Intent detection and somatosensory feedback

#02: Intent Detection: overview, definitions, biosignals

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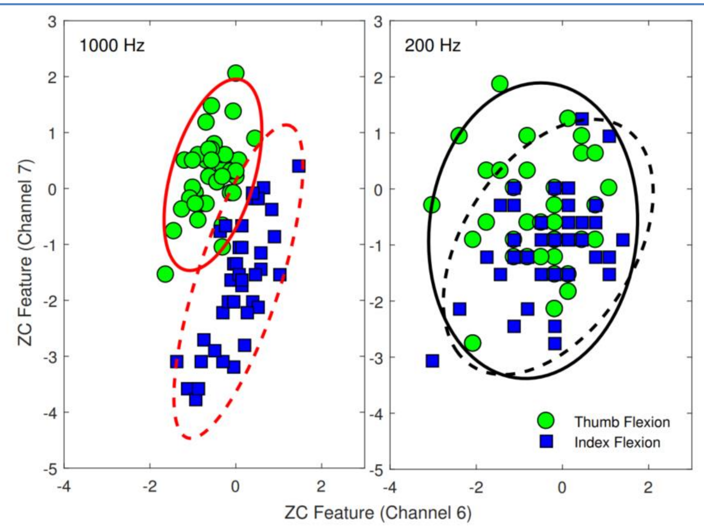


Figure 2. Differences in EMG patterns between using: (**left**) a 1000 Hz sampling rate; and (**right**) a 200 Hz sampling rate. ZC features are extracted from two different EMG channels (6 and 7) during thumb flexion (green circle markers and solid lines) and index flexion (blue square markers and dashed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

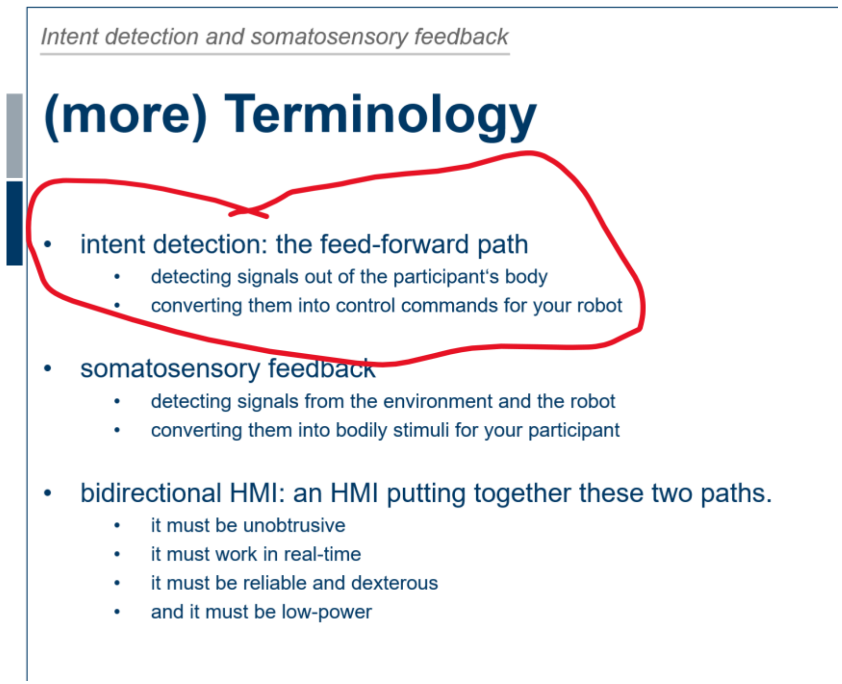
Lecture #02:

Intent Detection: overview, definitions, biosignals

- What is intent detection?
  - from intuition to mathematical formulation
- Machine learning for ID
  - the problem of ground truth
  - offline vs. online ID
- kinds of signals for ID
  - low- or high-density? surface or tomographic?
- Summary

What is intent detection?

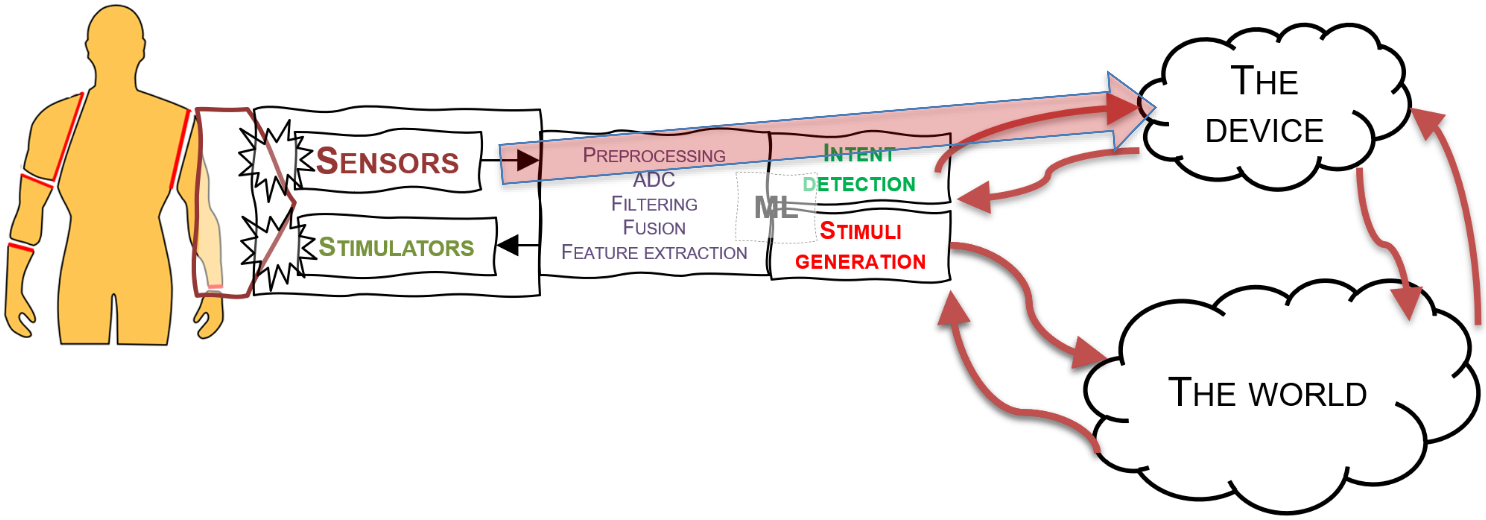
- Recall lecture #1:



What is intent detection?

- Recall lecture #1:

HMIs for the disabled



What is intent detection?

- Assumption / working hypothesis:
  - our participant can produce some voluntary muscle activity
- If this is the case, we need to gather signals related to (representing) muscle activity.
- **myocontrol:** control based upon direct muscle activity.
  - in the ideal world: **„user wants to do something, device does it.“**
  - more realistically: **„user does something, device does something reasonably related to what user wanted to do.“**
- example *(prosthetics):* the amount of residual muscle activity found in an **amputee‘s stump** even **decades after the operation** is *amazing*,
  - both quantitatively (denoting the intended level of activation)
  - and qualitatively (denoting what action to perform)

Intent c

1. Quantitatively, it's astonishing because the level of residual muscle activity often aligns closely with what would be expected in the intact limb. This means that the muscles in the residual limb are still capable of generating significant electrical signals, indicating that they retain much of their original functionality. Advanced prosthetic devices can harness this residual muscle activity through techniques like electromyography (EMG), which senses these electrical signals and translates them into corresponding movements in the prosthetic limb

2. Qualitatively, the residual muscle activity also plays a crucial role in conveying the intention of movement. Even though the limb may be missing, the brain's signals to perform certain actions still exist. These signals are picked up by the remaining muscles in the residual limb, providing valuable information about the desired movement.

3. Intent detection is possible because the muscle activity still exist in the residual limbs even after amputation.

Offline Intent Detection:

1. Timing: Analysis occurs after data collection.
2. Process: Data is recorded and stored first, then processed later.
3. Use Case: Suitable for situations where immediate feedback is not required.

Online Intent Detection:

1. Timing: Analysis occurs simultaneously with data collection.
2. Process: Data is processed in real-time, allowing for instant feedback or interaction.
3. Use Case: Crucial for applications requiring immediate responses.

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- example *(rehab):* **stroke survivor** tries to reach for a mug, the muscle activity she produces will be **different from a healthy participant‘s one**
  - but we should anyway be able to associate it to the action of reaching and grasping
  - and accordingly command a rehab exoskeleton to help the participant perform it!

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  - more realistically: **„user does something, device does something reasonably related to what user wanted to do."**
- example *(demo):* **surface electromyography** (sEMG) patterns can be associated to **intended actions**
  - then a pattern-recognition (machine learning) system can be used to retrieve the action corresponding to a pattern
  - and control a robotic artefact given the action.

Intent detection

- what you just saw:

1. Thalmic Labs' Myo armband represents an exciting advancement in wearable technology, allowing users to control electronic devices using the electrical impulses generated by their muscles. This innovative device essentially translates the natural movements of the user's arm and hand into commands for various electronics.
2. For instance, users can switch songs on a Sonos music system or change slides in a PowerPoint presentation simply by making specific gestures or movements with their fingers while wearing the Myo armband. This hands-free and intuitive control mechanism offers a seamless and futuristic interaction experience, eliminating the need for traditional input devices like keyboards or remote controls.

Intent detection

- working hypothesis:
    - we will use machine learning for intent detection. – but no need if we are just using 2 sensors for 1 degree of freedom
- not necessarily so in *all* cases!
    - e.g., myocontrol of a single DoF (open/close) using *two* sEMG sensors
- the standard / clinical practice myocontrol system:
    - place a sEMG sensor on each *locus* of residual activity, - sensor at each specific point where residual muscle activity is detected in the amputee's stump.
    - assign a motion of the prosthesis to each sensor. - Assigning a motion of the prosthesis to each sensor involves mapping the electrical signals detected by each surface electromyography (sEMG) sensor to specific movements or actions of the prosthetic limb.
- typical solution for a trans-radial amputee:
    - a one-DoF prosthetic gripper capable of opening/closing
    - opening velocity: proportional to EMG at the *M. Extensor Digitorum* (dorsal region of the forearm)
    - closing velocity: proportional to EMG at the *M. Flexor Digitorum Superficialis* (ventral region of the forearm)

Intent detection

- further assumption:
  - we will use machine learning for in
- not necessarily so in *all* cases!
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Intent detection

- A brachial plexus injury is a type of nerve injury that affects the network of nerves called the brachial plexus, which extends from the spinal cord in the neck down through the shoulder and into the arm. This network of nerves controls the movement and sensation in the shoulder, arm, and hand. Symptoms of a brachial plexus injury can include weakness or paralysis in the affected arm, loss of sensation, pain, and difficulty with movement or coordination.

- how much can you do with one DoF only? …an awful lot. check these ones out:

Intent detection

- the definition of „intent“ raises complicated philosophical issues
  - who knows what you want to do?
  - do *you* know what you want to do?
  - if so, *when* do you know it?
  - (does *free will* really exist?)

- so we resort to a more operational view:
  - the signals you produce contain enough information
  - for me to detect / anticipate what you are going to do in the next second or so

- that is, there is a function mapping your signals onto your actions
- and I want to use it to let you control the device!

Intent detection

- so I‘m building a function that approximates *that* function there. mathematically speaking:
  - define a d-dimensional *input space,* somehow representing your input signals
  - define an *output space,* somehow controlling your device (for simplicity: one single real number)
  - seek for an *approximant function* mapping the input space onto the output space

$$y = f(\boldsymbol{x}), \boldsymbol{x} \in \mathbb{R}^d, y \in \mathbb{R}$$

- since we use machine learning, we will be using *data* to build f, and data consist of a set of *pairs,* each pair consisting in turn of
  - a d-dimensional *observation* $\boldsymbol{x}$ and
  - a real *target value* y

- (extending to many outputs simiultaneously is easy: say we want to have one activation value for each of the m motors of the prosthesis, then we have means to have m such functions, $f_1, \ldots, f_m$, in parallel.) – approximating what each of the motors should do depending on the input.

Intent detection

- the set of data we use, S, consists then of n data pairs,

$$S = \{(\boldsymbol{x}_i, y_i)\}_{i=1}^{n} \text{ , where } \boldsymbol{x}_i \in \mathbb{R}^d \text{ and } y_i \in \mathbb{R}$$

- and can be compactly represented by a (matrix,vector) pair $(X, \boldsymbol{y})$, where

$$X = \begin{bmatrix} \boldsymbol{x}_1^T \\ \vdots \\ \boldsymbol{x}_n^T \end{bmatrix} \in \mathbb{R}^{n \times d} \qquad \text{and} \qquad \boldsymbol{y} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} \in \mathbb{R}^n$$

- in practice, juxtaposing each observation in an $n \times d$-element matrix and each target value in a n-dimensional vector.

- target values can be either real numbers or labels; altogether they are called *ground truth*.
  - ground truth is… the supposedly *true* value associated to an observation, i.e.,
  - the value the function we try to approximate would yield, given the associated observation.

Intent detection

- in other words: f maps *signal patterns* onto *actions*
- stationary intent detection:
    - signal pattern: a vector $\boldsymbol{x} \in \mathbb{R}^d$
    - action: a value $y \in \mathbb{R}$
- dynamic / non-stationary intent detection: possibly generalise to
    - signal pattern: a vector in time, $\boldsymbol{x}(t) \in \mathbb{R}^d, t = [0, T_x]$
    - action: a value in time $y(t) \in \mathbb{R}, t = [0, T_y]$
- in practice, in either case an *action* is an *activation configuration*,
    - which then gets somehow translated to a configuration of the device
- recall the demonstration:
    - 8 real-valued (really, in the range $[0,5] \subset \mathbb{R}$) input signals ($d = 8$),
    - one real-valued activation value in $[0,1] \subset \mathbb{R}$ for each action, e.g., flexion / extension of the wrist.

