Sensors Fusion techniques for eHealth: from theory to applications

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Presentation

Short BIO:

- Graduated in Telecommunications Engineering in 2019 in University of Padova.

- More than 1 year in the field of AI and Machine Learning applications in HealthTech Technologies.

- From 2019, Machine Learning Engineer in Cambridge at **Focal Point Positioning** .

Experience:

- Machine Learning for eHealth:
    - Unsupervised Anomaly Detection
- Sensors Fusion

- Deep learning:
    - Geometrical Deep learning

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Goals of the course

Theory

- Explaining the basis of Sensors Fusion and providing a **big picture** of the entire "Sensors Fusion Universe".
- Exploring the **main** frameworks and **techniques** used in the Sensors Fusion domain (with a bit of Machine Learning) for eHealth.

Practice

- Understanding **main applications** of Sensors Fusion eHealth
- Discussing about the **limits** and future development of Sensors Fusion in eHealth

Added value of this course

TARGET AUDIENCE:

- **Novel researchers** in the field of Sensors Fusion, Data Science or eHealth technologies

- **R&D tech employee** working in companies in the field of eHealth , Internet of Things and robotic.

- **Product managers and/or investors** interested in the opportunities, applications and challenges of Sensors Fusion in eHealth. (ONLY SECOND PART)

Outline

Part 1: State of Art of Sensors Fusion

- What is Sensors Fusion?
- Why we need Sensors Fusion
- Different categories of Sensors Fusion Techniques
- State Estimation Techniques:
  - Kalman Filters
- Decision Fusion Techniques:
  - Bayesian Inference (Bayesian Network)
  - Dempster-Shafer

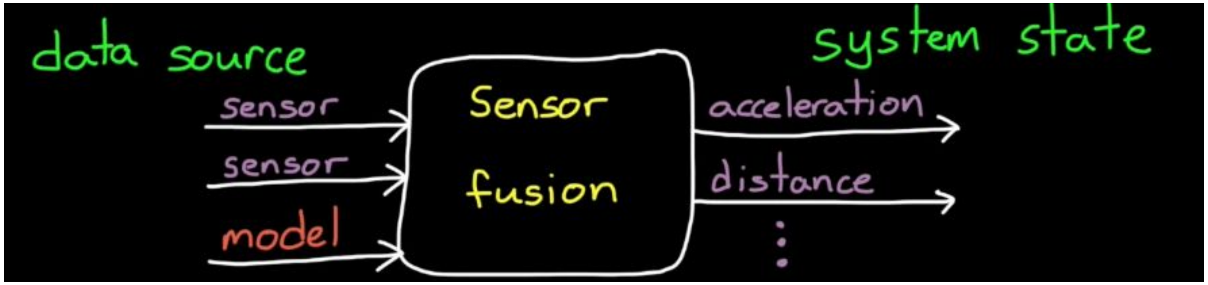
Part 2: Sensors Fusion in eHealth

- Main Applications
- Why we need it
- Sensors Fusion Vs Sensors Integration
- Sensors Integration Systems
- Practical Projects and Applications
- Requirements , Limits and Issues

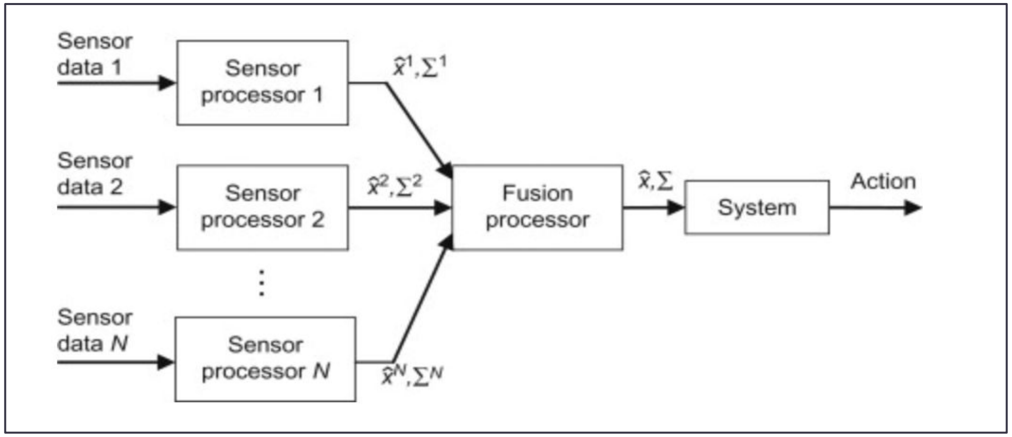
What is Sensors Fusion

- **Wikipedia Definition:** Sensors fusion is the process of combining sensory data or data derived from disparate sources such that the resulting information has less uncertainty than would be possible when these sources were used individually.

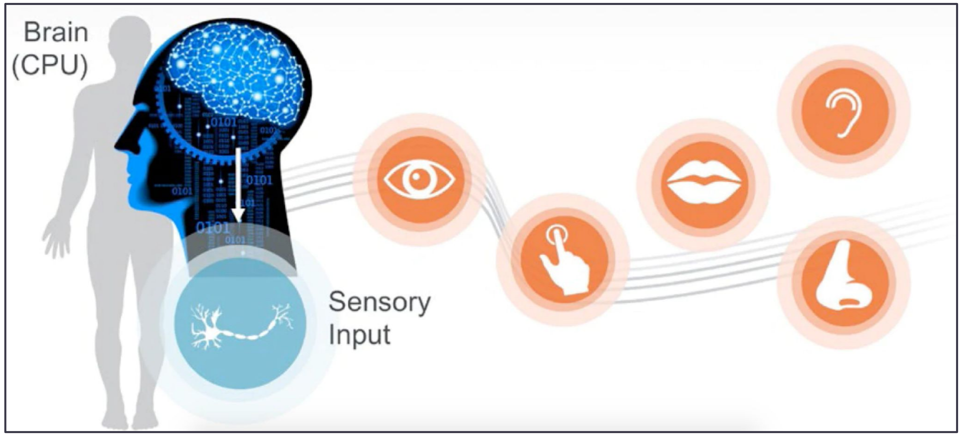
- **A "better" Definition (JDL) :**"Sensors Fusion" can be defined as an ensemble of techniques that combine data from multiple sensors and related information to achieve improved accuracy and more specific inferences than could be achieved by the use of a single sensor.



What is Sensors Fusion: a scheme



SCHEME:
A sensors fusion system is characterized by multiple inputs (data) that are processed by a fusion engine or fusion processor.



BRAIN:
Our brain IS a fusion engine or better it contains multiple fusion engines.

Why we need Sensors Fusion

- Try to blind yourself and you will understand why.

- *"Single stream of Sensors Data coming is usually not sufficient for having a **good and reliable** assessment of the external world".*

Why we need Sensors Fusion

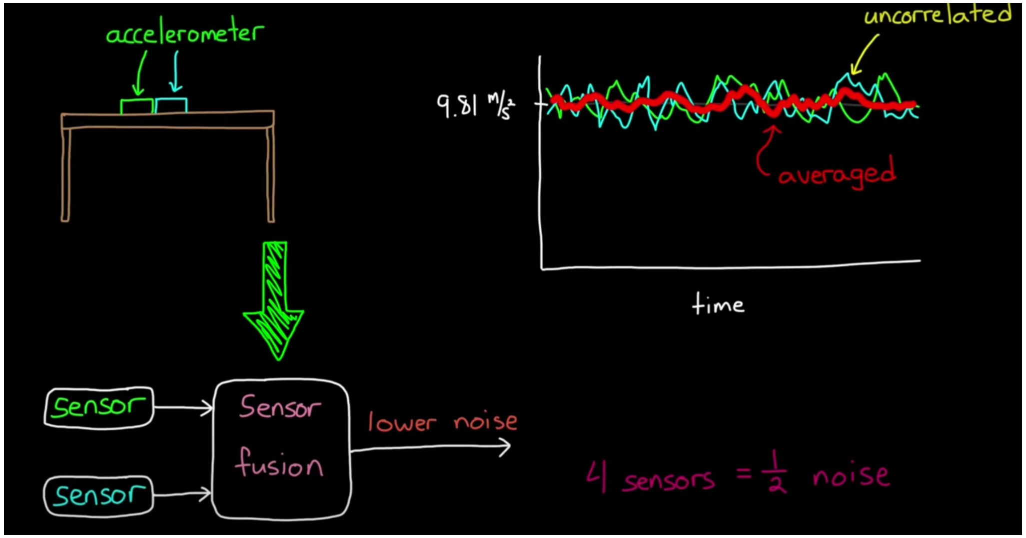
- **Sensors Deprivation:** The breakdown of a sensor element causes a loss of perception on the desired object.
- **Limited spatial coverage:** Usually an individual sensor only covers a restricted region.
- **Imprecision**: Measurements from individual sensors are limited to the precision of the employed sensing element.
- **Uncertainty**: Uncertainty, in contrast to imprecision, depends on the object being observed rather than the observing device. Uncertainty arises when features are missing (e.g., occlusions), when the sensor cannot measure all relevant attributes of the percept, or when the observation is ambiguous. A single sensor system is unable to reduce uncertainty in its perception because of its limited view of the object.

Sensors Fusion Example

TASK: we want to estimate the parameter *g* using an accelerometer on a table.

PROBLEM: Each measurement is affected by noise. If we use two accelerometers and we average the measurements we are able to reduce the noise.

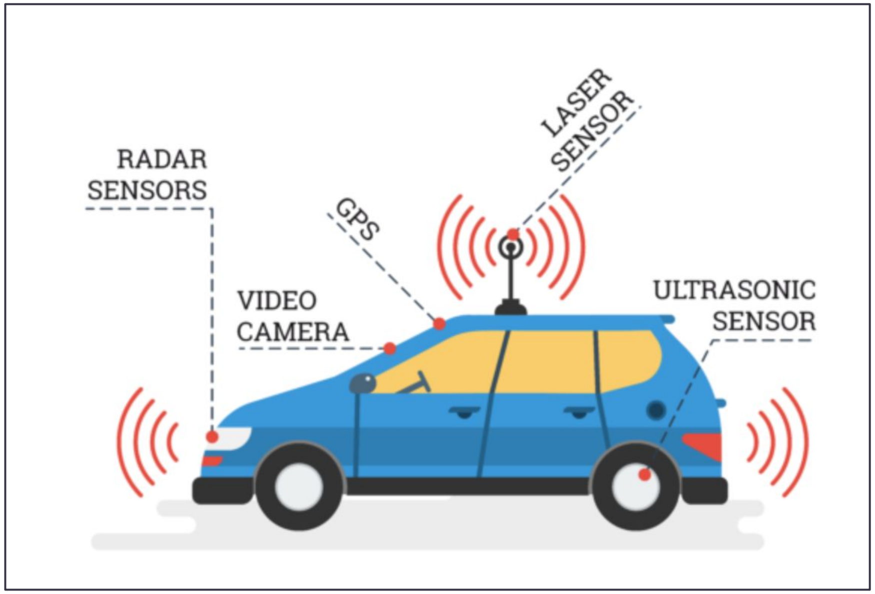
NOTE:
Just by averaging 4 measurements given by 4 different accelerometers we are able to half the noise (If the noise signal is uncorrelated on the other).

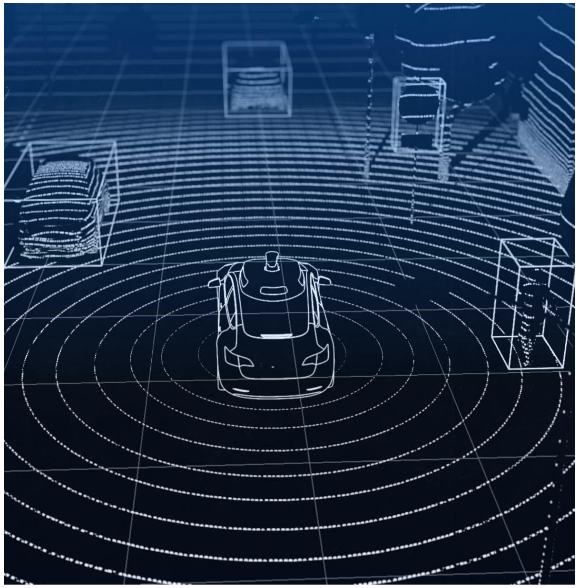


Sensors Fusion

Main fields of application

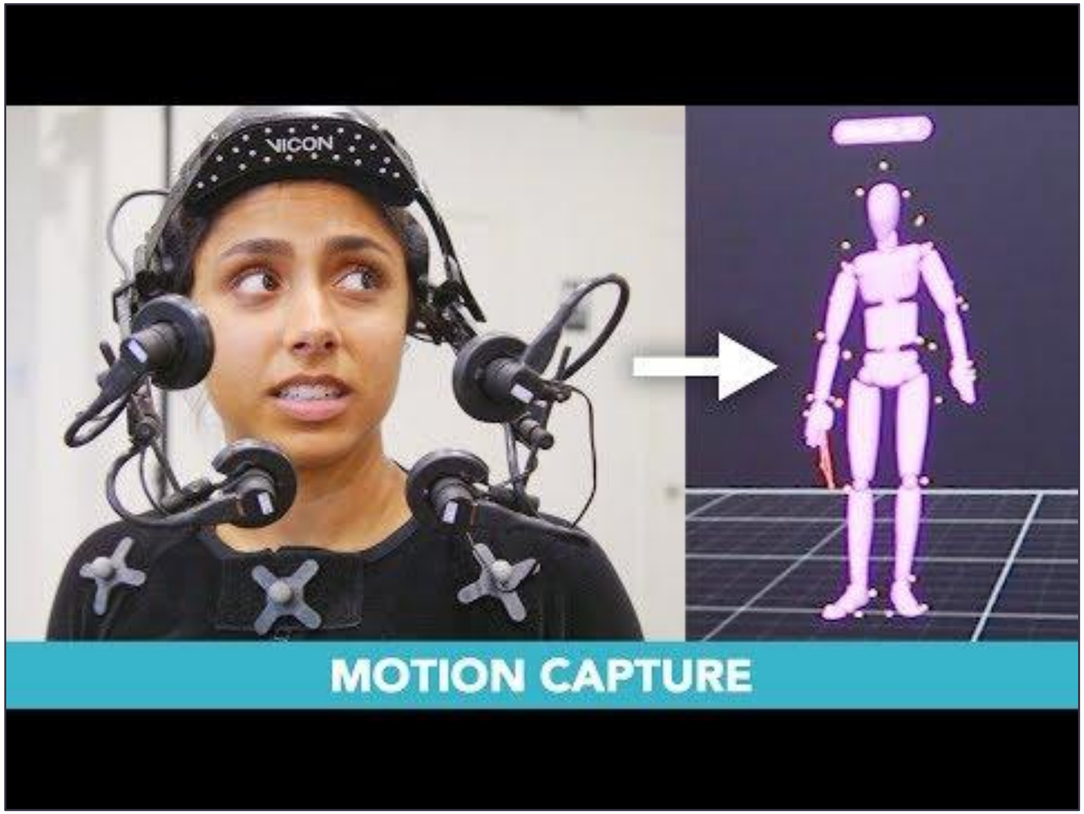
1) Navigation systems (self-driving car)





