Multiresolutional Multisensor Target Identification

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Abstract

An algorithm for multiresolutional multisensor target identification is presented. It uses the computationally efficient scale sequential approach to hypothesis testing during identification and implements the inverse discrete wavelet transform to fuse data from different multiresolution sensors. We show that fusion leads to an increase in the probability of correct identification without a significant increase in the number of computations.

[1]

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I. Introduction

The goal of this paper is to investigate a multisensor multiresolutional approach to target identification. One sensor often does not provide enough information to build an ATR (Automatic Target Recognition) system that performs effectively against targets in natural and man-made clutter. There are strong indications [5] that the use of several sensors gives for target identification better results than the use of one sensor. Distributed filtering is an effective and computationally efficient method for optimal dynamic data fusion for uniform resolution sensors [3]. The important problem is the fusion of data from sensors (multicolor IR, visual, microwave, etc.) that provide information in different frequency bands and at different resolutions. Recently, the algorithms for dynamic multiresolutional distributed filtering were proposed, [4, 9] as well. In [4] the Discrete Wavelet Transform (DWT) is utilized as a bridge linking signals at different resolution levels. However, in most ATR problems, like recognition of ground targets, there is no underlying dynamic model and we cannot apply the idea of multiresolutional dynamic filtering. In this work an algorithm for multiresolutional multisensor data fusion without a model is proposed. The Inverse Discrete Wavelet Transform (IDWT) is used to fuse data at different resolution levels. We assume that data from all sensors are registered and that signals at different resolution levels are linked by the DWT. In our experiments we use two sensors operating in different frequency bands with differing resolutions. We compare the performance of our multiresolutional multisensor identification algorithm with the performance of the scale sequential algorithm for one sensor.

In Section II a short background of the discrete wavelet decomposition is presented. Section III describes the problem of an M-ary target identification in a sequential procedure that proceeds from low to high scales (resolution levels) in the multiresolution analysis of data space [2] in a manner analogous to sequential hypothesis testing in time [7]. Section IV discusses the problem of sensor/data fusion. It describes two common approaches to fusion. In the first approach data are fused at the levels as close to sensors as possible (fuse-then-abstract). In the second approach, information is first abstracted and then fused (abstract-then-fuse). Section V describes the simulated scenario for target identification and Section VI presents the results of experiments. And finally, Section VII discusses directions for future research.

II. Discrete Wavelet Decomposition

It is shown in [6] that a discrete signal can be decomposed into multiresolution frequency channels by using the DWT. Consider the space $l^2(Z)$ consisting of the square summable sequences $s^j(i)$, $i \in \mathbf{Z}$. For a given signal $s^j(i) \in l^2(\mathbf{Z})$ at resolution level j, a lower resolution low frequency signal can be derived by using a lowpass filter with an impulse response $h(i)$ and then by subsampling the output of the lowpass filter by two,

$$s^{j-1}(i) = \sum_n h(2i-n)s^j(n). \tag{1}$$

Similarly, a lower resolution high frequency signal can be derived by using a highpass filter with an impulse response $g(i)$ and then by subsampling the output of highpass filtering by two,

$$w_s^{j-1}(i) = \sum_n g(2i-n)s^j(n). \tag{2}$$

The original signal $s^j(i)$ can be recovered from the two lower resolution signals $s^{j-1}(i)$ and $w_s^{j-1}(i)$. However, filters $h(i)$ and $g(i)$ must meet some constraints in order to guarantee perfect reconstruction: the regularity constraint [1] and the orthonormality of the filter impulse responses. In such a case (1) and (2) can be considered as a decomposition of the signal onto an orthonormal basis. The original signal $s^j(i)$ can be reconstructed by

$$s^j(i) = \sum_n h(2n-i)s^{j-1}(n) + \sum_n g(2n-i)w_s^{j-1}(n). \tag{3}$$

In the *discrete wavelet decomposition* mode the output of the lowpass filter $h(i)$ is further decomposed (see Fig. 1) according to the procedure described above. This decomposition gives "details" (wavelet coefficients $w_s^j(n)$) of the signal as the output of highpass filter $g(i)$ at each resolution level j and the "average signal" (scaling coefficients $s^{j_0}(n)$) as the output of the lowpass filter at the lowest resolution level j_0.