Intent detection

- now, seemingly trivial question: *how do we gather ground truth?*
- that is, how do we decide which action to associate to a signal pattern, and when?
- since we use machine learning, it is mostly about
  - the data you collect, and
  - the semantics you give it (labelling / target values)
- usually, data are labelled…
  - either manually, e.g. image classification for face recognition
  - or mechanically, using sensors on hands and fingers
- …but here things are definitely more complicated!
  - the data you collect depends on the user.
  - the semantics depends… on the user, too!

Intent(ion) detection

- user wants to perform a specific action at a specific time
- activates muscles in a corresponding way
- the activation generates a detectable signal pattern
- we associate this pattern to the intended action.

- this is
  - the best way to define „intent detection“
  - without running into serious philosophical issues about the free will and such.

- so what we need to have is
  - many, good sensors, well housed
  - *(experimental protocol)* a happy user doing something we know about
  - *(machine learning)* well-recorded signals and their patterns, among which to find correspondances
  - *(structured interaction)* the chance to update and correct in the course of time („generalisation of the experimental protocol“)

Intent(ion) detection - Ground-truth data refers to accurate and trustworthy information about the user's intentions or actions, which is essential for training machine learning models or assessing the effectiveness of interventions.

- main lesson: *patients cannot, in general, produce any reliable ground-truth.*

- (example) amputees: no sensors for ground truth!
  - no cybergloves / instrumented clothing / motion tracking
  - no force sensors for fingers, no torque sensors / load cells for joints
- (example) stroke patients: sensors would yield the wrong ground truth!
  - because they cannot really do what they want to do!

- so, in order to label our data, how do we know what the user wants to do?

- the easy answer: we do not.
  - and neither do users!
  - better: they know what they want to do but *they don‘t know what they are doing,* since
  - at best, they have no sensori-motor feedback any longer;
  - in the worst case they have a wrong, painful or jumbled feed-back.

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- so, in order to label our data, how do we know what the user wants to do?

- the less-easy answer: we ask them or we induce them to reveal it
  - the experimental protocol induces the user to perform an action (*stimulus*),
  - we record the signal in the time proximity and associate it to the requested action

- how do we know that the labelling is correct? we don‘t.
  - errors must be corrected by collecting more data and updating the model,
  - in the course of time, as the participant grows more aware of the procedure.

Intent(ion) detection

three amputees were induced to "perform" actions with their absent limb while EMG was recorded from it.

1. by imitating the experimenter's hand
2. by performing bilaterally symmetric actions
3. by looking at a mirror

questions:
a. how rich in information is the EMG gathered?
b. which protocol yields the best data?

Castellini, Claudio, Gruppioni, Emanuele, Davalli, Angelo and Sandini, Giulio, *Fine detection of grasp force and posture by amputees via surface electromyography,* **Journal of Physiology (Paris)**, 2009, vol. 103, No. 3-5, p. 255-262

Intent(ion) detection

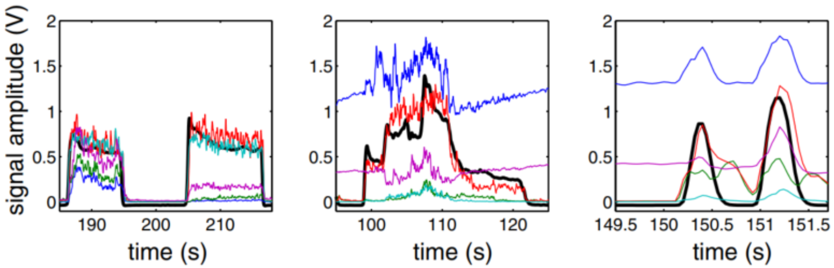

Fig. 4. Three examples of force (black thick line) and EMG signals (coloured thin lines). (left panel) Subject 1 in the teacher imitation modality switches from po to pw at about 200 s of activity—notice the sharp change in relative average magnitude of the EMG signals, before and after the switch (center and right panels). Subject 3 in the mirror-box modality, slow and fast power grasping.

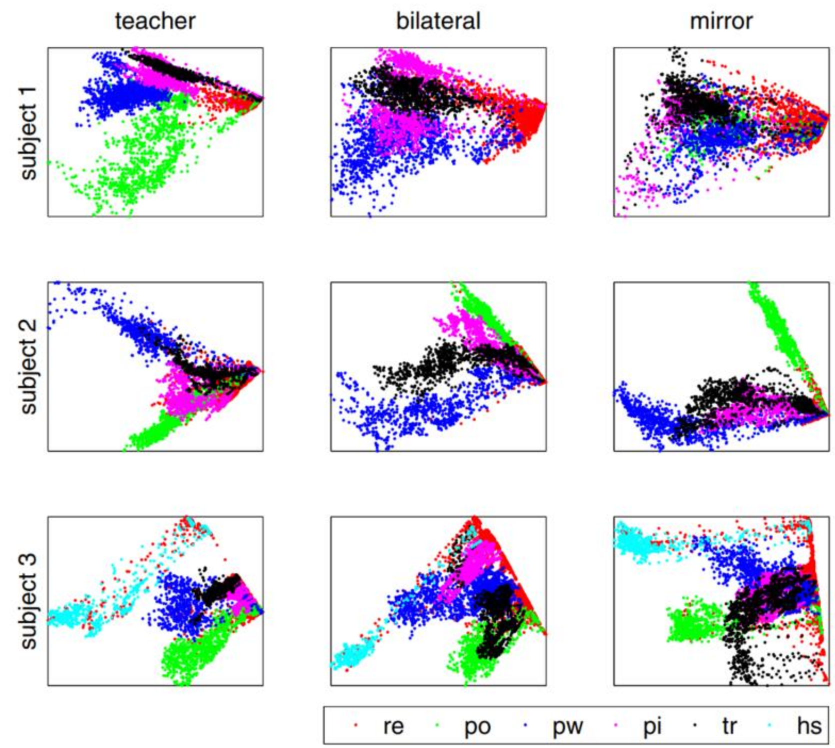

Fig. 5. Visualisation of the PCA-reduced EMG signals.

Castellini, Claudio, Gruppioni, Emanuele, Davalli, Angelo and Sandini, Giulio,
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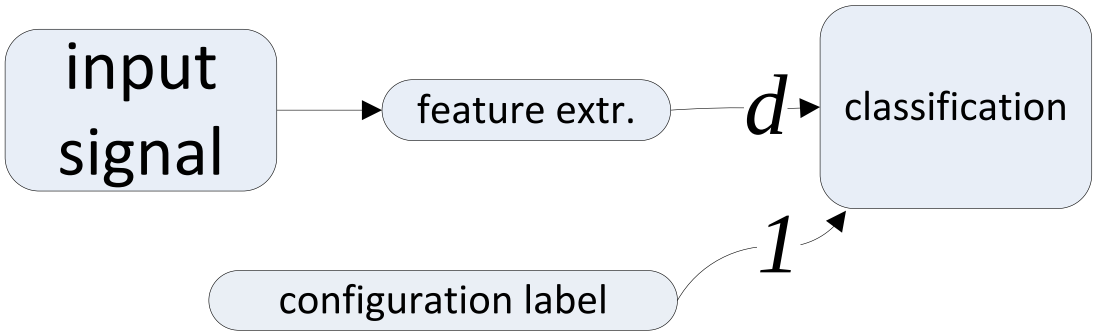

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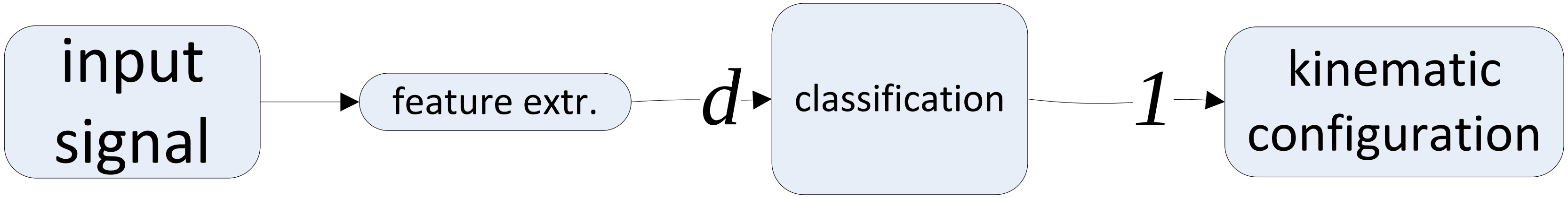

- kinematic configuration- refers to the specific arrangement or configuration of the joints and segments of a system, typically a human body or a robotic system.
- configuration labels such as "open hand," "closed fist," "pointing finger," etc. These labels help categorize and identify the various configurations that the system may exhibit during different movements or actions

Intent(ion) detection

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- big problem: *offline vs. online intent detection!*

- offline:
    - (experimental protocol) induce user to do something at a specific time,
    - (data collection) record input signals while user does „that something“,
    - *(exit user, forever)*
    - (model building) use part of the data to map data→“that something“,
    - (model evaluation) test model on the remaining data

- that is what we just saw.

Intent(ion) detection

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- big problem: *offline vs. online intent detection!*

- online:
  - (experimental protocol) **have the user do something** at a specific time,
  - (data collection) record input signals while user does that something,
  - *(user stays in the experiment!)*
  - (model building) **use all data to update map** data→something,
  - (model evaluation) **test in real life and go back to beginning**

- this is harder but more realistic.

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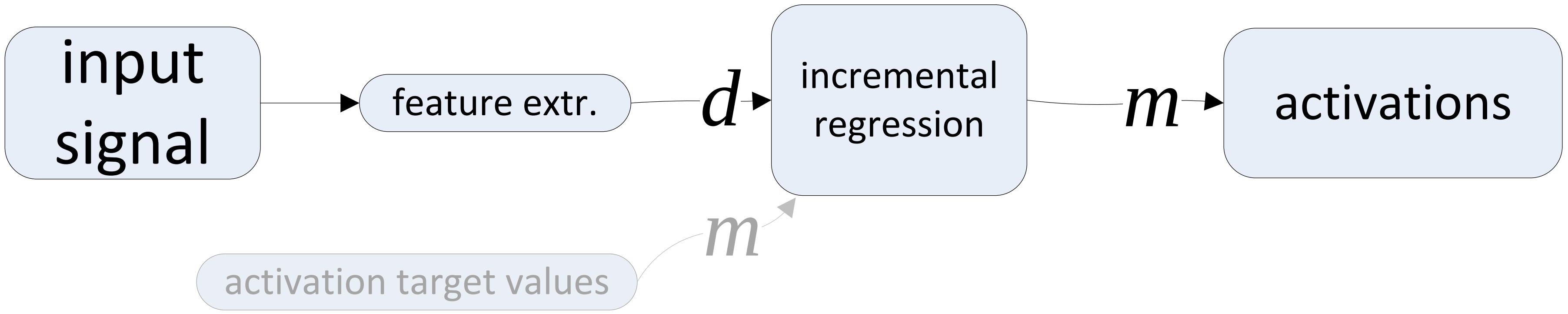

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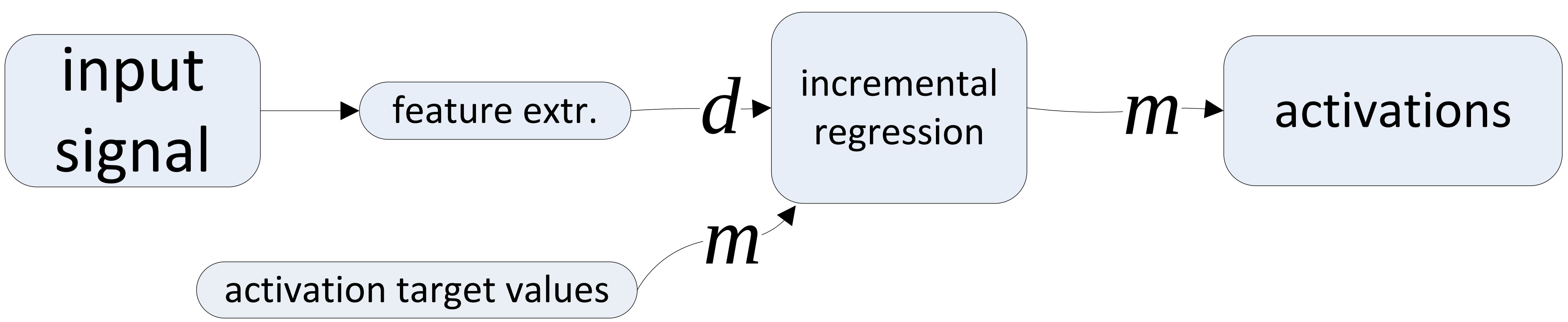

Activations are the predictions
Activation target values – collected for training
Both training and testing happen - in online as users are with us

Intent(ion) detection

- how useful is offline intent detection?
- not very much.

