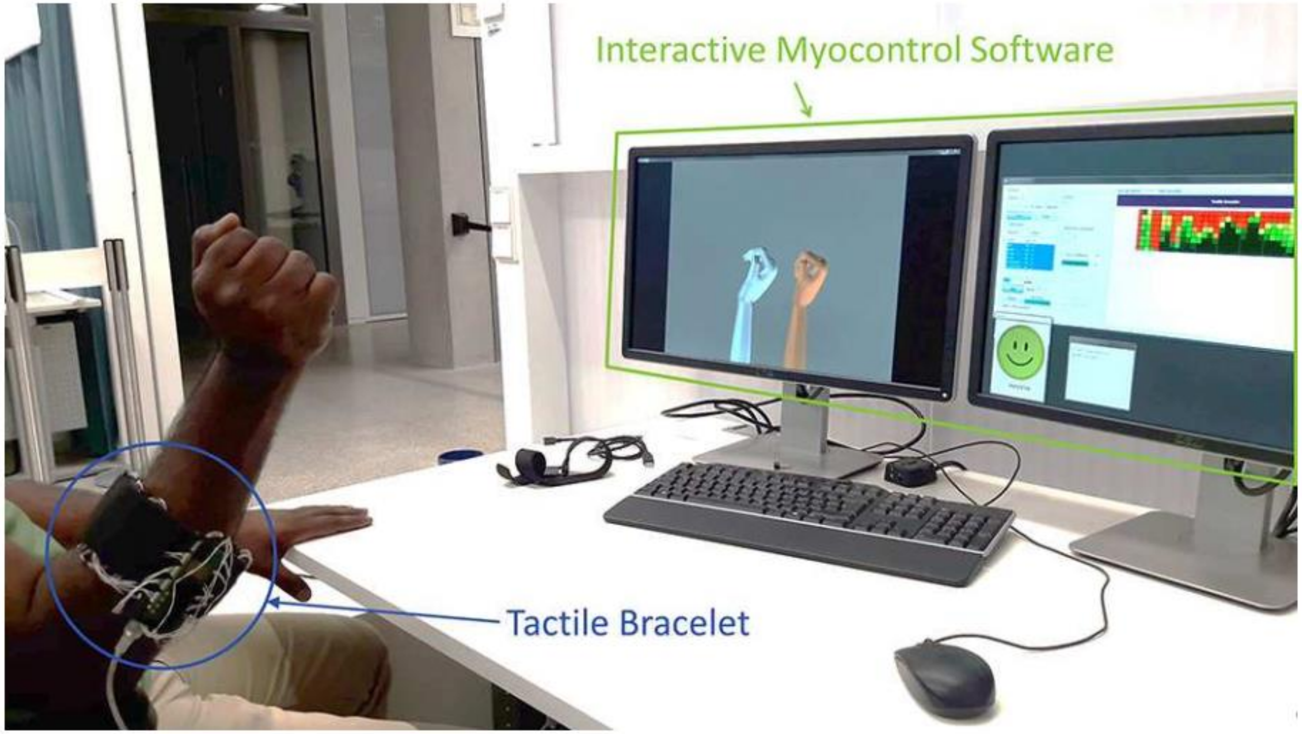

FIGURE 6 | A bird's-eye view of the experiment.

Intent detection and somatosensory feedback

1. The TAC (Target Achievement Control) test is designed to evaluate the ability of participants to control a prosthetic or assistive limb. Here's a step-by-step breakdown of the process:
2. **Show a target**: Present the participant with a specific target configuration for a limb. This could mean positioning a limb or a prosthetic hand in a particular orientation or location.
3. **Reach the target**: The participant is asked to move their tactile-controlled hand (or other assistive device) to match the configuration of the target. This involves the participant actively driving the prosthetic to the desired position.
4. **Stay close to the target**: Once the participant reaches the target configuration, they need to maintain their hand in that position within a specified tolerance threshold for 2 seconds. This tests not only the ability to reach the target but also to hold the position accurately.
5. **Timeout**: The participant is given a maximum of 20 seconds to complete the task. If they are unable to reach and maintain the target configuration within this time, the test for that specific target is considered a failure.
6. This test assesses the participant's precision, control, and stability in using the prosthetic or assistive device, providing valuable feedback for both the user and the developers of such devices.