Another well known decomposition mode is the *discrete wavepacket decomposition* mode in which both outputs from the lowpass filter and highpass filters are further uniformly decomposed into low and high frequency signals.

III. Multiresolutional Analysis

In this section we describe the general idea of the scale sequential approach to target identification. More details can be found in [2].

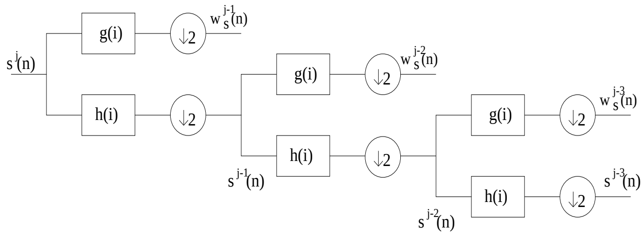

Fig. 1. Discrete Wavelet Decomposition.

We assume that the target signature database is available. The candidate hypotheses for a target ID are defined by

$$H_k : \quad y(t) = s_k(t) + N(t), \tag{4}$$

where $y(t)$ is the measured signal, $N(t)$ is noise and $s_k(t)$, $k = 0, 1, \cdots, K-1$, are target signatures. The multiple hypotheses H_k are assumed to be mutually exclusive. The optimal procedure is to test all $k \neq 0$ hypotheses against the null hypothesis $H_0 : \quad y(t) = N(t)$ and select that hypothesis that maximizes the log likelihood ratio over this set. However, such a procedure is computationally very intensive. In order to reduce the number of computations, we decompose the target signatures $s_k(t)$ and the measured signal $y(t)$ into the lower resolution signals using the wavelet decomposition. Computational savings during hypothesis testing are important in the case when we deal with large target signatures databases. They can be large not only because of a large number of targets we want to identify, but also because often there is a need for a large number of signatures corresponding to the same target (for example for different orientations of the target in a case of radar identification).

Let $w_y^j(n)$, $w_{s_k}^j(n)$ and $w_N^j(n)$ be the wavelet coefficients of the data $y(t)$, the k'th hypothesis signal $s_k(t)$ and the noise process $N(t)$ at the resolution level j and the time index n. Then, the candidate hypotheses in the wavelet space W^j are defined by

$$H_k : \quad w_y^j(n) = w_{s_k}^j(n) + w_N^j(n). \tag{5}$$

The wavelet basis is assumed to be orthonormal and the noise to have the Gaussian distribution. These hypotheses are tested by applying a log likelihood ratio approach in the sequential procedure which proceeds from coarse to finer resolution levels. At each resolution level those hypotheses that fail the test are rejected and removed from consideration at higher resolution levels. The sequential decision process is a generalization of Wald's theory of sequential binary hypothesis testing [7]. [7]. For $\sigma = 1$, the log likelihood ratio becomes

$$L(k) = \log \frac{P_k(y)}{P_0(y)} = \sum_j \sum_n w^j_{s_k}(n) w^j_y(n) - 1/2 \sum_j \sum_n w^j_{s_k}(n)^2. \qquad (6)$$

In general $j = -\infty$ to $+\infty$. However, in practical applications $j = j_0$ to J, where j_0 is the finest resolution and J is the coarsest resolution. Then Eq.(6) becomes

$$L(k) = \sum_{j=j_0}^{J} \sum_n w^j_{s_k}(n) w^j_y(n) - 1/2 \sum_{j=j_0}^{J} \sum_n w^j_{s_k}(n)^2 + L_0(k), \qquad (7)$$

where $L_0(k)$ is the log likelihood ratio computed at the coarsest resolution:

$$L_0(k) = \sum_n s^{j_0}_k(n) y^{j_0}(n) - 1/2 \sum_n s^{j_0}_k(n)^2, \qquad (8)$$

and where $y^{j_0}(n)$ and $s^{j_0}_k(n)$ are the scaling coefficients at the coarsest resolution j_0.

