Multi-Modal Data Fusion

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Lecture 2: Sensors and Architectures

Outline

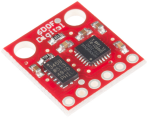
- Sensors
- Sensor observations
- Sensor model
- Fusion node
- Fusion networks
- Fusion topologies

Sensors

Sensors

- Sensor element
  - Measuring / perceiving physical property or environmental attribute
  - E.g., heat, light, sound, pressure, magnetism, motion





  - The sensor must map the value of the property or attribute to a quantitative measurement in a *consistent* and *predictable* manner

(Figures: Wikipedia creative commons)

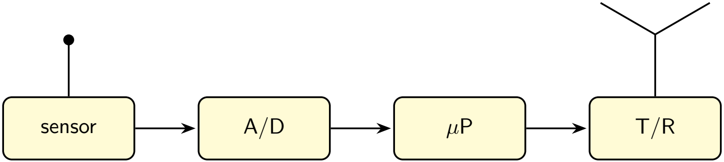
Sensors (cont'd)

- Compensation
  - Ability to detect and respond to environmental changes
  - Self-diagnostic tests, self-calibration, adaptation
- Information processing
  - Extract or enchance information content of raw sensor measurements
  - Signal conditioning, data reduction, event detection, decision-making
- Communication
  - Standardized interface and communication protocols
  - Transmission of information between the sensor and outside world
- Integration
  - Embedding of the sensing and computation processes on the same silicon chip (e.g., MEMS technology)

Sensors (cont'd)

- Smart sensor
  - Hardware/software device
  - Combining units of sensor element, micro-controller, communication controller, and software for signal processing and communication
- Logical sensor
  - Any sensor (physical or virtual) functioning as a source of information
  - Can be an input to any other fusion node

Smart Sensor



- Smart sensor comprises
  - Sensor element measuring the physical property
  - A/D transformer to transform raw analog sensor signal to standardized digital representation
  - Microprocessor (μP) to check and calibrate the signal
  - Transmitter to send the digital signal to outside world
    - May also contain receiver to get command intructions

(Figure adapted from the course book)

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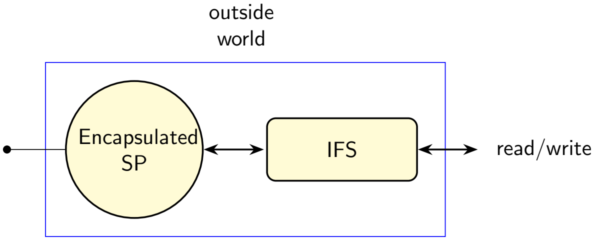
Smart Sensor (cont'd)



- Smart sensor with a sensor element and the encapsulated signal processing and interface file system (IFS) units

(Figure adapted from the course book)

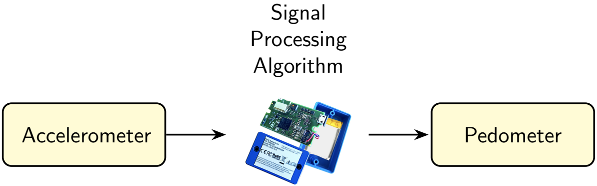
Smart Sensor: Example of Multimodal IoT Device

- Example of wearable / Internet-of-things device (SensorTile.box from STMicroelectronics)
- Combines several sensors: temperature, inertia, accelometer, magnetometer, pressure, microphone, humidity
- Ultra-low-power ARM Cortex-M4 microcontroller with DSP and FPU
- Bluetooth Smart connectivity v4.2 for wireless communication

Figure from STMicroelectronics: https://www.st.com/resource/en/data_brief/steval-mksbox1v1.pdf

Logical Sensor

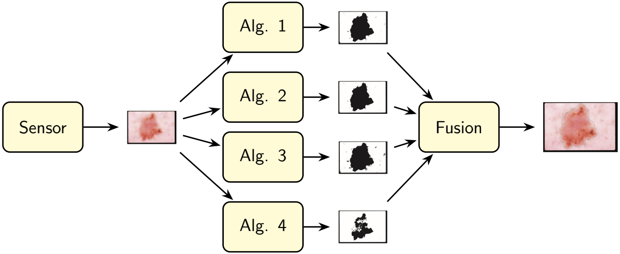
- Logical (or virtual) sensor extends physical sensor with other data sources
- Any device/software producing input data source to fusion node can be considered as logical sensor