Main fields of application

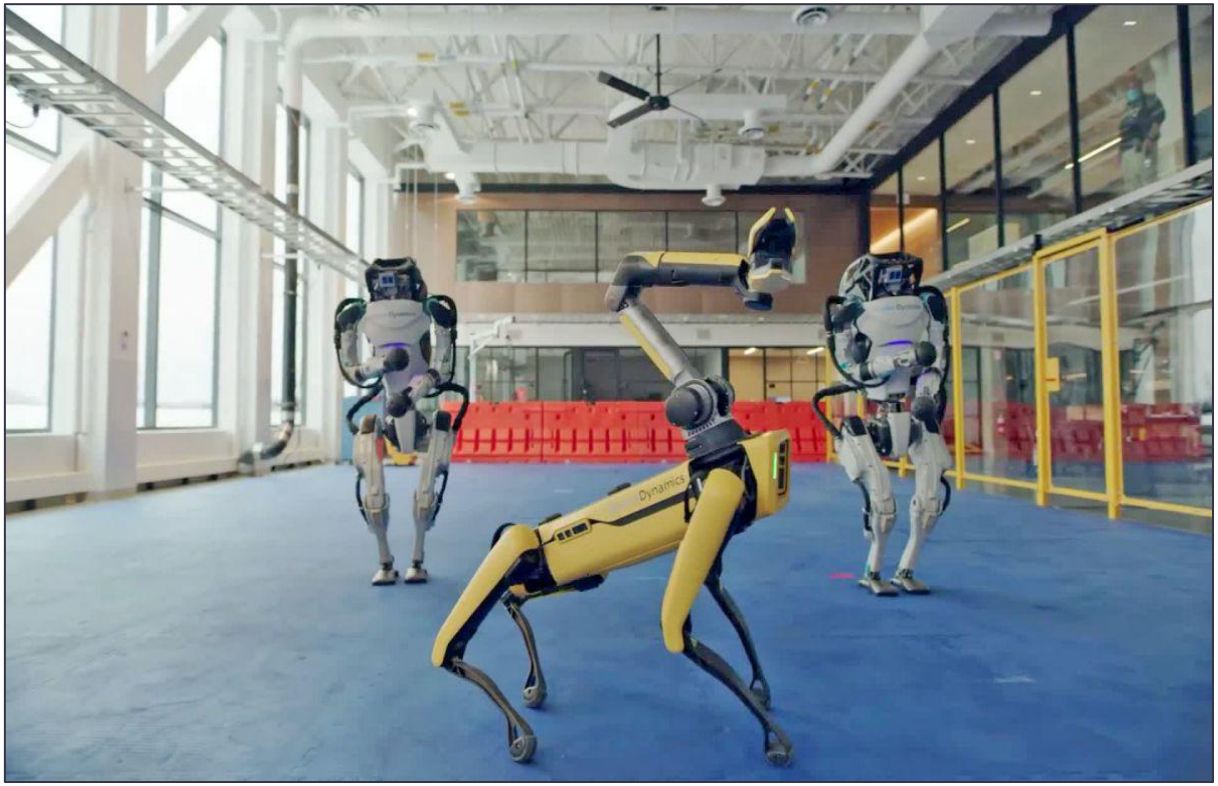
2) Virtual Reality – Motion Capture



Sensors Fusion

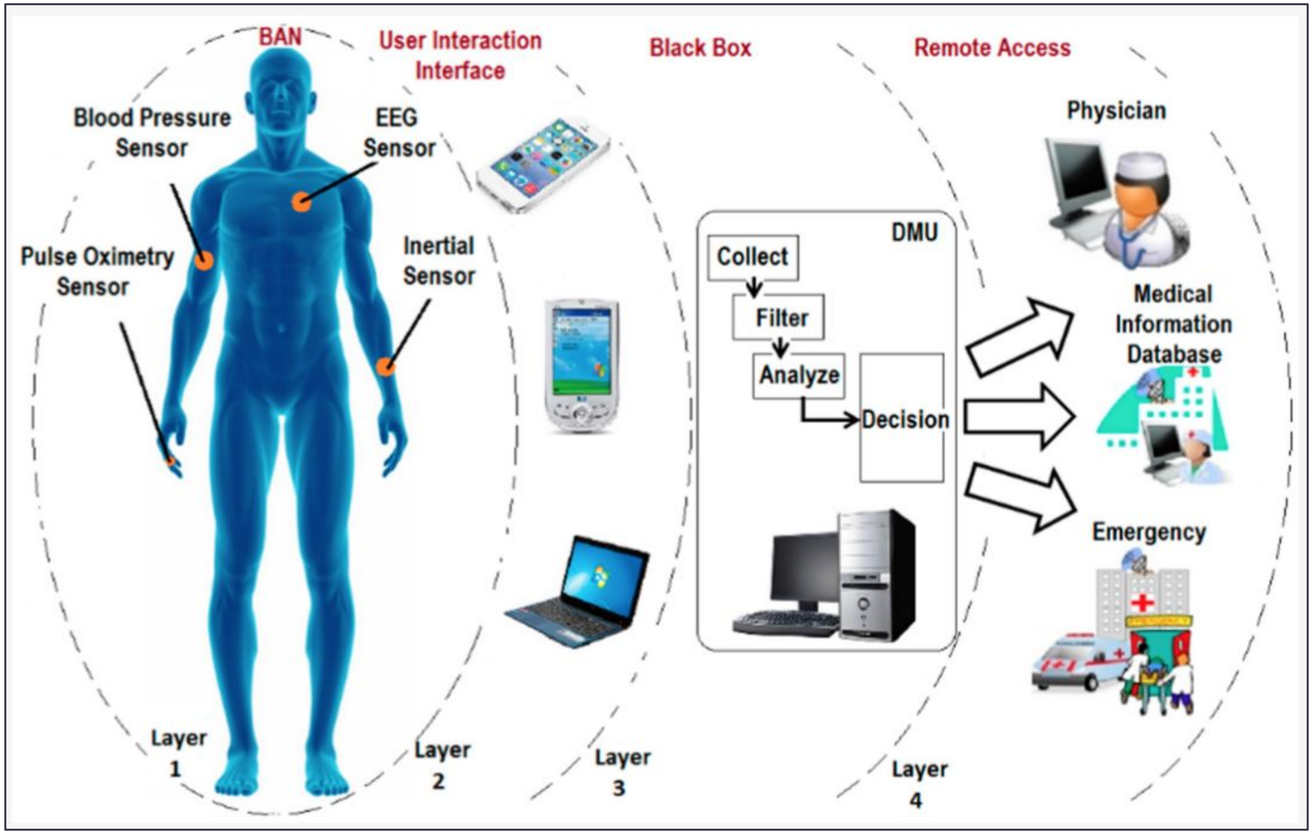
Main fields of application

3) Robotic Motion and Control

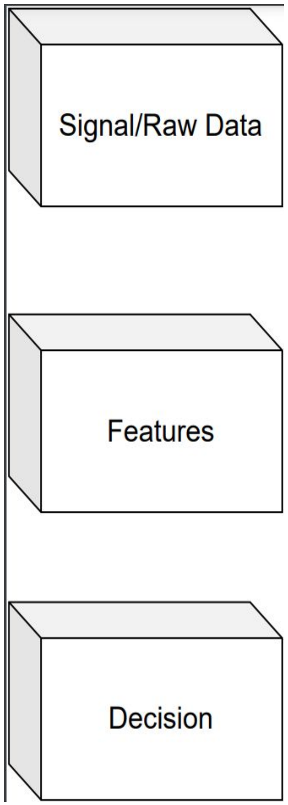


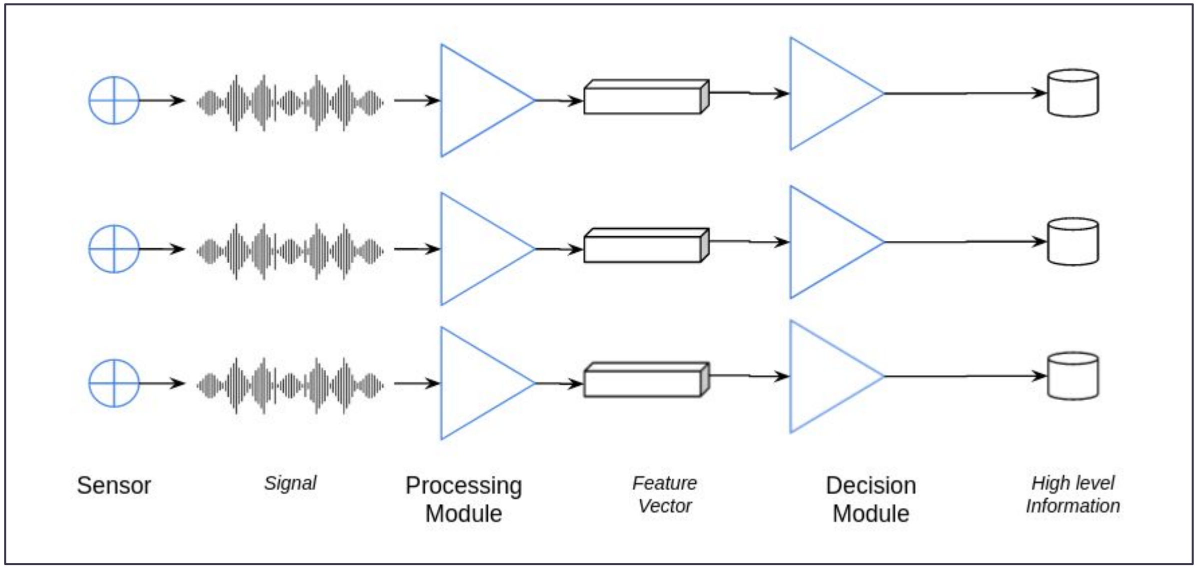
Main fields of application

4) E-health and Telemedicine



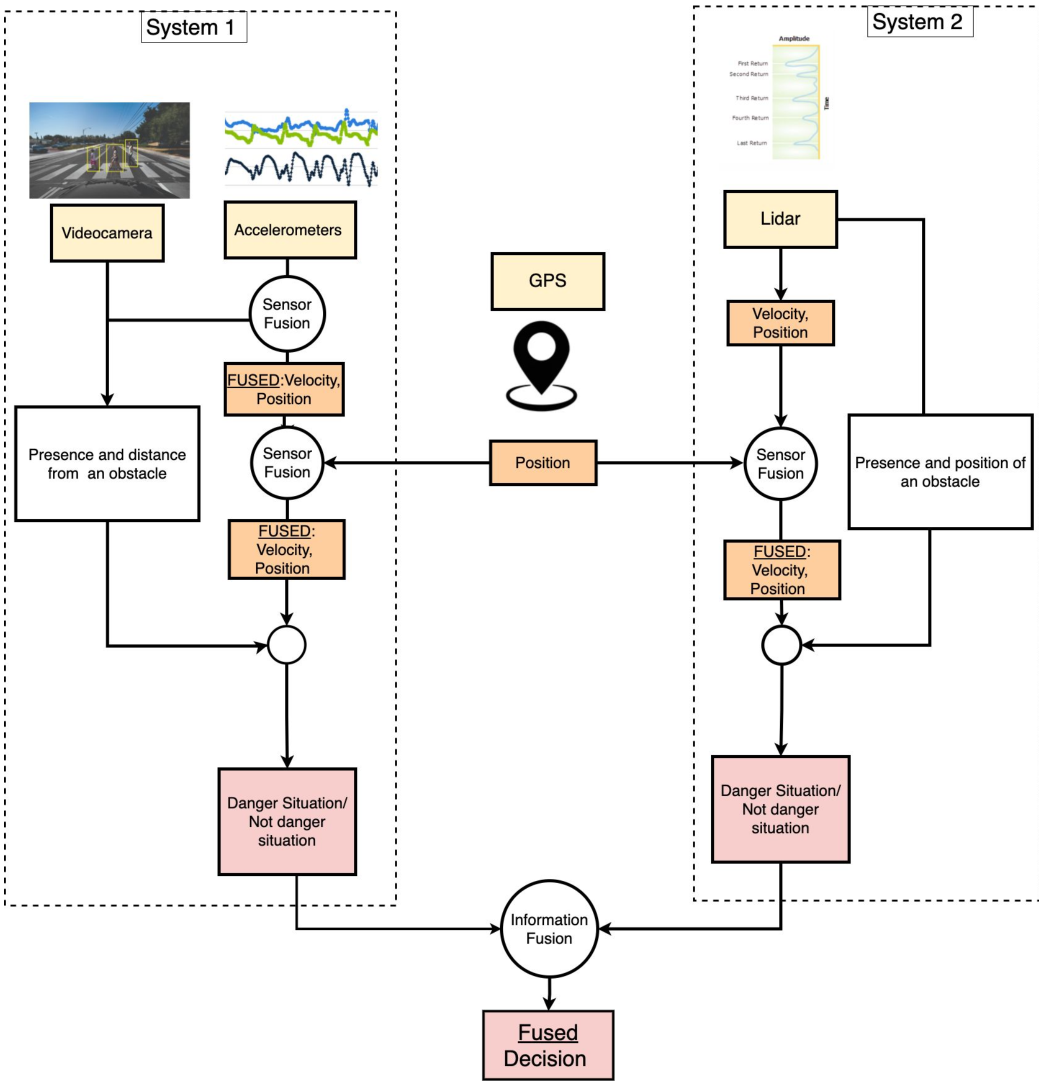
The objects of Sensors Fusion





Sensors Fusion

Example: Self-Driving Car



- Signal
- Features
- Decision

Criteria for dividing Sensors Fusion Techniques

Different criteria can be used to divide the different Sensors Fusion techniques:

1. Target
2. Relationship between the type of data sources
3. Types of data Input/Out
4. Type of Architecture

Criteria 1: Target

- **State Estimation** :
  Determining the value of a state in a given system.
  - Example: Estimating the position of a car.