The main reason that we use the wavelet based sequential approach to target identification is due to computational savings. The number of coefficients $w^j_{s_k}(n)$ of each hypothesis signal is $N_j = 2^j$ so that the number of computations for computing the log likelihood ratio decreases geometrically with resolution level. According to [2] the number of computations (the number of multiplications and additions) required to test K hypotheses at the finest resolution is

$$N_{fine} = 4K(2^{J_{max}} - 1/4). \qquad (9)$$

In the wavelet based sequential approach we need only

$$N_{seq} = 4K(2^{j_0} - 1/4 + J_{max} - j_0) \qquad (10)$$

computations if 50% of candidate hypotheses are rejected at each resolution level. The computational savings ratio S is

$$S = \frac{N_{fine}}{N_{seq}} = \frac{2^{J_{max}} - 1/4}{2^{j_0} - 1/4 + J_{max} - j_0}. \qquad (11)$$

For example, for $J_{max} = 10$ and $j_0 = 5$ we get $S \approx 38$.

IV. Fusion For Target Identification

Our primary goal in this work is to investigate whether fusing data from two sensors, operating in different frequency bands with differing resolutions, can improve target identification in the presence of noise. The expectation of improved target identification probability based upon the combined information of two different signals over that of just one signal is quite intuitive. It is natural to expect that, through fusing signals from a number of sensors, some complementary information can be obtained that is not obtainable through only one sensor. For example, the radar provides range information and its signal is less affected by atmospheric attenuation as compared to the infrared image, while the infrared sensor provides information of greater resolution and is able to operate at night.

There are two common approaches to perform target identification (classification). In the first one, target is identified by individual sensors separately. Then the information from all sensors is fused to obtain a final decision (abstract-then-fuse). In the second approach, data from all sensors are combined together by so called low level (or sensor level) fusion. Then the target is identified using the fused data (fuse-then-abstract).

Our main objective is to determine how to perform sensor integration and data fusion at levels closer to the sensor. The goal is to increase available information while reducing the amount of processing. By using partially redundant information from different sensors, robustness of the ATR system is increased. A failure of one sensor does not necessarily result in the failure of the rest of the system. Because of this, less expensive sensors can be used, thus improving the economy of the ATR system.

VI. Multisensor Target Identification Scenario

For the purpose of illustrating the performance of our multisensor identification algorithm we were considering the problem of target identification using two sensors and a database (DBT) of target signatures. Fig. 2 shows our simulated scenario for target identification. There are two sensors s_1 and s_2 operating in different frequency bands with differing resolutions. In particular, sensor s_1 operates in a high frequency band and its resolution is twice as big as that of sensor s_2 which operates in a low frequency band. We assume that the DBT is created using a high quality sensor operating in the frequency band which completely covers the frequency bands of sensors s_1 and s_2. This high quality sensor has also higher resolution than sensors

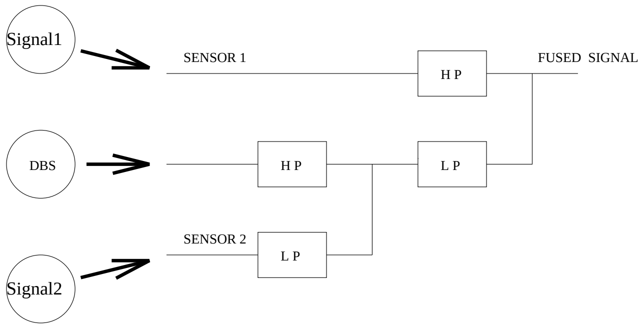

Fig. 2. Multisensor Scenario for Target Identification.

