CH-1

1.Prosthetic Control:Prosthetic control involves the interface between the user and the prosthetic limb, allowing the user to manipulate the limb in a way that simulates natural movement. This can include various control methods such as myoelectric control, where muscle signals from the residual limb are used to control the prosthetic, or mechanical control using cables and harnesses.

2.Myocontrol: Myocontrol specifically refers to a type of prosthetic control method that relies on electromyography (EMG) signals from the muscles in the residual limb. These signals are detected by sensors placed on the surface of the skin and are used to control the movements of the prosthetic limb. By contracting or relaxing specific muscles, the user can trigger different movements in the prosthetic device.

3.Exoskeleton Control: Exoskeletons are wearable robotic devices that augment the user's strength and endurance or assist with mobility. Exoskeleton control involves the interface between the user and the exoskeleton, allowing the user to command its movements. Control mechanisms can vary and may include joystick control, gesture recognition, or even brain-computer interfaces, where the user's brain signals are used to control the exoskeleton.

4.Exo-suit Control: Exo-suits are similar to exoskeletons but are typically more lightweight and focused on providing assistance with specific tasks rather than full-body support. Exo-suit control involves similar principles as exoskeleton control, allowing the user to manipulate the suit to perform desired actions. Control methods may include sensors embedded in the suit that detect the user's movements or external controllers.

Teleoperation refers to the remote control of a device or system from a distance. In teleoperation, the operator is typically located away from the physical location of the device being controlled, often using some form of communication technology to transmit commands and receive feedback.

controlling an
avatar in VR – Virtual Therapy arm

SEMG (Surface Electromyography): SEMG is a technique used to measure and record the electrical activity produced by muscles. It involves placing electrodes on the skin surface above the muscles of interest and detecting the electrical signals generated by muscle contractions. SEMG signals can provide information about muscle activation patterns, muscle fatigue, and force exertion.

IMU (Inertial Measurement Unit): An IMU is a device that measures and reports specific forces (acceleration) and angular rates (rotation) applied to the object it is attached to, typically in three axes (x, y, and z). It usually comprises sensors such as accelerometers, gyroscopes, and magnetometers. IMUs are commonly used in various applications, including motion tracking, navigation systems, robotics, and virtual reality. In the context of exoskeletons or prosthetics, IMUs can be used to detect the movement and orientation of limbs or joints, providing valuable data for control algorithms to adjust the behavior of the device accordingly.

Accelerometer: An accelerometer is a sensor that measures acceleration forces along one or more axes. It detects changes in velocity and can determine the direction and magnitude of acceleration, whether it's caused by linear motion, gravity, or vibration.

Gyroscope: A gyroscope is a sensor that measures angular velocity or rotational motion around one or more axes. It provides information about changes in orientation and helps determine the rate of rotation or angular displacement.

Magnetometer: A magnetometer is a sensor that measures the strength and direction of a magnetic field. It can detect changes in magnetic fields caused by nearby ferromagnetic or magnetic materials, as well as the Earth's magnetic field.

- characteristics of a HMI:
- (feedforward) converts signals generated by a human being into control commands
- (such commands operate a machine in an environment)
- (feedback) converts environmental signals into physical stimuli

reliability

- does the HMI enable you *precisely control* your machine?does your machine do *exactly* what you want it to do,
- exactly *when and only when* you want it to do it?

Dexterity - "Dexterity" refers to skill and agility in performing tasks, especially those that require precision and coordination.

- can you fully control your machine?does it enable you use all its potential?can you control each of its degrees of freedom?

ease of use

- how long does it take you to master your machine, using this HMI?
- how big is the user's manual?
- how exciting and fun is it to use your machine via this HMI?

flexibility

- how much do you need to adapt to it?
- how much do you need to know about your machine to use it?
- is it suited for both end-users and experts?

HMIs for the disabled

- replace commands issued via fingers and hands with **signals denoting the intended activity**
- replace force / contact feedback with **somato-sensory feedback**
- replace standard physical interacting devices (joystick, handle, touchscreen, …) with a *socket*

- Specialized sensory receptors located in the skin, muscles, joints, and other tissues detect changes in the environment or the body.

Stimulating, on the other hand, refers to the act of applying controlled signals or energy to the human body or a biological system to evoke a response.

Sensing: Sensing refers to the ability of a device to detect or perceive information from its environment or from the human body itself.

- *Flexion* Decreasing the angle between two bones
- *Extension* Increasing the angle between two bones
- *Abduction* Moving a body part away from the midline
- *Adduction* Moving a body part towards the midline
- *Rotation* Turning movement of a bone about its long axis
- *Supination* Rotation of the forearm or foot so that the palm or sole is moved to face anteriorly
- *Pronation* Rotation of the forearm or foot so that the palm or sole is moved to face posteriorly

- intent detection: the feed-forward path
  - detecting signals out of the participant‘s body – using sensors
  - converting them into control commands for your robot

- somatosensory feedback: the feed-back path
  - detecting signals from the environment and the robot
  - converting them into bodily stimuli for your participant – for force adjustment

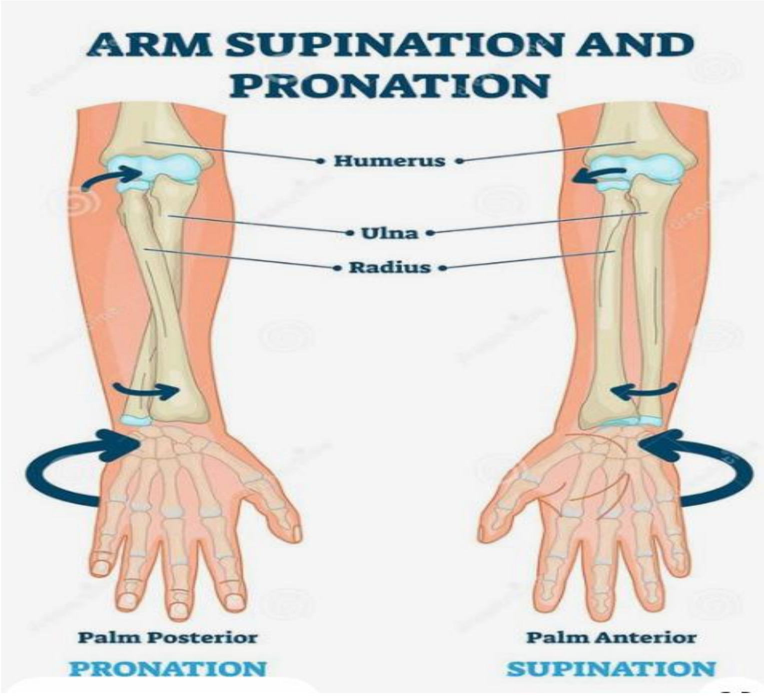
- bidirectional HMI: an HMI putting together these two paths.
  - it must be unobtrusive - When something is described as "unobtrusive," it means that it doesn't attract attention or interfere with normal activities. In the context of sensing and stimulating technologies, designing them to be unobtrusive is important for ensuring that they integrate seamlessly into the user's life without causing discomfort or inconvenience.
  - it must work in real-time
  - it must be reliable and dexterous
  - and it must be low-power

- anatomy of the upper limb, muscles

- Biceps
  - actuates the flexion of the elbow
- Triceps
  - actuates the extension of the elbow
- Biceps and Triceps operate in an *agonist / antagonist* fashion
  - if they both work at the same time, *co-contraction* is obtained
  - leading to no movement but increasing the *stiffness* of the elbow joint

  - An antagonist is a compound that has
  - the opposite effect of an agonist.

- upper arm
  - *M. Biceps Brachii*
  - *M. Triceps Brachii*
  - *M. Brachialis*



1.Biceps: The biceps brachii muscle is located on the front of the upper arm and is responsible for flexing the elbow joint, which brings the forearm closer to the upper arm. When you bend your arm, like when you're lifting a weight towards your shoulder, the biceps muscle contracts.

2.Triceps: The triceps brachii muscle is located on the back of the upper arm and is responsible for extending the elbow joint, which straightens the arm. When you push something away or straighten your arm, like when you're pushing yourself up from a chair, the triceps muscle contracts.

3.When both the agonist and antagonist muscles contract simultaneously in a state of co-contraction, it can indeed lead to no movement occurring at the joint. Instead, co-contraction increases the stiffness of the joint, making it more resistant to movement.

4.Agonist Muscles: These muscles are primarily responsible for producing a specific movement.

5.Antagonist Muscles: These muscles oppose the action of the agonist muscles to provide balance and control.

Arm Flexion:

1.Agonist: Biceps contract to bend the elbow.

2.Antagonist: Triceps relax to allow the bending motion.

Arm Extension:

1.Agonist: Triceps contract to straighten the elbow.

2.Antagonist: Biceps relax to allow the straightening motion.

3.In co-contraction, both the agonist muscle (the muscle primarily responsible for a movement) and the antagonist muscle (the muscle opposing the movement) contract at the same time.