Abstract—In this paper, we present a systematic analysis of the relationship between the accuracy of the mapping between EMG and hand kinematics and the control performance in goal-oriented tasks of three simultaneous and proportional myoelectric control algorithms: nonnegative matrix factorization (NMF), linear regression (LR), and artificial neural networks (ANN). The purpose was to investigate the impact of the precision of the kinematics estimation by a myoelectric controller for accurately complete goal-directed tasks. Nine naïve subjects performed a series of goal-directed myoelectric control tasks using the three algorithms, and their online performance was characterized by 6 indexes. The results showed that, although the three algorithms' mapping accuracies were significantly different, their online performance was similar. Moreover, for LR and ANN, the offline performance was not correlated to any of the online performance indexes, and only a weak correlation was found with three of them for NMF ($r^2 < 50\%$). We conclude that for reliable simultaneous and proportional myoelectric control, it is not necessary to achieve high accuracy in the mapping between EMG and kinematics. Rather, good online myoelectric control is achieved by the continuous interaction and adaptation of the user with the myoelectric controller through feedback (visual in the current study). Control signals generated by EMG with rather poor association with

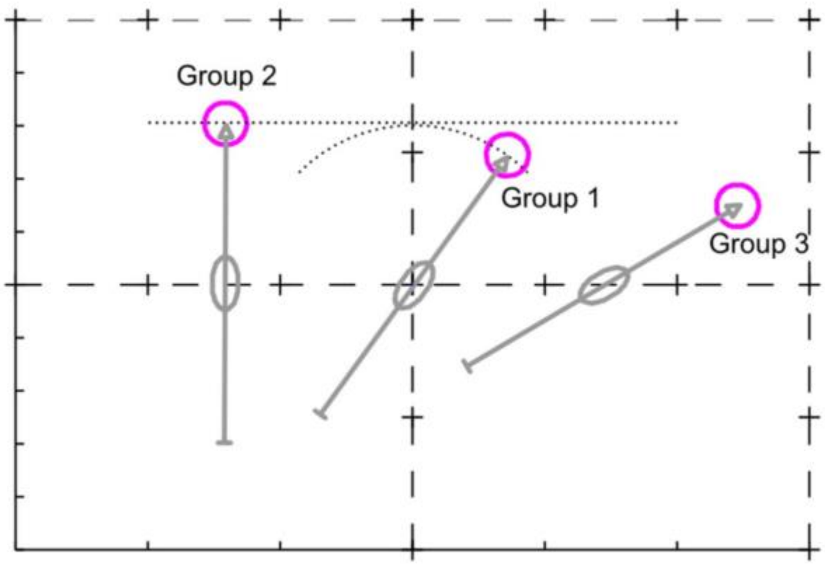

Fig. 1. Feedback presented to the subject during the experiment. Left–right movements of the arrow represented flexion and extension (DoF1), and the rotational movements of the arrow represented wrist rotation (DoF2). A representative target during the online target hitting task is illustrated as well.

Ning Jiang, Ivan Vujaklija, Hubertus Rehbaum, Bernhard Graimann, and Dario Farina, *Is Accurate Mapping of EMG Signals on Kinematics Needed for Precise Online Myoelectric Control?*, **IEEE TRANSACTIONS ON NEURAL SYSTEMS AND REHABILITATION ENGINEERING,** VOL. 22, NO. 3, MAY 2014.

Intent(ion) detection

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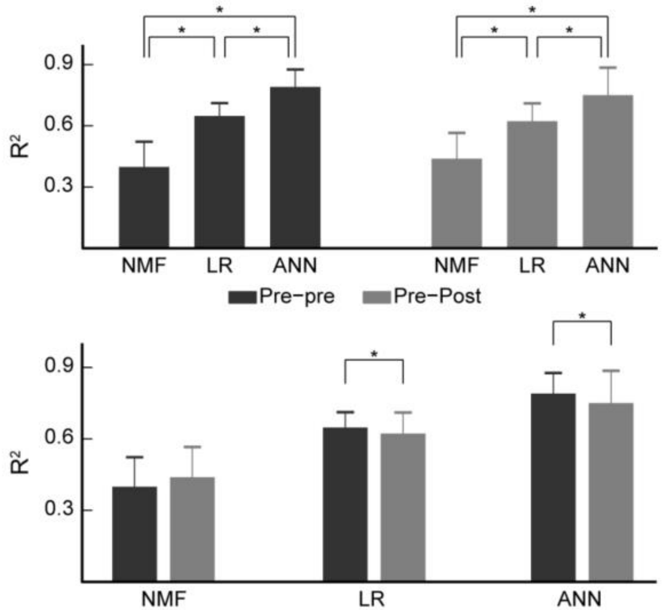


Fig. 4. Results of the statistical analysis of the offline performance (R^2 values). Tests revealing significance are marked by stars.

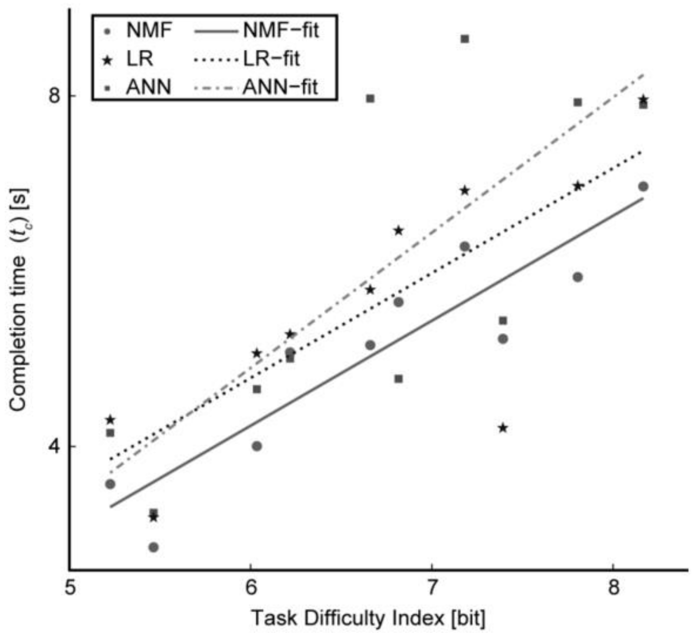


Fig. 5. Correlation between task difficulty (T) and the corresponding task completion time (t_c) of the three algorithms. The r^2 values of the linear fits of NMF, LR, and ANN are 0.85, 0.65, and 0.59, respectively.

Ning Jiang, Ivan Vujaklija, Hubertus Rehbaum, Bernhard Graimann, and Dario Farina, *Is Accurate Mapping of EMG Signals on Kinematics Needed for Precise Online Myoelectric Control?*, **IEEE TRANSACTIONS ON NEURAL SYSTEMS AND REHABILITATION ENGINEERING,** VOL. 22, NO. 3, MAY 2014.

Intent(ion) detection

- how useful is offline intent detection?
- not very much:
- essentially no correlation between offline and online performance measures.
- take-home lesson: offline intent detection is (almost) a waste of time and effort.

If the performance of offline is a good predictor of the online, then there should be a correlation between pm indexes.
Correlation is nearly close to 0
A correlation of 0 indicates no linear relationship between the variables.

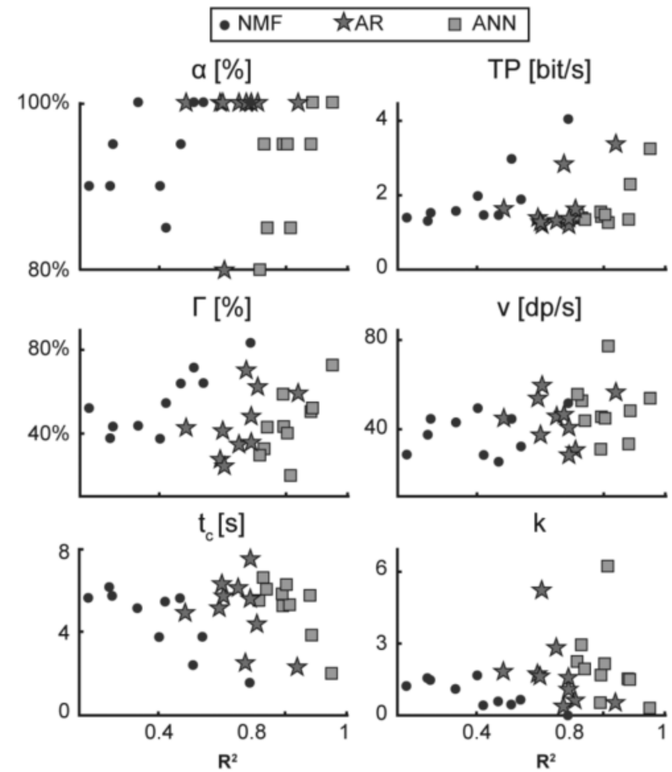


Fig. 7. Correlation between the offline performance metric, R^2, and the six online performance metrics. Each data point corresponds to the result from one subject, using one of the algorithms. That a particular point, the R^2 value presented is the average value over the cross-validation, and the value of the online performance metric is the average value sets over all trials performed by that subject using that algorithm. The only significant correlations found in NMF for t_c, Γ and k.

Ning Jiang, Ivan Vujaklija, Hubertus Rehbaum, Bernhard Graimann, and Dario Farina, *Is Accurate Mapping of EMG Signals on Kinematics Needed for Precise Online Myoelectric Control?*, **IEEE TRANSACTIONS ON NEURAL SYSTEMS AND REHABILITATION ENGINEERING,** VOL. 22, NO. 3, MAY 2014.

Intent detection and somatosensory feedback

The scatter plot shows the correlation between two things by looking at how close the data points are to a straight line. Here's a breakdown:

1. **Spread of Points:** Imagine a straight line drawn through the middle of the data points. If the points are scattered randomly around this line, there's no correlation. The more the points cluster together and follow a diagonal trend (up or down), the stronger the correlation.

2. **Direction of the Trend:** The direction of the diagonal trend tells you if the correlation is positive or negative.
   - **Positive Correlation (Upward Diagonal):** As the value on the x-axis (R^2) increases, the values on the y-axis (online performance) also tend to increase. This suggests that higher R^2 is associated with better online performance.
   - **Negative Correlation (Downward Diagonal):** As the value on the x-axis increases, the values on the y-axis tend to decrease. This suggests that higher R^2 is associated with worse online performance.

In the graph you described, the researchers likely found a positive correlation between R^2 and some online performance metrics for the NMF algorithm. This means the data points for NMF would likely form a cluster with an upward diagonal trend.
Remember, the scatter plot itself doesn't tell you the strength of the correlation. That's usually calculated using a statistical value called a correlation coefficient.

What is calibration?

In the context of myoelectric control, calibration typically refers to the process of setting up or adjusting a myoelectric device to interpret signals from the user's muscles accurately. Myoelectric control involves using electrical signals generated by muscle contractions to control external devices such as prosthetic limbs or robotic devices.
During calibration, the user typically performs a series of specific muscle contractions or movements while the myoelectric sensors are active. These contractions help the device learn the user's unique muscle signal patterns and establish a baseline for interpreting future muscle signals. Calibration ensures that the device accurately recognizes and responds to the user's intended movements, improving the overall performance and usability of the myoelectric system.

Muscle activity / activation

- Just how does it work?
- muscles can only contract, giving rise to
    - force at the attachment to the bone, then in turn
    - torque at a joint, resulting in
    - force at the end-effector (e.g., the wrist)
- flexion / extension and stiffening up (co-contraction) enforced via
    - the agonist / antagonist mechanism
    - e.g., biceps and triceps
- basic contractile unit: the motor unit (MU), consisting of
    - an α-motoneuron, innervating
    - one or more muscle cells (muscle fibres)
    - at a neuromuscular junction (NMJ)
- a spike train in the α-motoneuron will cause sustained contraction of the MU.

Intent detection and somatosensory feedback

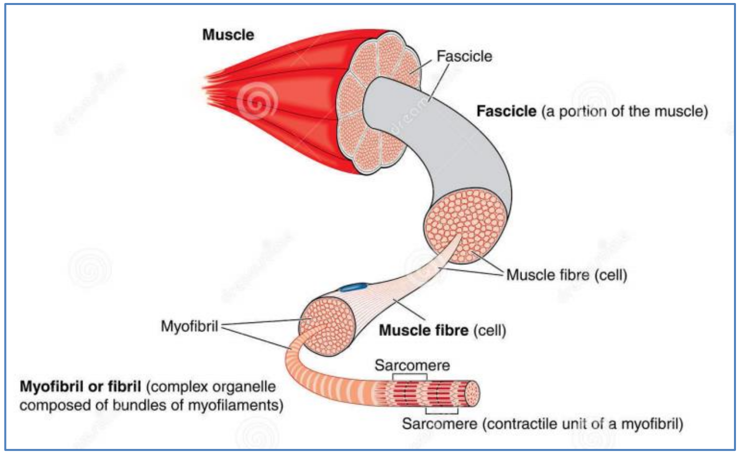
1. **Muscle Contraction**: Muscles can only contract, meaning they can shorten or tighten. This contraction occurs when muscle fibers generate tension in response to signals from the nervous system.
2. **Force at Attachment to the Bone**: Muscles are attached to bones via tendons. When a muscle contracts, it pulls on the tendon, which in turn pulls on the bone it's attached to. This pulling generates force at the attachment point on the bone.
3. **Torque at a Joint**: When a muscle pulls on a bone, it creates a turning effect known as torque around the joint. Torque is the product of force and the distance from the axis of rotation (in this case, the joint). So, the force generated by the muscle, combined with the lever arm (the distance between the muscle's attachment point and the joint), results in torque.
4. **Force at the End-Effector**: The end-effector refers to the part of the body or device that interacts with the environment. For example, in the case of the wrist, the hand and fingers are the end-effectors. The torque generated at the joint by muscle contraction results in force at the end-effector. This force allows for movement or manipulation of objects in the environment.
5. Co contraction – when both the opposing muscles contract leading to stiffness.

