Approaches on Multi-Sensor Fusion Under Time-Evolving Conditions

Ren C. Luo, Woo Suk Yung, and Min-Hsiung Lin

Robotics and Intelligent Systems Laboratory
Electrical and Computer Engineering Department
North Carolina State University, Raleigh, NC 27695-7911

ABSTRACT

The objective of this paper is to develop a paradigm for optimum estimation of fused multiple sensor data in order to best use the sensor information in the time evolving environment. Two basic approaches have been developed: dynamic moving quadratic curve fitting and weighted least mean square error (LMSE). These two approaches are advantageous in terms of accuracy, speed, and versatility. The theoretical frameworks presented are supported by sets of simulation data.

1. Introduction

There has been a growing interest in recent years in the possible upgrading of robot intelligence through the integration of multiple sensors in order to widen the range of tasks possible within an increasingly unrestricted environment. For example, two panels of experts at the recent workshops on research needs for intelligent machines and manufacturing automation have identified multisensor integration and fusion as an issue of highest priority [1, 2]. Some notable work related to multisensor integration and fusion has been presented primarily with respect to mobile robots (although application is not restricted to this domain).

Early work in multisensor data integration and fusion appears to have been driven by the necessity to information from other sensor domains. In 1977, Nitzan et al. discussed a laser-based system to acquire registered reflectance and range data for scene analysis [3].

The number of publications on multisensor-related work has increased since the early 1980's. If we are to understand how to fully utilize the capability of a sensor, we need to develop a model of sensor behavior. The need for such models has been realized by Henderson et al. [4, 5] in their logical sensor framework and multisensor kernel system concept. These models describe sensor capabilities by the logical relationship between processing elements. They provide a good descriptive ability but fail to account for the uncertainty of sensor operation in a consistent manner and are not readily expandable to new sources of information.

Durrant-Whyte [6] has developed a model of a multisensor system that represents the task environment as a collection of uncertain geometric objects. Each sensor in the system is described by its ability to extract useful static description of the objects. A "contaminated" Gaussian distribution is used to represent the geometric objects. The sensors in the system are considered as a team of decision makers. Together, the sensors must determine a team consensus view of the environment. Pau [7] presented some ideas on multisensor data fusion from the point of view of Static Pattern Recognition, primarily referring to high-level multisensor data fusion independent of a particular application.

Some papers have introduced the concepts of Knowledge Engineering and Expert Systems to the integration and programming of assembly cells and robotic systems [8-11]. Gordon, Shortliffe and Peral [12,13] have discussed an Artificial Intelligent method for managing evidential reasoning in a hierarchical hypothesis space using Dempster-Shafer theory in the field of medicine. This method could be expanded to deal with the uncertainty of multisensor data fusion. Huntsberger and Jayaramanurthy [14] have used fuzzy logic to fuse information for scene analysis and object recognition. Consistent logical inference can take place if the uncertainty of the fusion process is modeled in some systematic fashion.

Today, many existing complex mobile robots employ multiple sensors. Sensor data fusion becomes important in improving a complex robot's performance by providing hybrid information, by reducing sensor errors, and by maximizing sensor use. Military applications provide another incentive to pursue R & D in multisensor integration [15]. Bowman et al. [16] deal with high-level integration of information supplied by four radar and infrared sensors on board fighter aircraft. Rauch [17] discusses the probability concepts for rule-based expert systems as decision aids for tactical data fusion. A more recent account of some work related to sensor fusion for military appli-
A generalized sensor fusion approach which is concerned with the central issues of sensor data consistency, complementarity, error detection, and the coordination of sensors becomes an important research topic. Although many good individual ideas have been explored, several key issues remain to be resolved for the fusion of multiple sensors. One of the key issues is the synchronization problem of sensors, especially sensors are used in the time evolving conditions. Due to the different sensor response time, we should predict all the different sensor data at certain time and proceed the data fusion.

One of the approaches for fusing low-level multisensor data is the use of the Kalman filter. This filter uses the statistical characteristics of the error modeled for each sensor to recursively determine estimates for the fused data that are optimal in a statistical sense. If the system can be described with a linear model and both the system and sensor error can be modeled as white Gaussian noise, the Kalman filter will provide unique statistically optimal estimates for the fused data. However, the numerical instability and the linearity assumption of the system model may present the potential problems.

