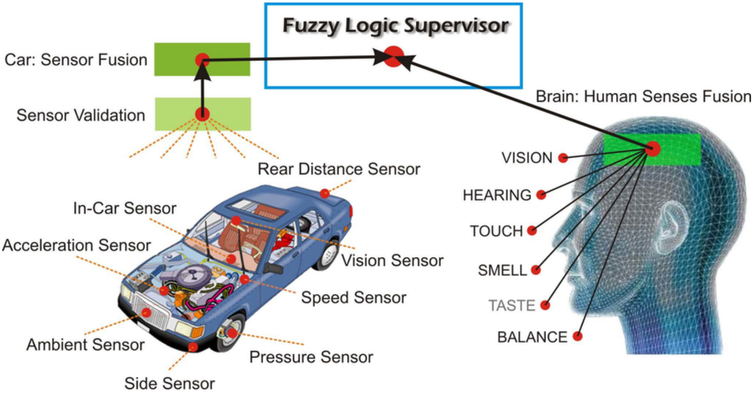
Statistics and Sensor Data Fusion

5. Sensor Data Fusion – Introduction and Overview

Sensor Data Fusion – Introduction and Overview

What is Sensor Data Fusion?



A Hybrid Method in Driver and Multisensor Data Fusion, Using a Fuzzy Logic Supervisor for Vehicle Intelligence - Scientific Figure on ResearchGate. Available from: https://www.researchgate.net/figure/Hybrid-multi-data-fusion-Human-Sensor-Fusion-Physical-Sensor-Fusion_fig1_4296527

Sensor Data Fusion – Introduction and Overview

What is Sensor Data Fusion?

> "Fusion is the act or process of combining or associating data or information regarding one or more entities considered in an explicit or implict knowledge framework to improve one's capability (or provide new capability) for detection, identification, or characterization of that entity."
>
> *Percivall, 2010*

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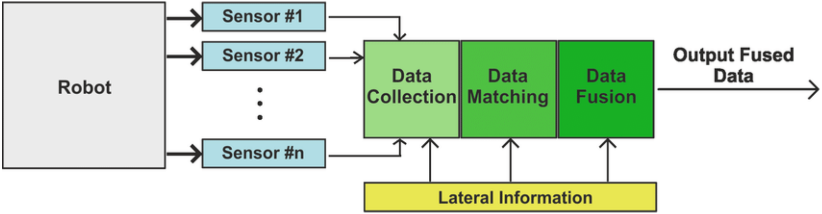
Sensor Data Fusion in Robotics:



Sensory Feedback Performance Improvement on RoboCab: An Experimental Approach to Wire-Driven Parallel Manipulator - Scientific Figure on ResearchGate. Available from: https://www.researchgate.net/figure/Sensor-level-data-fusion-scheme_fig5_315768453

Sensor Data Fusion – Introduction and Overview

Sensor data fusion is the process of **combining information from multiple sensors** to achieve inferences that are more accurate than that provided by any individual sensor.

The fusion of information from multiple sensors with different physical characteristics enables or enhances the understanding of the state of the environment and thus provides the basis for **autonomous and intelligent machines**.

The huge variety of sensor data fusion processes can be categorized as **low**, **intermediate**, or **high**, depending on the processing stage at which sensor fusion takes place:

- Data fusion: Combination on **signal level** (low)
- Feature fusion: Combination on **feature level** (intermediate)
- Decision fusion: Combination on **symbolic level** (high)

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Example:

In order to illustrate the different fusion levels, we look again at the example of the fish cannery, where the distinction between salmon and sea bass should be done on the basis of **grayscale images**.

For the **single sensor application**, we have considered the following processing steps:

1. Camera shot (original image)
2. Preprocessing of the image (noise filtering, calculation of grayscale values, segmentation, . . .)
3. Feature extraction and selection (lightness and width)
4. Classification

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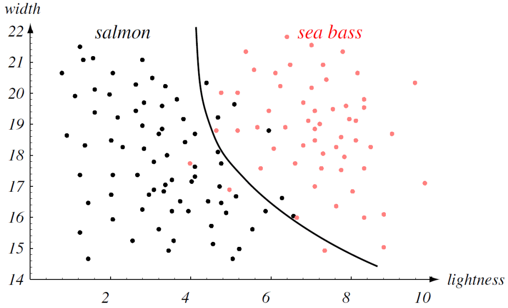
Possible Classification:



Based on the measured values of the two features **lightness** and **width**, a binary valued classifer might reach a decision on the type of the fish according to the plotted black line.

Observe that in general the classifier will **not** be error-free.

R. Duda, P. Hart, D. Stork, Pattern Classification, 2nd edition, Wiley, 2001

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In order to increase the performance of the binary classifier in terms of a reduction of its probability of error, the implementation of a **multi-sensor system** might be advantageous.

When using multiple sensors (e.g. cameras) for the classification task at hand, the **processing level** on which sensor fusion should take place has to be specified.