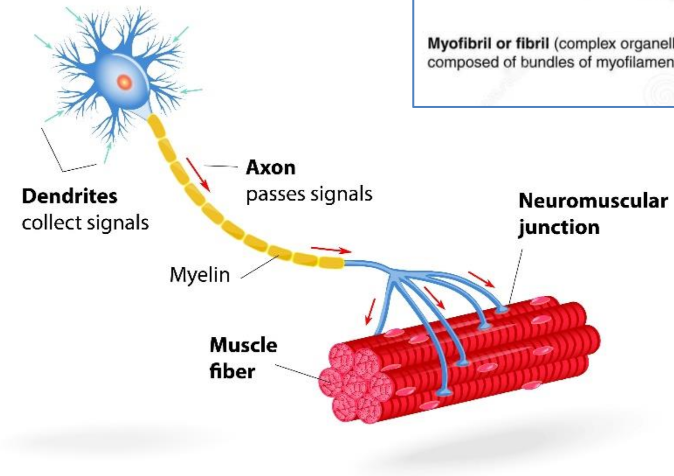
Alpha-Motoneuron (α-Motoneuron): This is a type of motor neuron located in the spinal cord. Alpha-motoneurons are responsible for transmitting signals from the central nervous system (CNS) to the muscles they innervate. Each alpha-motoneuron can control multiple muscle fibers within a muscle.

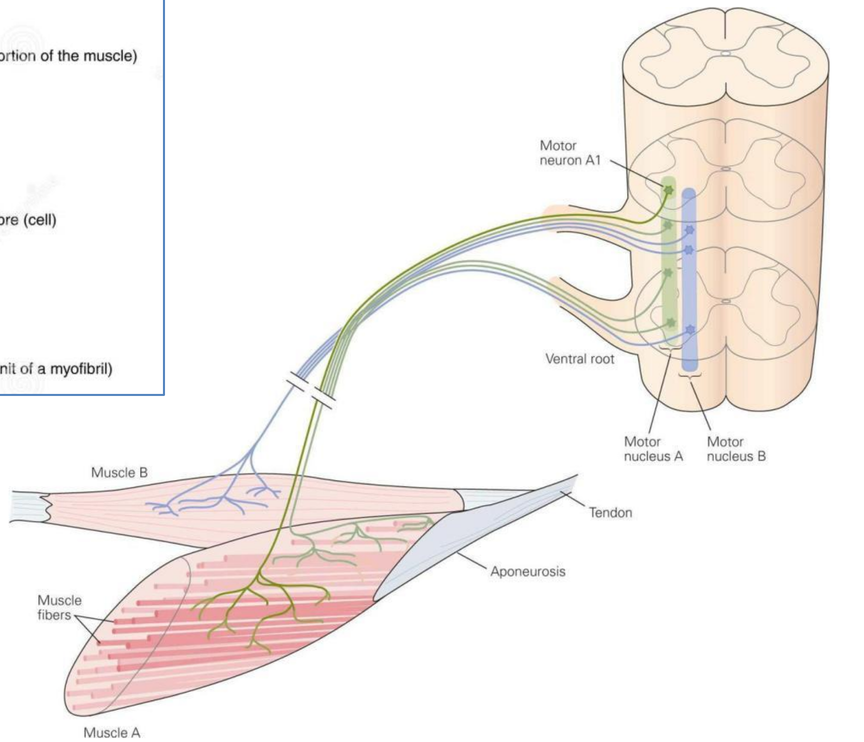
6. **Neuromuscular Junction (NMJ)**: This is the point of communication between the alpha-motoneuron and the muscle fibers it innervates. At the NMJ, the alpha-motoneuron releases a chemical neurotransmitter called acetylcholine (ACh) in response to an action potential. ACh binds to receptors on the muscle fiber, initiating a series of events that lead to muscle contraction.
7. **Muscle Fibers (Muscle Cells)**: Muscle fibers, also known as muscle cells or muscle fibers, are the individual cells that make up skeletal muscle tissue. Each muscle fiber is innervated by a single alpha-motoneuron at the neuromuscular junction. When the alpha-motoneuron sends a signal to the muscle fiber, it triggers a contraction by releasing calcium ions, which initiate the sliding of actin and myosin filaments within the muscle fiber.

Muscle activity / activation

- Just how does it work?







Muscle activity / activation

- Just how does it work?

- long story cut short:
  - spike train emitted by α-motoneuron
  - results in *acetylcholine* being released at the NMJ, in turn
  - promoting the release of *Calcium* in the innervated muscle cells,
  - promoting the sliding of *actin* against *myosin* (contraction)
  - also promoting a *wave of depolarisation* all along the cells

- as the spike train stops, the MU comes
- back to its resting state

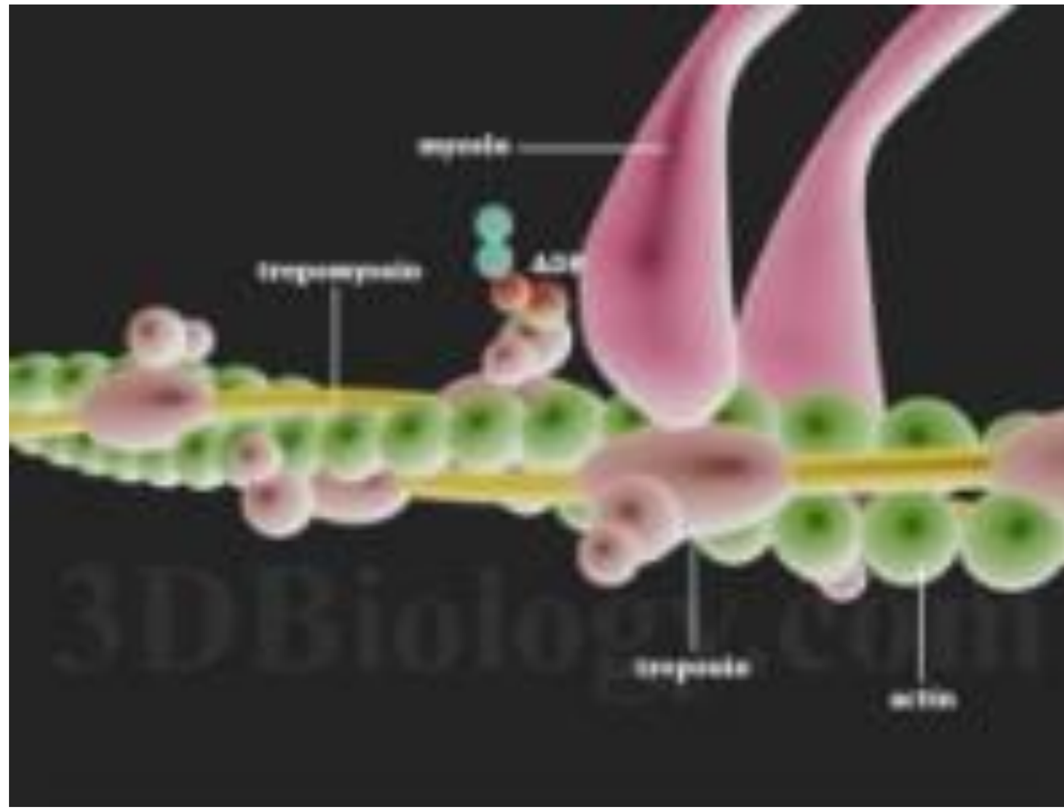
- (which *absolutely does not mean* resting position!)

1. The binding of acetylcholine to its receptors on the muscle fiber membrane initiates a series of events that result in the depolarization of the muscle cell membrane. This depolarization activates voltage-gated calcium channels on the membrane of the muscle cell, allowing calcium ions (Ca2+) to enter the cell from the extracellular space.

2. **Promotion of Sliding of Actin Against Myosin (Contraction)**: The influx of calcium ions into the muscle cell triggers a cascade of biochemical reactions within the cell that lead to the exposure of binding sites on the actin filaments. These binding sites allow myosin heads to attach to actin, forming cross-bridges. The subsequent hydrolysis of ATP by the myosin heads powers the sliding of actin filaments past the myosin filaments, resulting in muscle contraction.
3. **Promotion of a Wave of Depolarization Along the Muscle Cells**: The initial depolarization triggered by the binding of acetylcholine to its receptors spreads along the muscle cell membrane in a wave-like fashion. This wave of depolarization, known as an action potential, propagates along the length of the muscle fiber, leading to the contraction of the entire muscle fiber.

Muscle activity / activation

- Just how does it work?



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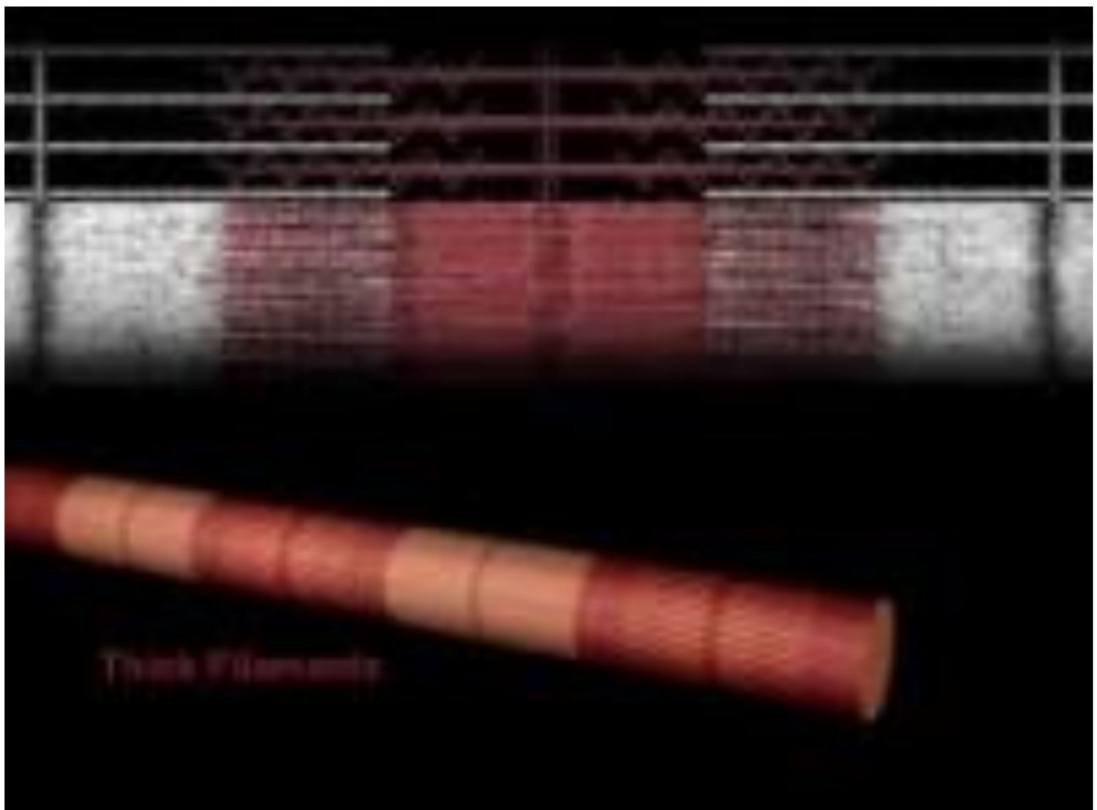
Muscle activity / activation

- Just how does it work?



Graham Johnson

Effects of muscle activity

- muscle activity, then, means *contraction of muscle cells* at a microscopic scale

- but now we are after any possible *macroscopic* effect we can *measure*
  - with a reasonable effort, that means
  - with sensors we can embed in a rehabilitation robot / a prosthesis / any artefact we want to control.

- macroscopic effects of muscle activity include:
  - kinematic / dynamic (body motion and generation of forces / torques);
  - electric,
  - pressure,
  - kinematic (structural change inside the body part of interest).

  Torque is the rotational force around an axis, calculated as the product of the force applied and the distance from the axis of rotation.

  When muscles contract, they produce forces that can cause movement in the body. These forces result in changes in the position, velocity, and acceleration of body segments, leading to body motion. Additionally, muscles generate torques (rotational forces) around joints, which are essential for producing and controlling movement. For example, when the biceps muscle contracts, it generates a force that causes the forearm to move upwards, and it also generates a torque that bends the elbow joint.

Jeremy Mouchoux, Stefano Carisi, Strahinja Dosen , Member, IEEE, Dario Farina , Fellow, IEEE, Arndt F. Schilling , and Marko Markovic, *Artificial Perception and Semiautonomous Control in Myoelectric Hand Prostheses Increases Performance and Decreases Effort*, **IEEE TRANSACTIONS ON ROBOTICS**, 2020

Body motion / forces

- we‘re talking *residual* body motion capabilities, of course!
- example: optical tracking in upper-limb prosthetics

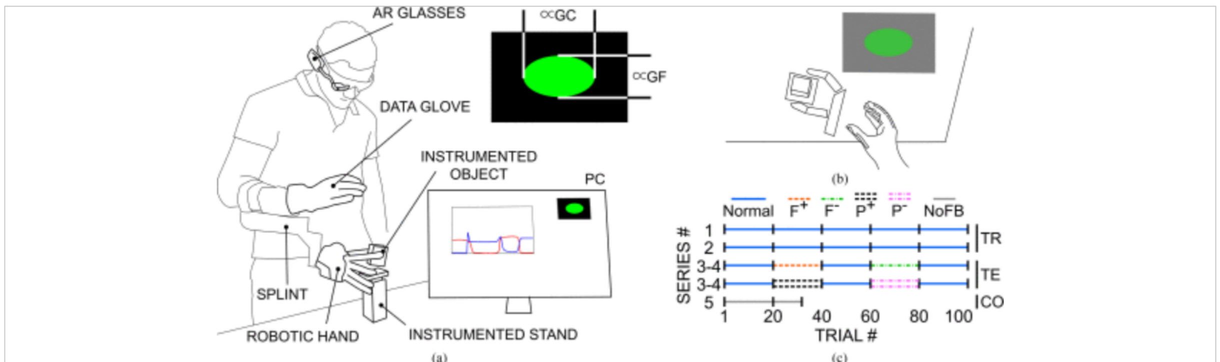


Fig. 1.
Experimental setup. (a) Participant performing the pick-and-lift task of an instrumented object by controlling the robotic hand through the data glove. Among other information, the GF exerted on the instrumented object and the robotic GC were recorded by a PC and used to compute and deliver sensory feedback information (inset) to the participant through AR glasses. The screen of the PC monitor was visible only to the experimenter. (b) Scene as seen by the participant. The adjustable screen of the AR glasses allowed placing the AR feedback in the peripheral sight without interfering with the instrumented object and robotic hand view. (c) Each participant performed four series of 100 trials (divided in blocks of normal and different types of catch trials, where the AR feedback was manipulated) plus a fifth series of 30 trials performed without AR feedback (NoFB, gray). F^{+}, F^{-}, P^{+}, and P^{-} denote the type of the catch trial (see text). The order of the third and fourth series was randomized among participants. TR, TE, and CO denote the name of the experiment phase, i.e., training, test, and control, respectively.