- E.g., signal processing algorithm fusing and transforming raw physical acceleration sensor measurements to logical pedometer sensor

Figure from STMicroelectronics: https://www.st.com/resource/en/data_brief/steval-mksbox1v1.pdf

Logical Sensor: Skin Lesion Image Segmentation



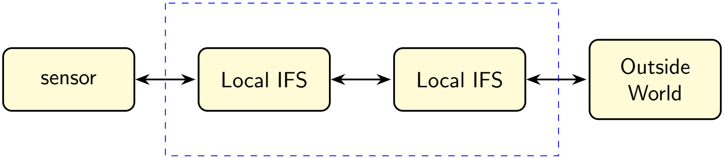
- Skin lesion segmentation from dermatoscopy images fusing different thresholding algorithms
- Thresholding algorithms (Alg. 1, Alg. 2, Alg. 3, Alg 4) work as logical sensors producing input to final fusion

(Figure adapted from the course book and Celebi et al. (2010) "Robust border detection in dermoscopy images using threshold fusion". Proc. IEEE Int. Conf. Image Proc. pp. 2541-2544)

Sensor Interfaces

- Interface File System (IFS)
  - Structured space communicating information between smart sensor and outside world
- Interface types
  - Real-time service (RS) interface
    - Provides time sensitive information to outside world
  - Diagnostic and management (DM) interface
    - Establishing the connection to smart sensor
    - Calibration and diagnostic information to support maintenance activities
  - Configuration and planning (CP) interface
    - Configures smart sensor for particular application
- Timing of communication and computation between interfaces
  - Event trickered system: initiated when significant change of state happens
  - Time trickered system: initiated at pre-defined times

Sensor Interfaces (cont'd)



- Interface File System (IFS) as a temporal firewall with two separate local interface file systems
  - Avoiding direct communication between sensor and outside world

(Figure adapted from the course book)

Sensor Observations

- Sensor observation
  - The output of a sensor, "snapshot" of the measured process

$$O =< E, \boldsymbol{x}, t, \boldsymbol{y}, \Delta\boldsymbol{y} >$$

  - **Entity-Name** E: the name of the physical property which is measured (and its unit)
  - **Spatial Location** $\boldsymbol{x}$: the position in space to which measured property refers
  - **Time Instant** t: the time when the physical property is measured
  - **Measurement** $\boldsymbol{y}$: the value of the physical property as measured by the sensor element (scalar or vector)
  - **Uncertainty** $\Delta\boldsymbol{y}$: different types of errors in $\boldsymbol{y}$
  - *Censored* observation (i.e., with missing field) can be represent by an asterix (*)

$$O =< E, *, t, \boldsymbol{y}, * >$$

Sensor Observations (cont'd)

- Sensor uncertainty
  - Sensor gives only estimate of measured physical property
  - Inherits from different type of errors, possibly occuring simultaneously
  - Can be defined *a priori* or calculated internally "on-the-fly"

  - Random errors
    - Lack of repeatability in the output, measurement noise
    - E.g., fluctuations, limited resolution of sensor
  - Systematic errors
    - Consistent and repeatable errors
    - E.g., calibration, loading, environmental, common representational format errors
  - Spurious readings
    - Non-systematic measurement errors
    - E.g., detecting false object with ultrasonic sensor

Sensor Characteristics

- State
  - Device measuring internal systems parameters, e.g., position, velocity, acceleration
  - Device measuring external geometric or dynamic relations to task or environment
- Function
  - Parameters or measurands sensor is measuring, e.g., displacement, velocity, acceleration, mass, force
- Performance
  - E.g., accuracy, repeatability, linearity, sensitivity, resolution, reliability, range
- Output
  - Nature of output signal: analog, digital, frequency, and coded
- Energy type
  - Type of energy transfered to sensor, e.g., thermal or electrical

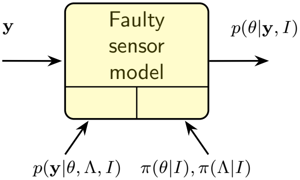
Sensor Model

- A priori probability density function (pdf) $\pi(\boldsymbol{\theta}|I)$
  - Continuous pdf describing *a priori* beliefs about $\boldsymbol{\theta}$, e.g., Gaussian distribution with a mean $\boldsymbol{\mu}$ and a covariance matrix $\boldsymbol{\Sigma}$

$$\pi(\boldsymbol{\theta}|I) \sim \mathcal{N}(\boldsymbol{\theta}|\boldsymbol{\mu}, \boldsymbol{\Sigma})$$