In principle, the following fusion levels can be considered:

- **Fusion of obtained grayscale values** from different cameras $\rightarrow$ Data fusion
- **Fusion of feature values** computed on the basis of individual grayscale images $\rightarrow$ Feature fusion
- **Fusion of decisions** obtained by the classification of individual feature values $\rightarrow$ Decision fusion

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From Sensor Data to the Fusion Result:

$$\begin{array}{ccccc} \textbf{Sensor Data} & \longrightarrow & \boxed{\text{Data Fusion}} & & \\ \downarrow & & & \searrow & \\ \textbf{Features} & \longrightarrow & \boxed{\text{Feature Fusion}} & \longrightarrow & \textbf{Fusion Result} \\ \downarrow & & & \nearrow & \\ \textbf{Decisions} & \longrightarrow & \boxed{\text{Decision Fusion}} & & \end{array}$$

In extension to this general scheme, also a **combination of different fusion levels** can be considered.

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Data Fusion:

- In the case of data fusion, the fusion takes place on the level of the sensor data itself, that means on the **signal level**
- As a requirement for data fusion, the sensor data have to contain **redundant** or **complementary** information
- For example, the process of data fusion might result in the **reduction of the noise level** contained in the different signal measurements
- For data fusion on the signal level, the sensors have to be **homogeneous** in the sense that their measurements refer to the same physical property (e.g. grayscale values)

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Feature Fusion:

- In feature fusion, the combination of information takes place **after** relevant features have been extracted and selected from the sensor raw data
- The features are assumed to capture **characteristic** and **meaningful** properties of the sensor signal
- Examples for typical features extracted from signals are the **signal energy** or **dominant frequencies**, in the case of image data one might consider detected edges or derived quantities (e.g. the width of an object)
- Feature fusion might also be applied if relevant features are distributed across the data of several sensors

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Decision Fusion:

- Eventually at the symbolic level, decision fusion combines information obtained by a **classification step**, requiring preprocessing and feature extraction at the individual sensors
- For example, the symbolic information fused might refer to **local decisions** with respect to the presence or type of an object in a surveillance area
- Decision fusion at the symbolic level imposes the **fewest requirements** concerning the homogeneity of the combined sensor measurements
- **Every possible relationship** between the individual sensor measurements might be exploited, as long as the symbolic information obtained refers to the scenario under consideration

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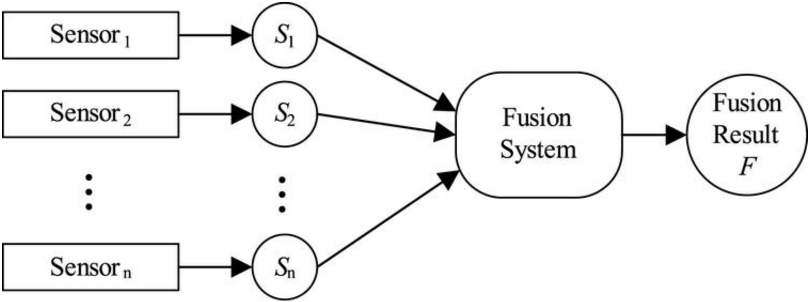
Decision Fusion – Parallel Fusion Network:



Zhu, Yungang et al. 'Selective and Incremental Fusion for Fuzzy and Uncertain Data Based on Probabilistic Graphical Model'. Journal of Intelligent & Fuzzy Systems, vol. 29, no. 6, pp. 2397-2403, 2015

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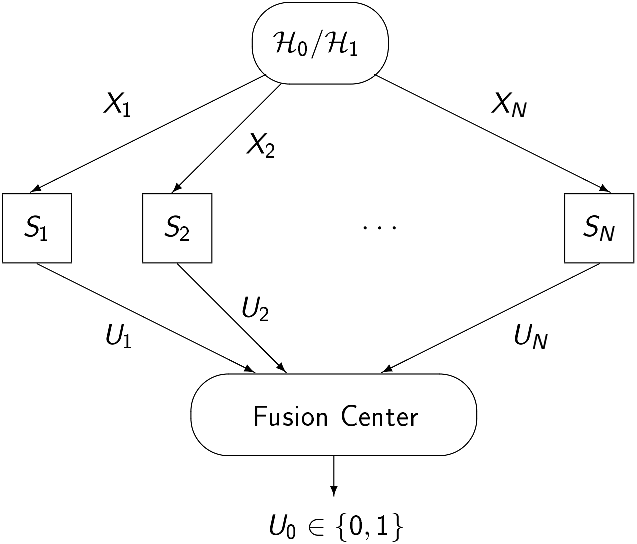
Statistical Model of the Parallel Fusion Network:



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Statistical Model of the Parallel Fusion Network:

- In a parallel fusion network, N distributed sensors $S_1, \ldots, S_N$ make **local measurements** $X_1, \ldots, X_N$ referring to a common scenario, e.g. target absent ($\mathcal{H}_0$) or present ($\mathcal{H}_1$)
- The two hypotheses $\mathcal{H}_0$ and $\mathcal{H}_1$ are assumed to have the **prior probabilities** π_0 and π_1, the local measurements $X_1, \ldots, X_N$ are modeled as **random variables**
- Based on the measurements, the sensors make **local decisions** $U_1, \ldots, U_N$ before transmitting these to a fusion center, which has to combine the decisions in an optimal way
- Assuming that the sensors make **binary** or **hard decisions**, it is possible to characterize them by their local error probabilities
- By taking the local error probabilities into account, the fusion center can implement an **optimal fusion rule**

Statistical Model of the Parallel Fusion Network:

The local error probabilities of the sensors $S_1, \dots, S_N$ are given by

$$p_{f_i} = P(U_i = 1 \mid \mathcal{H}_0) \quad \text{probability of false alarm}$$

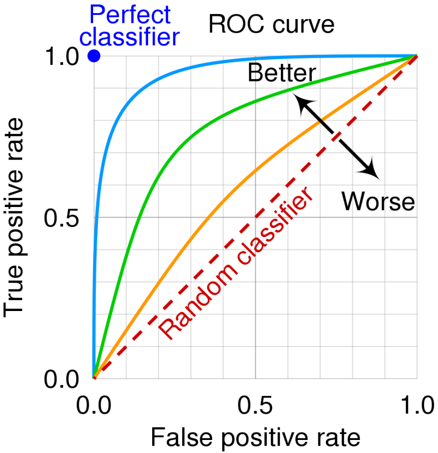
$$p_{m_i} = P(U_i = 0 \mid \mathcal{H}_1) \quad \text{probability of miss}$$

The **probability of false alarm** $p_{f_i} \in [0, 1]$ indicates the probability with which sensor S_i decides for "1", although no target is present.

The **probability of miss** $p_{m_i} \in [0, 1]$ indicates the probability with which sensor S_i decides for "0", although the target is present.

The two local error probabilities are related to each other by the so-called receiver operating characteristic (ROC).

Receiver Operating Characteristic of a Single Sensor:



Statistical Model of the Parallel Fusion Network:

Assuming conditionally independent local decisions $U_1, \ldots, U_N$, the **conditional joint pmfs** of the local sensor decisions are given by

$$f_{\mathcal{H}_0}(u_1, \ldots, u_N) = P(U_1 = u_1, \ldots, U_N = u_n \mid \mathcal{H}_0) = \prod_{i=1}^{N} P(U_i = u_i \mid \mathcal{H}_0)$$
$$= \prod_{i=1}^{N} \left(\frac{p_{f_i}}{1 - p_{f_i}}\right)^{u_i} \cdot (1 - p_{f_i})$$

and

$$f_{\mathcal{H}_1}(u_1, \ldots, u_N) = P(U_1 = u_1, \ldots, U_N = u_n \mid \mathcal{H}_1) = \prod_{i=1}^{N} P(U_i = u_i \mid \mathcal{H}_1)$$
$$= \prod_{i=1}^{N} \left(\frac{p_{m_i}}{1 - p_{m_i}}\right)^{u_i} \cdot (1 - p_{m_i})$$

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Statistical Model of the Parallel Fusion Network:

Introducing the **sensor weights**

$$\lambda_i = \log\left(\frac{(1-p_{f_i})(1-p_{m_i})}{p_{f_i}p_{m_i}}\right), \quad i = 1, \ldots, N$$

and the **decision threshold**

$$\vartheta = \log\left(\frac{\pi_0}{\pi_1}\right) + \sum_{i=1}^{N} \log\left(\frac{1-p_{f_i}}{p_{m_i}}\right)$$

the **optimal fusion rule** is given by the so-called Chair-Varshney fusion rule (Z. Chair, P. K. Varshney, 1986) according to

$$\boxed{\sum_{i=1}^{N} \lambda_i u_i \quad \underset{u_0=0}{\overset{u_0=1}{\gtrless}} \quad \vartheta}$$

Exercise:

A parallel fusion network consists of four sensors S_1, S_2, S_3, S_4 which are characterized by the local error probabilities

$$p_{f_1} = 0.1, \quad p_{f_2} = 0.2, \quad p_{f_3} = 0.3, \quad p_{f_4} = 0.4$$

$$p_{m_1} = 0.3, \quad p_{m_2} = 0.3, \quad p_{m_3} = 0.2, \quad p_{m_4} = 0.1$$

According to the relative frequency of the presence of targets in the surveillance area, the prior probabilities of $\mathcal{H}_0$ and $\mathcal{H}_1$ are given by

$$\pi_0 = 0.8 \quad \text{and} \quad \pi_1 = 0.2$$

During operation, the fusion center receives the local decisions

$$u_1 = 1, \quad u_2 = 0, \quad u_3 = 0, \quad u_4 = 1$$

What would be the result $u_0 \in \{0, 1\}$ of the optimal fusion rule?