- ~~**Data Association:**~~
  In a cluttered environment there are many objects to be measured. In many context we don't know which object has generated an observation. Therefore we need to associate each measurement to the object which has generate it.

- **Decision Fusion:**
  Fusing different decisions (classifications). .
  - Example: Combining the diagnosis of two different doctors : what is the final diagnosis?

Criteria 2: Relationship among data sources

Complementary:
when the information provided by the input sources represents different parts of the scene and could thus be used to obtain more complete global information.

Redundant:
when two or more input sources provide information about the same target and could thus be fused to increment the confidence.

Cooperative:
when the provided information is combined into new information that is typically more complex than the original information

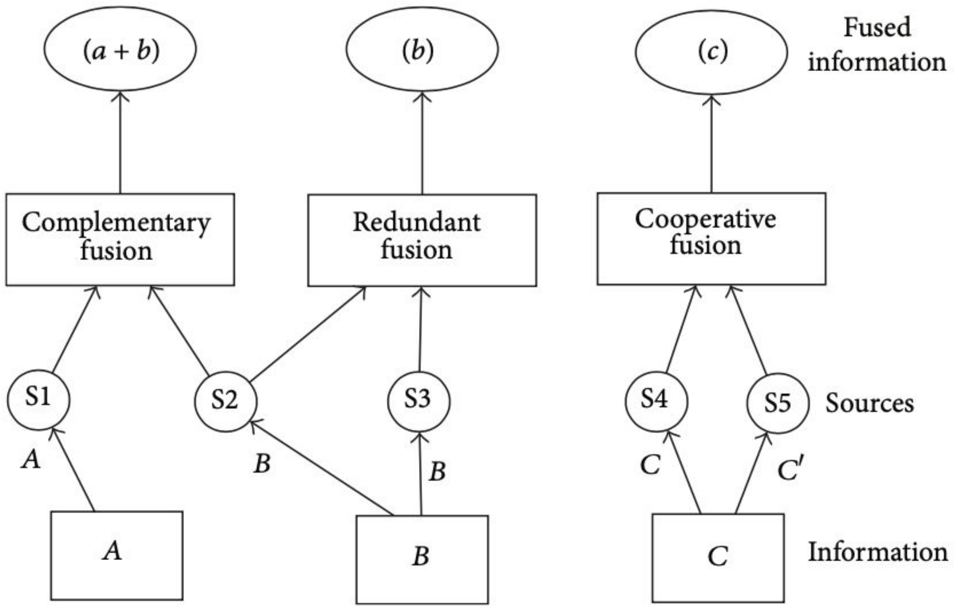


FIGURE 1: Whyte's classification based on the relations between the data sources.

Sensors Fusion

Criteria 3: Data Input/Output

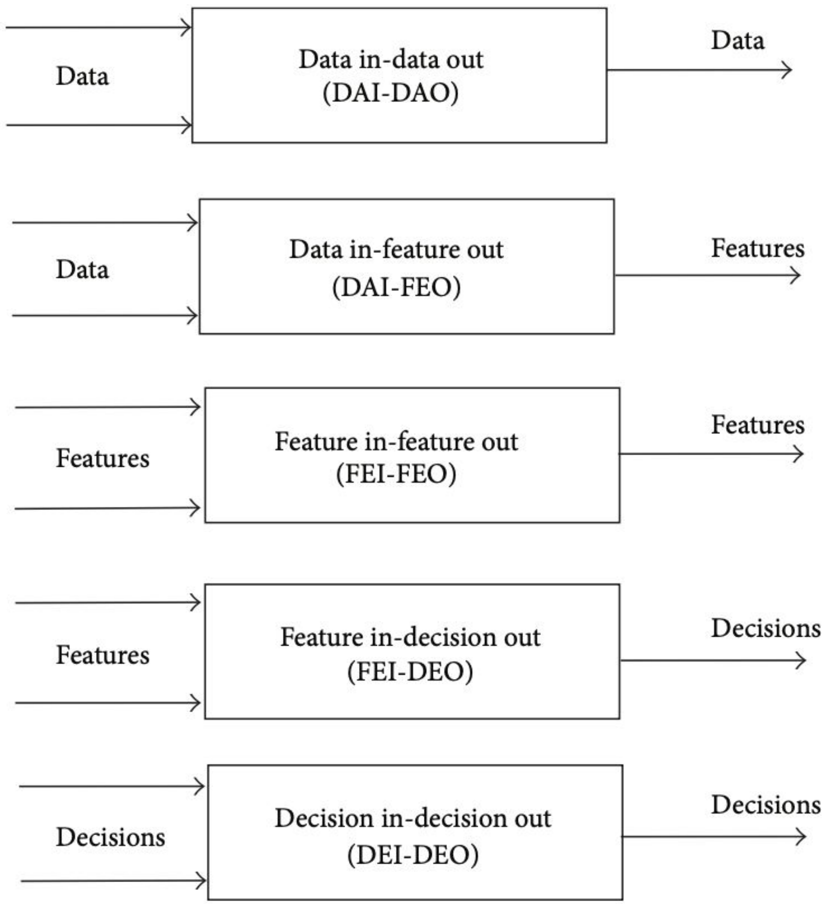
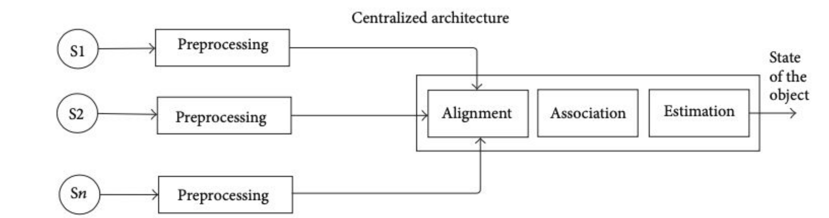
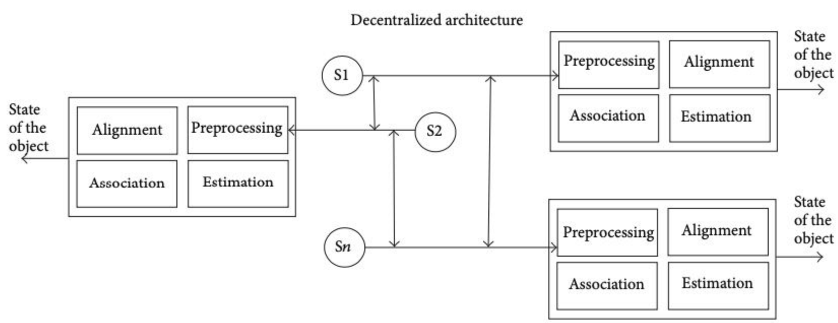


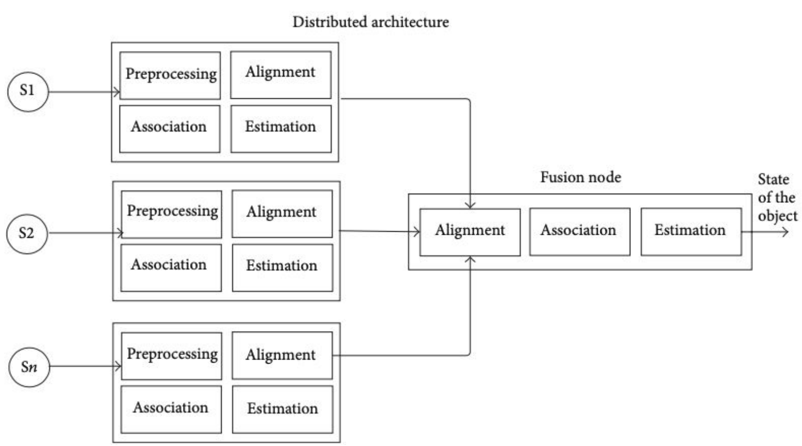
FIGURE 2: Dasarathy's classification.

Sensors Fusion

Criteria 5: Architecture







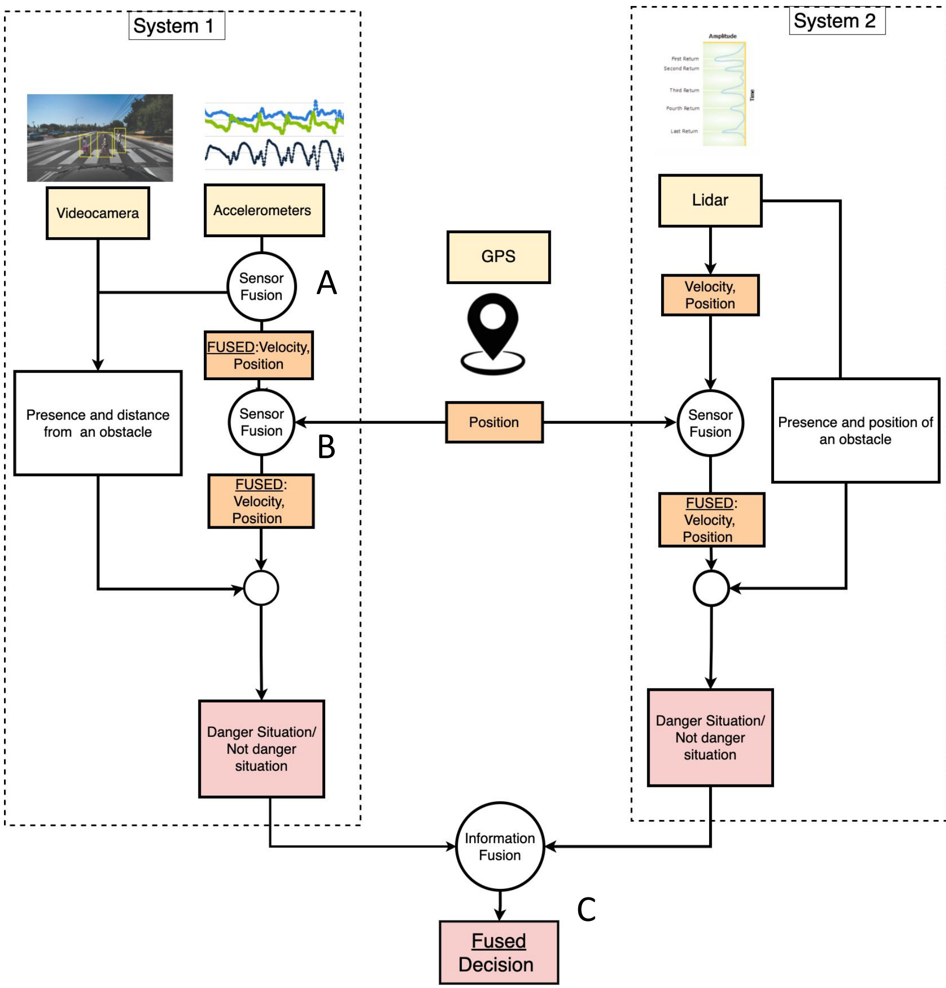
Centralized:
In a centralized architecture, the fusion node resides in the central processor that receives the information from all of the input sources. Therefore, all of the fusion processes are executed in a central processor that uses the provided raw measurements from the sources

Decentralized:
a decentralized architecture is composed of a network of nodes in which each node has its own processing capabilities and there is no single point of data fusion. Therefore, each node fuses its local information with the information that is received from its peers. Data fusion is performed autonomously, with each node accounting for its local information and the information received from its peers.

Distributed:
in a distributed architecture, measurements from each source node are processed independently before the information is sent to the fusion node;

Sensors Fusion

Example: Self-Driving Car



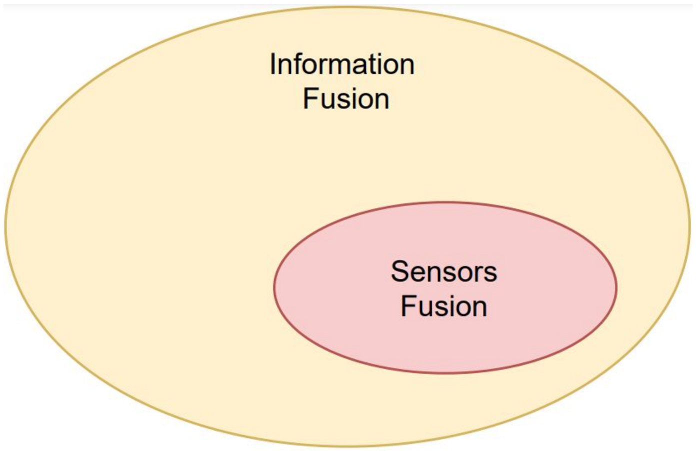
A) Velocity + position estimation
- State estimation
- Complementary
- Data IN - Feature OUT

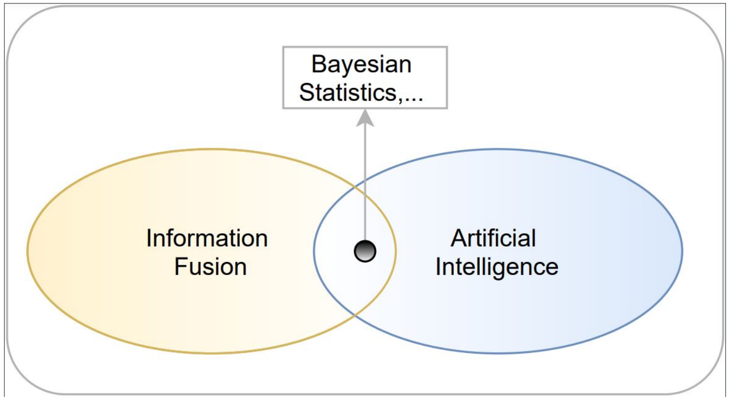
B) Velocity + position estimation (2)
- State estimation
- Complementary
- Feature IN - Feature OUT

C) Danger Situation Assessment
- Decision Fusion
- Redundant
- Decision IN - Decision OUT

Sensors Fusion in Data Science

- **Sensors Fusion** belongs to a wider set which is usually referred as *information fusion* .
- **Artificial Intelligence** and Sensors Fusion can be both referred as data-sciences techniques.
- The distinction between Machine Learning and Information Fusion is blurred and some techniques are common between these two big sets.
- However :
  - **Machine Learning** is based on the idea that systems can learn from (past) data , identifying patterns and correlations.
  - Sensors Fusion do not involve the so-called “learning from past data” paradigm.