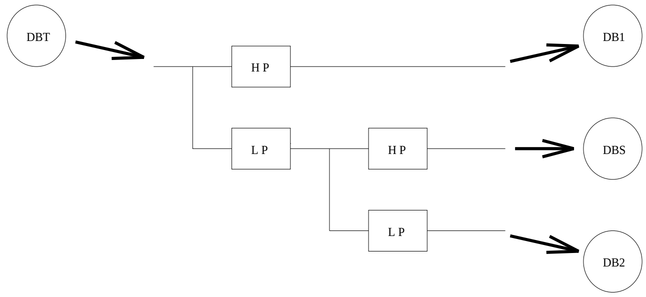

Fig. 3. Decomposition of the Target Signatures Database (DBT).

s_1 and s_2. Additionally, we require that it is possible to decompose the DBT (Fig. 3) into three new databases DB1, DB2 and DBS such that DB1 consists of the target signatures for sensor s_1 and DB2 consists of the target signatures for sensor s_2. The DBS is the complement signature database such that completeness of the DBT's information is preserved. The DBS database provides data for the middle branch of the scenario presented in Fig. 2.

The M-ary hypothesis testing is performed for both sensors separately. We accept N_1 hypotheses based on data from sensor s_1 and N_2 hypotheses based on data from sensor s_2. The number of hypotheses N_1 and N_2 depends on the way in which we implement the scale sequential hypothesis testing. In general, both N_1 and N_2 are very small. Next, we fuse signatures from the DBS database, which are determined by N_1 and N_2 hypotheses, with the data from sensors s_1 and s_2. This fusion utilizes the perfect reconstruction properties of the IDWT. The reconstructed signal has two advantages. First, it has a higher resolution than each of the individual signals separately. Second, the reconstructed signal will is less noisy, because the measurement data are fused with the deterministic signatures. If we assume that the standard deviation of the measurement noise for each sensor is σ then the standard deviation of the reconstructed signal will be less than σ. In particular, for the fused signal in our scenario, the standard deviation σ_f is:

$$\sigma_f = \sqrt{((\sqrt{\sigma^2/2})^2 + \sigma^2)/2} = \sqrt{3}\sigma/2 < \sigma. \tag{12}$$

After the fused signal is obtained, we perform hypothesis testing on the fused data. All N_1 and N_2 hypotheses are considered. We directly apply a likelihood ratio test to test these hypotheses. The log likelihood ratio then becomes

$$L(k) = \log \frac{P_k(f)}{P_0(f)} = \sum_i s_k(i)f(i) - 1/2 \sum_i s_k(i)^2, \tag{13}$$

where $f(i)$ is the fused signal, $s_k(t)$ are target signatures from the DBT and index i is discrete time. In general, the number of tested hypotheses using the fused signal is not large and the computational overhead is not significant. It could be as few as one hypothesis accepted by each sensor.

VII. Results of Experiments

In our experiments, we performed an M-ary hypothesis testing in a scale sequential procedure for each of the two sensors separately until only one hypothesis was accepted for each sensor. In the case that these two hypotheses differ fusion of the two signals was performed. The final decision were made based on the fused signal using the likelihood ratio test. We formed the DBT by generating random sequences of 256 samples each. The signatures were mapped into the wavelet domain by using the Haar basis.