We have developed two approaches including quadratic moving curve fitting and weighted LMSE for fusing the multisensor under time-evolving conditions in the Robotics and Intelligent Systems Laboratory at North Carolina State University.

2. Fusion under Time-Evolving Condition

We have developed a general method for the fusion of redundant information from multiple sensors that can be used within their hierarchical phase-template paradigm. The central idea behind the method is to first eliminate from consideration the template paradigm. Although many good individual ideas have been explored, several key issues remain to be resolved for the fusion of multiple sensors. One of the key issues is the synchronization problem of sensors, especially sensors are used in the time evolving conditions. Due to the different sensor response time, we should predict all the different sensor data at certain time and proceed the data fusion.

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The objectives of the local estimator are 1) to convert the raw sensor data into an unified data format and 2) to minimize the observation noise and 3) to synchronize the sensor reading. In the static or quasi-static environment, the sensor measurements are constant or approximately constant with respect to time, and a static Fisher model will give the optimal estimation. If the object properties being observed are varying with respect to time or dynamic environment, we can not fuse the sensor data directly because the object position and orientation are subject to change between samples. To fuse the multiple sensor readings from different sensors in a dynamic environment, we must be able to obtain the sensor readings, from each of the sensors used at the specified time, e.g., $T_i$ in Figure 2. Generally speaking, the sensing timing (the time required to obtain a set of sensor reading) for different sensors will not be the same. One way to obtain the sensor readings from different sensors with different sensing timing at a specific time, for example $T_j$, is to use the previous sensor data to have the prediction of the sensor reading at $T_j$.

Assume that we have $n$ sensors which measure the same object property whose measurements and required sampling time are $x_i$ and $\Delta t_i$, $i = 1, \ldots, n$ respectively.

Generally speaking the time interval needed to fuse the sensor data (i.e., $T_j$ in Figure 2) is short enough for us to make the assumption that the object property does not change drastically during this time interval. Two approaches are introduces to estimate the sensor data at the specified time $T_j$.
2.1 Approach I
Moving Quadratic Curve Approximation

Assume that \( n_i \) is the number of sensor data to be used for the estimation of the measurement given by sensor \( i \) at time interval \( T_i \). The number of samples \( n_i \) used is incremented from 3 (the minimum number for a quadratic fit) up to a specified maximum number of samples. This curve fitting scheme has the capability to make use of historical data from previous subintervals up to the maximum number of samples, and thus the moving quadratic fit is achieved.

\[
E_{ij}(t) = a_{ij} + b_{ij}t + c_{ij}t^2
\]

where \( E_{ij}(t) \) is the moving quadratic fitting curve for sensor \( i \) at time interval \( T_i \), and \( t \) is the time elapsed from the beginning of the sampling till the data is fused.

The mean square error for this curve fitting \( E_{ij} \) is

\[
E_{ij} = \sum_{k=1}^{n_i} [a_{ij} + b_{ij}t_k + c_{ij}(t_k)^2 - f_{ij}(t_k)]^2
\]
2.2 Approach II

Weighted LMSE Approximation

Usually, multi-sensor data fusion algorithms assume that the basic statistics of data, such as probability density function, error mean, and error covariance, etc. are already known. These statistics are used to provide a consistent basis for data fusion. However, under the dynamic environment, targets may move randomly and its statistics are hardly known. Moreover, if a target moves, the timing of the observation at each sensor becomes a matter of concern. Since it is almost impossible to synchronize all the sensors to a global clock cycle, but a fused data should be generated at every given time interval, a certain algorithm would be needed at the sensor level to predict the state of the next stage rather than to estimate the current state.

The uncertain sensor data can be represented in the following mathematical model:

\[ z(n) = H x(n) + \eta(n) \]  (5)

Where \( z(n) \) is an observed sensor data vector at sampling time \( n \).

\( x(n) \) is a state vector at sampling time \( n \).

\( H \) is a relation matrix determined by each sensor.

\( \eta(n) \) is a noise vector at sampling time \( n \).