- Sensor reliability $\pi(\Lambda|I)$
  - Discrete probability distribution specifying the *a priori* reliability of the sensor
  - The simplest model: $\Lambda = \{\lambda_0, \lambda_1\}$, where λ_0 denotes fault-free and λ_1 faulty operation
- Likelihood $p(\boldsymbol{y}|\boldsymbol{\theta}, \Lambda, I)$
  - Continuous pdf describing how sensor measurements $\boldsymbol{y}$ depends on $\boldsymbol{\theta}$, Λ, and background information I
  - Measures the goodness of fit

Sensor Model (cont'd)



- Faulty sensor model based on Bayesian framework

$$p(\boldsymbol{\theta}|\boldsymbol{y}, I) \sim \pi(\boldsymbol{\theta}|I) \int p(\boldsymbol{y}|\boldsymbol{\theta}, \Lambda, I)\pi(\Lambda|I) d\Lambda$$

(Figure adapted from the course book)

Multi-Sensor Data Fusion with Spurious Measurements

- Considering K scalar measurements $y_k, k \in \{1, 2, \ldots, K\}$ of a given parameter θ and a Gaussian sensor model

$$p(y_k|\theta, \Lambda_k = \lambda_0, I) = \frac{1}{\sigma_k\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{\theta - y_k}{\sigma_k}\right)^2\right].$$

- And probability that the measurement from the kth sensor is *not* spurious

$$p(\Lambda_k = \lambda_0|\theta, y_k, I) = \exp\left[-\left(\frac{\theta - y_k}{\alpha_k}\right)^2\right].$$

Multi-Sensor Data Fusion with Spurious Measurements (cont'd)

- The posterior pdf of parameter can be written based on Bayes theorem as

$$p(\theta|y_1, y_2, \ldots, y_K, I) = \frac{\pi(\theta|I)}{p(y_1, y_2, \ldots, y_K|I)} \prod_{k=1}^{K} \pi(\Lambda_k = \lambda_0|I) \times \frac{p(y_k|\theta, \Lambda_k = \lambda_o, I)}{p(\Lambda_k = \lambda_0|\theta, y_k, I)}.$$

- The value of the parameter α_k is assumed to be given by

$$\alpha_k^2 = \beta_k^2 / \prod_{l=1, l\neq k}^{K} (y_k - y_l)^2.$$

Multi-Sensor Data Fusion with Spurious Measurements (cont'd)

- Substituting the expression for α_k into $p(\theta|y_1, y_2, \ldots, y_K, I)$ gives

$$p(\theta|y_1, y_2, \ldots, y_K, I) = \frac{\pi(\theta|I)}{p(y_1, y_2, \ldots, y_K|I)} \prod_{k=1}^{K} \pi(\Lambda_k = \lambda_0|I) \frac{1}{\sigma_k \sqrt{\pi 2}} \times \exp\left[-(\theta - y_k)^2 \left(\frac{1}{2\sigma_k^2} - \prod_{l=1, l\neq k}^{K} (y_k - y_l)^2 / \beta_k^2\right)\right].$$

- To ensure Gaussian *a posteriori* probability distribution with a single peak, the value of the parameter β_k^2 is chosen by

$$\beta_k^2 \geq 2\sigma_k^2 \prod_{l=1, l\neq k}^{K} (y_k - y_l)^2.$$

Fusion Architectures

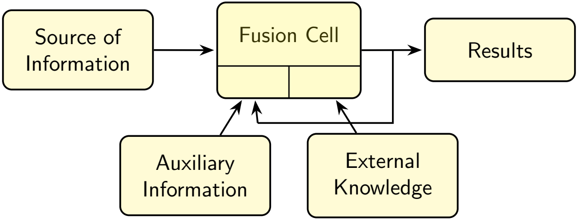
Fusion Node

- Receives input sensor observations

$$O_i =< E_i, \boldsymbol{x}_i, t_i, \boldsymbol{y}_i, \Delta \boldsymbol{y}_i >, i \in \{1, 2, \dots\}$$

- Sensor information
  - Data coming directly from sensors S_m, $m \in \{1, 2, \dots M\}$ or from other fusion node
- Auxiliary information
  - Additional data derived by specific processing of the sensor observations
  - E.g., different feature representation of input
- External knowledge
  - Additional data consisting all the elements of the *a priori* external knowledge
  - E.g., trained machine learning model

Fusion Node (cont'd)



