Sensor Fusion

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The fusion of sensors or data is today often used for increasing precision in navigation, position and location of mobile objects in the shipping industry, GPS systems, and smartphones. This is due in part that some information may not be reliable when using the sensor data sources individually. By fusing several independent sensors containing individual information, their combined data may represent precise and usable information or distributions.

Furthermore, sensor fusion can be an improvement of single sensor measurements with sensory deprivation, limited spatial coverage, limited temporal coverage, imprecision or uncertainties being reduced. Therefore, sensor fusion can be designed in competitive, complementary or cooperative configurations. This chapter will mainly focus on complementary fusion where sensor fusion can be used to increase precision or reduce uncertainties by using multiple OF sensors for monitoring different parameters.

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Principle of Sensor Fusion

The terminology of fusing sensory data has often been defined as data fusion, sensor fusion, information fusion or multisensor integration. The terminologies are often used for online sensors, offline sensors or intelligence data used in combination with offline and online sensors. Tools and methods are used to combine a set of intelligence data or sensor data from different sources, so the resulting information is better than if the sources were used individually [1]. The resulting information may be obtained from independent heterogeneous or homogeneous sensor sources. Some limitations of using single sensors may include:

Limited Temporal Coverage Single sensors may suffer from long response times due to the processing of data such as frequency filters, curve fitting and statistical analysis. Long response times may also be due to the collection of measurements to obtain a sufficiently high signal.

Limited Spatial Coverage Single sensors may only observe a limited section of a process with spatial differences. The single sensor may only then detect the likelihood of this state that can largely differ from the mean average. The use of several sensors may resemble the mean average state of a process with spatial differences.

Sensory Deprivation The failure of a sensor causes a loss in the observation of a process. By employing sensor fusion, it is still possible to observe a process with sensor failures.

Evolution in nature has already implemented multisensor integration of acoustic sensing (hearing), light detection (sight), pressure detection (touching) and chemical detection (taste and smell) to increase the precision in measuring the observed environment. For humans, our precise perception of the environment is highly dependent on using all our five senses to estimate the state of the surrounding nature. The state (temperature) of water may not be accurately estimated only by using either of the five senses individually. Evaporation of water can be observed with our eyes to estimate water temperature. Our touch sensors can feel the temperature of the environment (cold, hot) to relate observed water vapour with external temperature.

When combining sensors, the total information may be represented as follows. In cold environments, the difference in temperature between hot water and the external environment is high, and water may also evaporate at temperatures far from boiling point. With human hearing, water boiling can be sensed acoustically without detecting it with sight. The resulting information is perceived as high-temperature water, which we can process to decide not to make physical contact with the water. This exemplifies how the combination of information from different sensors are increasing the precision and reducing uncertainty in the state estimation of a parameter.

Sensor Fusion Possibilities

The sensor fusion possibilities may be systemised into three categories that summarise their configuration.

Cooperative Configuration The sensor fusion may be cooperative configured when two independent sensors monitor the same parameters to derive more information about a process than the information obtained when using a single sensor. Stereoscopic vision is a cooperative sensor fusion configuration where several images are obtained at different viewpoints. The different images at different viewpoints are then used to resemble a three-dimensional image of the observed object [2].

Competitive Configuration The sensor configuration can be competitively configured if the sensors monitor independent parameters of the same property. This way, the sensors with the largest signal-to-noise ratio, or the sensors that have a response accordingly to a statistical model, will be included in the parameter computations. Competitive systems can often be combined with the cooperative configuration.

Complementary Configuration A complementary sensor fusion configuration applies sensors that either monitor two different environments or monitors the same environments with two different and independent sensor systems with different signal and noise functions. By using multiple cameras to observe separate parts of a room or using an electronic and an optic sensor in combination to monitor temperature can be categorised as a complementary sensor fusion configuration. This configuration can offer an increase in monitoring precision of a process that would not be possible with single independent sensors.

Data Handling

The simplest form of sensor fusion can be obtained by using two different sensor parameters and by performing an averaging process, or to choose the maximum value of energy and transfer it to the result. The signal to noise ratio may be increased by fusing two sensor responses $A\times1$ and $A\times2$. The wavelet transforms contain a signal, a and b, and an error or noise as c and d. The sensor fusion has obtained an average of the signal, and error $A\times1$ and $A\times2$. The result increased signal to noise ratio from a/b to $(a + b)/(c + d)$. For the maximum value method signal to noise is also increased.

The Kalman filter method may increase precision for systems such as the two-sensor fusion example above [3]. Instead of averaging over the signal and noise, each sensor parameter measurement is weighted differently based on its variance σ^2. The sensors with minimal covariance are weighted more than the sensors with higher covariances. This leads to filtering out noise from using the multiple sensors with independent parameter measurements. For a simple sensor fusion using two sensors performing one measurement only, the Kalman filter can be used to compute the best estimate of the state as:

$$\widehat{x} = z_1 + K(z_2 - z_1) \tag{5.1}$$

$$\sigma^2 = (1 - K)\sigma_1^2 \tag{5.2}$$

$$K = \frac{\sigma_1^2}{\sigma_1^2 + \sigma_2^2} \tag{5.3}$$

where z_1 and z_2 are the two sensor measurements, K is Kalmar gain, and σ_1^2 and σ_2^2 are the gaussian noise of sensor measurement z_1 and z_2, respectively. The variances from the two sensors are used to weigh the measurement to find the best estimate of the state.

Note that the statements above are a simplification of using a Kalman filter for sensor fusion. The filter may be extended for non-Gaussian noise and for time dependence. In most situations, it is not only a low signal to noise that is the issue but also drift in measurement due to the time dependence of the sensor monitoring the state of a system. Some extensions of Kalman filter methods are:

Non-linear Systems Since linear modelling is not always possible, extended Kalman filter methods have been derived that use non-linear stochastic difference equations to perform the system modelling [4].

Estimation of System Parameters Statistical parameters are not always prior known and are not constant over time. Therefore, a version of the Kalman filter method has been produced to estimate statistical parameters [5].

Least Mean Square Optimisation Alternatives The use of the least mean square approach minimises the error in the Kalman filter method. Other alternatives may be better suited for specific applications, such as the H_∞ norm [6].

Other sensor fusion algorithms of importance are also support vector machine, Bayesian inference technique and fuzzy logic.

Bayesian Inference Technique Multiple sensor parameters can be used to find the probability of a process to be described in a specific state, such as a rock blocking the road. The process is described either being in a state of a clear or blocked road. The multiple sensors are providing information about whether there the road is blocked or not and by using the inference technique, the highest probability is found for either of these states. This sensor fusion is increasing the completeness in estimating an observed process.

Fuzzy Logic Fuzzy logic is a method where the uncertainty in multisensor fusion can be categorised in the inference processes. The inconsistent information from the sensor parameters is "truth" valued with a number between 0 and 1. Based on the process observed, the most trustworthy sensor parameters are valued as significant depending on the rule applied. The rules added to the model may also be weighted differently statically or dynamically.

Support Vector Machine Multiple sensor parameters can be combined with support vector machine algorithms that are supervised, learning models. Classification and regression analysis about a process is performed in advance and serves as a set of training examples. The SVM is optimising a hyperplane based on the input sensor parameters and minimises structural error or maximising margins. This sensor fusion method is increasing the completeness of an observed process by including several sensors.

Sensor fusion allows physical limitations to be overcome in sensor systems. There are a host of different fusion techniques, some of which have been briefly covered here. Although many methods have been left out, Kalman Filter and Bayesian reasoning methods are generally used most frequently when fusing sensors.

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