\( H x(n) \) can be represented as a Fourier series such as:

\[ Hx(n) = \sum_{i=-L}^{L} A_i \exp(i\omega_{s}f_{s}n) \]  (6)

where \( A_i \) is a Fourier coefficient.

The sinusoidal discrete process can be represented by the second order difference equations[22]. For example, let \( y(n) \) be a sinusoidal process, then:

\[ w_2y(n) + w_1y(n-1) + w_0y(n-2) = 0, \]

where the angular frequency of the sinusoid is given by the angle which the upper plane root on the unit circle subtends with the real axis, and \( w_i \) represents a filter coefficient.

It is reasonable to consider that noise has a wider band than a data signal. Then, \( Hz(n) \) can be approximated as:

\[ Hz(n) = \sum_{i=-L}^{L} A_i \exp(i\omega_{s}f_{s}n) \]  (7)

Without a loss of generality, let \( H \) be a unit matrix for simplicity. Then, \( z(n) \) can be represented by:

\[ z(n) = \sum_{i=1}^{2L} w_{2L-i}z(n-i) \]  (8)

This is an autoregressive filter equation with order \( p = 2L \).

Let’s assume that the stochastics of the target are not known, and derive some kind of preprocessor which estimate \( \dot{x}(n) \) with some stochastic data instead of passing the observed data \( z(n) \) directly to fusion process. With a given model as in equation (8), a lot of estimators have been introduced since the early 50’s. As aforementioned, some researchers show interests in the Kalman filter algorithm for the multi-sensor data fusion problem. However, since the Kalman filter algorithm requires that the dynamics of the target is pre-specified (Kalman filter estimates \( \dot{x}(n) \) with given \( w_i \) for \( i = 1, 2, \ldots, p \)), there are difficulties in using the Kalman filter under the dynamics environment where system dynamics are not known. A number of recursive algorithms have been developed to deal with dynamic estimation problem which estimate the system parameters \( w_i \). It is better
to estimate \( w \) than to estimate \( i(n) \) directly if sensors are not synchronized. However, since \( w \)'s may be time-variant, there is a need to emphasize the effect of current data more than past data values. Consider the following cost function:

\[
S_{N+1}(w) = \lambda S_N(w) + |z(N+1) - \hat{z}_N|^2
\]

(9)

Where

\[
\begin{align*}
\hat{w} &= \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_p \\ \hat{z}_{m} \\ \vdots \\ \hat{z}(m) \end{bmatrix} \\
\hat{z}_N &= \begin{bmatrix} \hat{z}(m+1) \\ \hat{z}(m+2) \\ \vdots \\ \hat{z}(m+p+1) \end{bmatrix}
\end{align*}
\]

\( \lambda \) is a weighting factor such that \( 0 < \lambda < 1 \). Note that \( \lambda = 1 \) gives the standard least square adaptive algorithm.

If we assume \( S_N(w) \) to be:

\[
S_N(w) = (w - \hat{w}_N)^T \hat{P}_N^{-1} (w - \hat{w}_N) + \beta_N
\]

(10)

Then, by using induction, we can obtain least square estimator which minimizes \( S_{N+1}(w) \) as follows.

\[
\hat{w}_{N+1} = \hat{w}_N + K_N(z(N+1) - \hat{z}_N)
\]

(11)

Where

\[
K_{N+1} = P_N z_N / (\lambda + \hat{z}_N^T P_N \hat{z}_N)
\]

(12)

\[
P_{N+1} = \frac{1}{\lambda} \left[ I - P_N \frac{z_N \hat{z}_N^T}{\hat{z}_N^T P_N \hat{z}_N} \right] P_N
\]

(13)

\[
\beta_{N+1} = \beta_N + (1 + \hat{z}_N^T K_{N+1})(z(N+1) - \hat{z}_N^T \hat{w}_N)^2
\]

(14)

\( \beta_{N+1} \) is a resulting cost function \( S_{N+1}(w) \) at \( w = \hat{w} \).