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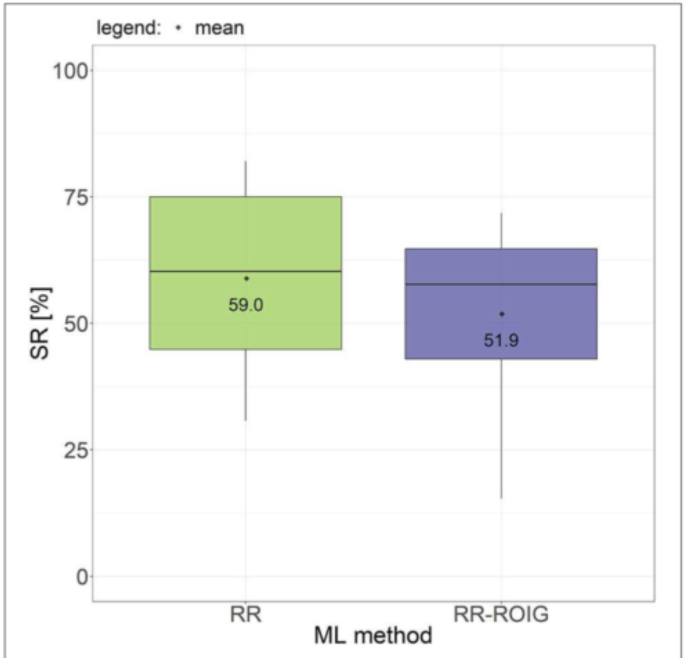
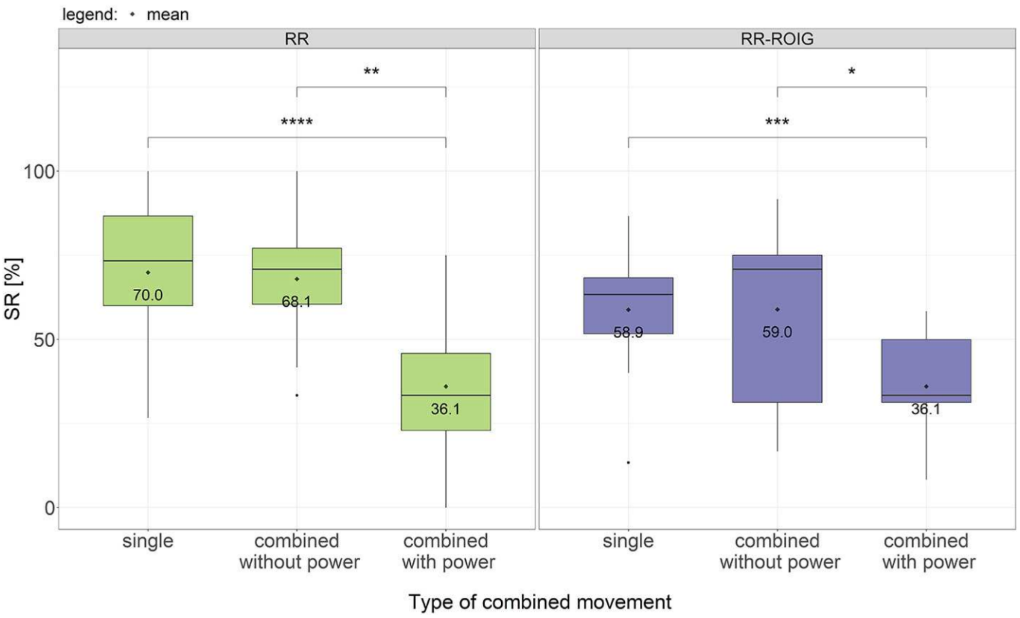


FIGURE 8 | Boxplots and means of the success rates for all tasks across all participants grouped according to the machine learning method used.