- **anatomy of the upper limb, muscles**
- Flexor
  - actuates the flexion of wrist / fingers
- Extensor
  - actuates the extension of wrist / fingers
- Flexors and extensors operate, too, as a agonist / antagonist pair
  - helping control the stiffness of wrist and fingers
- Brachioradialis and Pronator operate the pronation / supination of the wrist
  - they operate close to the bones, so
  - their activity remains mostly deep

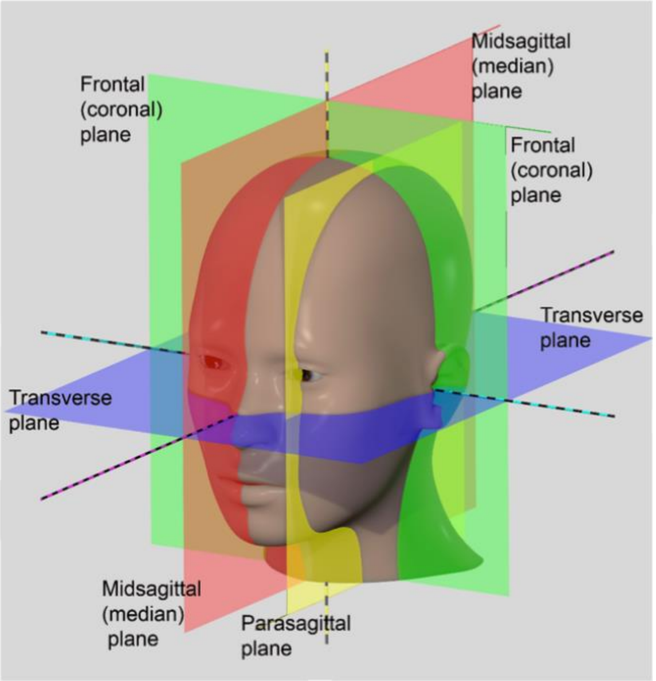
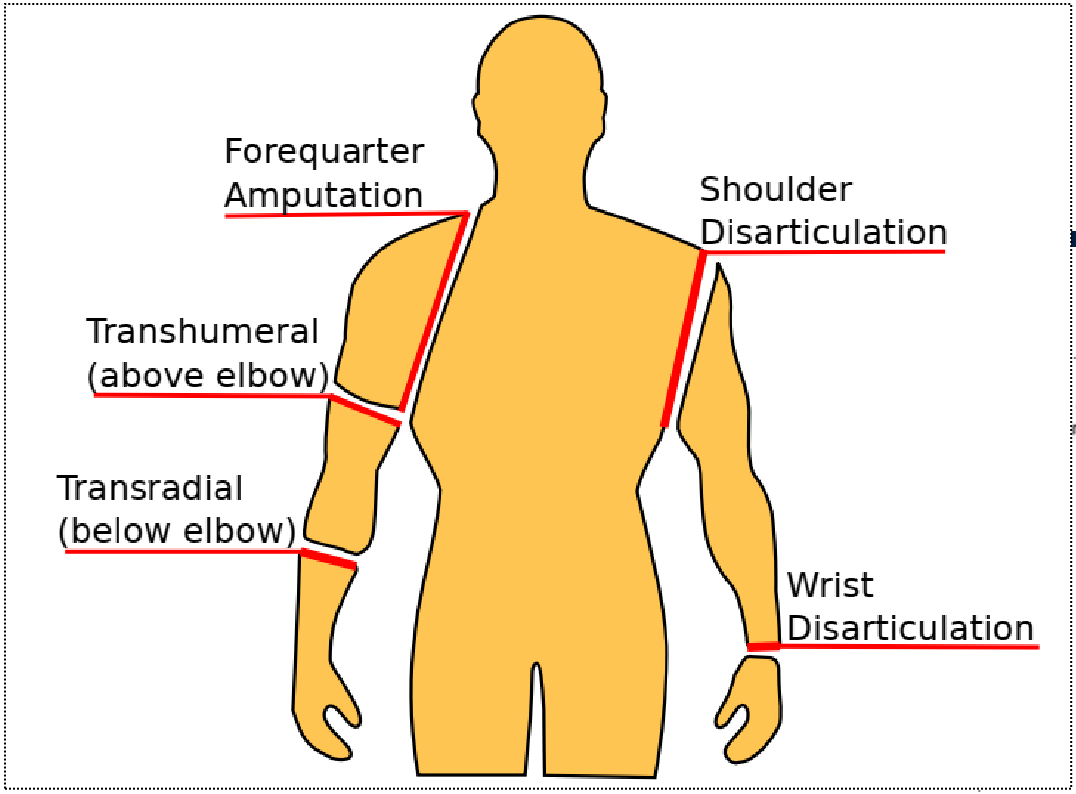
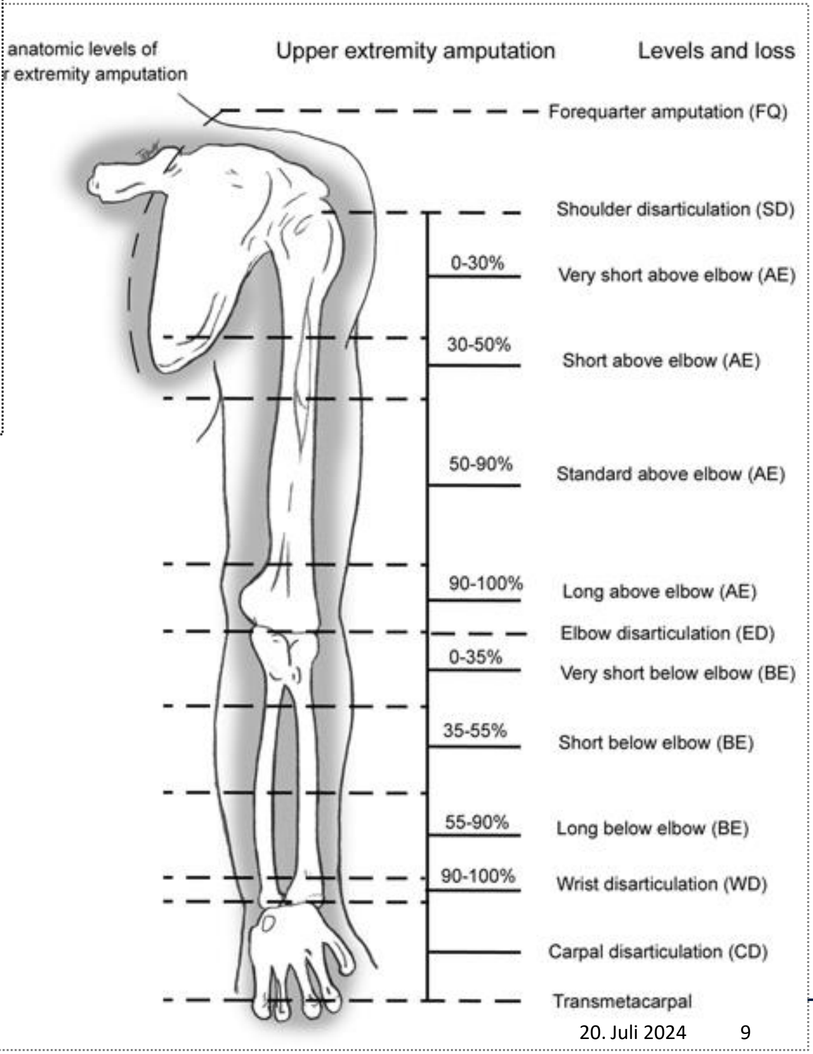


Figure 1-2. The different sectional planes used to expose internal structures.

- lower arm (forearm or *antebrachium*)
  - *M. Flexor Digitorum Superficialis*
  - *M. Extensor Digitorum*
  - *M. Brachioradialis*
  - *M. Pronator Teres*


Forequarter Amputation
Shoulder Disarticulation
Transhumeral (above elbow)
Transradial (below elbow)
Wrist Disarticulation


anatomic levels of
r extremity amputation
Upper extremity amputation
Levels and loss
Forequarter amputation (FQ)
Shoulder disarticulation (SD)
0-30%
Very short above elbow (AE)
30-50%
Short above elbow (AE)
50-90%
Standard above elbow (AE)
90-100%
Long above elbow (AE)
Elbow disarticulation (ED)
0-35%
Very short below elbow (BE)
35-55%
Short below elbow (BE)
55-90%
Long below elbow (BE)
90-100%
Wrist disarticulation (WD)
Carpal disarticulation (CD)
Transmetacarpal

Find the mug	visual feedback
Track the mug	visual feedback
Perform trajectory planning	internal process
Move hand to the mug	interaction with real world & feedback
Perform grasp planning	internal process
Open the hand	interaction with real world & feedback
Orient the hand properly	interaction with real world & feedback
Close the hand	interaction with real world & feedback
Adjust force	interaction with real world & feedback
Perform trajectory planning	internal process
Move mug to mouth	interaction with real world & feedback
Drink	interaction with real world & feedback

Ch-2

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

Offline Intent Detection:

Timing: Analysis occurs after data collection.

Process: Data is recorded and stored first, then processed later.

Use Case: Suitable for situations where immediate feedback is not required.

Online Intent Detection:

Timing: Analysis occurs simultaneously with data collection.

Process: Data is processed in real-time, allowing for instant feedback or interaction.

Use Case: Crucial for applications requiring immediate responses.

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)

ID - 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.

Gathering ground truth

by imitating the experimenter’s hand

by performing bilaterally symmetric actions

by looking at a mirror

errors must be corrected by collecting more data and updating the model,

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

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,

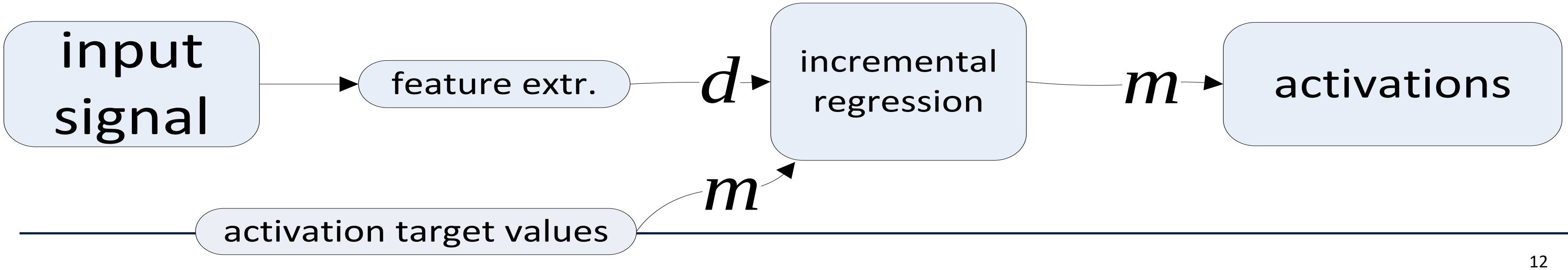
(model evaluation) test in real life and go back to beginning

10.start with an empty model

20.load new data, process it, update model

30.load new data, process it, predict, evaluate

40.goto 20



Ch-7

filter out whatever carries no useful information (noise)

subsample as much as possible - Subsampling reduces the number of samples in the signal to decrease the amount of data for processing.

filtering: eliminating frequency components which carry no information (noise)

bandpass filtering - Allows frequencies within a certain range to pass through and attenuates frequencies outside this range.

lowpass filtering - Allows frequencies below a certain cutoff to pass through and attenuates higher frequencies.

subsampling: only retain 1 in N samples, N given by the bandwidth after filtering

When a signal is sampled below the **Nyquist rate**, different frequency components of the signal become indistinguishable from one another in the sampled data. This phenomenon is called **aliasing,** where high-frequency components are misrepresented as lower frequencies, leading to distortion.

how do you synchronise signals coming from multiple sources?

obtain a precise timestamp for each sample, - Each sample from each sensor should have an associated timestamp

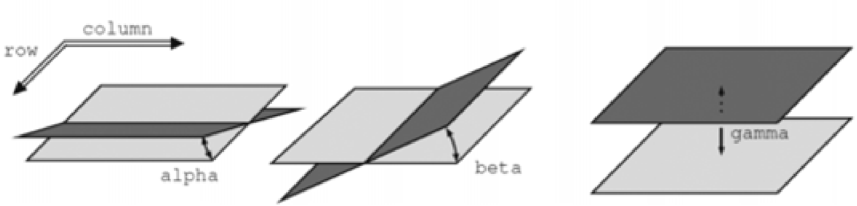
check that the sampling rates make sense,- Verify that the sampling rates are as expected and consistent throughout the data collection process.