Jeremy Mouchoux, Stefano Carisi, Strahinja Dosen , Member, IEEE, Dario Farina , Fellow, IEEE, Arndt F. Schilling , and Marko Markovic, *Artificial Perception and Semiautonomous Control in Myoelectric Hand Prostheses Increases Performance and Decreases Effort*, **IEEE TRANSACTIONS ON ROBOTICS**, 2020

Body motion / forces

- we‘re talking *residual* body motion capabilities, of course!
- example: optical tracking in upper-limb prosthetics

Abstract—**Dexterous control of upper limb prostheses with multiarticulated wrists/hands is still a challenge due to the limitations of myoelectric man–machine interfaces. Multiple factors limit the overall performance and usability of these interfaces, such as the need to control degrees of freedom sequentially and not concurrently, and the inaccuracies in decoding the user intent from weak or fatigued muscles. In this article, we developed a novel man–machine interface that endows a myoelectric prosthesis (MYO) with artificial perception, estimation of user intention, and intelligent control (MYO–PACE) to continuously support the user with automation while preparing the prosthesis for grasping. We compared the MYO–PACE against state-of-the-art myoelectric control (pattern recognition) in laboratory and clinical tests. For this purpose, eight able-bodied and two amputee individuals performed a standard clinical test consisting of a series of manipulation tasks (portion of the SHAP test), as well as a more complex sequence of transfer tasks in a cluttered scene. In all tests, the subjects not only completed the trials faster using the MYO–PACE but also achieved**

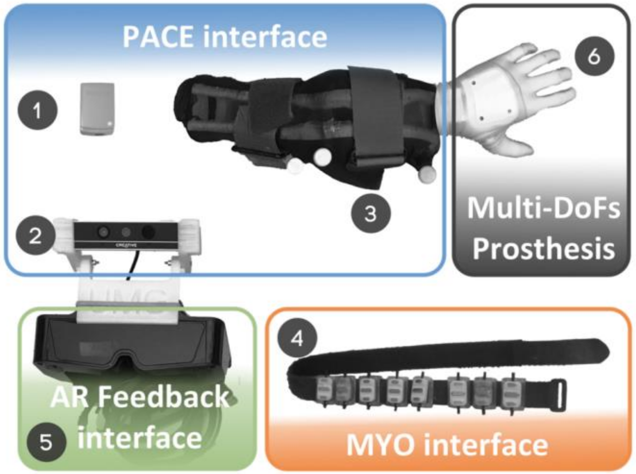


Fig. 1. System comprises (1) an inertial measurement unit, (2) a color and depth camera, (3) three retroreflective markers, (4) eight dry surface EMG electrodes, (5) augmented reality glasses, (6) a prosthesis with two grip types, active wrist and flexor, and a standard PC (not illustrated in the figure).

Intent detection and somatosensory feedback

1. The paper discusses how artificial perception and semiautonomous control can improve the performance and decrease the effort required to control a myoelectric hand prosthesis.
2. Optical tracking is a technique that uses cameras or other optical sensors to track the movement of the user's residual limb and prosthetic arm. This information can then be used to control the myoelectric prosthesis.
3. optical tracking can be used to provide sensory feedback to the user, which can further improve their control of the prosthesis.
4. **Artificial Perception**: This term refers to the ability of the prosthetic device to perceive or sense information about its environment, including the objects being manipulated and the forces exerted during interaction. In the context of the experiment, artificial perception likely involves integrating sensors and algorithms into the prosthetic device to provide feedback about grip force, object texture, or other relevant sensory information.
5. Semiautonomous control involves a combination of manual control by the user and automated assistance or adaptation by the prosthetic device. In other words, the prosthetic device can interpret the user's intentions based on input signals (such as muscle activity in the case of myoelectric control) and environmental cues, and adjust its behavior accordingly.
6. The AR glasses provided visual feedback to the participants, allowing them to perceive the grip force**(GF)** exerted by the robotic hand on the object. This feedback likely helped participants adjust their grip strength and manipulate the object more effectively.

Yi Long, Zhi-jiang Du, Chao-feng Chen, Wei Dong and Wei-dong Wang, *Online Sparse Gaussian Process Based Human Motion Intent Learning for an Electrically Actuated Lower Extremity Exoskeleton*, **ICORR 2017**

Body motion / forces

- we‘re talking *residual* body motion capabilities, of course!
- example: torque-based control for a leg exoskeleton

Abstract—**The most important step for lower extremity exoskeleton is to infer human motion intent (HMI), which contributes to achieve human exoskeleton collaboration. Since the user is in the control loop, the relationship between human robot interaction (HRI) information and HMI is nonlinear and complicated, which is difficult to be modeled by using mathematical approaches. The nonlinear approximation can be learned by using machine learning approaches. Gaussian Process (GP) regression is suitable for high-dimensional and small-sample nonlinear regression problems. GP regression is restrictive for large data sets due to its computation complexity. In this paper, an online sparse GP algorithm is constructed to learn the HMI. The original training dataset is collected when the user wears the exoskeleton system with friction compensation to perform unconstrained movement as far as possible. The dataset has two kinds of data, i.e., (1) physical HRI, which is collected by torque sensors placed at the interaction cuffs for the active joints, i.e., knee joints; (2) joint angular position, which is measured by optical position sensors. To**

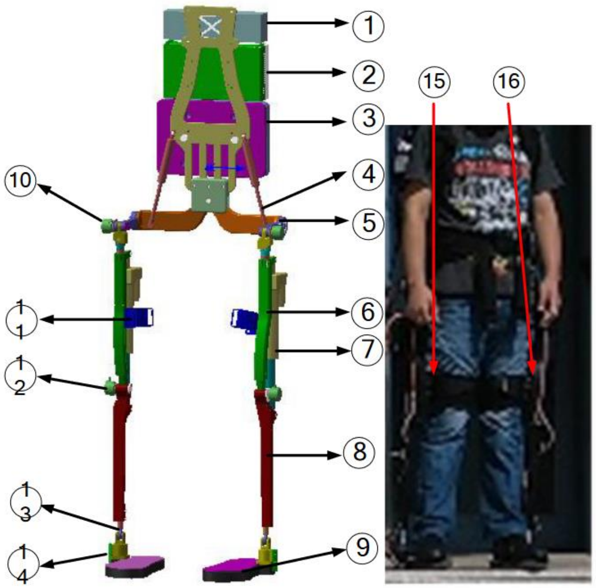


Figure 1 Mechanical structure of the exoskeleton. 1: power source of battery, 2: control system enclosure, 3: carrying load, 4: springs connecting the backpack with the waist part, 5: waist part, 6: thigh segment, 7: actuation system consists of DC motor, gear pair and screw, 8: shank segment, 9: wearable shoes which have pressure sensors, 10: hip joint, 11: connection cuff interacting with human limbs, 12: optical encoder on knee joint, 13: ankle joint, 14: signal transfer for foot pressure, 15: torque sensor on the left; 16: torque sensor on the right.

Intent detection and somatosensory feedback

1. A method for controlling lower extremity exoskeletons by inferring **human motion intent** (HMI) using machine learning techniques, specifically Gaussian Process (GP) regression. The goal is to improve the collaboration between humans and exoskeletons by accurately predicting the user's intended motions. The paper mentions the challenge of modeling the nonlinear relationship between **human-robot interaction** (HRI) information and HMI, which is addressed by using GP regression due to its suitability for high-dimensional and small-sample nonlinear regression problems.
2. The method involves collecting a training dataset while the user wears the exoskeleton system with friction compensation to perform unconstrained movements. This dataset includes two types of data: physical HRI data collected by torque sensors placed at the interaction cuffs for active joints (e.g., knee joints), and joint angular position data measured by optical position sensors.
3. The proposed online sparse GP algorithm aims to learn the HMI from this dataset, allowing for real-time adaptation and prediction of user intent during interaction with the exoskeleton. This approach could potentially enhance the responsiveness and naturalness of human-exoskeleton collaboration.

Two things being measured to improve performance:-

4. **Force the suit felt:** Imagine wearing the exoskeleton suit. As you move, the suit's motors and joints exert force to assist your movements. Sensors within the suit can detect these forces. For example, if you're walking and the suit helps lift your leg, there's a force applied by the suit's motor to aid in that movement. This force can be measured using sensors placed within the exoskeleton. Understanding these forces helps in determining how much assistance the exoskeleton is providing and how it aligns with your natural movements.
5. **Joint movement:** The exoskeleton suit has joints that mimic the joints of your body, like knees and hips. As you move, these joints also move. Sensors, such as optical position sensors mentioned in the text, are placed at these joints to track their movement. For instance, when you bend your knee, the sensor at the knee joint detects the angle at which your knee is bent. This information is crucial for the exoskeleton to synchronize its movements with yours. By tracking joint movement, the exoskeleton can adjust its assistance to match your intended actions more accurately.

Yi Long, Zhi-jiang Du, Chao-feng Chen, Wei Dong and Wei-dong Wang, *Online Sparse Gaussian Process Based Human Motion Intent Learning for an Electrically Actuated Lower Extremity Exoskeleton*, **ICORR 2017**

Body motion / forces

- we‘re talking *residual* body motion capabilities, of course!
- example: torque-based control for a leg exoskeleton

(a) stair ascent (b) stair descent (c) ramp ascent (d) ramp descent (e) level-ground walking

Figure 4 Experiments with the exoskeleton system, the subject wears the exoskeleton system at a natural speed.

Yi Long, Zhi-jiang Du, Chao-feng Chen, Wei Dong and Wei-dong Wang,
Online Sparse Gaussian Process Based Human Motion Intent Learning for an Electrically Actuated Lower Extremity Exoskeleton, **ICORR 2017**

Body motion / forces

- we‘re talking *residual* body motion capabilities, of course!
- example: torque-based control for a leg exoskeleton

Command – by robot
Actual – movement by human

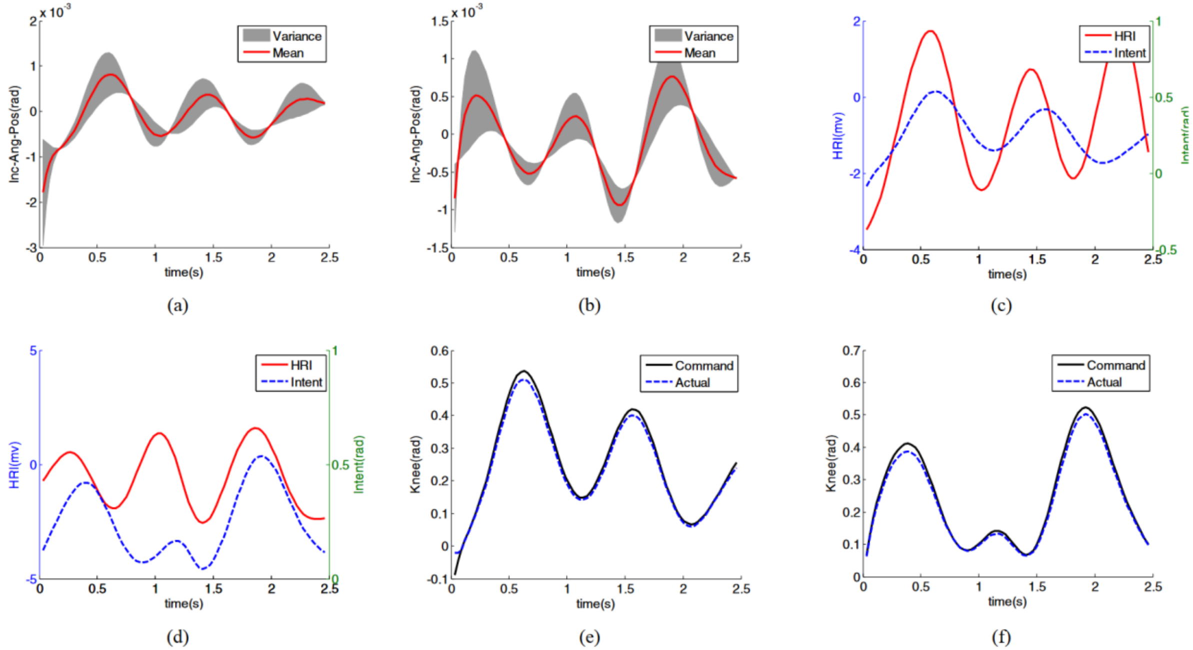


Figure 5 Walking experiments wearing the exoskeleton system. (a) HRI and HMI relationship for left knee joint, (b) HRI and HMI relationship for right knee joint, (c) mean and variance output of online GP for left knee joint, (d) mean and variance output of online GP for right knee joint, (e) trajectory tracking of adaptive controller for left knee join, (f) trajectory tracking of adaptive controller for right knee join.