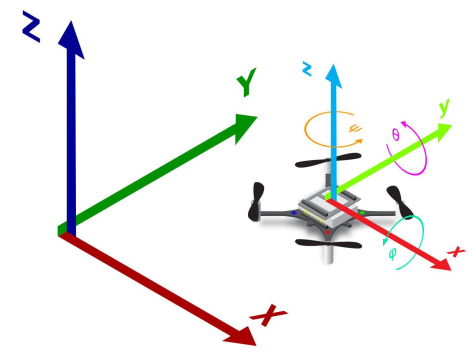


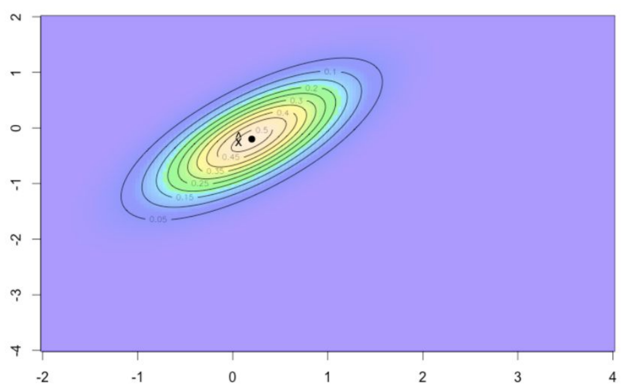
State estimation techniques

State estimation techniques aim to determine the state of a stystem which can be obtained from the analytical or empirical models of the sensors.

This set techniques include a quite large number :

- **Linear Kalman filter (KF)**
- Extended Kalman filter (EKF)
- **Maximum Likelihood and Maximum Posterior**
- Particle filter
- Interacting multiple model (IMM) filter





ML and MAP estimator

TASK: Estimating the constant of gravity.
x=g

WHAT WE HAVE:

- two accelerometers
- observations z = (z_1 , z_2)
- noise description (observer description)

$$z_1 = g + v_1 \qquad v_1 \sim N(0, \sigma_1^2)$$

$$z_2 = g + v_2 \qquad v_2 \sim N(0, \sigma_2^2)$$

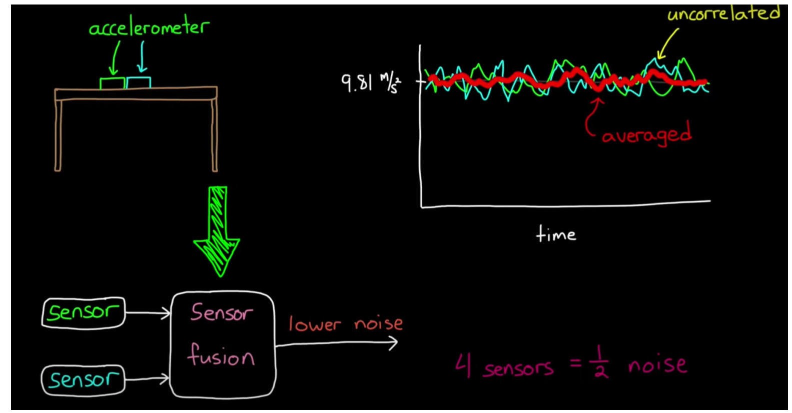
1) ML ESTIMATOR :

$$\hat{x}(k) = \arg\max_x p(z \mid x)$$

2) MAP ESTIMATOR:

If we know the distribution of the state *p(x)* then we can use the:

$$\hat{x}(k) = \arg\max_x p(x \mid z)$$



1) $$p(Z|g) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left(\frac{z-g}{\sigma}\right)^2\right)$$ likelihood probability definition

2) $$-log[L(g)] = -log[p(z_1|g) \cdot p(z_2|g)] = \sigma_1^{-2}(z_1 - g)^2 + \sigma_2^{-2}(z_2 - g)^2 + cost$$ log-Likelihood minimization

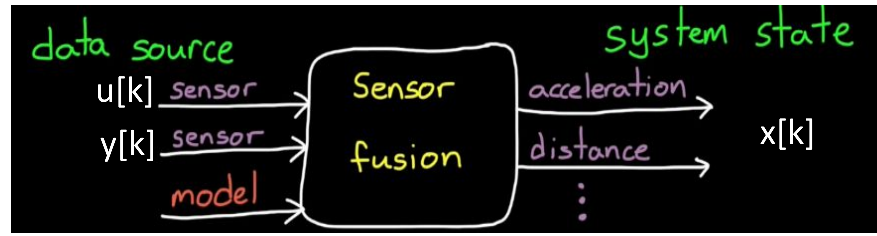
3) $$g_{MLE} = \frac{\sigma_1^{-2} \cdot z_1 + \sigma_2^{-2} \cdot z_2}{\sigma_1^{-2} + \sigma_2^{-2}}$$ MLE estimator

since we suppose *g* as a deterministic parameter and constant in time, we know its distribution so the MAP estimator and the ML estimator are the same

Linear Kalman Filter

WHAT DOES A KALMAN FILTER DO:

The goal of the Kalman filter is to take a probabilistic estimate of the state and update it in real time using two steps; prediction and correction.



WHAT WE HAVE:

- **state observer** (or measurement model): basically what we can measure of the state x.
- **Input signals u[k]** : measurable through a set of sensors
- **a model**: tell us how the states evolve in time with respect to the previous state and an input signals ($\mathrm{u[k]}$).

Linear system equation

$$x[k+1] = \mathbf{A}_q x[k] + \mathbf{B}_q u[k]$$
$$y[k] = \mathbf{C}_q x[k] + \mathbf{D}_q u[k]$$

Motion model: $\mathbf{x}_k = \mathbf{F}_{k-1}\mathbf{x}_{k-1} + \mathbf{G}_{k-1}\underbrace{\mathbf{u}_{k-1}}_{input} + \underbrace{\mathbf{w}_{k-1}}_{noise}$

Measurement model: $\mathbf{y}_k = \mathbf{H}_k\mathbf{x}_k + \underbrace{\mathbf{v}_k}_{noise}$

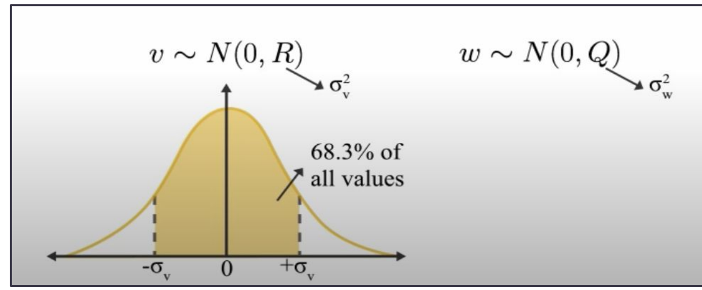
Linear Kalman Filter

The problem : the noise

$$\text{Motion model:} \quad \mathbf{x}_k = \mathbf{F}_{k-1}\mathbf{x}_{k-1} + \mathbf{G}_{k-1}\underbrace{\mathbf{u}_{k-1}}_{\text{input}} + \boxed{\underbrace{\mathbf{w}_{k-1}}_{\text{noise}}}$$

$$\text{Measurement model:} \quad \mathbf{y}_k = \mathbf{H}_k\mathbf{x}_k + \boxed{\underbrace{\mathbf{v}_k}_{\text{noise}}}$$

- **w_k : Process Noise:** Uncertainty on the model.
- **v_k : Measurement Noise:** Uncertainty on the measure.

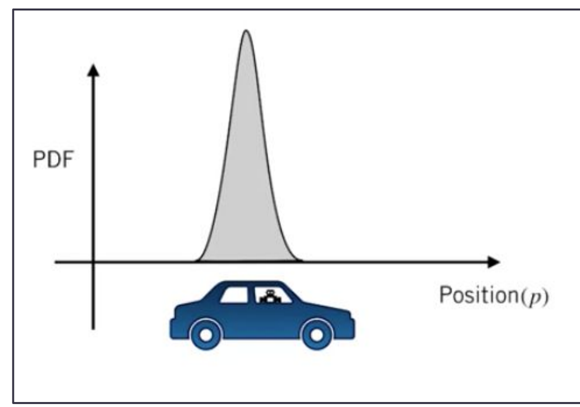


TASK: we want to estimate the position of a car.

We can write the *u[k], x[k], y[k]* as below:.

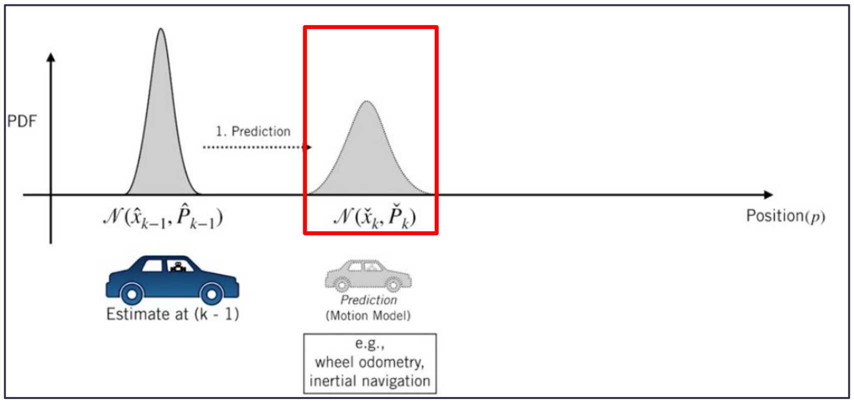
- ***u[k]*** = acceleration = *a[k]*
- ***x[k]*** = [velocity , position*]* = ***(v[k], p[k])***
- ***y[k]*** = position = *p[k] [GPS]*

$$\mathbf{x} = \begin{bmatrix} p \\ \frac{dp}{dt} = \dot{p} \end{bmatrix} \qquad \mathbf{u} = a = \frac{d^2p}{dt^2}$$



Linear Kalman Filter

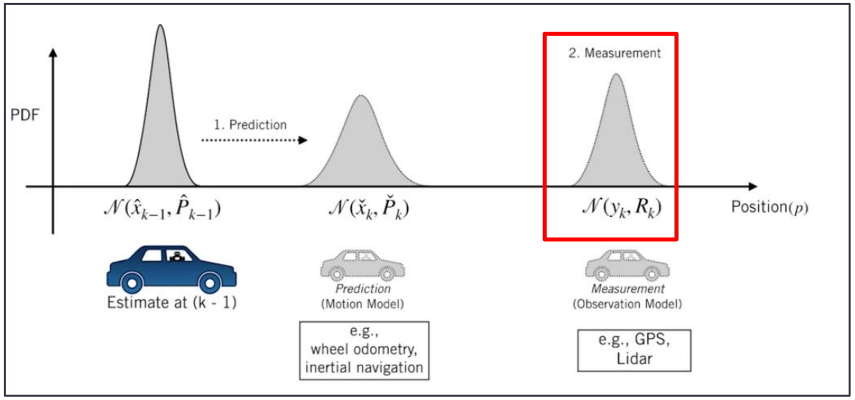
1) PREDICTION: a[k] is measurable through a first set of sensors **s_1** . We can write a model that connect the state **x[k-1] and the state x[k]** through the cinematic laws.
With this model we can calculate the position x[k].



Motion/Process Model

$$\mathbf{x}_k = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \mathbf{x}_{k-1} + \begin{bmatrix} 0 \\ \Delta t \end{bmatrix} \mathbf{u}_{k-1} + \mathbf{w}_{k-1}$$

2) MEASUREMENT: Through a second set of sensors **s_2** (GPS) we can measure the position.

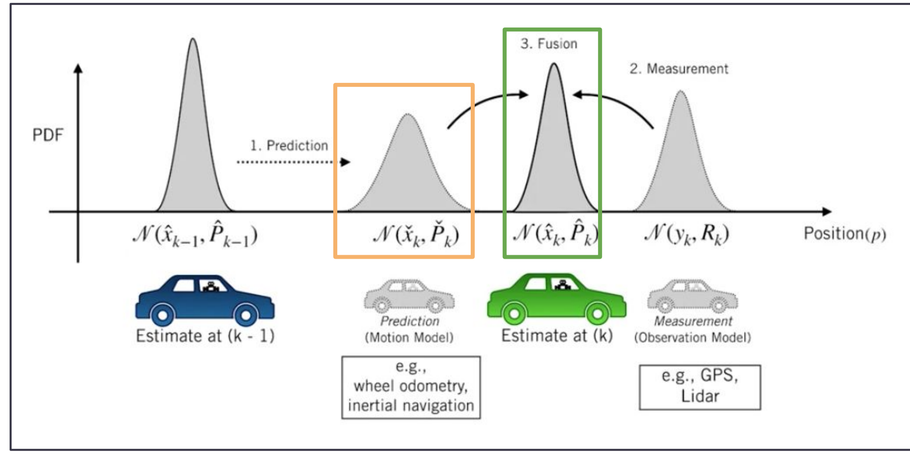


Position Observation

$$y_k = [1 \quad 0]\,\mathbf{x}_k + v_k$$

Linear Kalman Filter : the equations

3) UPDATE STEP: At each time k, we estimate the state x[k] by combining the position MEASURED (observed) position and the position calculated by the model.



OVERALL

Model prediction

$$\boxed{\check{\mathbf{x}}_k} = \mathbf{F}_{k-1}\mathbf{x}_{k-1} + \mathbf{G}_{k-1}\mathbf{u}_{k-1}$$

Update Step

$$\boxed{\hat{\mathbf{x}}_k} = \boxed{\check{\mathbf{x}}_k} + \mathbf{K}_k\boxed{(\mathbf{y}_k - \mathbf{H}_k\check{\mathbf{x}}_k)}$$

Corrected state

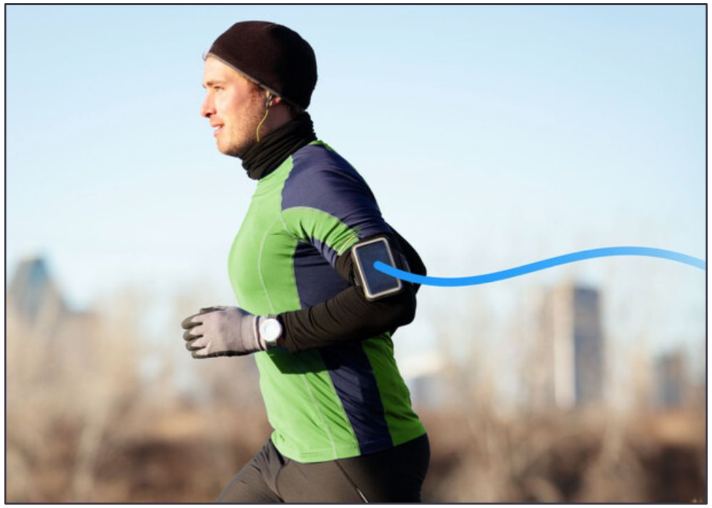
Correction

Kalman Filter in eHealth (1)

- Almost everything related to motion tracking with inertial units.