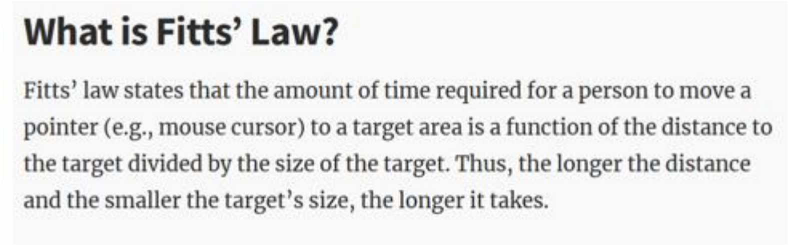
interpolate signals over the fastest signal‘s timestamps.-Choose the highest sampling rate as the reference. Here, it’s the sEMG signal sampled at 2 kHz. Interpolate the IMU and visual stimulus data to match the timestamps of the sEMG data.

Feature Ex

example: linearisation of grey values in a RoI.

- build the plane approximating the grey-value distribution in each of the N RoIs
- each plane is represented by a vector $(\alpha_i, \beta_i, \gamma_i)$
- end up with $3N$ features
- started out with $500 * 400$ pixels!





What is Fitts' Law?

Fitts' law states that the amount of time required for a person to move a pointer (e.g., mouse cursor) to a target area is a function of the distance to the target divided by the size of the target. Thus, the longer the distance and the smaller the target's size, the longer it takes.

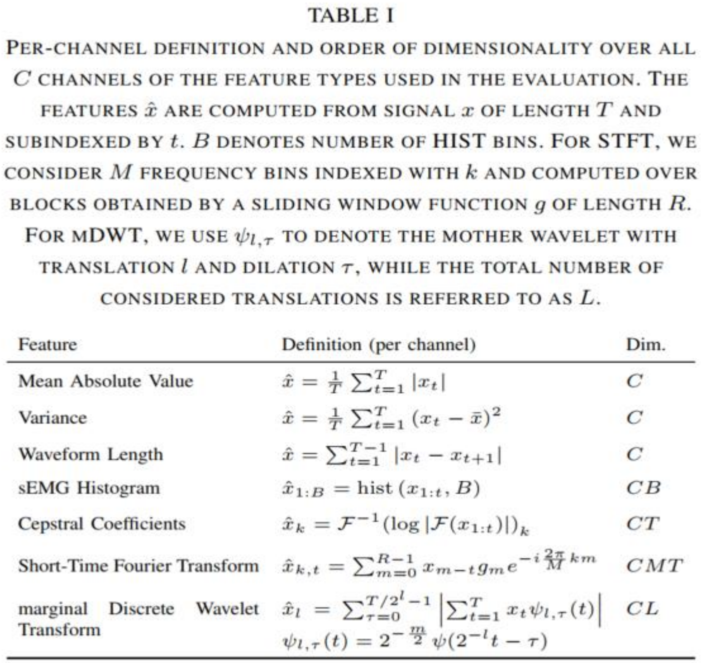
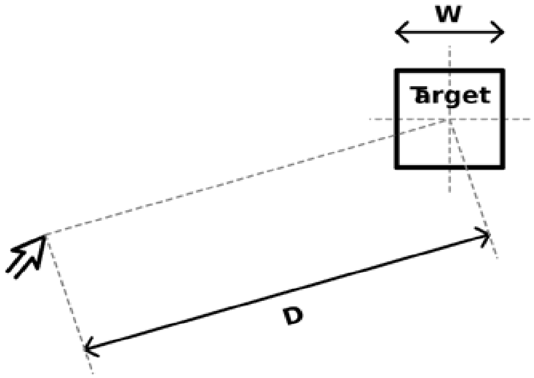


TABLE I

PER-CHANNEL DEFINITION AND ORDER OF DIMENSIONALITY OVER ALL C CHANNELS OF THE FEATURE TYPES USED IN THE EVALUATION. THE FEATURES $\hat{x}$ ARE COMPUTED FROM SIGNAL x OF LENGTH T AND SUBINDEXED BY t. B DENOTES NUMBER OF HIST BINS. FOR STFT, WE CONSIDER M FREQUENCY BINS INDEXED WITH k AND COMPUTED OVER BLOCKS OBTAINED BY A SLIDING WINDOW FUNCTION g OF LENGTH R. FOR MDWT, WE USE $\psi_{l,\tau}$ TO DENOTE THE MOTHER WAVELET WITH TRANSLATION l AND DILATION τ, WHILE THE TOTAL NUMBER OF CONSIDERED TRANSLATIONS IS REFERRED TO AS L.

Feature	Definition (per channel)	Dim.
Mean Absolute Value	$\hat{x} = \frac{1}{T}\sum_{t=1}^{T} \lvert x_t \rvert$	C
Variance	$\hat{x} = \frac{1}{T}\sum_{t=1}^{T} (x_t - \bar{x})^2$	C
Waveform Length	$\hat{x} = \sum_{t=1}^{T-1} \lvert x_t - x_{t+1} \rvert$	C
sEMG Histogram	$\hat{x}_{1:B} = \mathrm{hist}\,(x_{1:t}, B)$	CB
Cepstral Coefficients	$\hat{x}_k = \mathcal{F}^{-1}(\log \lvert \mathcal{F}(x_{1:t}) \rvert)_k$	CT
Short-Time Fourier Transform	$\hat{x}_{k,t} = \sum_{m=0}^{R-1} x_{m-t} g_m e^{-i\frac{2\pi}{M}km}$	CMT
marginal Discrete Wavelet Transform	$\hat{x}_l = \sum_{\tau=0}^{T/2^l-1} \left\lvert \sum_{t=1}^{T} x_t \psi_{l,\tau}(t) \right\rvert$ $\psi_{l,\tau}(t) = 2^{-\frac{m}{2}} \psi(2^{-l}t - \tau)$	CL

- the time required to complete a target-reaching task is



$$ID = \log_2\left(\frac{2D}{W}\right)$$

$$TCT = a + b \cdot ID$$

Muscle Activity

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.

Co contraction – when both the opposing muscles contract leading to stiffness.

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

1.Exoskeleton –

2.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.

3.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.

Ch-3

SMEG -

Force & Torque

each α-motoneuron discharge causes a depolarisation wave in the cells of its MU

also called MUAP: **Motor Unit Action Potential**

net effect: the superposition of many MUAPs on the surface of the muscle

SMEG is exactly all about measuring the superposed MUAPs
and sometimes, trying to decompose the signal back into its constituent MUAPs

The lower frequencies capture slower changes in muscle activity, while the higher frequencies capture rapid changes, such as individual motor unit action potentials.

Higher amplitudes indicate stronger muscle activity, while lower amplitudes indicate weaker activity

bandwidth: 15-450Hz,
amplitude: 1µV-10mV

Crosstalk in electromyography (EMG) refers to the interference or contamination of EMG signals from one muscle by signals from neighboring muscles. When EMG sensors are placed on the surface of the skin to detect muscle activity, they may pick up electrical signals not only from the target muscle but also from nearby muscles due to their proximity. In addition to interference from neighboring muscles, crosstalk can also occur between different channels of EMG recordings. For example, if multiple EMG sensors are placed on the skin surface, signals from one sensor may inadvertently influence or contaminate the signals detected by neighboring sensors.

The **end-of-fiber effect** occurs because the electrical activity at the ends of muscle fibers, near the neuromuscular junction, may differ from the activity along the length of the fiber. This can impact EMG recordings

Processing:-

ARVs (Averaged-Rectified Values):in which case there is one feature per channel

a purely temporal feature (not spectral), monotonically related to the intensity of the contraction

either consider a time windows and evaluate the root-mean-squared (RMS) signal over it, or

first rectify then apply a low-pass filter - *obtain a signal which is roughly monotonically related to muscle contraction* features (characteristics) evaluated on a window of raw signal,

there can be several for each channel, - the **Hudgins features** are 4 per channel

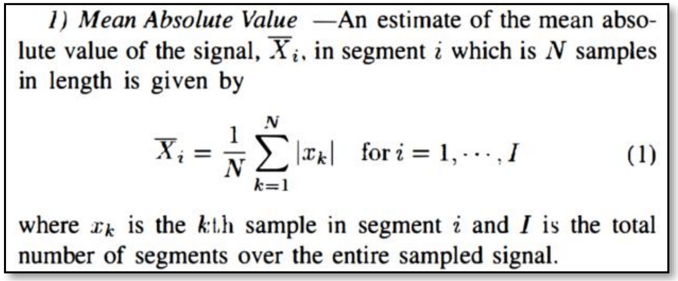
these are sort-of spectral features, i.e., related to the frequency content of the signal.