Electric effect

- muscle contraction (activity) is initiated by discharge of α-motoneurons
  - usually, many of them at the same time,
  - with different levels of activation,
  - carefully controlled by the CNS/PNS
- each α-motoneuron discharge causes a depolarisation wave in the cells of its MU
  - also called MUAP: Motor Unit Action Potential
  - A single motor neuron can innervate multiple muscle fibers, and all the muscle fibers innervated by a single motor neuron constitute a motor unit.
- net effect: the superposition of many MUAPs on the surface of the muscle
- (Surface) electromyography is exactly all about measuring the superposed MUAPs
  - and sometimes, trying to *decompose the signal* back into its constituent MUAPs

Roberto Merletti, Matteo Aventaggiato, Alberto Botter, Ales Holobar, Hamid Marateb, Taian M.M. Vieira, *Advances in Surface EMG: Recent Progress in Detection and Processing Techniques*, **Critical Reviews™ in Biomedical Engineering,** 38(4):305–345 (2010)

Electric effect

- surface electromyography
  - an oscillating signal related to the contraction of muscles
  - bandwidth: 15-450Hz, amplitude: 1µV-10mV

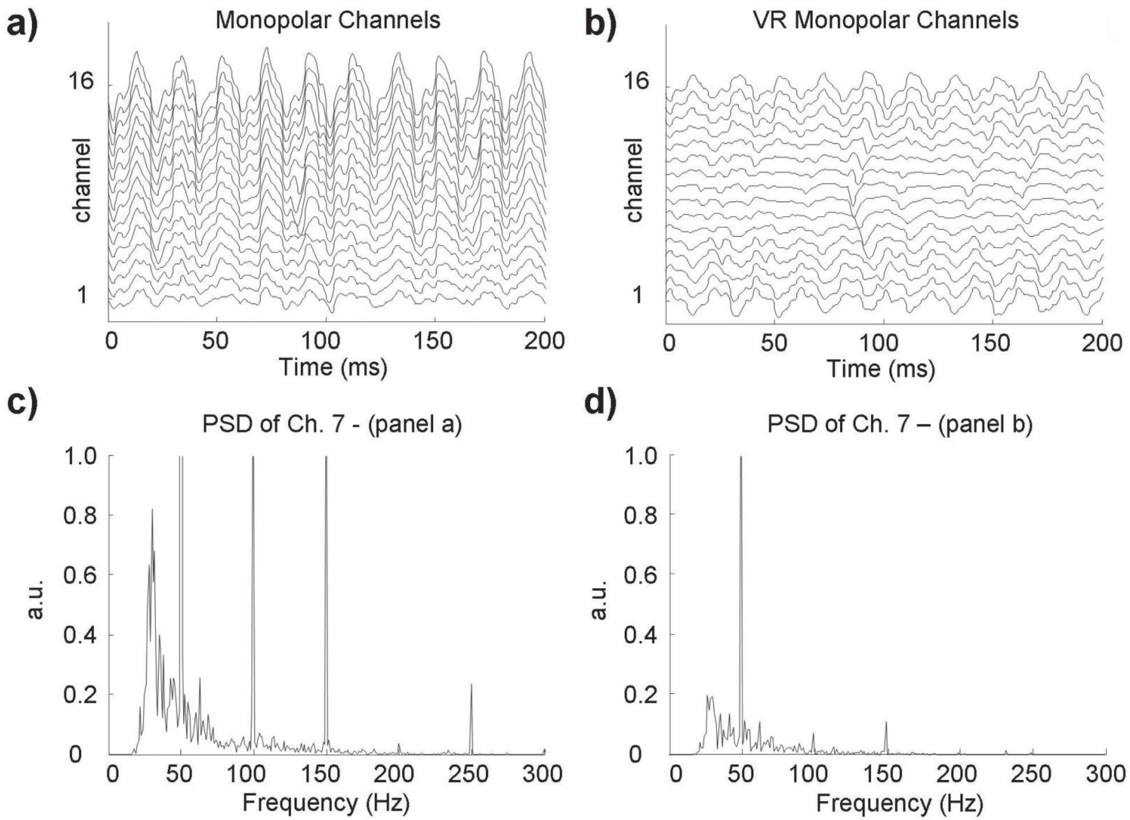


FIGURE 5. a) Example of 16 EMG channels detected with a linear array aligned with the fibers on the biceps brachii muscle. Detection with respect to a remote reference electrode (no VR). Artificial power line interference (50 Hz and four additional harmonics) was added with intensity increasing from ch 1 to ch 16. b) spectrum of ch 7. c) signals from a) measured with respect to the average of the signals in a) (VR). d) spectrum of ch. 7 of c). Note the reduction of physiological common mode signals indicated by the smaller spectral area. Arbitrary units (a.u.) are the same in b) and d).

Intent detection and somatosensory feedback

1. The electrical activity produced by muscles during contraction is not constant but fluctuates over time. This fluctuating signal is what is being measured by surface electromyography.
2. 16 sensors are used
3. **Monopolar Channels**:
   1. In monopolar recording, one electrode (the active electrode) is placed over the muscle of interest, and another electrode (the reference electrode) is placed at a distant location, often on a non-muscular area of the body.
   2. The active electrode measures the electrical activity generated by the muscle, while the reference electrode provides a baseline or reference point against which the activity is measured.
   3. The electrical potential difference between the active electrode and the reference electrode is recorded, giving information about the muscle's activity.
4. **VR (Virtual Reference) Monopolar Channels**:
   1. VR monopolar channels also use an active electrode placed over the muscle of interest, but instead of using a physical reference electrode, a virtual reference is computed.
   2. The virtual reference is typically calculated as the average of the electrical potentials measured by all the active electrodes in the recording setup.
   3. By using a virtual reference, VR monopolar channels can reduce the effects of common noise and interference that may affect the recording, providing a cleaner signal.

Monopolar channels and VR (Virtual Reference) monopolar channels are both types of electrode configurations used in electromyography (EMG)

Pressure

- while contracting, muscles *change their shape*
- and this leads to change in the body structure containing them.
- such changes can be detected by pressure sensors inside a semi-rigid structure
- applied to the body part of interest.
- is easy and cheap to detect.

1. **Detection of Pressure Changes**: As the muscle contracts, it applies pressure to the surrounding structure, including the pressure sensors embedded within the semi-rigid structure. These pressure sensors can detect the changes in pressure exerted on them due to muscle contraction.
2. **Signal Processing**: The pressure signals detected by the sensors are then transmitted to a data acquisition system for processing and analysis. By monitoring changes in pressure over time, the system can infer muscle activity and contraction dynamics.
3. **Interpretation of Data**: The data collected from the pressure sensors can provide valuable insights into the timing, intensity, and duration of muscle contractions. This information can be used to assess muscle function, monitor rehabilitation progress, or provide real-time feedback for controlling external devices like exoskeletons or prosthetic limbs.

Pressure

- is easy and cheap to detect.

Pressure

- is easy and cheap to detect.

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

Pressure

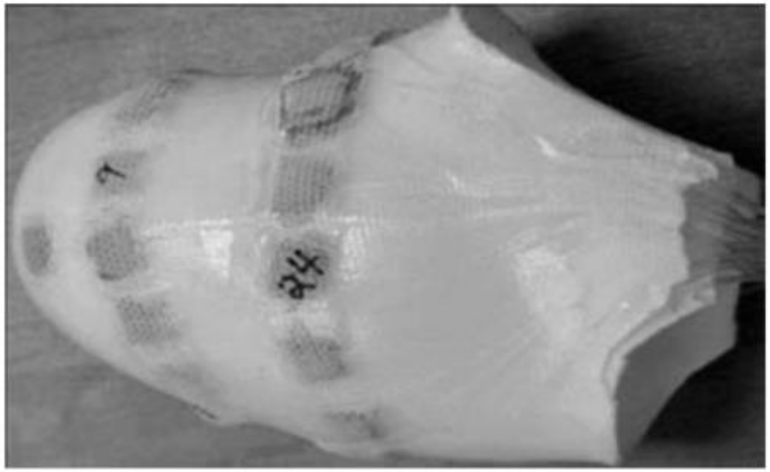


Fig. 1. A *Smart-Sleeve*. The final product is a custom-formed silicone sleeve with sensors (black squares) embedded inside in predetermined locations. Sensor hoses exit the sleeve at right. Total Length from the distal end to the olecrenon posteriorly, and to the fold of the elbow anteriorly, for subject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

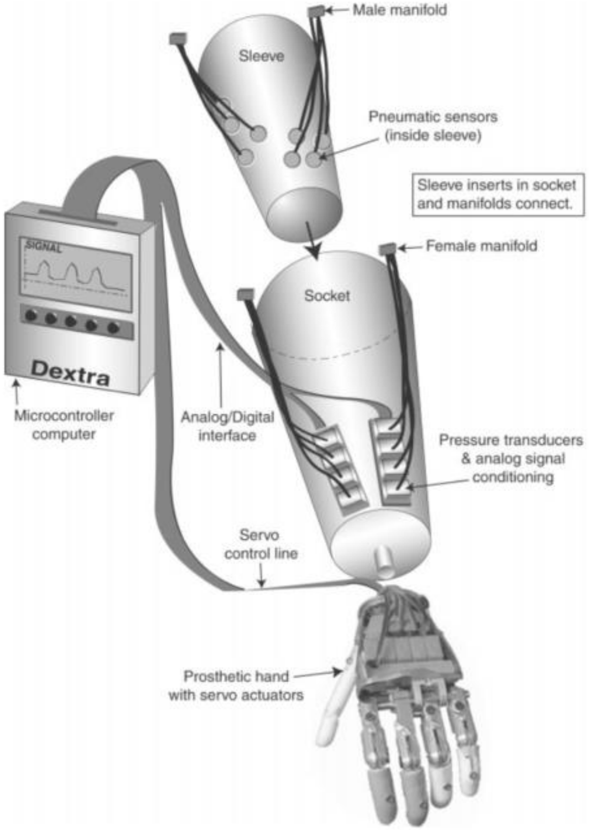


Fig. 2. Biomimetic *Dextra* hand prosthesis. The silicone "smart sleeve" fits snugly over the residual limb and registers 3D forces produced by muscle activity within the hard socket. The pocket computer allows the user to retrain the robotic hand for optimal performance. The hand can flex and extend 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.

Pressure

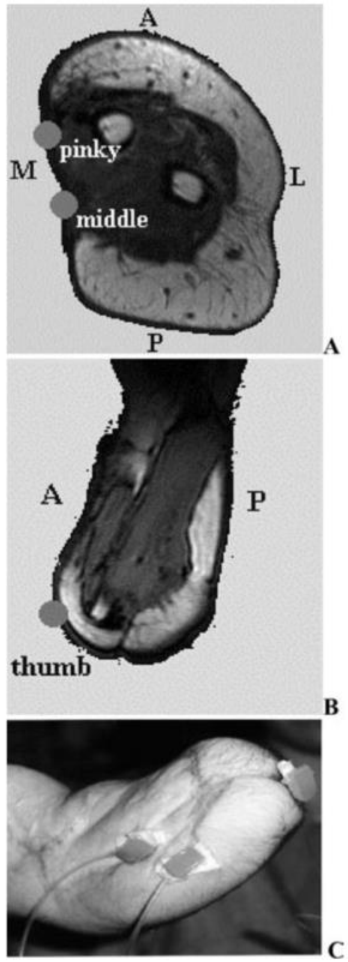


Fig. 5. MRI photographic images and of subject one's residual limb. Panel A shows a transverse slice near the distal end. Panel B is a longitudinal slice. Areas of movement have been superimposed as discs on the image. 5C is a photograph of Subject A's residual limb for comparison. M-P sensors are attached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

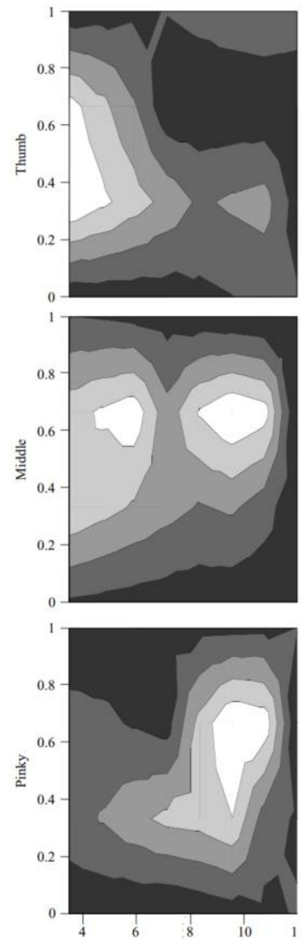


Fig. 2. RKI of residual limb movements for subject A during requested finger tapping. Each requested movement is identified by a unique image of pressure energies. Maximum pressures were approximately 3 kPa with white being the greatest and black being no change.

Pressure


ASU
Arizona State University
Movement reduced when the foot is not on the floor.

Pressure (HD)

- what if we use *many* such sensors instead of 10?
- obtained extremely good results in controlled conditions

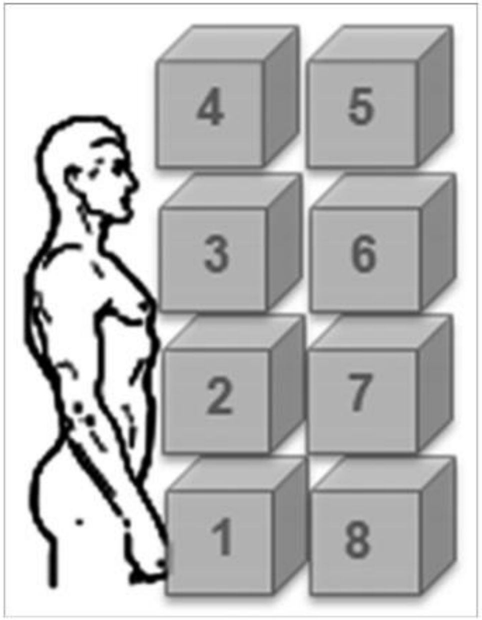


Figure 2.
Subjects were asked to perform four sets of contractions corresponding to eight classes of motion while holding their arm such that the hand was located in each of the eight static positions represented by the boxes numbered 1 through 8. Reprinted with permission from Radmand et al. [28].

