Sensors: Modeling and Management

A Two days seminar on
Wireless Sensor Networks: Security Issues and Applications
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- smart sensor is a hardware/software device that comprises in a compact small unit
- a sensor element, a micro-controller, a communication controller
- the associated software for signal conditioning, calibration, diagnostic tests and communication

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- sensor as a small "window" through which it is possible to view a physical property which is characteristic of the outside world or environment
- the physical property is evolving continuously in time and value
- the sensor provides a snapshot of the process: often output of a sensor is reduced to a single scalar value

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- time instant t - it is time when the physical property was measured
- in real time systems the time of a measurement is often as important as the value itself

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- sensor observation 5-tuple $O = \langle E, \mathbf{x}, t, \mathbf{y}, \triangle\mathbf{y}\rangle$
- spatial location $\mathbf{x}$ is censored, represented by $*$

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- Sensor uncertainty $\triangle \mathbf{y}$
- sensor measurements are uncertain, which means that they can only give an estimate of the measured physical property

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- loading errors - arise if the sensor is intrusive which, through its operation, alters the measurand
- envrionmental erros - arise from the sensor being affected by environmental factors which are not taken into account

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- spurious readings in ToF ultrasonic sensor
- sensor will detect an obstacle at a given range r when there is no object at r,
- this can happen if the sensor receives a pulse emitted by second sensor and interprets the pulse as if it were its own pulse

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- Function - sensors classified in terms of their functions, i.e. in terms of the parameters or measurands which they measure
- measurands include displacment, velocity, acceleration, dimensional, mass and force

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- Energy type - sensors classified according to the type of energy transfered to the sensor
- for example, thermal energy involves temperature effects in materials including thermal capacity, latent heat and phase change properties, or
- electrical energy involves electrical parameters such as current, voltage, resistance and capacitance

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- heterogeneous sensors - different characteristics and types
- redundant sensors
- contradictory sensors - different information about the same entity
- different granuality sensors - provide redundant data but which observe the environemt at different scales
- synchronous/asynchronous sensors - provide data which are temporally concordant or not

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- data sources are distributed, complementary and heterogeneous

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- this information will also be required when the fusion of multi-sensor input data is considered
- in that case include the sensor model within the general background information I

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- θ represents the true value of the variable of interest Θ
- $\mathbf{y} = (\mathbf{y}_1^T, \mathbf{y}_2^T, \ldots, \mathbf{y}_N^T)^T$ denotes the vector of N sensor measurements
- Bayesian viewpoint assumes that all the available information concerning Θ is contained in $p(\Theta = \theta | \mathbf{y}, I)$

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- A priori pdf $\pi(\theta|I)$ - continuous probability density function which describes a priori beliefs about θ
- in the absence of any further information, often model the distribution using a histogram of historical data or may construct it from a priori information (have concerning typical θ values)

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- unless stated otherwise assume θ and $\mathbf{y}_i$ $i \in \{1, 2, \ldots, N\}$ are continuous
- in this case a probability which is a function of Θ or $\mathbf{y}$ should be interpreted as a probability density function or distribution

Sensor Model

- there are two states $\Lambda = \{\lambda_0, \lambda_1\}$
- λ_0 denotes fault free operation and λ_1 denotes faulty operation
- ordinarily $P(\Lambda = \lambda_0) \approx I$
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- Λ_i denotes the status of the sensor when it makes the ith measurement $\mathbf{y}_i$
- Likelihood $p(\mathbf{y}|\theta, \Lambda, I)$ - continuous function
- describes how the raw sensor measurements $\mathbf{y}$ depend on the true value θ, the background information I and the sensor status Λ

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- integrity monitoring in a Satellite Navigation System
- it refers to the detection and isolation of faulty measurement sensors
- system is described by a linear Gaussian model

$$\mathbf{y} = H\theta + \mathbf{b}(\Lambda) + \mathbf{w}$$

- $\mathbf{y} = (y_1, y_2, \ldots, y_N)^T$ denotes the vector of N input measurements
- $\theta = (\theta_1, \theta_2, \ldots, \theta_M)^T$ is the unknown vector of navigation parameters
- H is a known $N \times M$ measurement matrix
- $\mathbf{b}(\Lambda) = (b_1(\lambda_1), b_2(\Lambda_2), \ldots, b_N(\Lambda_N))^T$ is a vector of unknown measurements biases described by two state model

$$b_i = \begin{cases} 0 & \text{if} \quad \Lambda_i = \lambda_0 \\ B_i & \text{if} \quad \Lambda_i = \lambda_1 \end{cases}$$

Sensor Model: Example

- $\mathbf{w} = (w_1, w_2, \ldots, w_N)^T$ is a vector of random measurement noise
- for $\mathbf{w}$ zero mean Gaussian pdf $\mathbf{w} \sim \mathcal{N}(\mathbf{0}, \Sigma)$
- assume that multiple failures do not occur
- use E_i to denote the case of a failure in the ith measurement and E_0 to denote the case of no failures
- posteriori pdf $p(\theta|\mathbf{y}, I)$ as sum over all E_i

$$p(\theta|\mathbf{y}, I) = \frac{\sum_{i=0}^{N} P(E_= E_i|I) p(\mathbf{y}|\theta, E = E_i, I)}{p(\mathbf{y}|I)}$$