The Hudgins features aim to extract meaningful data from the raw EMG signals to facilitate the control of myoelectric devices by distinguishing different muscle activation patterns.

establish a time window,

the mean absolute value (MAV)
the zero crossings (ZC)
the slope sign changes (SSC)
the waveform length (WL)

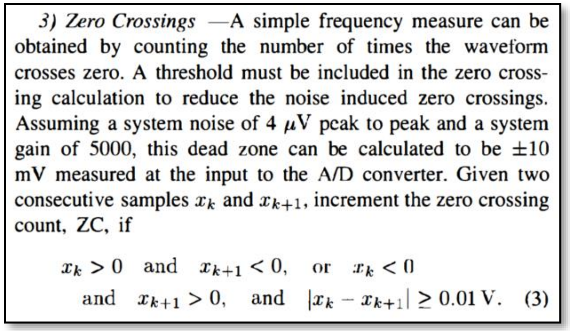
along the window.



1) Mean Absolute Value —An estimate of the mean absolute value of the signal, $\overline{X}_i$, in segment i which is N samples in length is given by

$$\overline{X}_i = \frac{1}{N}\sum_{k=1}^{N}|x_k| \quad \text{for } i = 1, \cdots, I \qquad (1)$$

where x_k is the kth sample in segment i and I is the total number of segments over the entire sampled signal.



3) Zero Crossings —A simple frequency measure can be obtained by counting the number of times the waveform crosses zero. A threshold must be included in the zero crossing calculation to reduce the noise induced zero crossings. Assuming a system noise of 4 μV peak to peak and a system gain of 5000, this dead zone can be calculated to be ±10 mV measured at the input to the A/D converter. Given two consecutive samples x_k and x_{k+1}, increment the zero crossing count, ZC, if

$$x_k > 0 \quad \text{and} \quad x_{k+1} < 0, \quad \text{or} \quad x_k < 0$$
$$\text{and} \quad x_{k+1} > 0, \quad \text{and} \quad |x_k - x_{k+1}| \geq 0.01\,\text{V}. \qquad (3)$$

<u>Mean Absolute Value (MAV):</u>

The MAV is computed by taking the average of the absolute values of the sEMG signal samples within the time window.

It represents the average magnitude of muscle activation during that time period.

MAV is a measure of the overall amplitude or intensity of muscle activity within the window.

<u>Zero Crossings (ZC):</u>

Zero crossings refer to the number of times the sEMG signal crosses the zero amplitude axis within the time window.

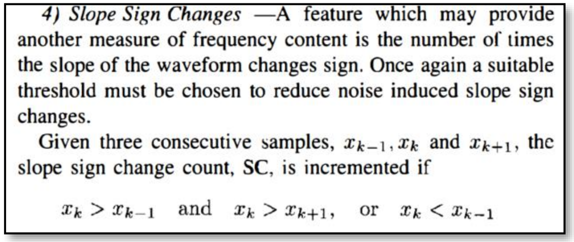
Zero crossings provide information about the frequency of changes in the sEMG signal, indicating transitions between positive and negative phases.

A higher number of zero crossings may indicate more dynamic or rapid changes in muscle activity.

Slope Sign Changes (SSC):

SSC counts the number of times the slope of the sEMG signal changes sign within the time window.

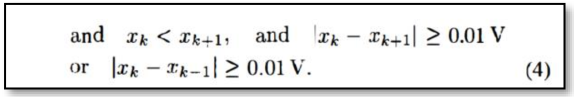
It captures variations in the rate of change of the signal, indicating abrupt transitions or fluctuations in muscle activity.



4) Slope Sign Changes —A feature which may provide another measure of frequency content is the number of times the slope of the waveform changes sign. Once again a suitable threshold must be chosen to reduce noise induced slope sign changes.

Given three consecutive samples, x_{k-1}, x_k and x_{k+1}, the slope sign change count, SC, is incremented if

$$x_k > x_{k-1} \quad \text{and} \quad x_k > x_{k+1}, \quad \text{or} \quad x_k < x_{k-1}$$



$$\text{and} \quad x_k < x_{k+1}, \quad \text{and} \quad |x_k - x_{k+1}| \geq 0.01 \text{ V} \quad \text{or} \quad |x_k - x_{k-1}| \geq 0.01 \text{ V}. \qquad (4)$$

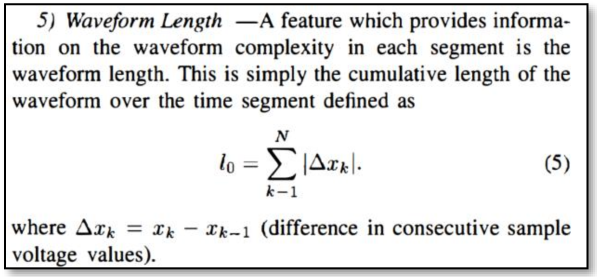
SSC is sensitive to changes in muscle activation patterns, such as the onset or cessation of muscle contractions.

Waveform Length (WL):

WL is calculated by summing the absolute differences between consecutive sEMG signal samples within the time window.

It quantifies the overall complexity or irregularity of the sEMG waveform, reflecting the degree of variability in muscle activity over time.

A higher WL value indicates a more variable or intricate sEMG waveform, whereas a lower WL value suggests a smoother or more regular waveform.



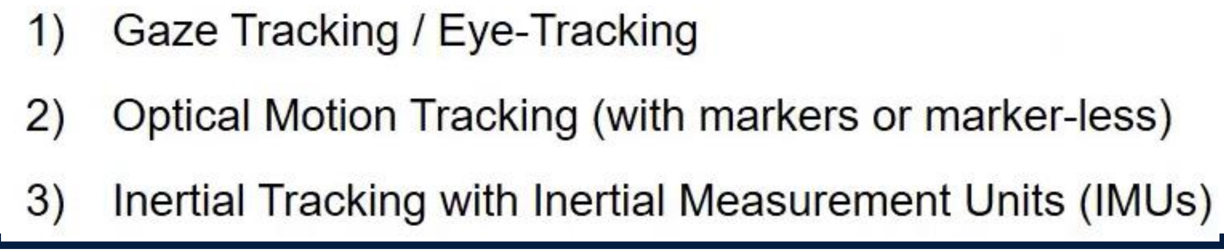
5) Waveform Length —A feature which provides information on the waveform complexity in each segment is the waveform length. This is simply the cumulative length of the waveform over the time segment defined as

$$l_0 = \sum_{k-1}^{N} |\Delta x_k|. \qquad (5)$$

where $\Delta x_k = x_k - x_{k-1}$ (difference in consecutive sample voltage values).

What is the output of an Smeg sensor - The sEMG signal is often represented as a time-series waveform, where the x-axis represents time and the y-axis represents the amplitude of the electrical signal. Each peak or fluctuation in the waveform corresponds to the firing of motor units within the muscle and the recruitment of muscle fibers during contraction.

Ch-4



1) Gaze Tracking / Eye-Tracking
2) Optical Motion Tracking (with markers or marker-less)
3) Inertial Tracking with Inertial Measurement Units (IMUs)

OMT consists of tracking a person‘s movements by looking at her

either using standard cameras (visible light)

or specific cameras / emitters / triangulation setup (laser, structured light, near-infrared)

uses active markers, passive markers or no markers

markers need be placed on the subject‘s body

and need react to the radiation emitted / detected by the cameras

markeless OMT relies on computer vision (very hard problem)

Eg-Vicon

What is the need of the markers?

- To mark the body with dots – algorithm looks at how the dots move around and then reconstruct the posture of the body and motion of the body.
- In marker-based OMT, reflective or active markers are attached to specific points on the subject's body. These markers reflect or emit light, which is then detected by the optical sensors(cameras)
- By tracking the movement of these markers over time, the system can reconstruct the motion of the person's body in three-dimensional space
- Markers are made of adhesive tape that can reflect light
- Markers are so small - can even track single finger movements

but useless in daily living,but feasible in a clinic,

and very useful to **measure compensation movements!**

less compensatory motion means motion more similar to able-bodied persons so, better control and functional recovery

Compensation movements refer to adjustments or modifications in movement patterns made by an individual to compensate for limitations, weaknesses, or imbalances in their musculoskeletal system.

Identify the wrong movements patients do ,understanding compensation movements is crucial for facilitating recovery, improving movement quality, and enhancing overall functional performance.

therefore, used to enhance functional assessment-both in prosthetics and rehab

GaMA stands for Gaze and Movement Assessment. It's a method for evaluating how well someone with an upper limb impairment (arm or hand) can perform tasks.

How GaMA works (Method):

•GaMA combines two technologies:

- •**Motion tracking:** This tracks the movement of the impaired limb (prosthesis, hand, or arm) during tasks.
- •**Eye tracking:** This tracks where the person is looking as they perform the tasks.

To detect the scene of the user, intent and the identify the objects in the scene

- using AR glasses,

  identify the objects in the scene (in front of the user),

  choose one according to proximity to the prosthesis,

  decide whether to start an autonomous grasp or use sEMG to detect „volitional" grasp. (Volitional means done of one's own will or choosing.)

inevitably **suffers from all computer-vision related problems** (illumination, perspective changes, etc.)

Gaze Tracking

- detecting what you are looking at by looking at your eyes!
- we just need to focus on the goal, brain will take care of our movement - Because our brain can handle these complex calculations unconsciously, thanks to proprioception, we are free to focus our attention on what we are trying to achieve with our movements, rather than how to move our bodies themselves.
  - usually via near-infrared camera(s) – we cannot see them
  - also measure the trust that someone has on prosthesis

- in rehabilitation robotics: *if you trust your robot,* you won‘t look at it but at the targets!
  - e.g. upper-limb prosthetics: users should *not* be looking at the prosthesis,
  - but at the places where they want to grasp and release!
  - e.g. lower-limb prosthetics: users should *not* be looking at the leg prosthesis,
  - but ahead, at where they want to go!

- while moving, *you seldom look at your own body.*
  - because you have *proprioception*,
  - and proprioception means *excellent body inverse kinematics*
  - which means you can *concentrate on your targets*.