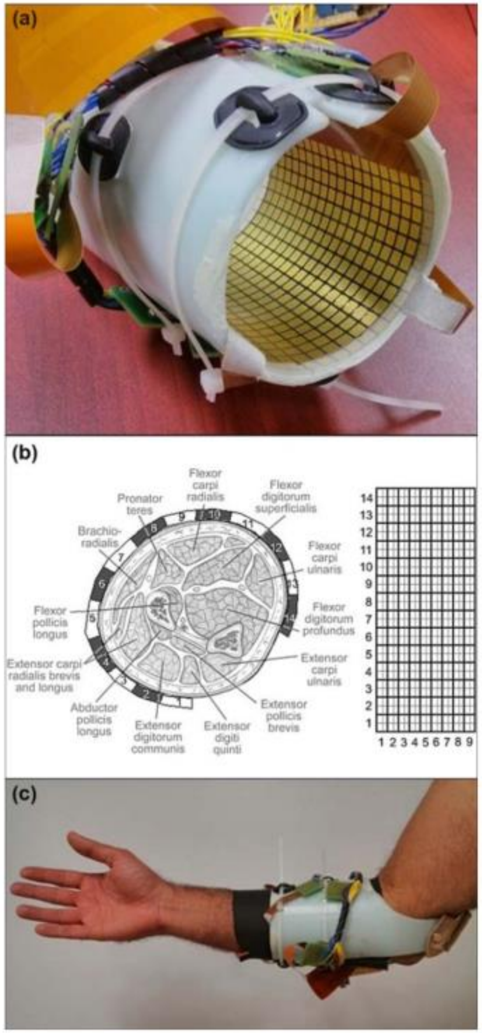


Figure 1.
(a) Adjustable pressure-sensing socket. Each 2 × 2 array of cells forms a single pressure sensor. **(b)** Sensor grid with its corresponding location on the muscles. **(c)** Placement of the socket with zip ties used to adjust socket size.

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

Pressure (HD)

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

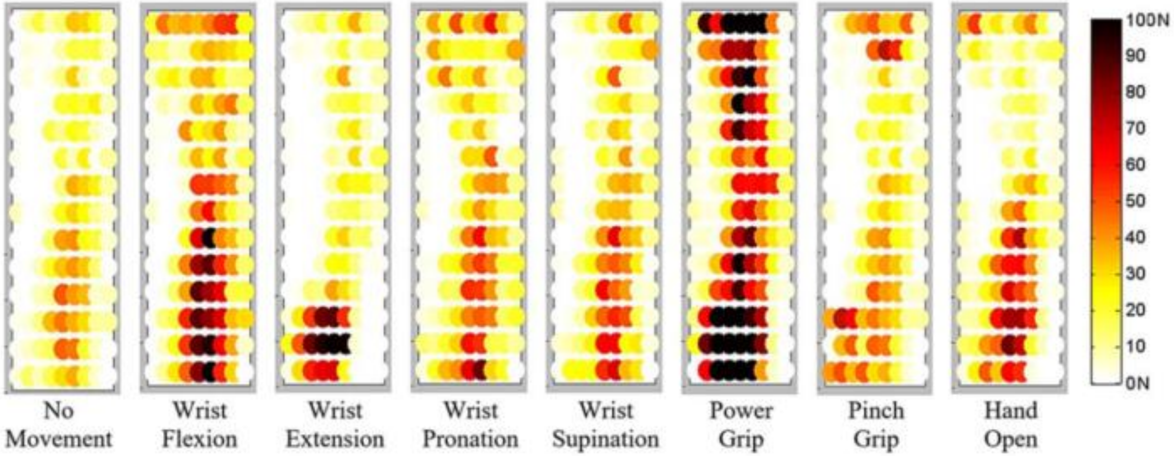


Figure 6.
Examples of acquired pressure map images for the motion classes performed in a fixed static position (darker areas correspond to higher pressure).

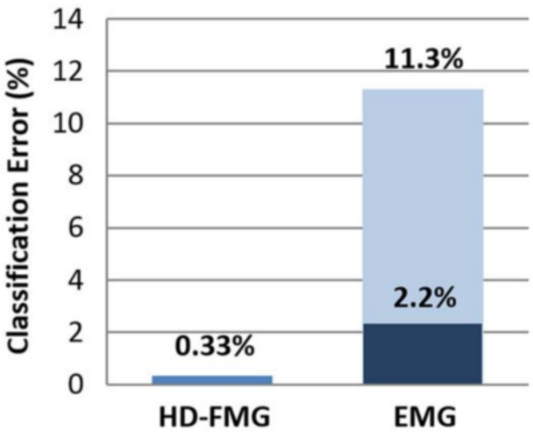


Figure 7.
Average classification errors of high-density force myography (HD-FMG) and electromyography (EMG) control methods for eight hand motion classes with arm in a fixed static position.

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

Pressure (HD)

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

Intent detection and somatosensory feedback

1. "High Density (HD) FMG," "high density" refers to the use of a large number of sensors or electrodes to capture fine-grained details of muscle activity. FMG stands for Force Myography, which is a technique for measuring muscle activity based on the mechanical deformations of the skin surface caused by muscle contractions.
2. So, "High Density FMG" indicates the use of a dense array of sensors or electrodes placed on the skin surface to capture subtle changes in muscle shape and movement with high spatial resolution.
3. Unlike electromyography (EMG), which measures electrical signals from muscles, FMG measures the force exerted by muscles on the skin.
4. **Advantages and Limitations of Traditional FMG**:
    1. Traditional FMG systems typically use a small number of sensors, which may limit their ability to capture fine-grained muscle activity patterns.
    2. This limitation can affect the precision and versatility of upper-limb prosthetic control.
5. **Introduction of High-Density FMG**:
    1. High-density FMG involves the use of a dense array of sensors placed over the skin surface to capture detailed muscle activity patterns.
    2. By using more sensors, HD-FMG offers higher spatial resolution and the potential to capture finer details of muscle activity compared to traditional FMG systems.

    Importantly, they employed an informed and symmetric channel reduction approach, which likely involved careful selection of sensor locations and balancing between reducing dimensionality and preserving relevant information.

Inner structural changes

- further way to detect structural changes: by looking inside the body!
- this is called *tomography*
- there are relatively simple and minimally invasive ways, such as
  - Electrical Impedance Tomography
  - Ultrasound imaging
- are they effective?

Electrical Impedance Tomography

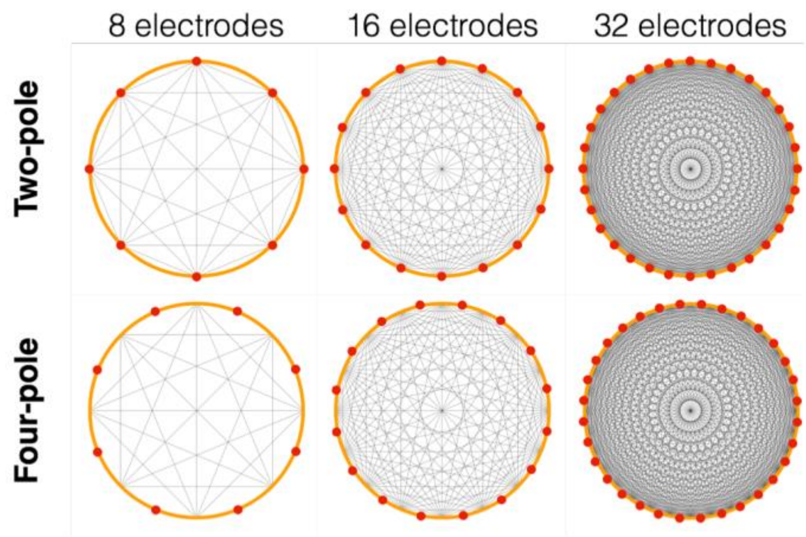


Figure 1. The number of sensed paths (grey lines) dramatically increases as electrode count grows (red dots). For reference, Tomo [43] uses a two-pole, 8-electrode scheme (upper left).

	Tomo (Two-pole)			New Setup (Two-pole)			New Setup (Four-pole)		
Number of Electrodes	8	16	32	8	16	32	8	16	32
Number of Measurements per Frame	28	120	496	28	120	496	40	208	928
Frame Rate (Hz)	10	2.3	0.6	100	22	6	87	16	3

Table 1. Performance characteristics of Tomo and our new setup. We extrapolate hypothetical performance (grey region) for 16 and 32 electrode versions of Tomo.

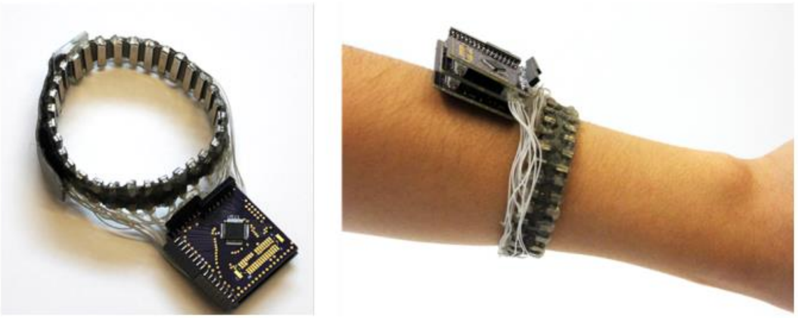


Figure 2. Our electrode band (left) and our EIT sensor worn on a user's arm (right).

Yang Zhang, Robert Xiao and Chris Harrison, Advancing Hand Gesture Recognition with High Resolution Electrical Impedance Tomography, ACM 2016

Intent detection and somatosensory feedback

1. Electrical impedance tomography (EIT) has been applied in the field of human-computer interaction due to its advantages including the fact that it is non-invasive and has both low power consumption and a low cost.
2. a current is injected into one pair of electrodes, and the voltage difference is measured between another pair of electrodes. The higher the voltage difference, the higher the conductivity between the injecting and measuring electrodes. This information is then used to reconstruct an image of the conductivity distribution within the hand.
3. Same electrodes for current injection and voltage measurement – 2 pole
4. Separate electrodes for current injection and voltage measurement – 4 pole
5. Different tissues in the body conduct electricity differently. For example, fluids like blood and water conduct electricity well, while bones and air conduct poorly. EIT measures the conductivity of tissues, which is how easily they allow electric currents to flow through them.
6. In the case of EIT, tomography refers to the creation of images showing the distribution of electrical properties within the body.

Electrical Impedance Tomography

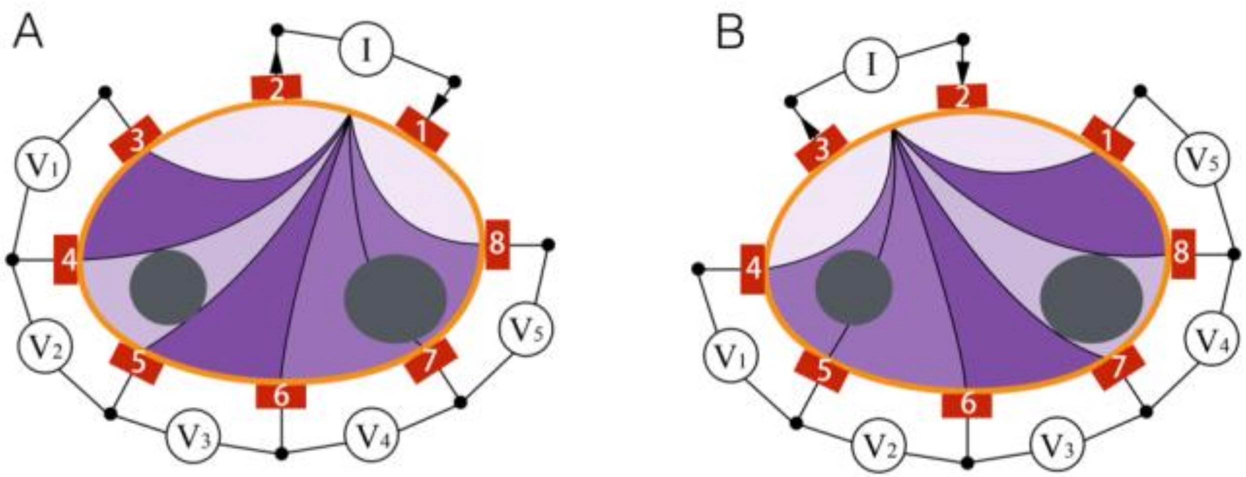


Figure 5. Two projection rounds in four-pole measurement scheme with 8 electrodes. Higher voltage difference is shown with brighter color.