- it can be shown that the a posteriori pdf may be rewritten as

$$p(\theta|\mathbf{y}, I) = c_i \mathcal{N}(\theta|H_{(i)}^{+}\mathbf{y}_{(i)}, S_{(i)})$$

Sensor Model: Example

- $H_{(i)}$ and $\mathbf{y}_{(i)}$ are respectively the matrix H and the vector $\mathbf{y}$ with the ith row removed
- $\Sigma_{(i)}$ is the covariance matrix Σ with ith row and column removed

$$H^{+}_{(i)} = (H^{T}_{(i)}\Sigma^{-1}_{(i)}H_{(i)})^{-1}H^{T}_{(i)}\Sigma^{-1}_{(i)}$$

$$S_{(i)} = (H^{T}_{(i)}\Sigma^{-1}_{(i)}H_{(i)})^{-1}$$

- $p(\theta|\mathbf{y}, I)$ describes the posteriori distribution of the unknown vector θ
- c_i describes the integrity or relative probability that the ith measurement is in error
- there are applications which require a different shaped pdf
- non-Gaussian asymmetric likelihood function is used in modeling an ultrasonic sensor

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- Konolige Model for a ToF ultrasonic sensor
- obtain a range reading equal to R then the fault free i.e. $\Lambda = \lambda_0$
- likelihood function is $p(r \circ R|r_0)$ and $r \circ R$ denotes that
- the first detected echo corresponds to a distance R $(r = R)$ and that no return less than R was received $(r \nless R)$
- Let $p(r = R|r_0)$ and $p(r \nless R|r_0)$ denote the conditional pdfs corresponding to $r = R$ and $r \nless R$ then
- likelihood function for a time of flight ultrasonic sensor is

$$p(r \circ R|r_0) = p(r = R|r_0) \times p(r \nless R|r_0)$$

$$p(r \nless R|r_0) = 1 - \int_0^R p(r = x|r_0)dx$$

Sensor Model: Example

to a good approximation

$$p(r = R|r_0) \propto \frac{1}{\sqrt{2\pi\sigma^2}} \exp -\frac{1}{2}\left(\frac{r - r_0}{\sigma}\right)^2 + F$$

- F is a small constant which takes into account multiple targets which may reflect the sensor beam, in additon to the target at r_0
- in practice the range error becomes proportionally larger and
- the probability of detection becomes proportinally smaller at increasing range
- incorporating this effeccts into the above likelihood function - the konolige likelihood function

Sensor Model: Example

$$p(r \circ R | r_0) = \gamma \left[\frac{\alpha(r)}{\sqrt{2\pi\sigma^2(r)}} \exp -\frac{1}{2} \left(\frac{r - r_0}{\sigma(r)} \right)^2 + F \right] \times \left(1 - \int_0^R p(r = x | r_0) dx \right)$$

- γ is a normalization constant
- $\alpha(r)$ describes the attenuation of the detection rate with increasing distance
- $\sigma(r)$ describes the increase in the range variance with increasing distance

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- requires sensor management
- a process that seeks to manage, or coordinate, the use of a set of sensors in a dyanmic, uncertain envrionment, to improve the performance of the system

Sensor Management

Sensor Management

- to data fusion block - for processing
- sensor observations O_i, $i \in \{1, 2, \ldots, N\}$ are sent from the sensors S_m, $m \in \{1, 2, \ldots, M\}$
- from data fusion block to human operator for monitoring the entire scene
- inputs to the sensor manager from the data fusion block and from operator
- need to transmit sensor observations $\mathbf{y}$ with minimal delay
- information passing between the sensor manager and the sensor and the data fusion blocks subjected to a significant delay
- action performed diagnostic, managment, configuration, planning

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- resource planning is the highest hierarchical level in the sensor management
- the placement of the sensors, or the optimal mixture of the sensors required for a given task

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Sensor Management: Example

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- i.e. to minimize the sum of the number of the number of genuine employees who are refused access and the number of imposters who are allowed access

Sensor Management: Example

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- new paradigm for detecting and predicting hazardous weather
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- a search volume V which occupies the lowest few kilometers of the earth's atmosphere
- heart of DCAS system is a meteorological command and control (MCC) unit which performs the systems main control loop
- important function performed by the MCC is the allocation / optimization processes
- that determines the strategy for taking radar measurements during the next radar scan

Sensor Management: Example

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- the object type e.g. scanning an areas with a tornado vertex will have higher utility than sensing clear air
- user based considerations, such as the distance from a population center
- e.g. among two objects with identical features, the one closer to a population center will have higher utility

Sensor Management: Example

- Mobile sensors observing an area of interest

Sensor Management: Example

- Mobile sensors observing an area of interest
- application needs the coordination of several autonomous sensors S_m $m \in \{1, 2, \ldots, M\}$
- the sensors S_m are required to co-operatively monitor an area of interest
- each sensor S_m has its own dynamics (specified by a velocity vector $\mathbf{V}_m$ and can only perceive a limited local area A_m)
- the local areas can be shared by the sensors
- a local picture from one sensor can be used to direct the attention of other sensors
- the sensor manager is responsible for coordinating the movements and sensing actions of the sensors so that
- an optimal picture of the entire surveillance area with minimal consumption of time and resources