Inertial measurement units (IMUs): are electronic devices that measure and report a body's specific force, angular rate, and sometimes the orientation of the body.

using IMUs – detect orientation,cheaper than OT

•IMUs were originally designed to help determine the location of a ship at sea.

•*main problem: the measurement tends to drift: Unfortunately, the accuracy of IMUs tend to drift over time, which can make them unreliable for long-term navigation.*

•*drift refers to the gradual deviation of the IMU's measured position, velocity, or orientation from the true values over time. This deviation occurs due to the accumulation of small errors in the sensor readings.*

•nowadays integrate a magnetometer, an accelerometer and a gyroscope: To improve accuracy, modern IMUs often combine three types of sensors:

- Magnetometer: detects magnetic fields and helps determine direction or heading.
- Accelerometer: measures acceleration.
- Gyroscope: measures rotational motion.

application:

direct kinematics - also known as forward kinematics, is a concept used in robotics to determine the position and orientation (pose) of the end effector (the gripper or tool at the tip of the robot's arm) given the specific joint angles or joint positions of the robot's arm.

body posture (kinematic configuration) detection

This is werable and cheaper than any kind of optical motion tracking to track the motion/orientation – eg BodyRig

A BodyRig is a wearable motion capture system designed to track the movement and orientation of a person's body. Unlike traditional optical motion tracking systems, which use cameras and markers to capture motion data, BodyRigs typically use a combination of sensors such as accelerometers, gyroscopes, and magnetometers

TCP/IP:

Characteristics:

Reliable: Ensures all data packets are delivered and in the correct order.

Overhead: More overhead due to error checking, acknowledgments, and retransmissions.

Latency: Higher latency due to the need for establishing connections and ensuring reliable delivery.

Usage: Suitable for applications where data integrity is critical, such as transferring files or command/control data for prosthetics.

UDP:

Characteristics:

Unreliable: No guarantee of packet delivery or order.

Overhead: Lower overhead, resulting in less latency.

Latency: Lower latency, suitable for real-time applications.

Usage: Suitable for applications where speed is critical, and occasional data loss is acceptable, such as streaming real-time sensor data.

Wi-Fi:

Higher data rates (up to several hundred Mbps).

Suitable for high-density sEMG data transmission.

Wider range than Bluetooth.

Wired Connection (e.g., USB):

Reliable and high data rate.

Eliminates issues with wireless interference.

Limits mobility compared to wireless solutions.

Ch-5

FMG and TMG

TM – high density FMG 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

generalisation problem:
the *limb position effect*

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.

- 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

Regions of interest - heatmaps

ROG and TAC

Gradient – vector with x,y,z values – high force – high absolute vector values

Combination of action – making a fist and wrist pronation

An ideal model is trained for single actions, but it should be able to predict combination of actions

RR- all 320 features

RR-ROIG – 60 features

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

In both we were able to predict combined actions even though they were trained for only single actions

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:

1. **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.

2. **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.

3. **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.

4. **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.

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.

Electrical Impedance Tomography(EIT)
Ultrasound scanning (A-mode, B-mode a.k.a. imaging)

An **interference profile** in the context of tomography refers to the pattern of waves that result from the interaction (interference) of energy waves (such as sound waves or electromagnetic waves) as they pass through and are affected by the internal structures of the tissue. This profile is crucial in reconstructing detailed images of the internal structures.

Tomography Types

Type 1: Wave of Energy at Specific Angles

Process:

A wave of energy (e.g., X-rays, sound waves) is sent into the tissue from many specific angles, rotating around the tissue.

The interference profiles (patterns of how the waves interact with the internal structures) are recorded at the opposite side.

These profiles are used to reconstruct an image of the internal structure.

Application: This method is commonly used in CT (Computed Tomography) scans.

1.Type 2: Wave of Energy from Specific Spots

1. **Process**:
    1. A wave of energy is sent into the tissue from many specific spots.
    2. The echoes (reflected waves) from each spot are recorded.
    3. These echoes are used to reconstruct an image.
2. **Application**: This method is typically used in ultrasound imaging.

Type-1-Attenuation Profile: For each angle from which the wave is sent, an attenuation profile is obtained, which represents how much the wave is attenuated as it passes through the tissue.

- for each angle an „attenuation profile“ is obtained
- from the complete set of attenuation profiles („sinogram“) the original image can be reconstructed

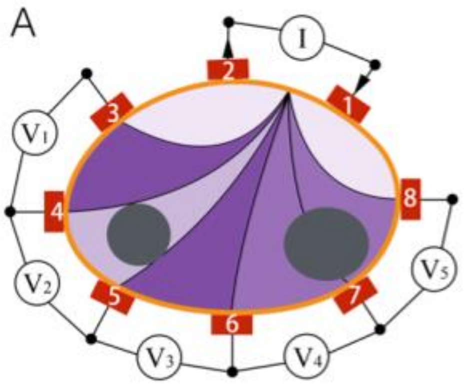
Type-2

- source and receiver of the wave are one and the same (e.g., piezoelectric effect)
- Transducers are made of piezoelectric crystals
- so they are in the same location
- and they both send the wave and record the „echo“ of the wave
- Acoustic impedance is a property of tissue that depends on its density and the speed of sound through it

High Impedance Tissues: Bone and dense connective tissues have high acoustic impedance. When an ultrasound wave encounters these tissues, a large portion of the wave is reflected back, creating a high amplitude signal.

Low Impedance Tissues: Soft tissues like fat and muscle have lower acoustic impedance compared to bone. The reflections from these tissues are weaker, resulting in lower amplitude signals.

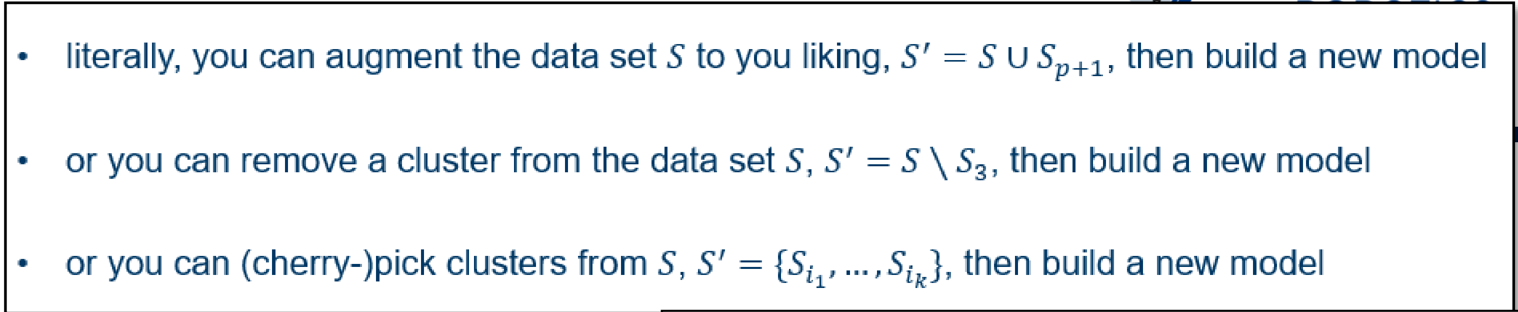
Electrical Impedance Tomography (EIT) works by injecting tiny oscillating currents into the body, detecting the impedance at other locations of the body typically, a ring of electrodes (metal plates on the skin) is used to inject a current through one pair of adjacent electrodes, detect an impedance at all other pairs of electrodes the next pair is then selected for the injection and so on till one full round has been performed



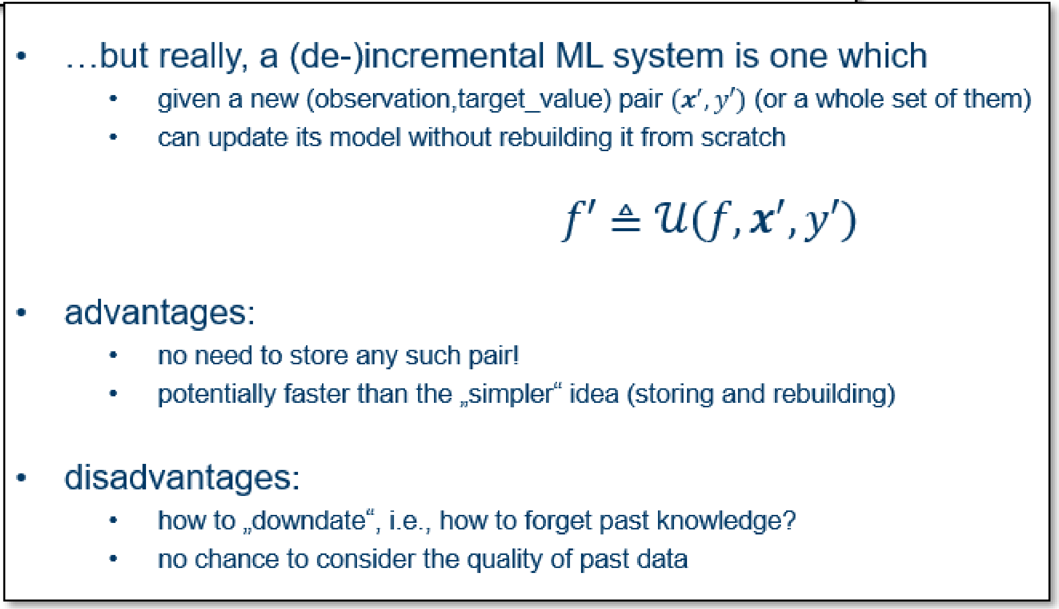
Ultrasound (B-mode) tomography works by injecting high-frequency (~10MHz) pressure waves (sound) into the body, detecting the „echo“ at the same location of the body typically, a „transducer“ (array of ceramic piezoelectric elements) placed on the skin emits a pressure wave by being electrically excited (exploit the piezo effect), detects the pressure impedance change profile (exploit the same effect) by carefully timing the emission and detection of each transducer in the array an image can be formed (beamforming)

- Need to make it smaller as possible
- possibly move from B-mode to A-mode scanning (single transducer elements)
- we use just 8 transducers – produce good results than same EMG sensors. Less transducers so that its wearable. The interface between one tissue and other as detectable via the impedenace change

CH-8-ML



- literally, you can augment the data set S to you liking, $S' = S \cup S_{p+1}$, then build a new model
- or you can remove a cluster from the data set S, $S' = S \setminus S_3$, then build a new model
- or you can (cherry-)pick clusters from S, $S' = \{S_{i_1}, \ldots, S_{i_k}\}$, then build a new model



- …but really, a (de-)incremental ML system is one which
  - given a new (observation,target_value) pair (x', y') (or a whole set of them)
  - can update its model without rebuilding it from scratch

$$f' \triangleq \mathcal{U}(f, x', y')$$

- advantages:
  - no need to store any such pair!
  - potentially faster than the „simpler“ idea (storing and rebuilding)
- disadvantages:
  - how to „downdate“, i.e., how to forget past knowledge?
  - no chance to consider the quality of past data

Knowledge composition is a method in myoelectric prosthesis control where control models are dynamically created in real-time by combining previously gathered data pairs (sample, target). This approach reduces the complexity of matching multiple patterns simultaneously and aims to improve the reliability and performance of prosthetic control systems.