Motion Tracking in VR (rehabilitation)

Sport monitoring



Sensors Fusion

Kalman Filter in eHealth (1)

- **Goal:** A real-time filtering system based on an adaptive Kalman filter approach that separates
  - **signal off-sets (C_k)** ,
  - **respiratory (X_s) and**
  - **heart signals (X_f)**

    from
  - **three different sensor channels (magnetic induction sensors)**.

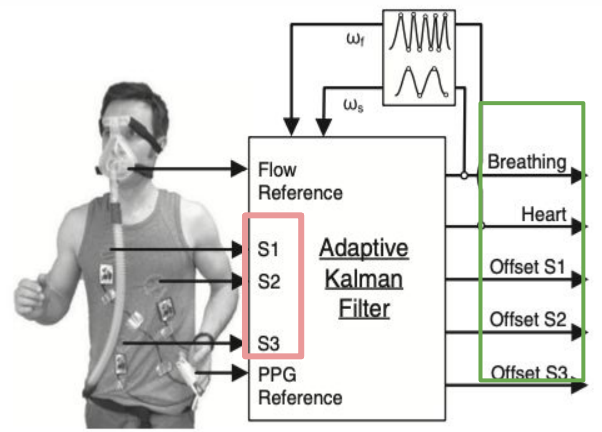
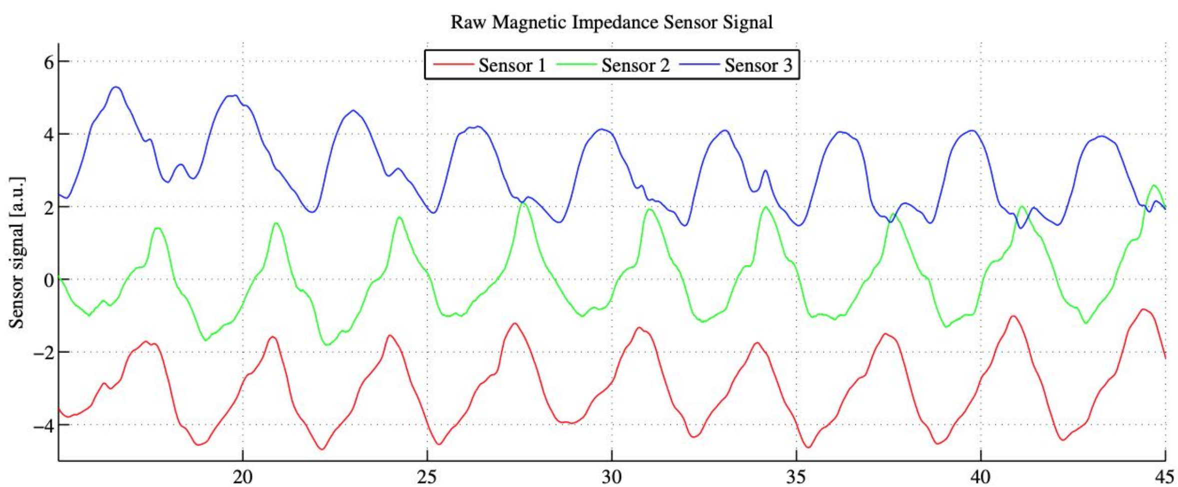


Figure 1 Kalman filter sensor fusion. Kalman filter sensor fusion (sensors: S1 to S3 with flow and PPG references) and vital signs extraction with frequency adaptation.



PAPER

An adaptive Kalman filter approach for cardiorespiratory signal extraction and fusion of non-contacting sensors

Jerome Foussier1*, Daniel Teichmann1, Jing Jia2, Berno Misgeld1 and Steffen Leonhardt1

Sensors Fusion

Kalman Filter in eHealth (2)

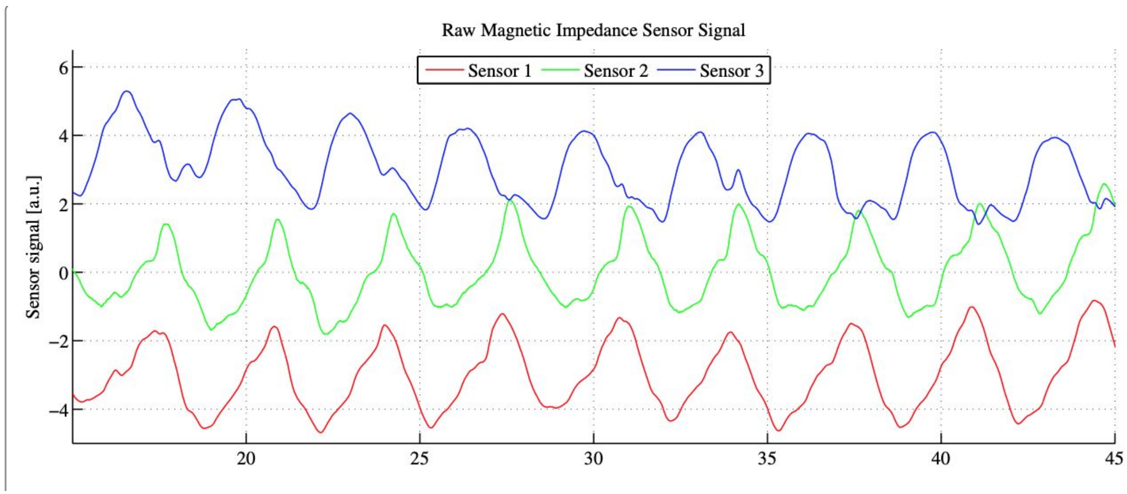
$$\boxed{\mathbf{x_k}} = \mathbf{A}\mathbf{x_{k-1}} + \mathbf{B}\mathbf{u_{k-1}} + \mathbf{w_{k-1}}$$

$$\mathbf{z_k} = \mathbf{H}\boxed{\mathbf{x_k}} + \mathbf{v_k}$$

$$\mathbf{x_k} = \boxed{\begin{pmatrix} X_{f,k} \\ V_{f,k} \\ X_{s,k} \\ V_{s,k} \\ C_{1,k} \\ C_{2,k} \\ C_{3,k} \end{pmatrix}}$$

$$\mathbf{A} = \begin{pmatrix} 1 & \Delta t & 0 & 0 & 0 & 0 & 0 \\ -\omega_f^2 \Delta t & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & \Delta t & 0 & 0 & 0 \\ 0 & 0 & -\omega_s^2 \Delta t & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

$$\mathbf{H} = \begin{pmatrix} h_{f,1} & 0 & h_{s,1} & 0 & 1 & 0 & 0 \\ h_{f,2} & 0 & h_{s,2} & 0 & 0 & 1 & 0 \\ h_{f,3} & 0 & h_{s,3} & 0 & 0 & 0 & 1 \end{pmatrix}$$



Sinusoidal Model

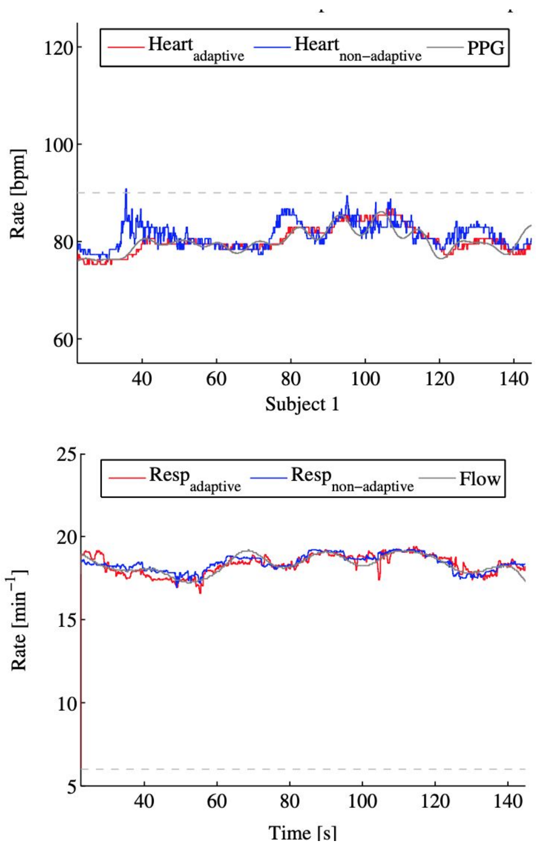
$$X(t + \Delta t) \approx X(t) + \Delta t \frac{dX(t)}{dt} = \Delta t V(t)$$

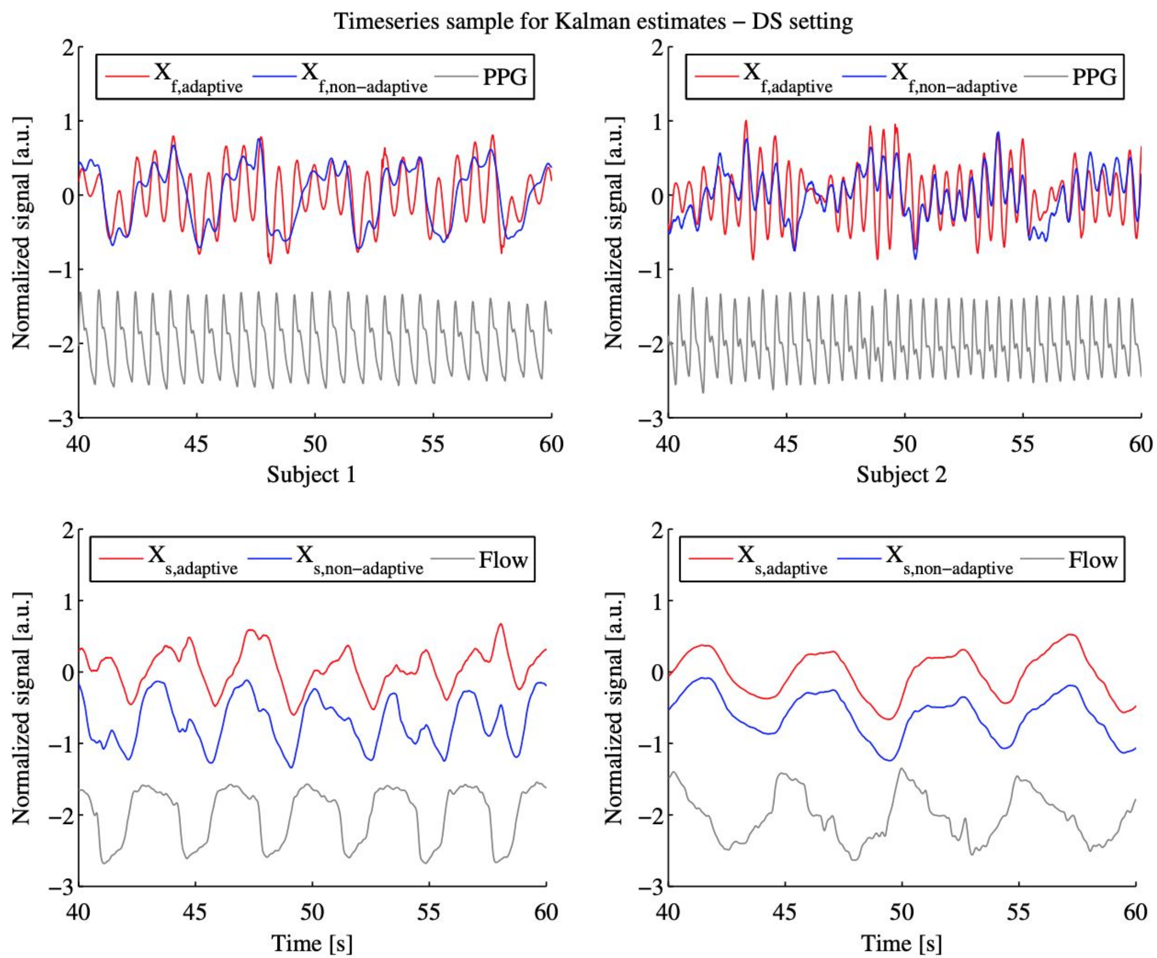
$$V(t + \Delta t) \approx V(t) + \Delta t \frac{dV(t)}{dt}$$

$$X(t) = sin(\omega \cdot t)$$

$$\frac{dV(t)}{dt} = -\omega^2 \cdot sin(\omega \cdot t) = -\omega^2 \cdot X(t)$$

Kalman Filter in eHealth (3)





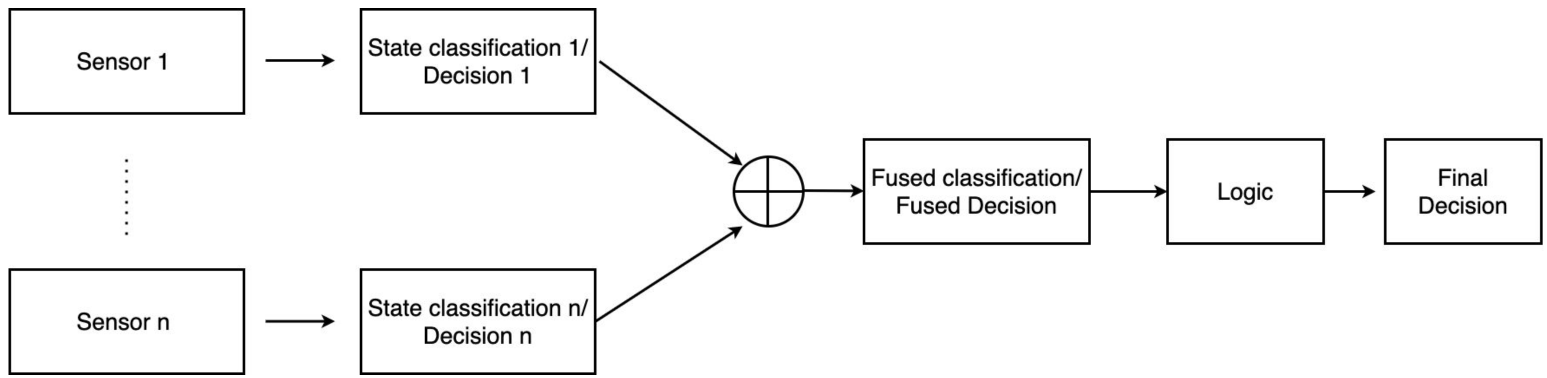
Decision Fusion Techniques

- **Decision = Classification**

- Decision fusion is one form of data fusion that **combines the decisions of multiple classifiers** into a common decision.