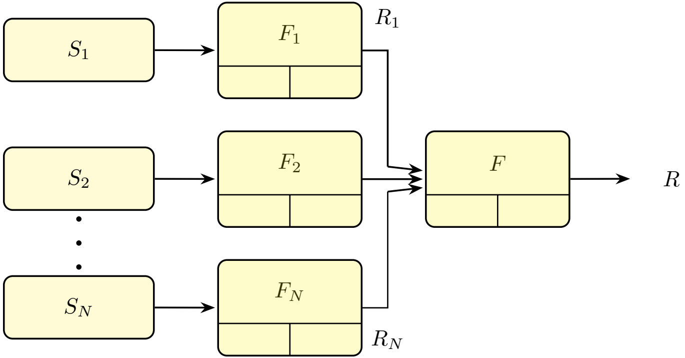
- Single fusion node (or cell) with three types of input data: source of information, auxiliary information, and external knowledge

(Figure adapted from the course book)

Fusion Networks

- Parallel network
  - Each fusion node process the input data separately and delivers its intermediate result to final fusion process
- Serial network
  - Each fusion node is connected and cascaded, and delivers its intermediate result as auxiliary input to next node until final fusion process
- Iterative network
  - Fusion node delivers its result as an auxiliary input to itself
  - Modeling dynamical systems and processing temporal data sources

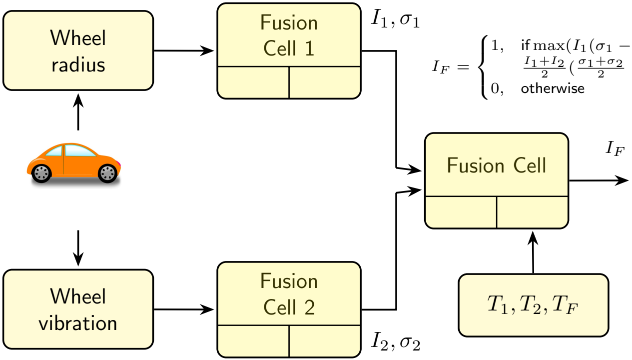
Parallel Network



- Parallel network of N fusion cells F_m, $m \in \{1, 2, \ldots, N\}$. Each cell F_m acts as a virtual sensor producing the input data R_m from the data source S_m. The R_m, $m \in \{1, 2, \ldots, N\}$ are fused together by F

(Figure adapted from the course book)

Parallel Network: Tire Pressure Monitoring

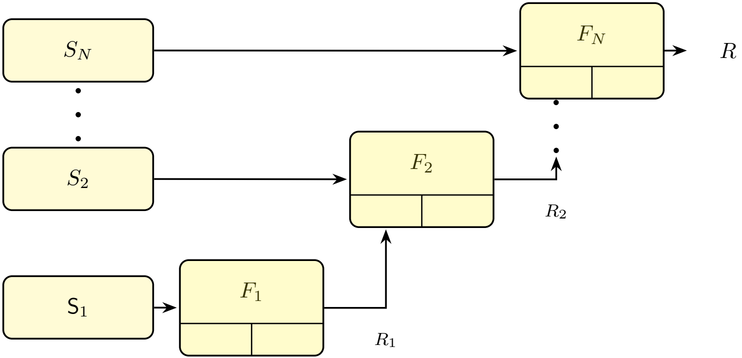


$$I_F = \begin{cases} 1, & \text{if } \max(I_1(\sigma_1 - T_1), I_2(\sigma_2 - T_2), \\ & \frac{I_1+I_2}{2}(\frac{\sigma_1+\sigma_2}{2} - T_F)) > 0 \\ 0, & \text{otherwise} \end{cases}$$

- Tire pressure estimation using the fusion of indirect measurements of wheel rolling radius differences and wheel vibration

(Figure adapted from the course book)

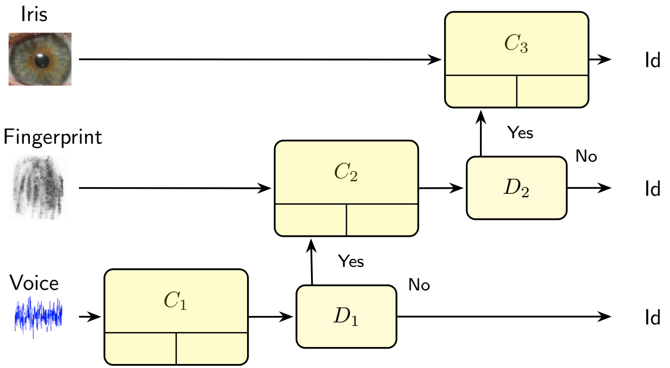
Serial network



- Serial network N fusion cells F_m, $m \in \{1, 2, \ldots, N\}$. Each cell F_m acts as a logical sensor producing the input data R_m by fusing the data source S_m and auxiliary input R_{m-1} until final fusion layers reached