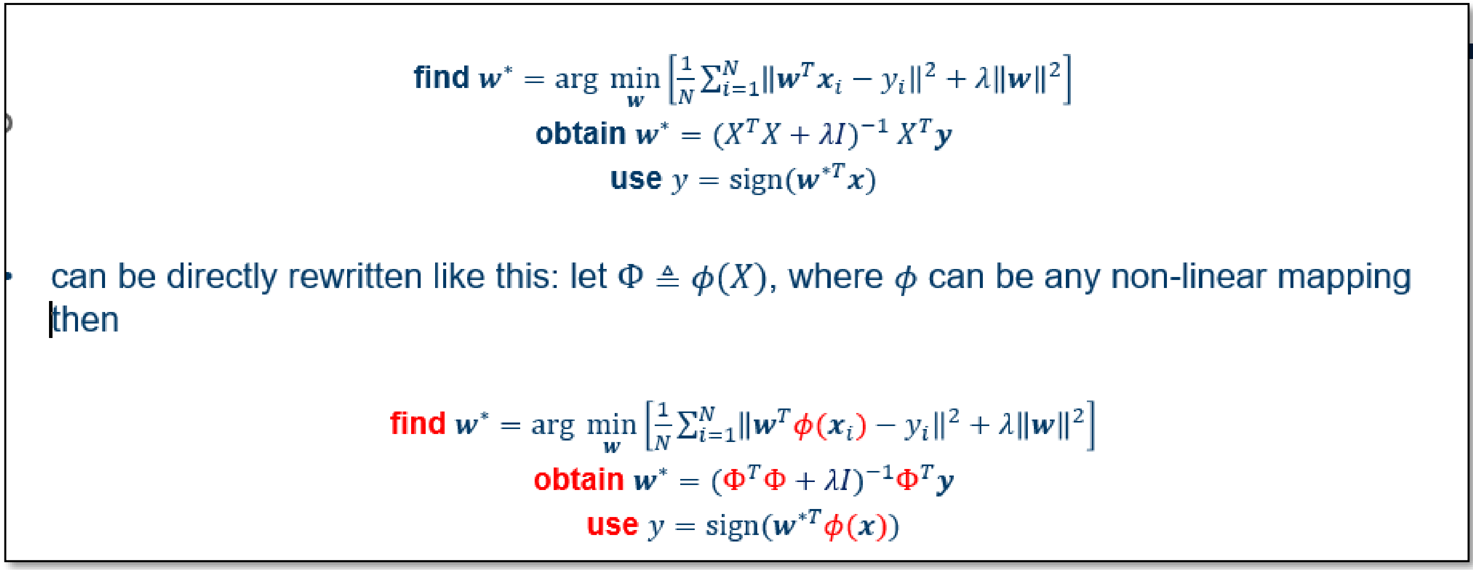
- yields a measure of confidence in its own prediction
- can be either a classifier or a regressor

interaction and incrementality

- is incremental / decremental

- is numerically stable and fast to be rebuilt / updated
- can tackle non-linear problems

CLASSIFICATION



$$\textbf{find } \boldsymbol{w}^* = \arg\min_{\boldsymbol{w}} \left[\frac{1}{N}\sum_{i=1}^{N}\|\boldsymbol{w}^T\boldsymbol{x}_i - y_i\|^2 + \lambda\|\boldsymbol{w}\|^2\right]$$

$$\textbf{obtain } \boldsymbol{w}^* = (X^TX + \lambda I)^{-1}\, X^T\boldsymbol{y}$$

$$\textbf{use } y = \operatorname{sign}(\boldsymbol{w}^{*T}\boldsymbol{x})$$

can be directly rewritten like this: let $\Phi \triangleq \phi(X)$, where ϕ can be any non-linear mapping then

$$\textbf{find } \boldsymbol{w}^* = \arg\min_{\boldsymbol{w}} \left[\frac{1}{N}\sum_{i=1}^{N}\|\boldsymbol{w}^T\phi(\boldsymbol{x}_i) - y_i\|^2 + \lambda\|\boldsymbol{w}\|^2\right]$$

$$\textbf{obtain } \boldsymbol{w}^* = (\Phi^T\Phi + \lambda I)^{-1}\Phi^T\boldsymbol{y}$$

$$\textbf{use } y = \operatorname{sign}(\boldsymbol{w}^{*T}\phi(\boldsymbol{x}))$$

- Fake – rebuilds from scratch
- True – updates the model

CH-9

Regression

the need to properly choose your hypothesis space $\mathcal{H}$

the need to find a balance between under- and overfitting

minimising a cost functional $f ^{\wedge} * = \arg\min \top f ⟦[\mathcal{L}(f, X, \boldsymbol{y}) + \mathcal{R}(f)⟧]$

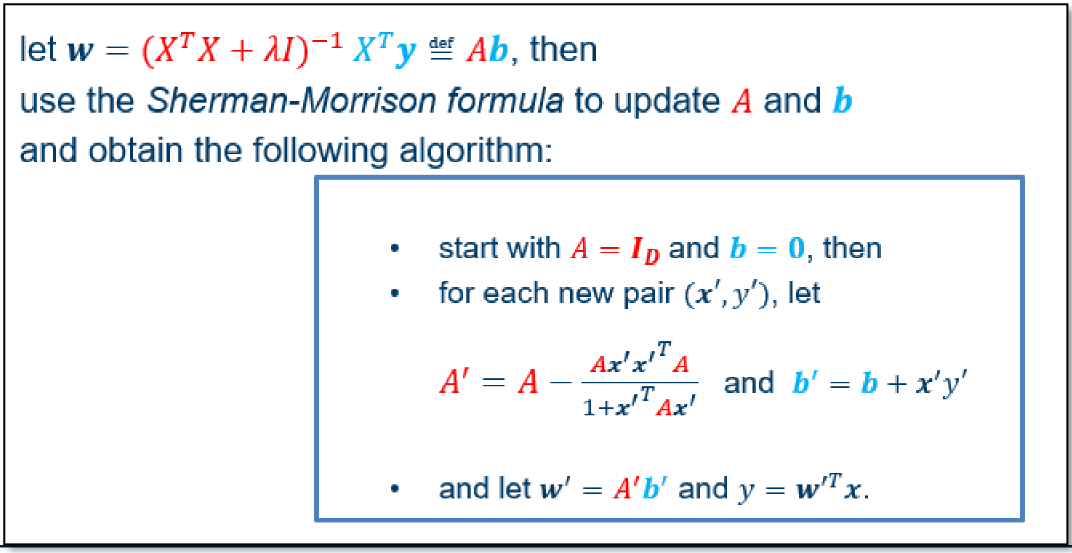
Why better?

naturally yields simultaneous control over many DoAs / motors

enables control on each single motor, proportionally

enables user control over an infinite manifold of activation configuration
(instead of over a few predetermined actions, on-off)

- $y = \boldsymbol{w}^{*T}\boldsymbol{x}.$
- this is called „regularised least-squares regression“ or **„Ridge Regression“.**
- Incremental learning involves updating the model parameters as new data points arrive, without retraining the model from scratch.



let $\boldsymbol{w} = (X^T X + \lambda I)^{-1}\, X^T \boldsymbol{y} \overset{\text{def}}{=} A\boldsymbol{b}$, then
use the *Sherman-Morrison formula* to update A and $\boldsymbol{b}$
and obtain the following algorithm:

- start with $A = \boldsymbol{I_D}$ and $\boldsymbol{b} = \boldsymbol{0}$, then
- for each new pair $(\boldsymbol{x}', y')$, let

$$A' = A - \frac{A\boldsymbol{x}'\boldsymbol{x}'^T A}{1+\boldsymbol{x}'^T A\boldsymbol{x}'} \quad \text{and} \quad \boldsymbol{b}' = \boldsymbol{b} + \boldsymbol{x}'y'$$

- and let $\boldsymbol{w}' = A'\boldsymbol{b}'$ and $y = \boldsymbol{w}'^T\boldsymbol{x}.$

Extracting features - π

fed raw input signals - > ϕ -> Extract right features from the signals

Ways to to *automatically* extract the „right“ features from your raw signals

use a deep-learning approach

use the kernel trick

use a finite approximation of the kernel trick

comparing and combining „learned“ and „handcrafted“ features- ADANN is an advanced algorithm designed to improve the generalization of deep learning models for EMG-based gesture recognition by employing domain adaptation and adversarial learning techniques. This allows the model to perform better across different individuals, overcoming the variability in EMG signals.