- Instead of fusing features or signals, we compute an assessment for each sensor (classification) and then we fuse them.

- **Example**:
  Combining the diagnosis of two doctors.
  D1: You have a cancer .
  D2: You don't have a cancer.
  What is the final solution?



Bayesian Inference and Bayes Networks

Bayes Inference in Decision Fusion: Determine the value of a categorical state X , given some evidences (different sensors data) that we can measure.

Bayesian Networks (BN) : Application of the bayes rule for a time evolving system.

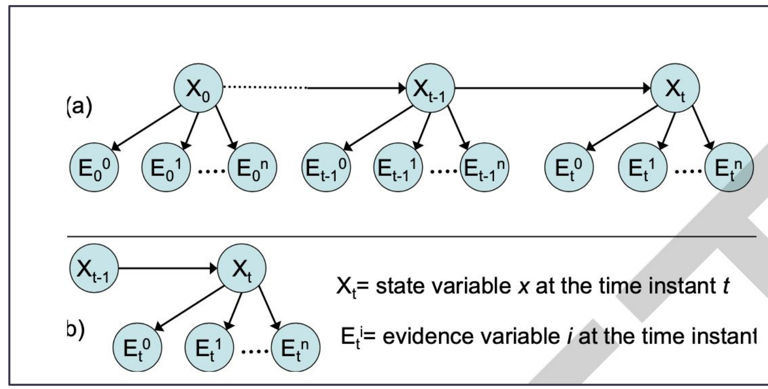
Input:

a) Each sensors provides categorical states
b) Likelihood distribution **P(E_i|X)**

c) OPTIONAL: Transition state probability **P(X_t|X_t-1)** (not necessary for all the bayesian networks but really useful for Hidden Markov model) .v

Output
An estimation of the value of the state X at time t (**X_t**)

$$\overbrace{P(\text{hypothesis}|\text{data})}^{\text{posterior}} = \frac{\overbrace{P(\text{data}|\text{hypothesis})}^{\text{likelihood}}\ \overbrace{P(\text{hypothesis})}^{\text{prior}}}{\underbrace{P(\text{data})}_{\text{evidence}}}.$$



Bayesian Inference : case study

Case Study:

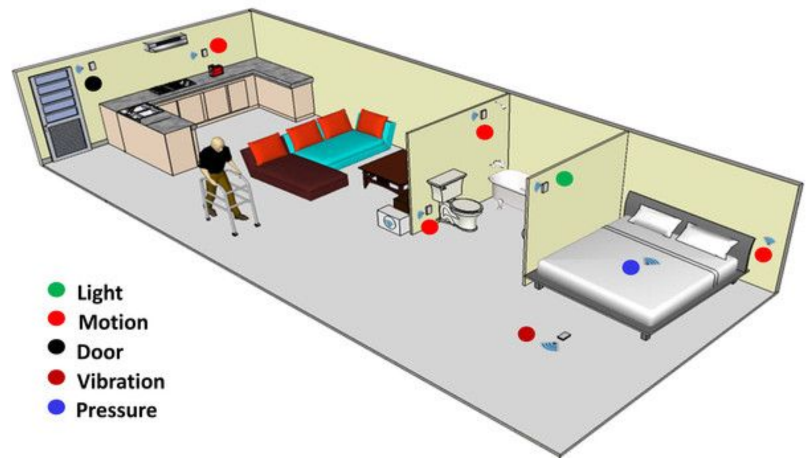
- <u>Domain</u>: Ambient Sensing
- <u>Goal</u>: determine if a user is occupying a room in that moment
- <u>State definition</u>:

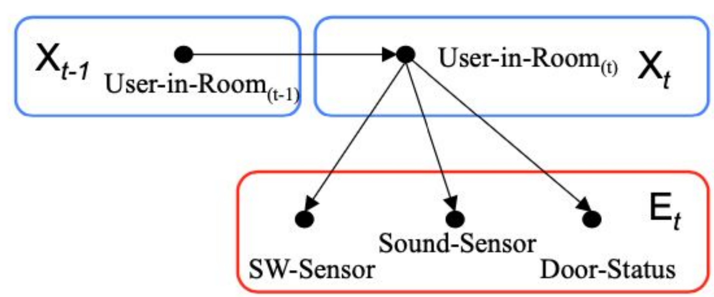
  X = {0 = non in the room , 1 = in the room}

- <u>Input Sensors</u>:

  1. E1: Door-Sensor -> { 0,1,2}
     ={Locked, closed,opened}
  2. E2: SW-Sensor -> {0,1}
  3. E3: Sound-Sensor -> {0,1}
     = { Occupancy , Not Occupancy}

Ambient Sensing





<u>PAPER:</u> **Multi-sensor fusion through adaptive bayesian network**
Alessandra De Paola, Salvatore Gaglio, Giuseppe Lo Re, and Marco Ortolani

Bayesian Inference :

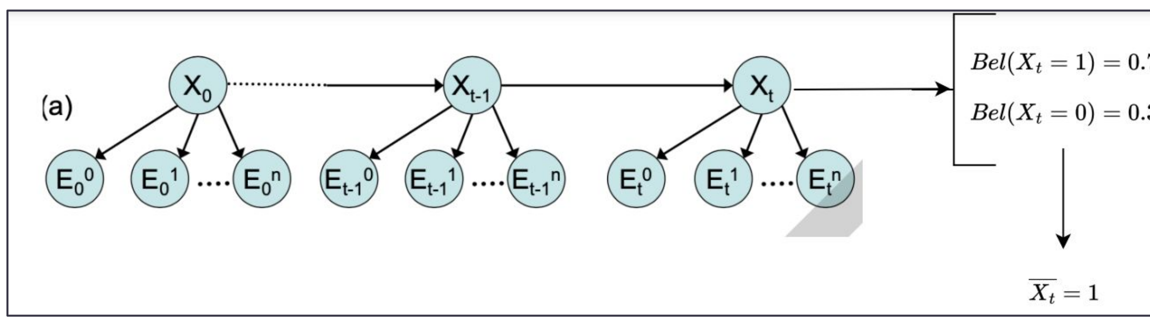
The target:

- Finding the value of the state at time k which maximize a belief calculated on the state x_t:

$$Bel(x_t) = P(x_t|e_1^1, e_1^2, \ldots, e_1^n, \ldots e_t^1, e_t^2, \ldots, e_t^n)$$
$$= P(x_t|E_1, E_2, \ldots, E_t) = P(x_t|E_1 : t)$$

- The final state is calculated:

$$\overline{X_t} = \arg\max_{i \in \{0,1\}} Bel(X_t = i)$$



Bayesian Inference : 2 steps

$$\overbrace{P(\text{hypothesis}|\text{data})}^{\text{posterior}} = \frac{\overbrace{P(\text{data}|\text{hypothesis})}^{\text{likelihood}}\ \overbrace{P(\text{hypothesis})}^{\text{prior}}}{\underbrace{P(\text{data})}_{\text{evidence}}}.$$

Step 1: Training

Dataset

Table 2. CPTs for sensor models: $P(E_t^1|X_t)$, $P(E_t^2|X_t)$ and $P(E_t^3|X_t)$.

		$\mathbf{E_t^1}$			$\mathbf{E_t^2}$		$\mathbf{E_t^3}$	
		0	**1**	**2**	**0**	**1**	**0**	**1**
$\mathbf{X_t}$	**0**	0.5	0.3	0.2	0.9	0.1	0.6	0.4
	1	0.1	0.1	0.8	0.4	0.6	0.2	0.8

Table 1. CPT for state transition: $P(X_t|X_{t-1})$.

		$\mathbf{X_t}$	
		0	**1**
$\mathbf{X_{t-1}}$	**0**	0.8	0.2
	1	0.2	0.8

Step 2: Prediction

$$Bel(x_t) = P(x_t|e_1^1, e_1^2, \ldots, e_1^n, \ldots e_t^1, e_t^2, \ldots, e_t^n)$$
$$= P(x_t|E_1, E_2, \ldots, E_t) = P(x_t|E_1 : t)$$

Assuming Markov hypothesis

$$Bel(x_t) = \eta \prod_{e_t^i} P(e_t^i|x_t) \cdot \sum P(x_t|x_{t-1}) Bel(x_{t-1})$$

$$\overline{X_t} = \underset{i \in \{0,1\}}{\arg\max}\, Bel(X_t = i)$$

t = 0

$P(X_0) =< 0.9, 0.1 >$

t = 1

$[E_1^1, E_1^2, E_1^3] = [2, 1, 1]$

$Bel(X_1) =< 0.906, 0.094 >$

$\overline{X_t} = 0$

The Dempster-Shafer Inference

What DST is used for *:* DST provides a framework for combining different sources of evidence into a global belief for a given hypothesis .

Problem with Bayes: Very difficult to compute the likelihood P(E|X) and the priori probabilities P(X) .

DIFFERENCE with Bayesian Inference:

- We can model the **uncertainty** : assigning a value to the probability of the system to be in **none of the states** or in **more than one state** at the same time.
- It provides a different and simpler way to combine to combine different sources of information.

Mass Probability function

This is done by function called mass function , *m()*

$$m : 2^{\Omega} \to [0, 1]$$

$$\Omega = \{X_0, X_1, .., X_N\}$$

$$2^{\Omega} = \{\emptyset, \{X_0\}, .., \{X_N\}, \{X_0, X_1\}, .., \{X_0, ..X_N\}\}$$

$$\sum_{A \in 2^{\Omega}} m(A) = 1$$

-

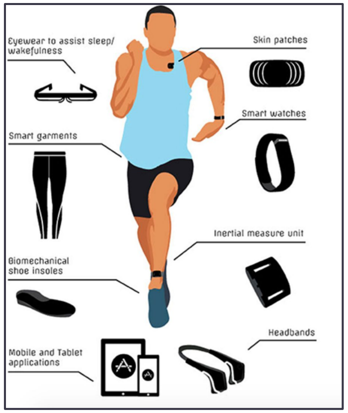
Sensors Fusion

Sensors Fusion

The Dempster-Shafer Inference: case study

Example: We want to determinate the level of "fatigue" of an athlete using a set of sensors. We define the level of fatigue of the athlete (X_i) based on the following table.

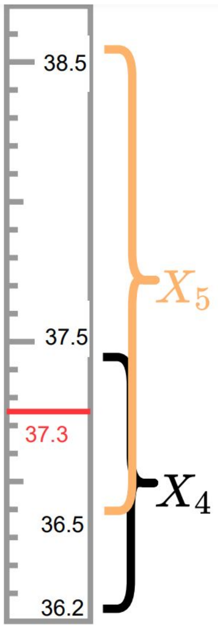
- oxygen saturation in blood sensor (SPO2),
- airflow sensor (spirometer-based)
- body temperature sensor (PTC),
- galvanic skin response sensor (skin conductance) (GSR)



	BPM/SPO2 (%)	Temp. (°C)	GSR (V)	Air Ampl. (V)/Rate (bps)
X_5	120–220/85–90	36.5–38.2	2.0–2.5	>1.7/>0.6
X_4	90–120/90–95	36.2–37.5	1.1–1.9	0.8–1.7/0.3–0.6
X_3	70–90/95–98	35.1–37.1	0.5–1.8	0.5–1.4/0.4–0.6
X_2	60–70/98–100	35.1–37.1	0.3–0.8	0.3–1.1/0.2–0.4
X_1	40–60/98–100	35.1–37.1	0.1–0.5	0.3–0.6/0.1–0.4

PAPER :
Cost-Effective eHealth System Based on a Multi-Sensor System-on-Chip Platform and Data Fusion in Cloud for Sport Activity Monitoring (https://www.mdpi.com/2079-9292/7/9/183)

	S_1
$m(X_4)$	0.2
$m(\{X_5\})$	0.3
$m(\{X_4, X_5\})$	0.5
else	0



Credibility and Plausibility

Credibility (or Belief)

The credibility of the hypothesis A is the sum of the mass functions of all the evidence that supports A: all and only the subsets of the hypothesis A.

$$Bel(A) = \sum_{B \subset A} m(B)$$

Plausibility

The plausibility of the hypothesis A is an upper bound of the confidence interval, which accounts for all the observations that do not rule out the given proposition.

$$Pl(A) = \sum_{B \cap A \neq \emptyset} m(B)$$

Example:
$$m(\{X_3\}) = 0.05, m(\{X_3, X_4\}) = 0.05, m(\{X_4\}) = 0.2,$$
$$m(\{X_5\}) = 0.3, m(\{X_4, X_5\}) = 0.4$$

$$\boxed{Bel(\{X_3, X_4\})} = m(\{X_3\}) + m(\{X_4\}) + m(\{X_3, X_4\}) = 0.3$$

$$\boxed{Bel(\{X_3\})} = 0.05$$

$$\boxed{Bel(\{X_4\})} = m(\{X_4\}) = 0.2$$

$$\boxed{Bel(\{X_5\})} = m(\{X_5\}) = 0.3$$

$$\boxed{Bel(\{X_4, X_5\})} = m(\{X_5\}) + m(\{X_4\}) + m(\{X_4, X_5\}) = 0.2 + 0.3 + 0.4 = 0.9$$

$$\boxed{Pl(\{X_3, X_4\})} = m(\{X_3\}) + m(\{X_4\}) + m(\{X_3, X_4\}) + m(\{X_4, X_5\}) = 0.4$$