Now, initial values of \( \hat{w}_0, \hat{z}_0, \) and \( P_0 \) will be specified which will ensure the fast convergence. We apply least mean square error (LMS) estimator instead of choosing arbitrary values. Consider the accumulated error \( S_0(w) \) for some initial data set.

\[
S_0(w) = (z_0 - \hat{w}_0)^T(z_0 - \hat{z}_0)
\]

(15)

Choose \( \hat{w}_0 \) which minimize \( S_0(w) \), and set this as an initial value. Then,

\[
\hat{w}_0 = (z_0^T z_0)^{-1} z_0^T \hat{z}_0
\]

(16)

And,

\[
P_0 = (z_0^T z_0)^{-1}
\]

(17)

3. Preliminary Experimental Results

To demonstrate the idea and the validity of the mathematical modeling of the uncertain multi-sensor data, a simulated multisensor data fusion process in time evolving environment has been conducted. Two sets of simulation data have been used to test the success of aforementioned methods. First, we generate an arbitrary equation, \( f(t) = 5.0 \cos(\pi t) + 9.0 \sin(2\pi t) \), and sample it. White noise will be added to these sampled data. For dynamic moving quadratic curve approximation, the coefficients of the fitted quadratic curve of the simulated sensing data can be obtained by solving the equation (3). We then obtain the estimated sensor data \( \hat{z} \) at time \( t \), by applying the equation (4). The simulation parameters and the estimated sensor data at \( t \) are listed in Table 1. For weighted LMSE approximation, Table 2 shows the estimated sensor data at each sampling time and at time \( T_f \).

References

1) "Research Needs in Intelligent Machines," Proc. of a Workshop, prepared for the Center for Engineering Systems Advanced Research, ORNL, Oak Ridge, TN; pub-

Equation (18) can be modified into a state variable form such that:

\[
x(n) = A x(n-1)
\]

(19)

Where

\[
A = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 \\
0 & 0 & 1 & \cdots & 0 \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
0 & 0 & 0 & \cdots & 1 \\
0 & 0 & 0 & \cdots & 0 \\
0 & 0 & 0 & \cdots & 0 \\
\end{bmatrix}
\]

(20)

Let's assume that the estimator at time \( t = n \Delta + \delta \) is required where \( \Delta \) is a sampling interval of a sensor and \( \delta \) is a difference between the sampling time and the time at which estimated data is desired.

Equation (18) can be a discrete version of following continuous function.

\[
\hat{x}(t) = \mathcal{X} x(t)
\]

(20)

Where \( x(t) \) is a \( p \times 1 \) vector, and \( A \) is a \( p \times p \) matrix. The solution of equation (20) with initial condition at time \( t_0 \) is:

\[
x(t) = \exp[t(t - t_0)] z(t_0)
\]

(21)

By an approximation, \( A = I + \Delta \mathcal{X} \). And, compensated sensor output at the time \( n \Delta + \delta \) becomes the \( p^\text{th} \) element of \( z(n + \delta) \) where \( z(n + \delta) = \exp[t \mathcal{X} z(n)] \) candidate.
Table 1. Simulation Data of Quadratic Curve Approximation

<table>
<thead>
<tr>
<th>Sensor Reading #1</th>
<th>Coefficients</th>
<th>Noise Power</th>
<th>Sampling Rate</th>
<th>( T )</th>
<th>( z(T) )</th>
<th>( z(T) )</th>
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</thead>
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<tr>
<td></td>
<td>a</td>
<td>b</td>
<td>c</td>
<td></td>
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<td>1.025</td>
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<td>4.833 21.786</td>
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<td>1.025</td>
<td>10.512</td>
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<td>-16.866</td>
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<td>0.10</td>
<td>1.025</td>
<td>10.853</td>
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<tr>
<td>4.028 23.884</td>
<td>-17.450</td>
<td>0.4</td>
<td>0.14</td>
<td>1.025</td>
<td>10.175</td>
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<tr>
<td>5.011 21.934</td>
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<td>0.2</td>
<td>0.2</td>
<td>1.025</td>
<td>10.679</td>
<td></td>
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Table 2. Simulation Data of Weighted LMSE Approximation

<table>
<thead>
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<th>Sensor #1</th>
<th>Noise Power</th>
<th>Sampling Rate</th>
<th>( T )</th>
<th>( z(T) )</th>
<th>( z(T) )</th>
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