Kernel trick

$$y = f(\boldsymbol{x}) = \sum_{i=1}^{n} w_i \, K(\boldsymbol{x}_i, \boldsymbol{x})$$

where K is a real-valued binary function of your input space. in the ideal case,

- $K(\boldsymbol{a}, \boldsymbol{b}) = 1$ iff $\boldsymbol{a} = \boldsymbol{b}$
- $K(\boldsymbol{a}, \boldsymbol{b}) \to 0$ iff $\|\boldsymbol{a} - \boldsymbol{b}\| \to \infty$

that is, K is an affinity / similarity function,
and the approximant is a weighted sum of „how similar $\boldsymbol{x}$ is to the $\boldsymbol{x}$s I already know“.

advantages:

universal – can solve any possible (classification/regression) problem in principle

models are really good if overfitting avoided (do cross-validation and grid-search on σ)

disadvantages:

long model-building (training) time – usually cubic in n !

non-incremental – still need to rebuild the model from scratch when new knowledge is available

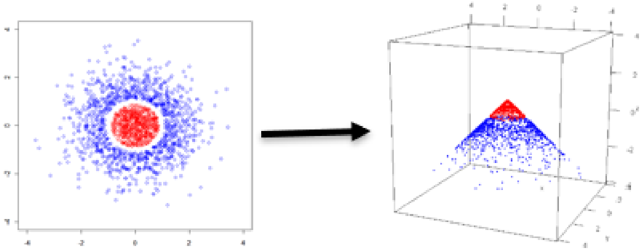
need optimisation – computationally hard if cost functional convex (SVM), otherwise prone to local minima there are conditions on K in order to be a „proper“ kernel function (Mercer‘s conditions), but its main property is that it implicitly defines a function ϕ

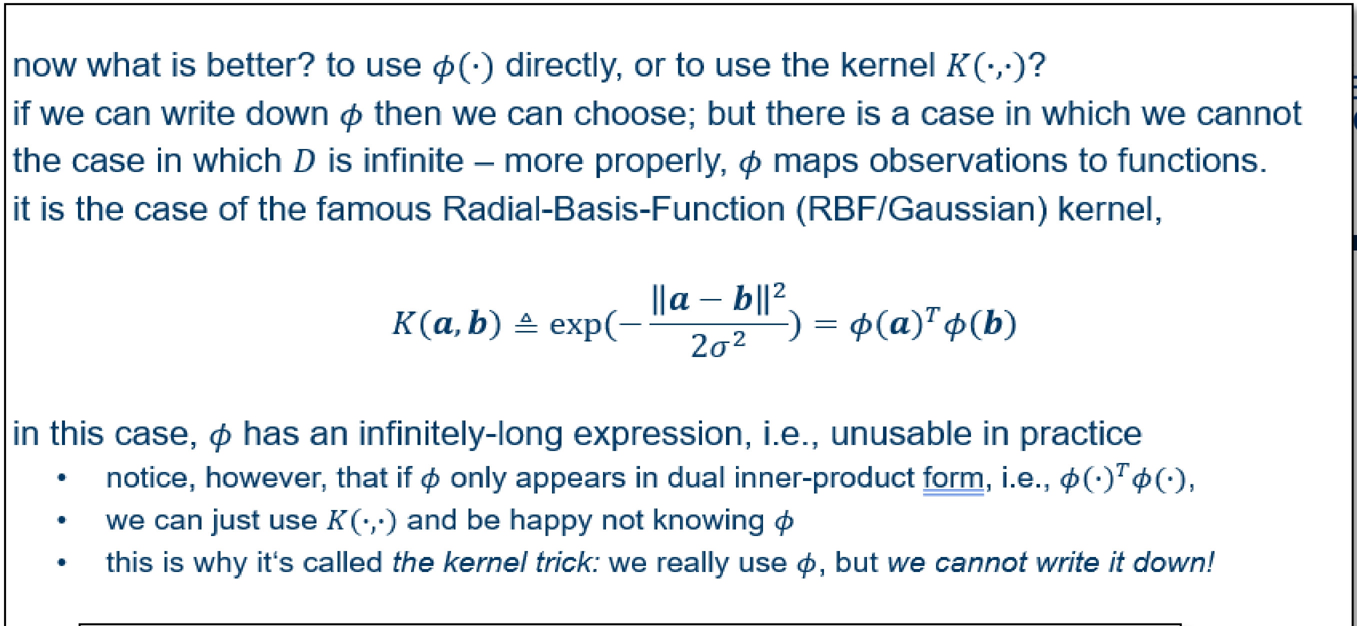
$$K(\boldsymbol{a}, \boldsymbol{b}) = \phi(\boldsymbol{a})^T \phi(\boldsymbol{b})$$

mapping observations onto a D-dimensional „feature space“!

simple example: our „cone-mapping“ $\phi(\boldsymbol{a}) = \ (a_1, a_2, -\|\boldsymbol{a}\|)$ (Lecture 8)
is implicitly defined by the kernel function

$$K(\boldsymbol{a}, \boldsymbol{b}) = [a_1 \ a_2 \ \ -\|\boldsymbol{a}\|] \cdot \begin{bmatrix} b_1 \\ b_2 \\ -\|\boldsymbol{b}\| \end{bmatrix} = a_1 b_1 + a_2 b_2 + \|\boldsymbol{a} \cdot \boldsymbol{b}\| = \boldsymbol{a} \cdot \boldsymbol{b} + \|\boldsymbol{a} \cdot \boldsymbol{b}\|$$



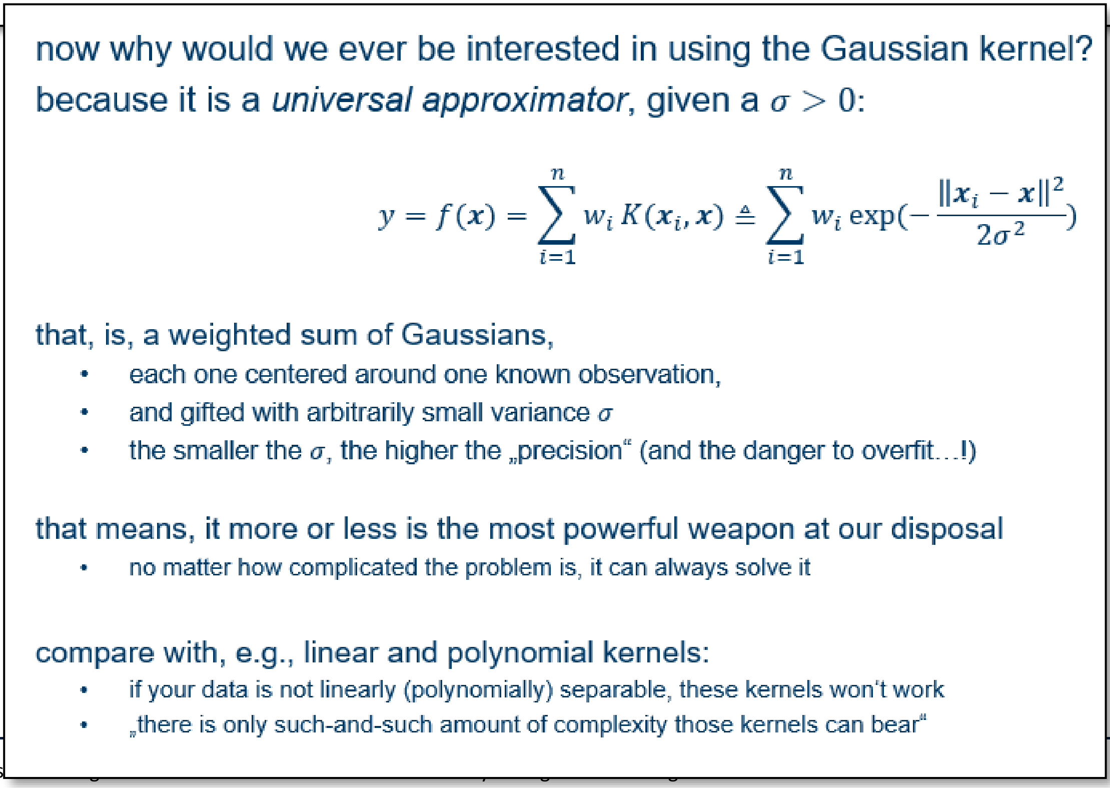


now what is better? to use $\phi(\cdot)$ directly, or to use the kernel $K(\cdot,\cdot)$?
if we can write down ϕ then we can choose; but there is a case in which we cannot
the case in which D is infinite – more properly, ϕ maps observations to functions.
it is the case of the famous Radial-Basis-Function (RBF/Gaussian) kernel,

$$K(\boldsymbol{a},\boldsymbol{b}) \triangleq \exp(-\frac{\|\boldsymbol{a}-\boldsymbol{b}\|^2}{2\sigma^2}) = \phi(\boldsymbol{a})^T\phi(\boldsymbol{b})$$

in this case, ϕ has an infinitely-long expression, i.e., unusable in practice

- notice, however, that if ϕ only appears in dual inner-product form, i.e., $\phi(\cdot)^T\phi(\cdot)$,
- we can just use $K(\cdot,\cdot)$ and be happy not knowing ϕ
- this is why it's called *the kernel trick*: we really use ϕ, but *we cannot write it down!*



now why would we ever be interested in using the Gaussian kernel?
because it is a *universal approximator*, given a $\sigma > 0$:

$$y = f(\boldsymbol{x}) = \sum_{i=1}^{n} w_i\, K(\boldsymbol{x}_i,\boldsymbol{x}) \triangleq \sum_{i=1}^{n} w_i \exp(-\frac{\|\boldsymbol{x}_i-\boldsymbol{x}\|^2}{2\sigma^2})$$

that, is, a weighted sum of Gaussians,

- each one centered around one known observation,
- and gifted with arbitrarily small variance σ
- the smaller the σ, the higher the „precision" (and the danger to overfit…!)

that means, it more or less is the most powerful weapon at our disposal

- no matter how complicated the problem is, it can always solve it

compare with, e.g., linear and polynomial kernels:

- if your data is not linearly (polynomially) separable, these kernels won't work
- „there is only such-and-such amount of complexity those kernels can bear"

Random Fourier Features

- suppose that, instead of taking the full Gaussian kernel $K(\boldsymbol{x}_1, \boldsymbol{x}_2) = \exp(-\frac{\|\boldsymbol{x}_1 - \boldsymbol{x}_2\|^2}{2\sigma^2})$,

- we *approximate it* using a finite number D of its Fourier coefficients.