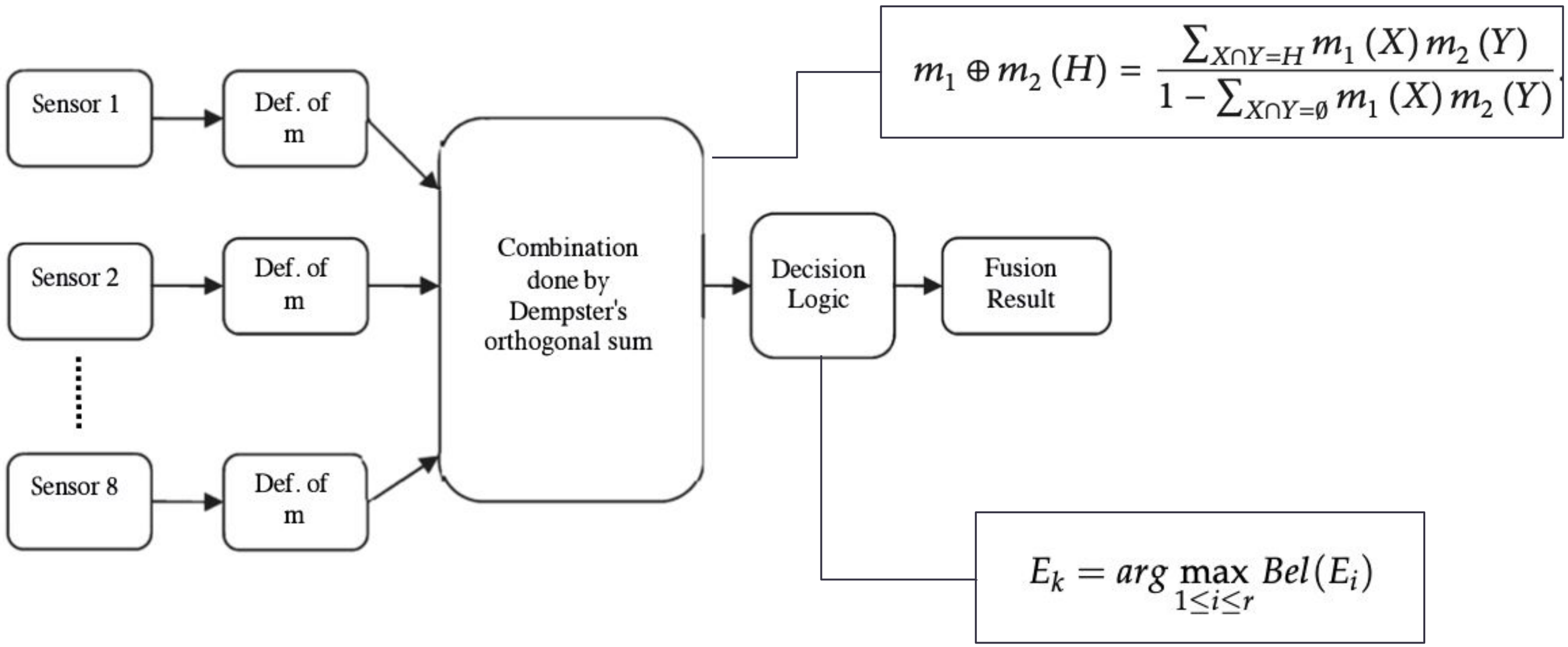
$$\boxed{Pl(\{X_3\})} = m(\{X_3, X_4\}) + m(\{X_3\}) = 0.1$$

$$\boxed{Pl(\{X_4\})} = m(\{X_3, X_4\}) + m(\{X_4\}) + m(\{X_4, X_5\}) = 0.05 + 0.2 + 0.1 = 0.35$$

$$\boxed{Pl(\{X_5\})} = m(\{X_5\}) + m(\{X_4, X_5\}) = 0.7$$

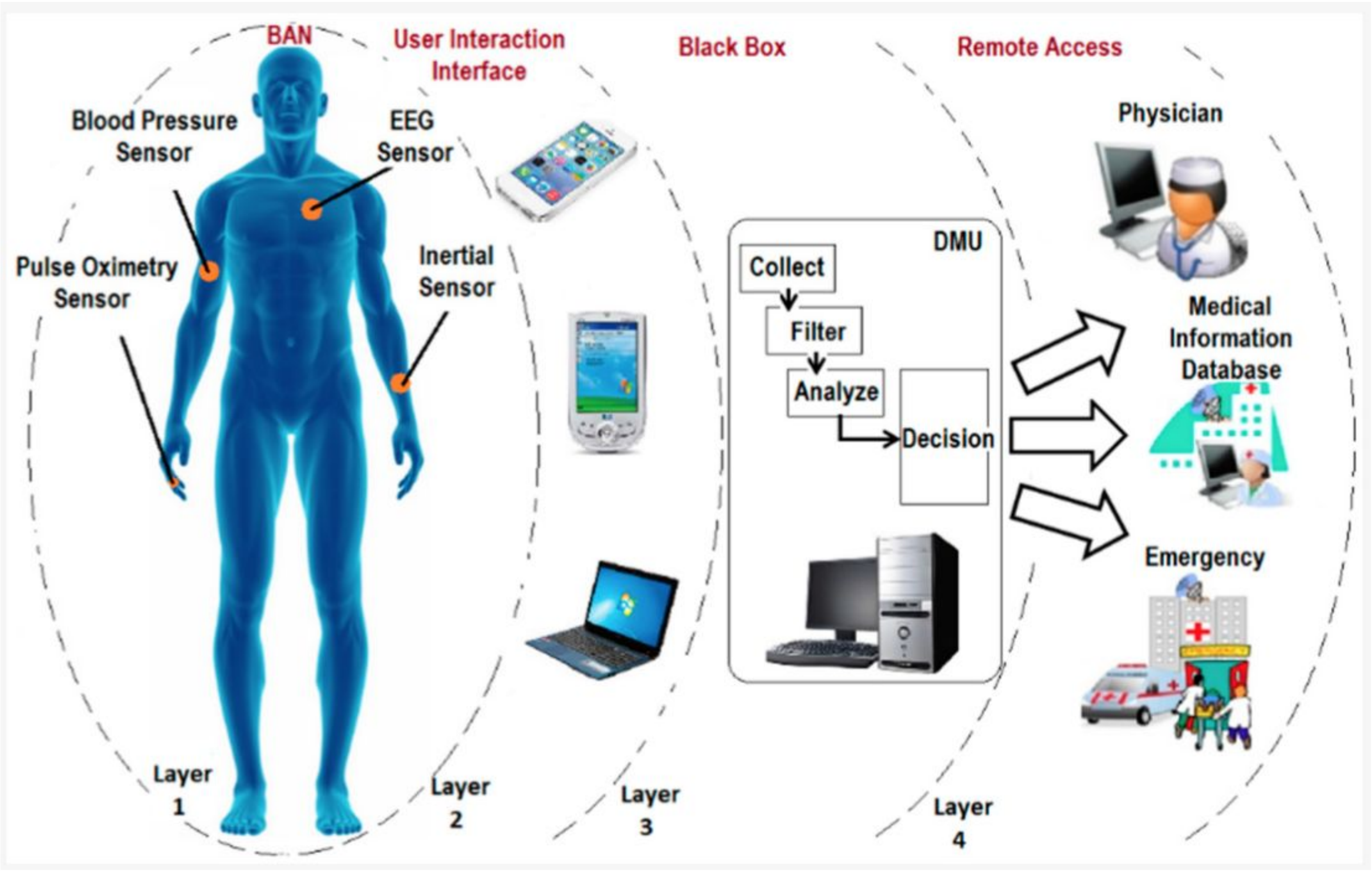
$$\boxed{Pl(\{X_4, X_5\})} = m(\{X_3, X_4\}) + m(\{X_5\}) + m(\{X_4\}) + m(\{X_4, X_5\}) = 0.95$$

The Dempster-Shafer Inference: combination

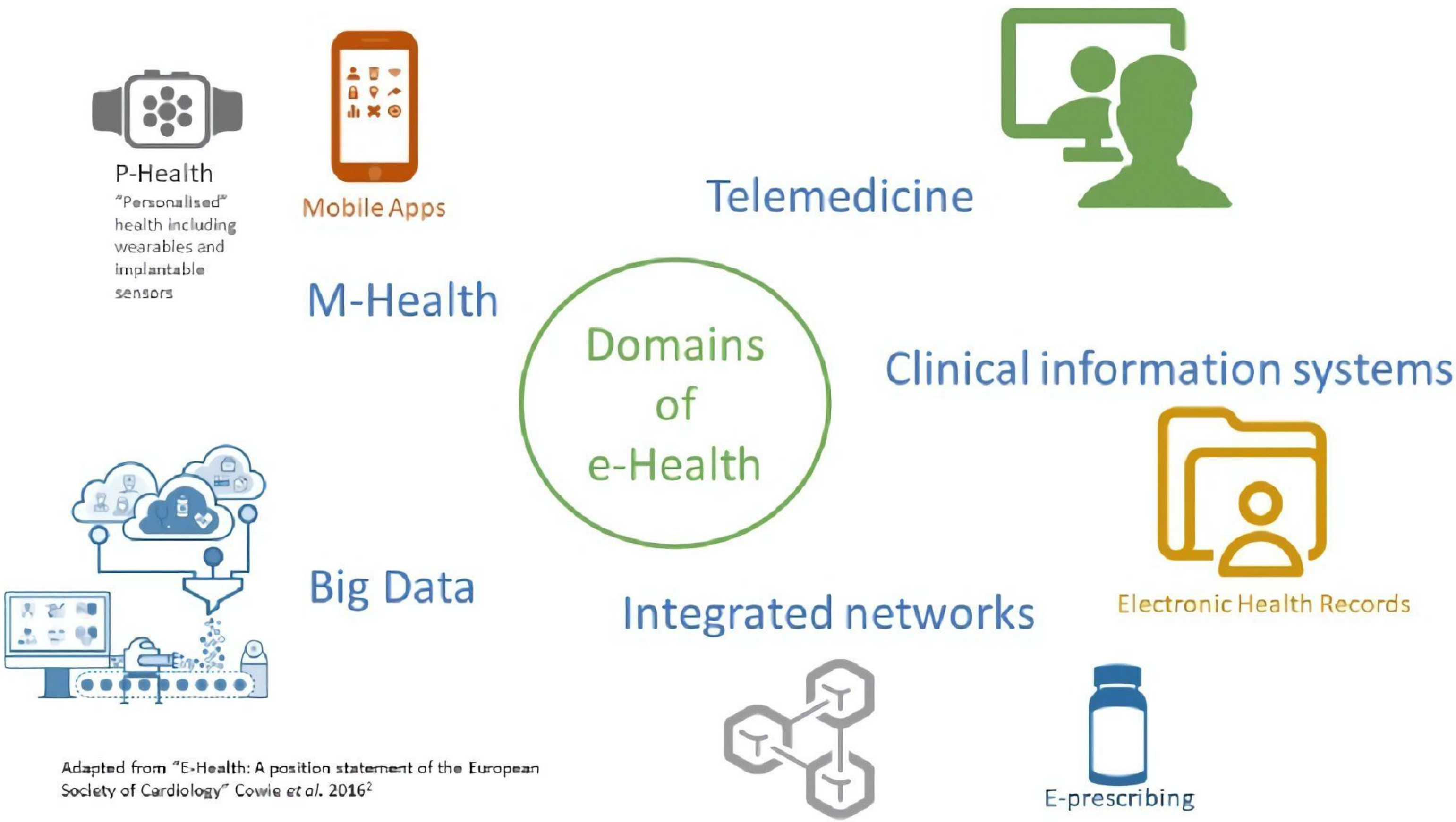


- With the formula represented in the "fusion step" , we can combine the mass function of each single sensor *s_1,....s_8* to get a final mass function.
  From this mass function we can then build the "belief" of the system on a single state and choosing the state which has the **highest belief** or **highest plausibility**.

Sensors Fusion in eHealth



What is eHealth?



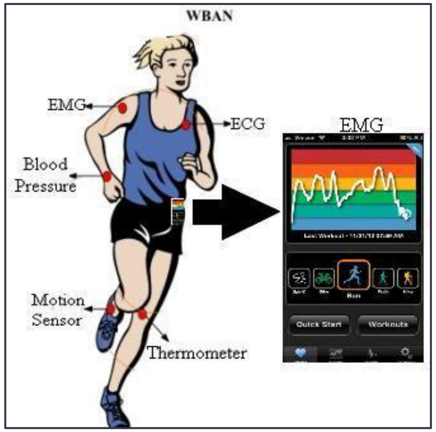
Source:
e-Health: a position statement of the European Society of Cardiology

Martin R. Cowie, Jeroen Bax, Nico Bruining, John G. F. Cleland, Friedrich Koehler, Marek Malik, Fausto Pinto, Enno van der Velde, Panos Vardas

Sensors Fusion in eHealth : main applications

Smart Assisted Living

Sport Monitoring



MAIN APPLICATION

Remote patient monitoring

Sensors Fusion in eHealth : why

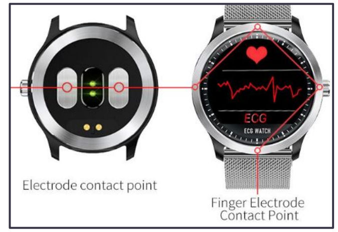
From an operative point of view all the tasks/issues related to the application of *Information Technology* in eHealth can be categorized in two main groups:

- **State Estimation / Classification**
- **Anomaly Detection**

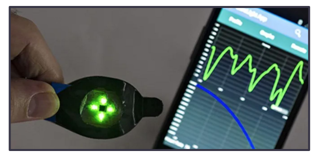
WHY :

- **Improving the accuracy** of the system in detecting and correct classifying a given state.
- **Consistent detection** of some health/non health states are not possible only using one sensor (one source of information) but only if we FUSE the information of many sensors.
- **Avoiding** centralized architectures.

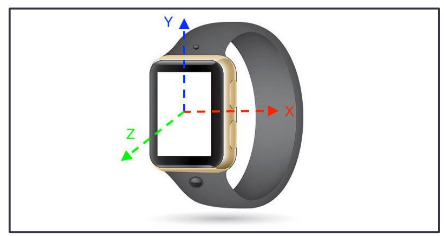
Example in Smart Watches



Electrical Sensors (ECG)



Optical Sensors (PPG , SpO2)



Inertial Sensors

- **Use case of Sensors Fusion for Anomaly Detection**:
    - Measuring heart parameters with ECG , PPG , SpO2 sensors.
    - Assessing user activity through Inertial Sensors
    - Fusing the two informations to spot heart anomalies .

Sensors Fusion

Real Life applications

Apple Watch saves motorcyclist's life after hit-and-run

Inc.

NEWSLETTERS SUBSCRIBE

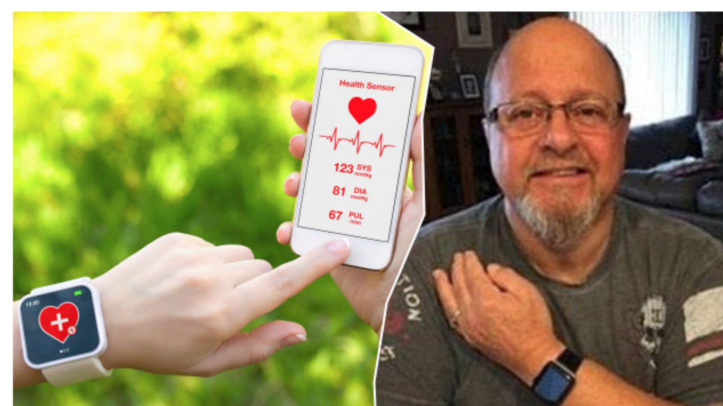
5G REVOLUTION

The Apple Watch Saved This Young Man's Life. Tim Cook's Response Is a Powerful Lesson

If you're passionate about your mission and vision, then what you communicate to customers doesn't always have to put products in the

Apple Watch saves life of 62-year-old man suffering heart attack

BY CAROLINA · MARCH 28, 2016 · 2 MINUTE READ



Sensors Fusion ≠ Sensors Integration

- **Sensors Fusion is usually confused with the Sensors Integration**. This is absolutely wrong. Sensors Integration is necessary for Sensors Fusion but it is not sufficient.