(Figure adapted from the course book)

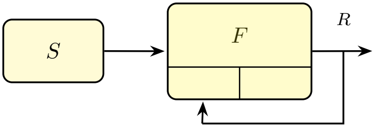
Serial Network: Biometric Identification



- Cascaded biometric identification where in each stage it is decided if new modality is needed (Yes/No) for accurate identification

(Figure adapted from the course book)

Iterative Network



- Iterative network of single fusion cell. The result R is re-introduced as auxiliary input into F
- Useful in temporal (i.e., dynamic time-dependent) systems

(Figure adapted from the course book)

Iterative Network: Heart Rate Estimation by Kalman Filter

- Dynamic and measurement models

$$\mu_{k|k} = \mu_{k-1|k-1} + v_{k-1}, v_{k-1} \sim \mathcal{N}(0, Q)$$

$$y_k = \mu_k + w_k, w_t \sim \mathcal{N}(0, R)$$

- The prediction step

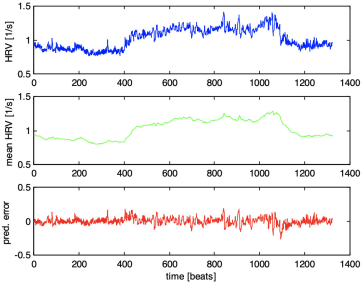
$$\mu_{k|k-1} = \mu_{k-1|k-1}$$

$$\Sigma_{k|k-1} = \Sigma_{k-1|k-1} + Q$$

- The update step

$$\mu_{k|k} = \mu_{k|k-1} + K_k(y_k - \mu_{k|k-1})$$

$$\Sigma_{k|k} = (I - K_k)\Sigma_{k|k-1}$$



- Kalman gain

$$K_k = \Sigma_{k|k-1}(\Sigma_{k|k-1} + R)^{-1}$$

(Figure: Schlogl,A. et. al (2001). Adaptive mean and trend removal of heart rate variability using Kalman filtering. In: Proc. 23rd Int. Conf. IEEE Engng. Med. Bio. Soc.)

Fusion Topogies

- Centralized fusion system
  - Sensor fusion unit is a central processor or node, collecting all information from different sensors
  - Communication bottlenecks, inflexibility, vulnerability, non-modularity, challenges in sensor alignments
- Decentralized (or distributed) fusion system
  - Sensor measurements and information is fused locally using a set of local fusion nodes
  - Reduced communication, scalable, robust, modular, insensitive to sensor alignments
  - Suffers from the effects of redudant information
- Hierarchical fusion system
  - Hybrid architecture mixing together the centralized and decentralized systems
  - Insensitive to sensor alignments, can reduce redudant information issues

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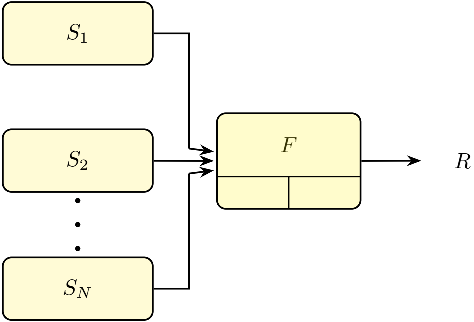
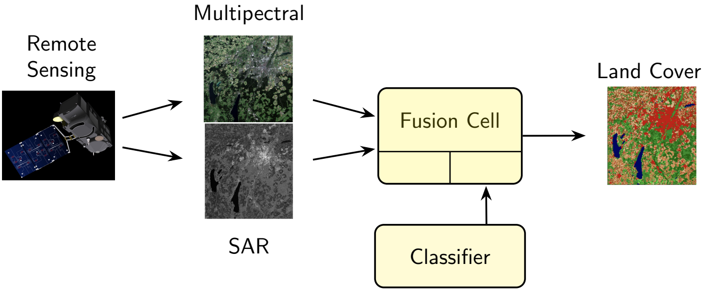
Centralized Architecture



- Centralized fusion network with a centralized node F. The input to F are produced by separate N logical sensors or data sources S_m, $m \in \{1, 2, \ldots, N\}$.