Yang Zhang, Robert Xiao and Chris Harrison, Advancing Hand Gesture Recognition with High Resolution Electrical Impedance Tomography, ACM 2016

Electrical Impedance Tomography

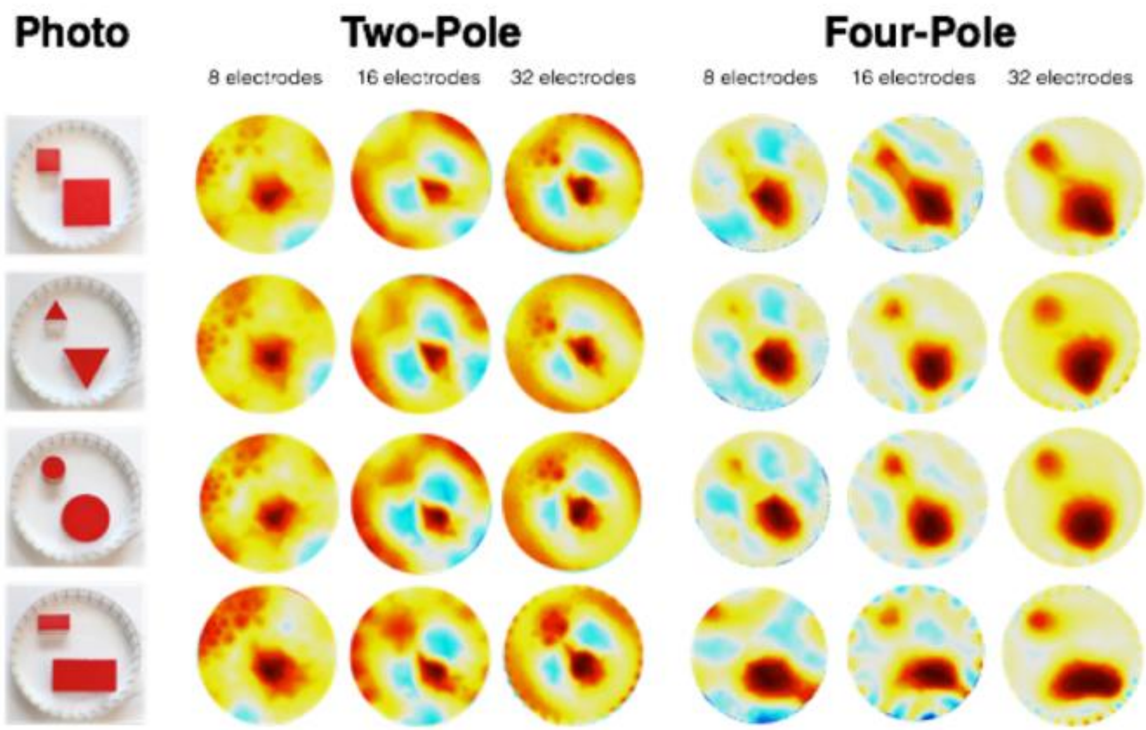


Figure 8. Reconstructed images of bath with different object shapes.

Yang Zhang, Robert Xiao and Chris Harrison, Advancing Hand Gesture Recognition with High Resolution Electrical Impedance Tomography, ACM 2016

Electrical Impedance Tomography

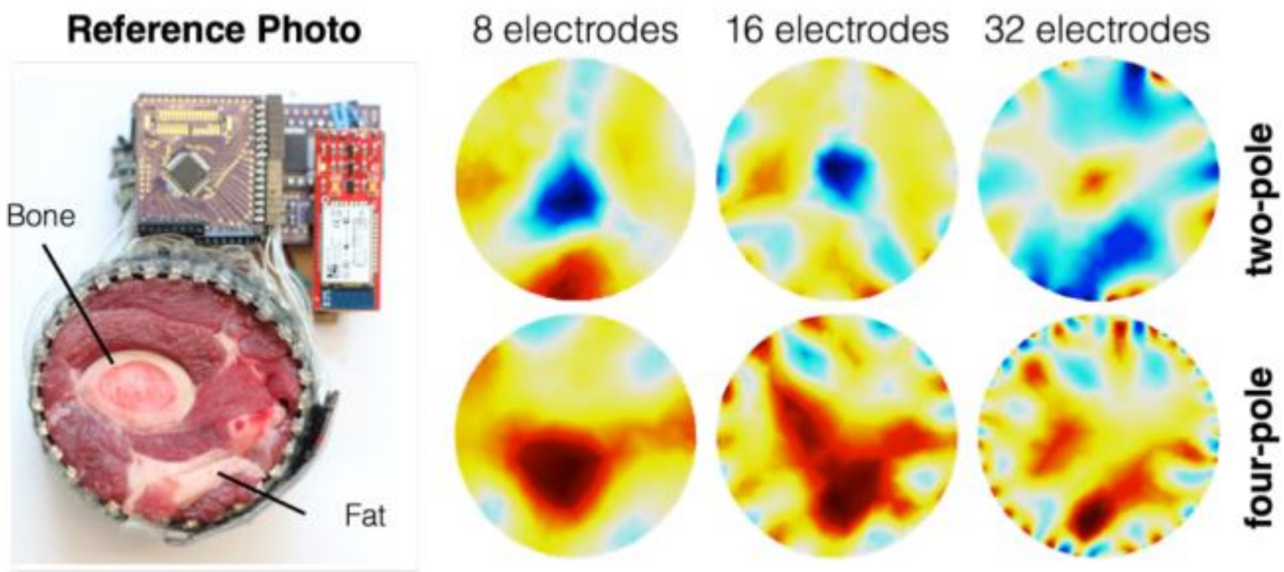


Figure 9. Reconstructed images of a cross-cut lamb shoulder with different EIT configurations.

Yang Zhang, Robert Xiao and Chris Harrison, Advancing Hand Gesture Recognition with High Resolution Electrical Impedance Tomography, ACM 2016

Ultrasound scanning

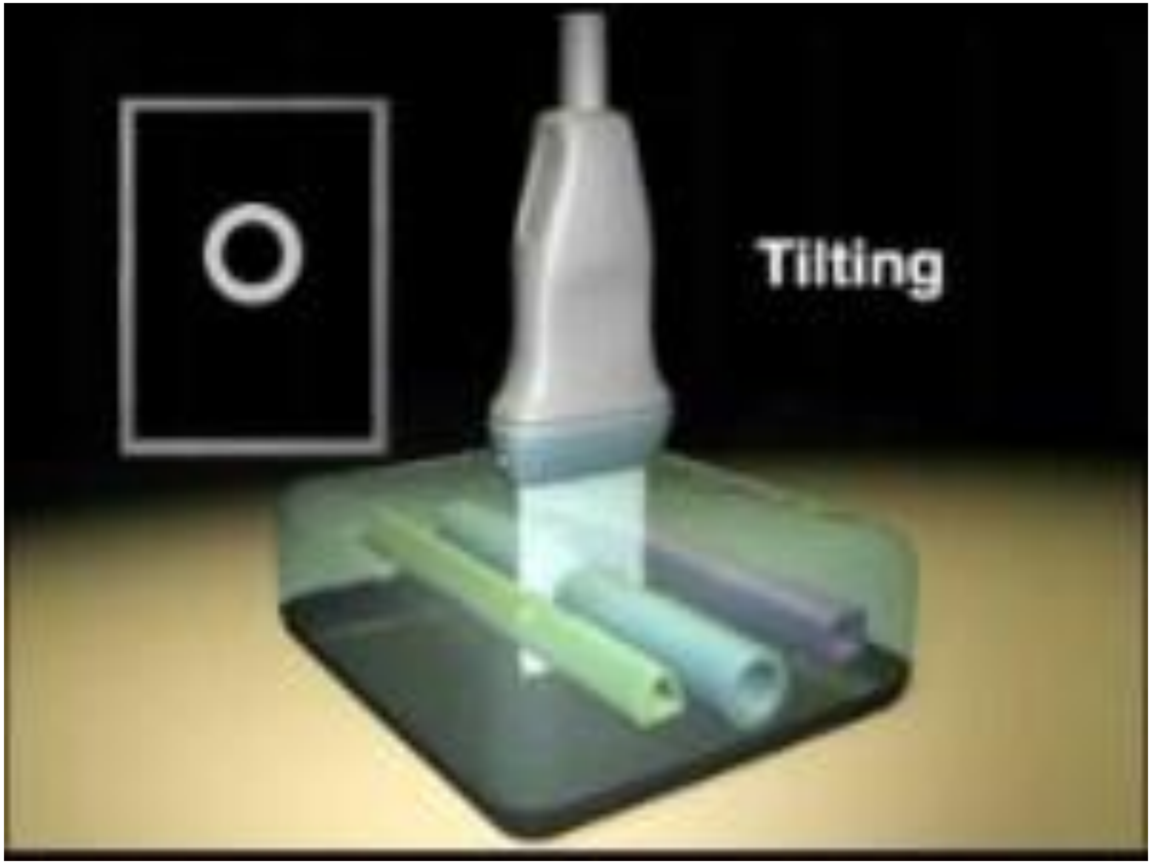
- principles of functioning

Intent detection and somatosensory feedback

1. **Sound Waves**: A small handheld device called a transducer emits high-frequency sound waves into the body. These sound waves are beyond the range of human hearing and are typically in the range of 2 to 18 megahertz (MHz).
2. **Interaction with Tissues**: When the sound waves encounter different tissues within the body, they bounce back (or echo) at different rates depending on the density and composition of the tissues. For example, sound waves bounce back differently from bone, fluid, and soft tissues.
3. **Echo Reception**: The transducer also acts as a receiver, picking up the echoes of the sound waves as they bounce back from the tissues. The device then converts these echoes into electrical signals.
4. **Image Formation**: A computer processes these electrical signals to create real-time images or videos of the internal structures being examined. These images appear on a monitor and are interpreted by a trained healthcare professional, such as a radiologist or sonographer.

Ultrasound scanning

- principles of functioning



Castellini, Claudio / Passig, Georg / Zarka, Emanuel,
Using ultrasound images of the forearm to predict finger positions, 2012
IEEE Transactions on Neural Systems and Rehabilitation Engineering 20(6)

Ultrasound scanning

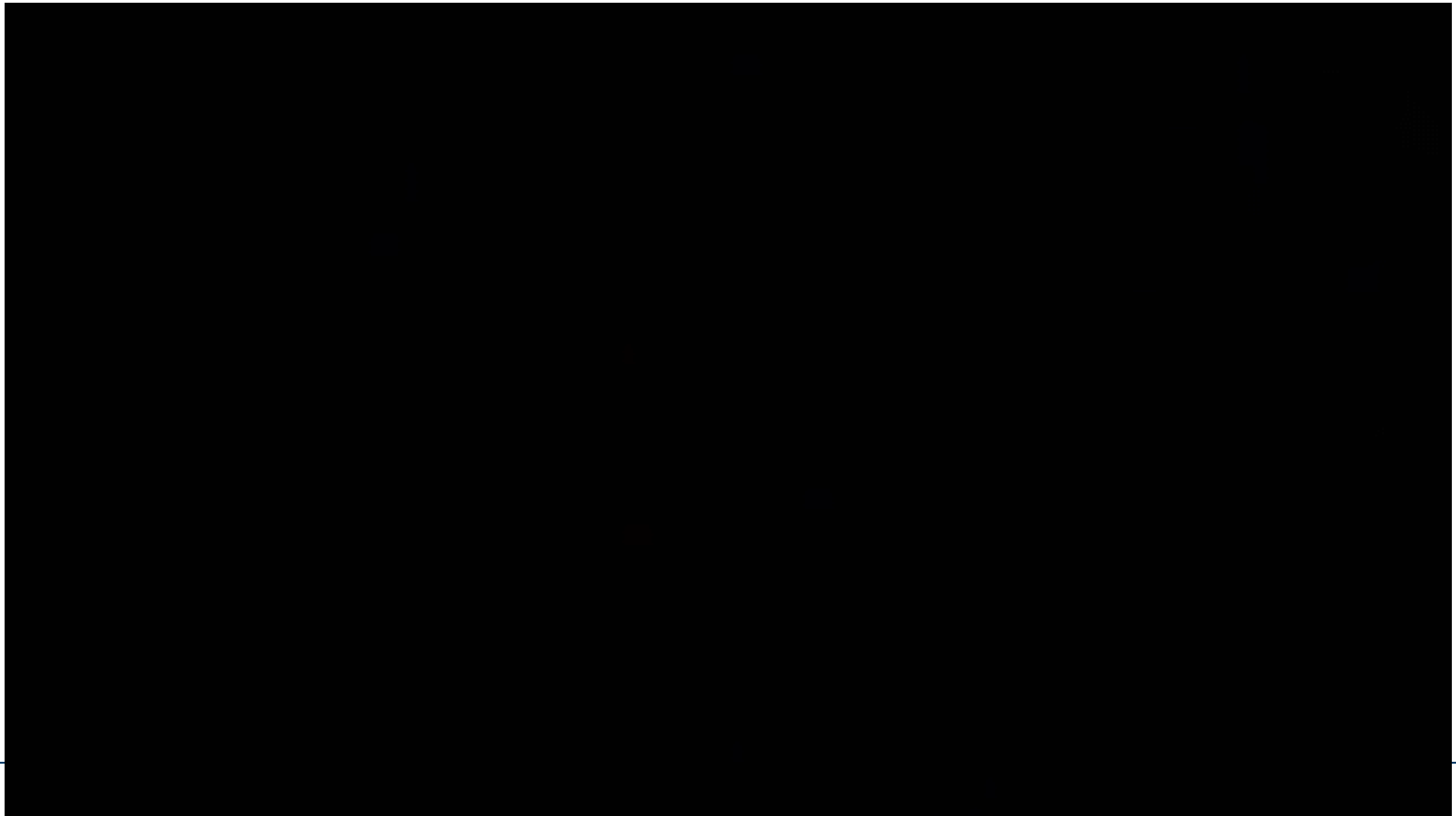
- so what can we see from the ultrasound scan… of the forearm?

Ultrasound images + cyberglove = training the system
Cyberglove – record the values corresponding to the position of the fingers

Castellini, Claudio / Hertkorn, Katharina / Sagardia, Mikel / Sierra González, David / Nowak, Markus,
A virtual piano-playing environment for rehabilitation based upon ultrasound imaging,
2014, Proceedings of BioRob - IEEE International Conference on Biomedical Robotics and Biomechatronics

Ultrasound scanning

- so what can we see from the ultrasound scan… of the forearm?



Summary

- today:
  - intent detection
  - signal patterns and how to associate them to an intended action
  - the problem of ground truth
  - offline vs. onilne data gathering / testing
- what about sEMG?
- what other kinds of signals can we use?

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