- in that case, what does ϕ look like? is it feasible to use it?
  and what coefficients do we really need?

- according to Bochner‘s theorem (1933):

$$K(\boldsymbol{x}_1 - \boldsymbol{x}_2) = \int_{\mathbb{R}^d} \boxed{e^{-i\boldsymbol{\omega}^T(\boldsymbol{x}_1 - \boldsymbol{x}_2)}} p(\boldsymbol{\omega}) d\boldsymbol{\omega}$$

- and $e^{-i\boldsymbol{\omega}^T(\boldsymbol{x}_1 - \boldsymbol{x}_2)}$ can be rewritten as

$$e^{-i\boldsymbol{\omega}^T(\boldsymbol{x}_1 - \boldsymbol{x}_2)} = \cos(\boldsymbol{\omega}^T \boldsymbol{x}_1 + b) \cdot \cos(\boldsymbol{\omega}^T \boldsymbol{x}_2 + b) \triangleq \phi(\boldsymbol{x}_1)^T \phi(\boldsymbol{x}_2)$$

- which tells us exactly how to build ϕ !

so we can explicitly build a non-linear mapping $\phi(\boldsymbol{x}) = \cos(\boldsymbol{\omega}^T \boldsymbol{x} + b)$, where

- the $\boldsymbol{\omega}$s are randomly drawn from a Gaussian distribution $\mathcal{N}(\mathbf{0}, \sigma)$ and
- the bs are randomly drawn from a uniform distribution $\mathcal{U}(-\pi, \pi)$.

and this is for one Fourier coefficient $\boldsymbol{\omega}$. We need to use D of them, leading to

$$\phi(\boldsymbol{x}) = \begin{bmatrix} \cos(\boldsymbol{\omega}_1^T\, \boldsymbol{x} + b_1) \\ \vdots \\ \cos(\boldsymbol{\omega}_D^T\, \boldsymbol{x} + b_D) \end{bmatrix}$$

this ϕ

- is a finite-(D-)dimensional approximation of the Gaussian kernel,
- it is easy to build, computationally fast,
- and it can be plugged into Ridge Regression like any other ϕ:

obtain $\boldsymbol{w}^* = (\Phi^T \Phi + \lambda I)^{-1} \Phi^T \boldsymbol{y}$

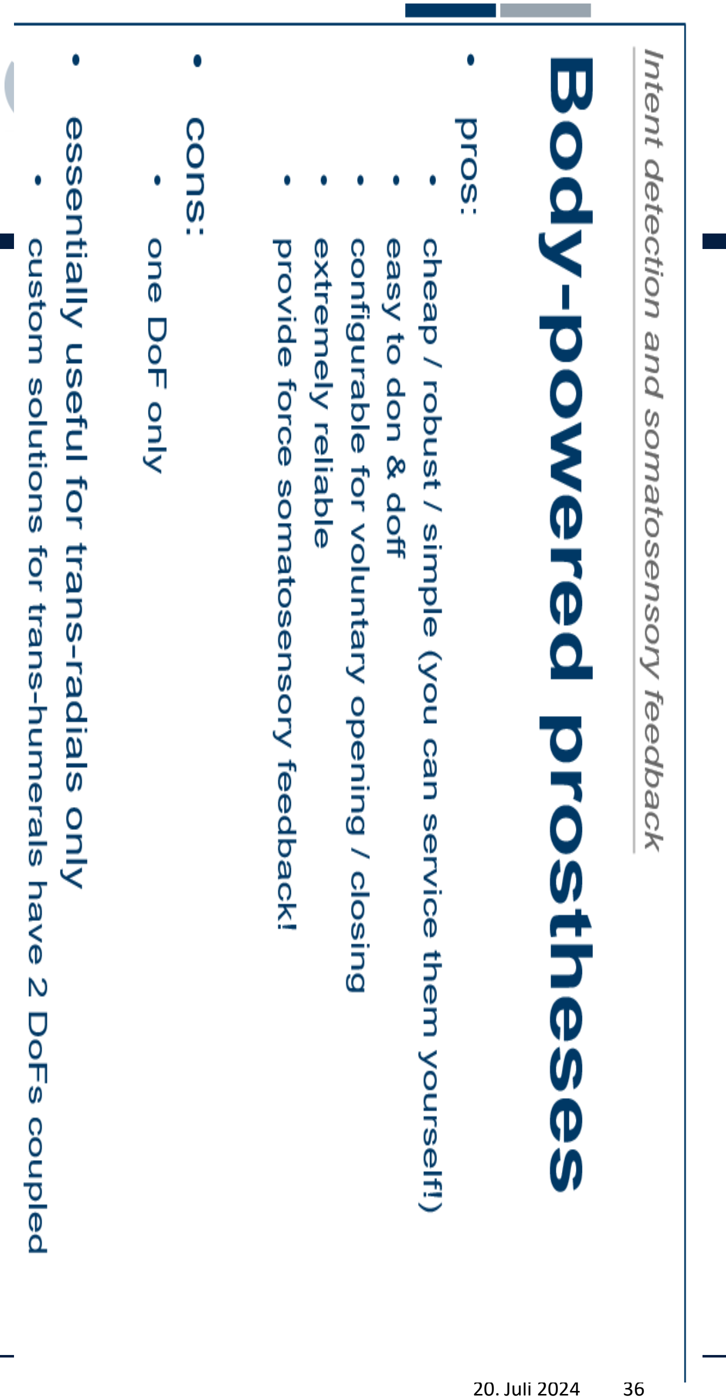
use $y = \boldsymbol{w}^{*T} \phi(\boldsymbol{x})$

Ch-10

Somatosensory feedback

- visual and audio feedback are already present:
  - users can *see* what their devices do (although not always! and sometimes they don't *want* to…)
  - users can hear what their devices do (noise associated to motors)
- what about providing *direct stimuli* on the body
  - in order to simulate proprioception and touch?

- really, there already is something the like:
  - the user naturally perceives the weight / resistance of any prosthesis or reha device; plus,
  - in some cases we get direct force-feedback "for free" – body-powered prostheses!



Intent detection and somatosensory feedback

Body-powered prostheses

- pros:
  - cheap / robust / simple (you can service them yourself!)
  - easy to don & doff
  - configurable for voluntary opening / closing
  - extremely reliable
  - provide force somatosensory feedback!
- cons:
  - one DoF only
- essentially useful for trans-radials only
  - custom solutions for trans-humerals have 2 DoFs coupled

Two ways for sensory substitution

mechanical (vibrotactile, indenting) – use vibrations/press on the skin to create patterns on the skin

If no visual feedback, then we rely on vibrotactile one – force sensors – force to vibrations

electrical (small currents through the skin)

Multichannel electrotactile stimulation using electrode arrays and matrices

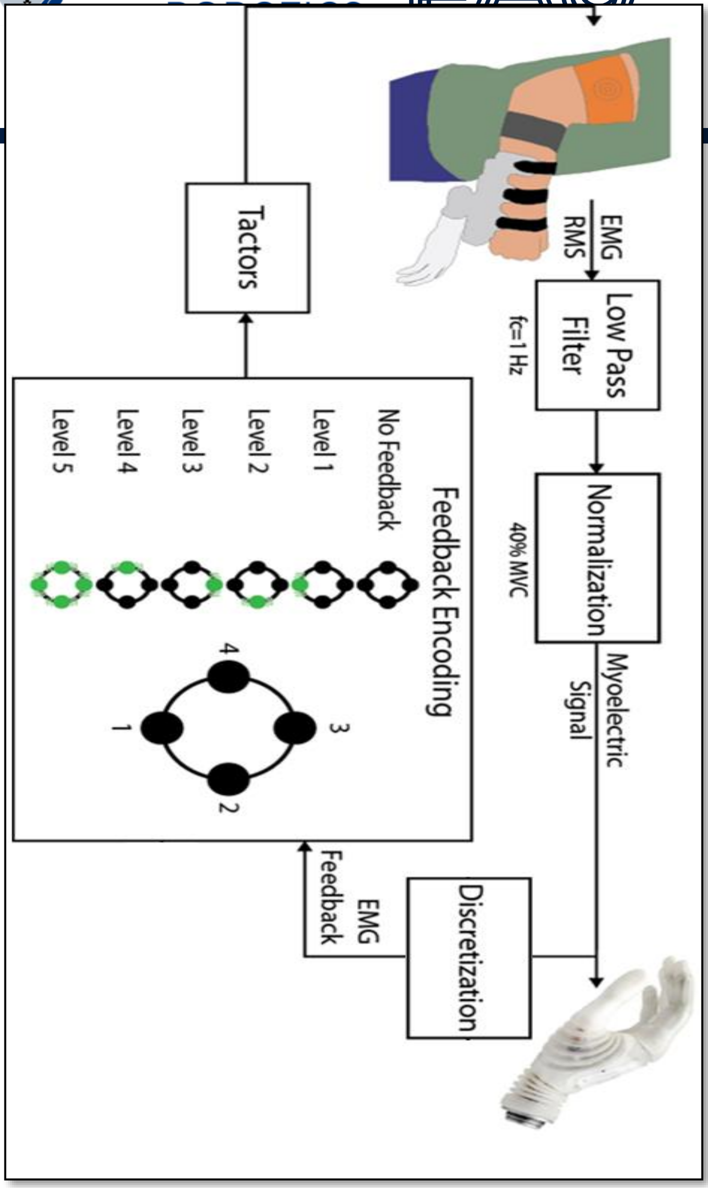
Feedback from a multifunctional prosthesis

1.Hand aperture feedback - Hand aperture refers to the distance or gap between the thumb and fingers when the hand is opened or positioned to grasp an object

2.Force feedback

3.Wrist rotation feedback

EMG feedback outperforms force feedback


EMG
RMS
Low Pass
Filter
fc=1 Hz
Normalization
40% MVC
Myoelectric
Signal
Discretization
EMG
Feedback
Feedback Encoding
No Feedback
Level 1
Level 2
Level 3
Level 4
Level 5
4
3
1
2
Tactors