(Figure adapted from the course book)

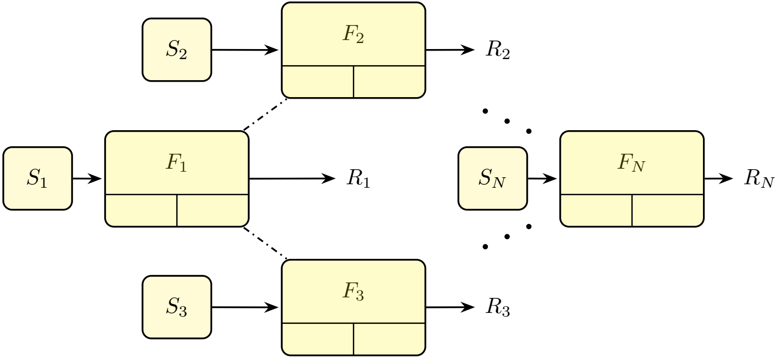
Centralized Architecture: Remote Sensing



- Satellite remote sensing for multimodal land cover classification
- Centralized architecture to fuse multispectral and synthetic aperture radar (SAR) images

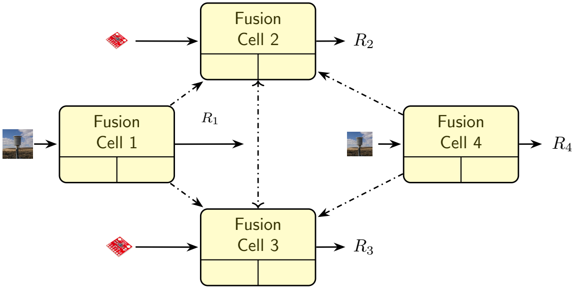
(Adapted from: R. Bahmanyar, D. Espinoza-Molina and M. Datcu, "Multisensor Earth Observation Image Classification Based on a Multimodal Latent Dirichlet Allocation Model," in IEEE Geoscience and Remote Sensing Letters, vol. 15, no. 3, pp. 459-463, March 2018.)

Decentralized Architecture



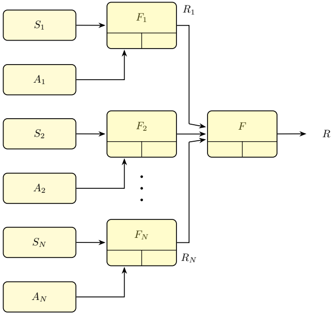
- Decentralized (or distributed) fusion network of N local fusion nodes F_m producing result R_m from its input data source S_m $m \in \{1, 2, \ldots, N\}$.

Decentralized Architecture: Environmental Monitoring



- Environmental monitoring (weather, air quality etc.) using spatially distributed sensors and data fusion network
- Each node fuses local sensor data with neighboring nodes (e.g., to calibrate more uncertain measurements)

Hierarchical Architecture

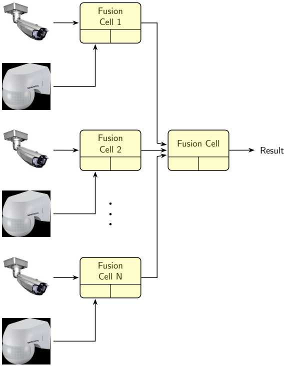


- Hiearchical fusion network with N decentralized local fusion nodes F_m producing intermediate result R_m from source S_m and auxiliary information A_m $m \in \{1, 2, \ldots, N\}$ to a centralized node F

(Figure adapted from the course book)

Hierarchical Architecture: Video Surveillance System

- Multi-modal surveillance system using network of locally combined motion detectors and cameras
- Motion detector can be used as an auxiliary data to start camera based tracking of a target
- In hierarchical architecture, tracking information of individual cells / camera views can be fused in centralized node



Recap

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Summary

- Smart sensor
  - Combines sensing, signal processing, and communication
  - Adapt to changes "intelligently"
- Sensor observation
  - Output of the sensor with relevant information
- Sensor uncertainty
  - Inherits from different error sources
  - Can be modeled and fused by Bayesian approach
- Data fusion node
  - Combines sensor data, auxiliary information, and external knowledge
  - A Bayesian computational framework can be applied
- Data fusion networks and topologies
  - Fusion networks can be parallel, serial or iterative
  - Topologies can be centralized, decentralized or hierarchical
  - Choices depends on the applications and the complexity of fusion problem