SENSORs INTEGRATION :

- EXAMPLE: An eHealth platform collect data from a SpO2 oximeter (oxygen saturation) and Portable ECG. The health parameters are tracked and sent to a care provider (clinician) which monitors the values on standard output.

SENSORs FUSION:

- EXAMPLE: A eHealth platform which collects data from a SpO2 oximeter and Portable ECG , fuse the two data and send to the care-provider the heart status of a patient (Normal, critical , Heartbreak). .

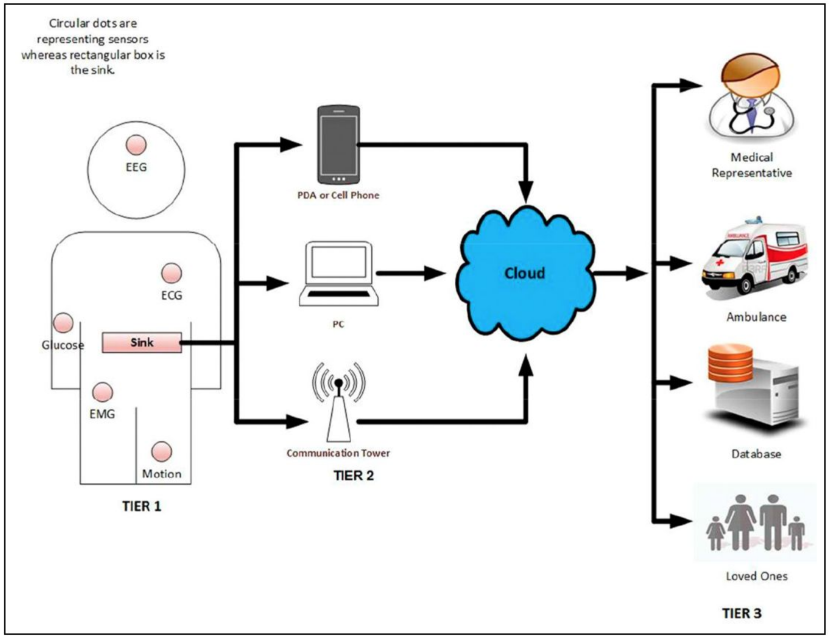
Sensors Integration Systems

Sensors Integration Systems incorporate WBAN (Wireless Body Area Network) + cloud service which collect and process the data measured by the sensors.

Such systems are divided usually divided in Tier 1, 2 , 3.

In Sensors Fusion domain , Tier 2 is usually referred as **mDCS** or "mobile data collection system".

- If the fusion occurs a **Tier 1 /2** level, so inside the mDCS, we can have a **Distributed Architecture.**
- If the fusion occurs a **Cloud** level, so in the cloud, we can have a **Centralized Architecture**.

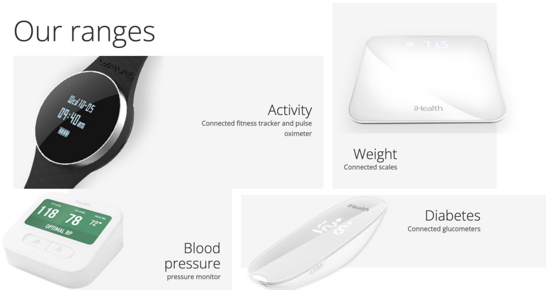


Sensors Integration Systems

Sensors Fusion

- In the eHealth market, the **main players** which provides services in the field of Sensors Fusion and Integration are :
  - *Fitbit* Cloud (partnership with google)
  - *iHealthLabs*: iHealthLabs Cloud
  - Apple: Apple Health

  These services integrate proprietary devices and also third-part devices.

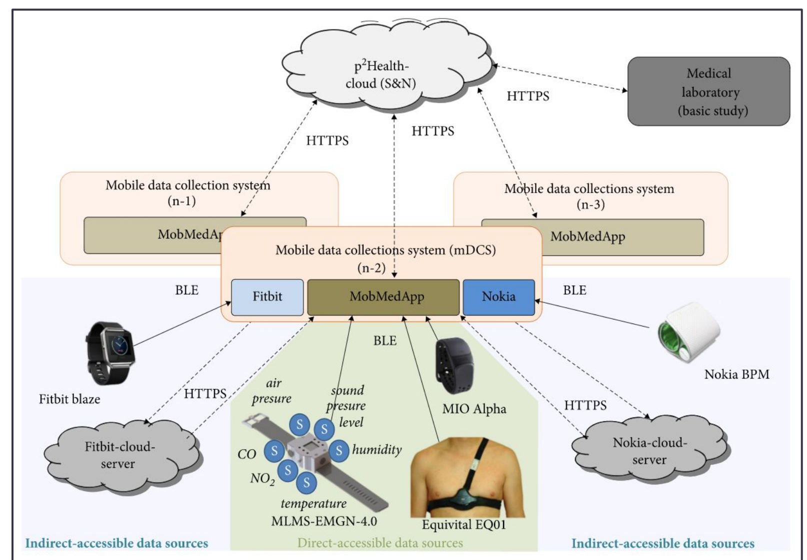


iHealth example

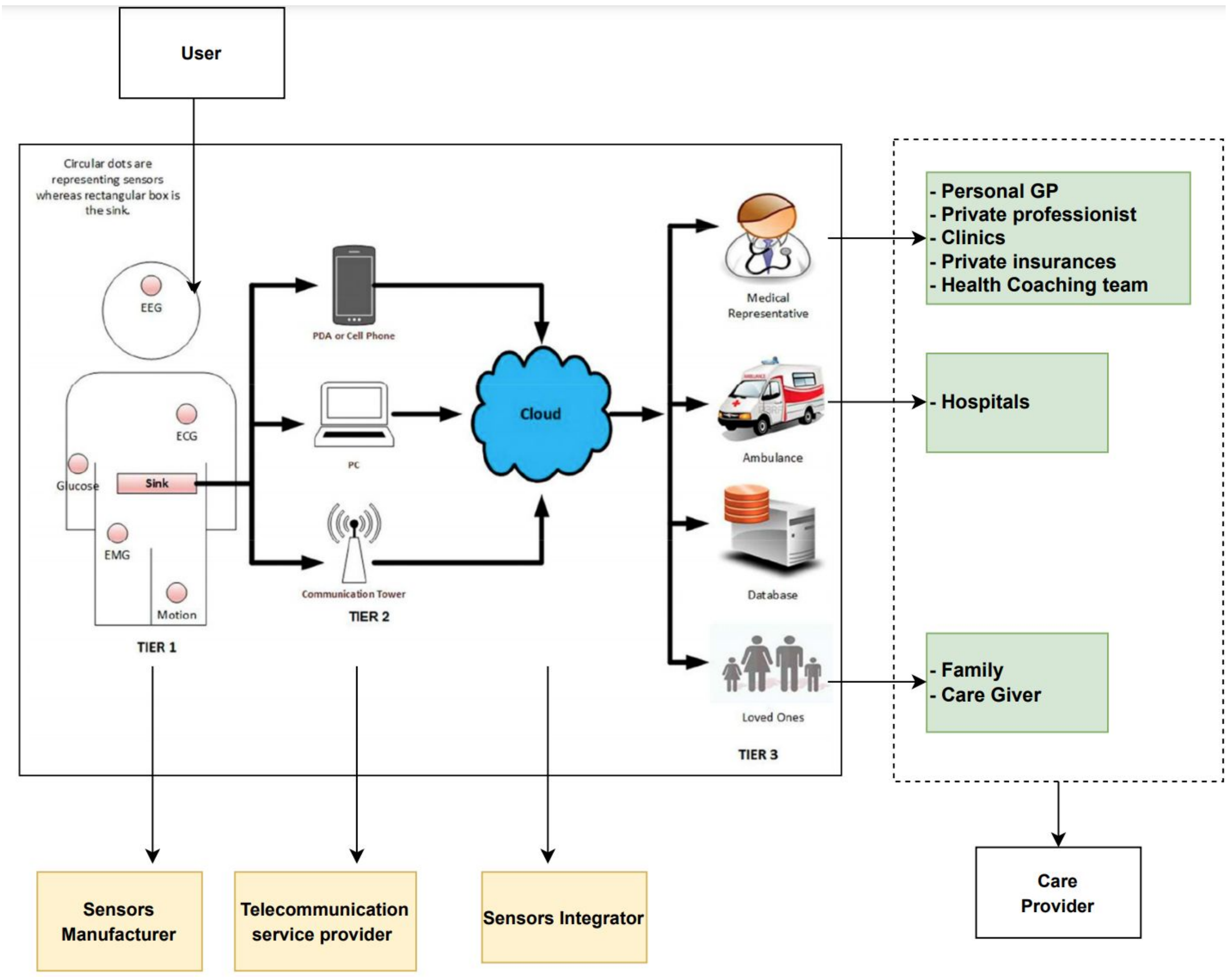
Integration of the integrators

p2Health project is a Sensor fusion platform created by researchers of University of Rostock which is able to integrate different mDCS and also a database with medical records.

PAPER: https://pubmed.ncbi.nlm.nih.gov/31687017/



Structure, Subjects and Stakeholders



Sensors Fusion

Smart Assisted Living

Goal:
Spotting health and behavioural anomalies in a smart home environment which monitor senior people.

Target user:

- Senior People
- Fragile People
- People living alone

Type of sensors:

- **Environmental sensors (PIR)**
- Wrist mounted watch
- Textile sensors

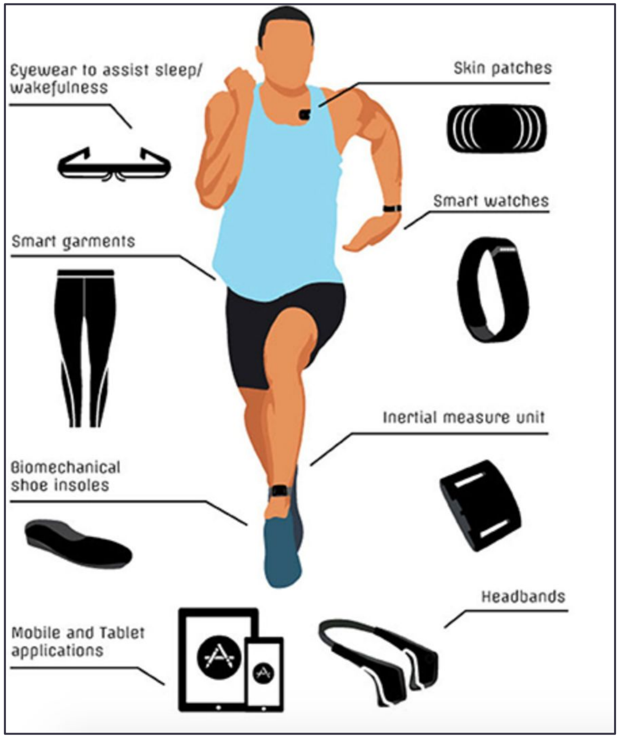
Sensors Fusion

Sport Monitoring

PAPERs:

- https://sportsmedicine-open.springeropen.com/articles/10.1186/s40798-022-00432-z
- https://www.mdpi.com/2079-6374/10/12/205/htm

- **Goal**:
  - Performance assessment: Using different sensors to estimate the level of performances of a movement or a sport act .
- **Target user**:
  - Medium level to professional athlete
  - Rehabilitation patient
- **Type of sensors**:
  - ECG sensors
  - IMU Sensors
  - Electrochemical sensor for skin and sweat analysis
  - Wearable textile-based sensors on dress and shoes
  - EMG sensors
  - Wearable pulse oximeter



Patient monitoring and diagnostic

- **Level 0: Parameter level tracking**
  Just integration system , each sensors decoupled from the others

- **Level 1: Anomaly detection and alarm detection**
  Detection of particular anomalous status such as
  loss of conscience , car accidents etc.
  - Smart watch sensors (ECG , IMU , SpO2)
  - Require minimal access to the clinical story of the patient.

- **Level 2: Advanced and pervasive diagnostic** early detection of general diseases and general health problems.
  - Integration with biochemical sensors
  - Complete access to the clinical story of the patient.

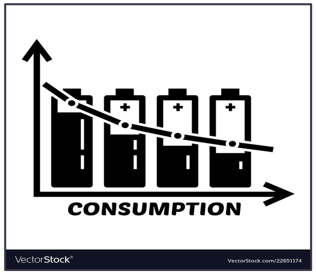
PAPER:
https://www.researchgate.net/publication/305788092_A_Framework_of_Sensor-based_Monitoring_for_Pervasive_Patient_Care

Sensors Fusion

Requirements

Requirements for designing a Sensors Integration System:

- **POWER CONSUMPTION**: low computational consumption for battery saving and time of execution;



- **SECURITY**: high data security and integrity;

- **AUTOMATIZATION**: automatic data processing , minimizing the human intervention.

- **SIMPLICITY** : simple and intuitive system handling (usability);

Challenges

- **STANDARDIZATION**: There is not a clear standardization of the stack to connect the customer (patient) to the care provider (clinician).

- **RAW DATA AVAILABILITY**: Sensors Manufacturers usually are not (basically never) the entity which provides Sensors Fusion and Integration systems. Most of the time only higher level data are available for the system integrator.

- **WEARABLE SENSORS** are user dependent. In many scenarios we cannot rely only on them.

Future Developments of SF in eHealth

- **Technological:**
  - Combining Sensors Fusion And Deep Learning in the feature extraction phase.
  - With ***higher and higher*** data availability ***Bayesian Networks*** will gain momentum especially for patient monitoring.
- **Practical**:
  - A new standard for exchanging **raw** data and **features** among sensors.
  - Sensors Integration Systems **targeted to the the context.**
    Sport Monitoring ≠ Elderly Care.
    PS: As a general rule, the fewer sensors your user have to wear , the better ;).

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Sensors Fusion

Sensors Fusion

Thank you

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