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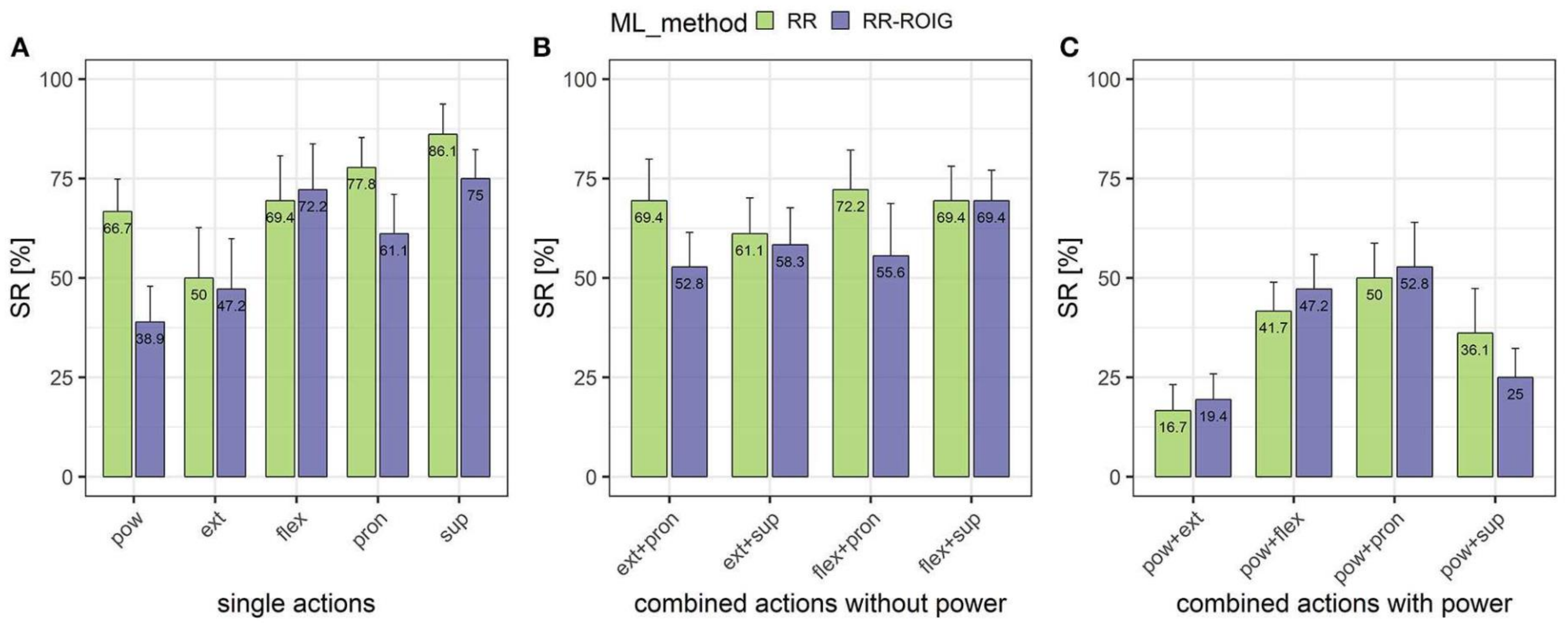

FIGURE 10 | Means and standard errors of the success rates per actions separated into 3 groups: single actions **(A)**, combined actions without the power grasp **(B)** and combined actions including the power grasp **(C)**.

Summary

- today:
  - muscle activity – detecting deformations induced by it
  - via simple force sensors
  - via high-density force sensors

- results?
  - somewhat disappointing – works great in the lab, fails to generalise
  - hasn‘t been used at all in the clinics so far
  - The technology needs further development to overcome challenges in generalization and practical application.

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