Extended Confidence-Weighted Averaging in Sensor Fusion

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Abstract — *Systems that deduce information about their environment from sensor data can increase the accuracy and reliability of such information by replicating sensors and combining or "fusing" their measurements. The corruption of single measurements through failures of the sensor or random noise can thus be masked. Research conducted in this field so far, however, has not taken into consideration that the errors committed by sensors are not always uncorrelated. Ignoring such dependencies can lead to a suboptimal fused result.*
In this work, the approach of confidence weighted averaging is extended to take such dependencies into consideration. The effect of the new approach on fusion results is analyzed using sensor information from a mobile robot.

I. Motivation

Due to the possible influence of hardware failures, uncertainties in a system's environment and random noise, measurements obtained from a single sensor are generally unreliable. Systems that depend on information about their environment acquired through sensors can increase the reliability of such information using multiple sensors. By estimating the true value of an observed variable by fusing the information obtained by various sensors, the effects of sensor errors like inaccurate measurements or a complete failure of a sensor on the behavior of the system can be overcome.

While many sensor fusion methods concentrate on the fusion of classifiers or decisions, the field relevant for this work, that of fusing continuous-valued variables, has not been treated as extensively. The task is to combine real-valued measurements of the same variable taken by various sensors at the same point in time to derive an estimate of that variable at that specific point in time. We will therefore not fuse measurements taken in the course of time, as methods like the Kalman filter [1] do.

Existing Methods for such a task, like those suggested by Marzullo [2], Schmid and Schossmaier [3], or Elmenreich [4], do not consider correlations between sensor errors. However, the behavior of sensors can be greatly correlated, for example if they are of the same make and show the same inherent behavior. We will propose a method of calculating a weighted average of measurements, where the weights are determined by the variance and correlations of measurement errors. The introduction of correlations not only improves the result of a single fusion process but also reduces the risk of propagating imprecise estimates in the case of a more complex architecture.

II. Confidence-Weighted Averaging

To combine the measurements, a simple mean of all the values does not usually perform well enough. The reason for that is that some sensors may be more reliable than others, so that their measurement can be expected to represent the true value more accurately. It is reasonable to assign more importance and therefore a greater weight to an observation x_i from a sensor that is more reliable than to one from a less accurate sensor and calculate a weighted average according to (1).

$$x_{FUSED} = \sum_{i=1}^{N} x_i w_i \tag{1}$$

One way to determine the weights w_i for such a weighted average is to base them on the variance of the measurement error committed by each sensor as expressed in (2)[4]. The variance of the fused result can be determined through expression (3). For the case that the errors are independent, assigning the weights in this way is optimal in the sense that the expected variance of the fused result is minimized.

$$w_i = \frac{1}{\sigma_i^2 \sum_{j=1}^{n} \frac{1}{\sigma_j^2}} \tag{2}$$

$$\sigma_{FUSED}^2 = \sum_{i=1}^{n} w_i^2 \sigma_i^2 \tag{3}$$

The assumption of independency of sensor errors cannot be made in the general case. Ignoring correlations between fusion inputs results in a suboptimal assignment of weights to each observation, and a distorted estimate of the variance of the result. In the case of a system that uses distributed sources of information and fuses data at various points in the process, the estimated fused variance of a fused value will determine its influence on further fusion processes. Positive correlations, for example, cause the fused variance calculated according to (2) to underestimate the true variance, which in turn leads to a greater weight in the next fusion process than should be assigned.

III. Extended Confidence-Weighted Averaging

To take advantage of known correlations, the method described above can be extended. The variances and covariances of the sensor errors are expressed in the covariance matrix $\mathbf{\Sigma} = \sigma_{ij}$. The variance of the result of a weighted average is now

$$\sigma^2_{FUSED} = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \sigma_{ij}. \tag{4}$$

The vector of weights $\mathbf{w} = w_i$ that minimizes this fused variance can be calculated as in expressions (5)-(7), where $\mathbf{c_1}$ represents the first column of $\mathbf{\Sigma}$ without its first element σ_{11}, $\boldsymbol{\sigma_{11}}$ is a vector of $n-1$ replications of σ_{11} and $\mathbf{C}^*$ represents $\mathbf{\Sigma}$ without its first column and first row:

$$\mathbf{w}^* = \left(\boldsymbol{\sigma_{11}}\mathbf{1}^T - \mathbf{c_1}\mathbf{1}^T - \mathbf{1}\mathbf{c_1}^T + \mathbf{C}^*\right)^{-1}\left(\boldsymbol{\sigma_{11}} - \mathbf{c_1}\right) \tag{5}$$

$$w_1 = 1 - \mathbf{1}^T\mathbf{w}^* \tag{6}$$

$$\mathbf{w} = \begin{bmatrix} w_1 \\ \mathbf{w}^* \end{bmatrix} \tag{7}$$

IV. Multi-Sensor Case Study

In order to obtain sets of real sensor measurements for the evaluation of this method we have used a mobile robot equipped with three infrared sensors and two ultrasonic sensors. The sensors installed on the robot are interfaced by a TTP/A smart transducer network via a gateway node on the robot. Figure 1 shows a schematic representation of the measurement setup. The test obstacles were placed at various distances, while the sensor measurements were logged at a connected PC.

An evaluation of the data has shown that our extended approach to confidence-weighting can reduce the error of fused results, but shows its greatest advantage in an improved estimation of the variance of the result. The estimate is generally much closer to the true variance, so that the reliability relative to other measurements is estimated more accurately.

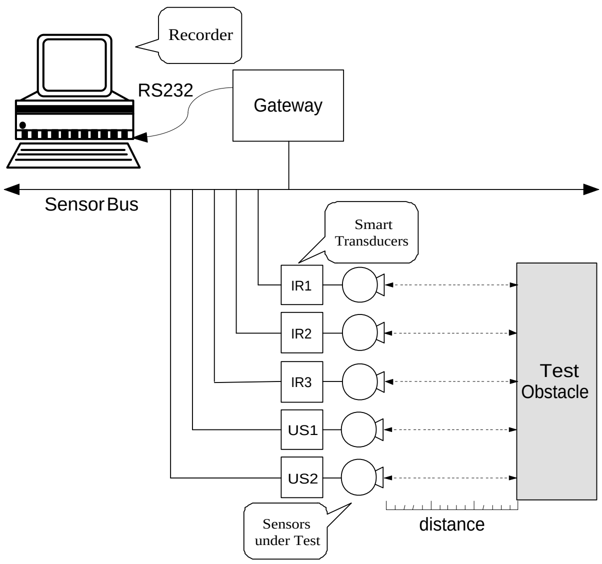

Figure 1: Setup for sensor fusion testing

If fused results are themselves used as inputs into another fusion process, we have found that the correlations between measurements can best be integrated when fusing highly correlated sensors in a first step. When fusing measurements with uncorrelated error first, dependencies between those fused inputs and others that will be added at a later point may be masked and cannot be fully considered in the calculations.

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