Sensor management techniques

Sensor management techniques

- information-theoretic criteria

Sensor management techniques

- information-theoretic criteria - from this point of view
- multi-sensor data fusion is concerned with increasing the information,
- i.e., reducing the uncertainty, about the state of the external world or environment
- the task of sensor managment is to optimize the multi-sensor data fusion process such that
- the greatest possible amount of information is obtained whenever a measurement is made
- the optimal selection of a sensor using an information tehoretic criteria assume a target is known to be present in a given surveillance area

Information-theoretic approach

- $\mathbf{x}$ dentoes the unknown location of the target
- $\mathbf{y}_m$ denotes the observation from sensor S_m
- Let $\pi(\mathbf{x}|I)$ denote the a priori location of the target
- suppose S_m $m \in \{1, 2, \ldots, M\}$ denotes a set of M sensors
- observation likelihoods are $p(\mathbf{y}_m|\mathbf{x}, I)$
- aim is to select the sensor S_m whose observation will maximize the mutual information $MI(\mathbf{x}, \mathbf{y}_m)$
- the mutual information $MI(\mathbf{x}, \mathbf{y}_m)$ is given by

$$MI(\mathbf{x}, \mathbf{y}_m) = \int p(\mathbf{x}, \mathbf{y}_m|I) \log \frac{p(\mathbf{x}, \mathbf{y}_m|I)}{p(\mathbf{x}|I)p(\mathbf{y}_m|I)} d\mathbf{x} d\mathbf{y}_m$$

Information-theoretic approach

- $p(\mathbf{x}, \mathbf{y}_m|I) = p(\mathbf{y}_m|x)p(\mathbf{x}|I)$
- $p(\mathbf{y}_m|I) = \int p(\mathbf{x}, \mathbf{y}_m|I)d\mathbf{x}$
- choose the observation, i.e., the sensor which maximizes the mutual information $MI(\mathbf{x}, \mathbf{y}_m)$

$$m_{\mathrm{OPT}} = \arg\max MI(\mathbf{x}, \mathbf{y}_m)$$

- with assumption of Gaussian distributions for the state of the target
- sensor selection using mutual information

$$MI(\mathbf{x}, \mathbf{y}) = \frac{1}{2}\log(|P_{\mathbf{x}}|/|P_{\mathbf{y}}|)$$

- $P_{\mathbf{x}}$ and $P_{\mathbf{y}}$ are the covariance matrices before and after a measurement has been made

Bayesian Decision-Making

Bayesian Decision-Making

- from this point of view
- sensor management as a decision-making task in which aim is to minimize a given loss function
- e.g. sensor control of the biometric sensors
- an adaptive mutimodal biometric management algorithm
- consider M independent biometric sensors S_m $m \in \{1, 2, \ldots, M\}$
- the task of identifying an unknown person O as a hypothesis testing problem with the following two hypotheses:
- $H = h_1$ the unknown person O is an imposter
- $H = h_2$ the unknown person O is genuine

Bayesian Decision-Making

- suppose each sensor S_m receives a measurement vector $\mathbf{y}_m$ from O and outputs the decision variable $U_m \in \{u_1, u_2\}$

$$U_m = \begin{cases} u_1 \text{ if } p(U_m = u_1 | H = h_1) \geq \lambda_m p(U_m = u_2 | H = h_2) \\ u_2 \text{ otherwise} \end{cases}$$

  λ_m is an appropriate threshold
- assuming each of biometric sensors are independent then
- the optimal fusion rule can be implemented by forming a weighted sum of the incoming local decisions U_m $m \in \{1, 2, \ldots, M\}$ and the comparing it with a threshold t
- the weights and the threshold are determined by the reliability of the decisions,
- i.e., by the probabilities of the false alarm and miss of the sensors S_m

Bayesian Decision-Making

- the output decision variable is $\tilde{U} = u_{\text{OPT}}$

$$u_{\text{OPT}} = \begin{cases} u_1 \text{ if } \left[\sum_{m=1}^{M} \left(z_m \log \frac{1-p_m^M}{p_m^F} + (1 - z_m) \log \frac{p_m^M}{1-p_m^F} \right)\right] \geq t \\ u_2 \text{ otherwise} \end{cases}$$

$$z_m = \begin{cases} 1 \text{ if } U_m = u_1, \\ 0 \text{ otherwise} \end{cases}$$

- p_m^F and p_m^M are the probabilities of false alarm and miss for the sensor S_m
- $p_m^F = p(U_m = u_2 | H = h_1)$ and $p_m^M = p(U_m = u_1 | H = h_2)$
- optimally choose the threshold t in order to minimize the cost of a output decision U
- the cost depends on the a priori probabilities $p(H = h_1 | I)$ and $p(H = h_2 | I)$ and on the loss function

Thank You