Fig. 4 to 6 show a progress of the process of signal identification based on measurement data from sensor s_1 only. The "x"-es on the diagrams show which hypotheses are accepted at different resolution levels. Originally, we have 16 hypotheses. The small circles indicate the "true" hypothesis. Fig. 7 shows the final decision for sensor s_1 at the finest scale (hypothesis 3 is accepted in our case). Fig. 8 to 11 show a progress of the process of signal identification based on measurement data from sensor s_2. The hypothesis 6 is accepted at the finest level. Sensor s_1 works at resolution twice as high as that of sensor s_2. In particular, in our simulation, sensor s_1 was providing 256 measurements and sensor s_2 was providing 128 measurements. Fig. 12

shows the final (fused) decision. The hypothesis 6 is chosen instead of hypothesis 3 and this decision is correct. In this experiment, the measurements were corrupted by white noise with the standard deviation $\sigma = 2$.

We ran experiments for different levels of noise. Fig. 13 shows the performance of our algorithm. There are 50 runs for each level of noise. The level of noise is characterized by the standard deviation. The "-." line denotes the number of correct decisions made by sensor s_1 only. The "–" line denotes the number of correct decisions made by sensor s_2 only. The solid line denotes the number of correct decisions based on fused data. Notice that for a lower level of noise all decisions are correct. However, in a more noisy environment, fused decisions are much more accurate than decisions made by each sensor separately.

VIII. Future Research

One of our research goals is to develop a generic sensory data fusion framework. Towards this aim we carry out both theoretical investigations and experimental work. In proposing new architectural and algorithmic solutions we try to take advantage of those solutions that are well established in the subject literature, but at the same time we try to both expand the applicability and to improve the performance of our system by adding new features. In this work we take advantage of the computationally efficient scale sequential approach to the target identification problem [2]. But in order to improve its performance, we extend this approach to multiple multiresolutional sensors. The IDWT was used to fuse data at different resolution levels. In particular, we employed the simple Haar wavelets to choose the filter coefficients $h(i)$ and $g(i)$. We are going to investigate performance of our algorithm for other wavelet bases. For example, for FIR filters of width $N + 1$, Daubechies [1] has defined a set of smoothness conditions which produce a unique set of coefficients $h(i)$ and $g(i)$, $i = 1, \ldots, N$. The filters defined by these coefficients have better bandpass characteristics than these defined by the Haar wavelets. It was shown in [2] that the Daubechies basis has potential to give better results than the Haar basis. Also, we intend to relax gradually the assumption that signals at different resolution levels are linked by the DWT. We are going to investigate the sensor/data fusion problem for unregistered signals. In such a case, in general, it will not be possible to reconstruct the "true" signal. However, we believe, we will be able to obtain an approximation that will lead to the improvement of the performance of the identification process.

IX. Conclusion

An algorithm for multiresolutional multisensor target identification using the IDWT is proposed. It is shown that identification decisions using fused data from two sensors are more reliable than using each sensor separately. The significant increase in the number of correct identification decisions (especially for a low signal/noise ratio) is achieved by only a small increase in the number of computations. Another advantage of this method is that we can use two cheap sensors instead of a very expensive one to perform a target identification. The experiments were limited to the multiresolutional sensors which are linked by the discrete wavelet transform.

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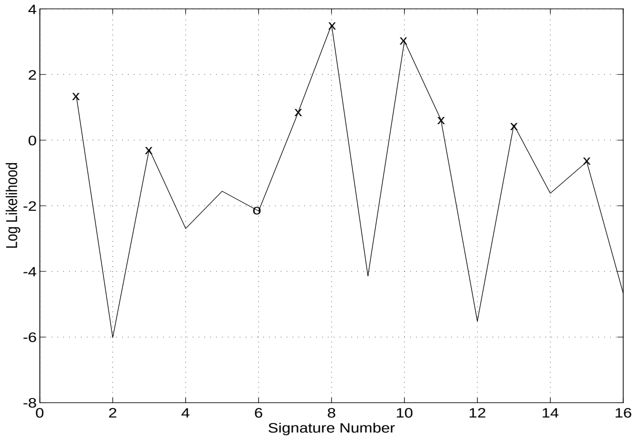

Fig. 4. Log Likelihood for Sensor 1 at Scale j=4.

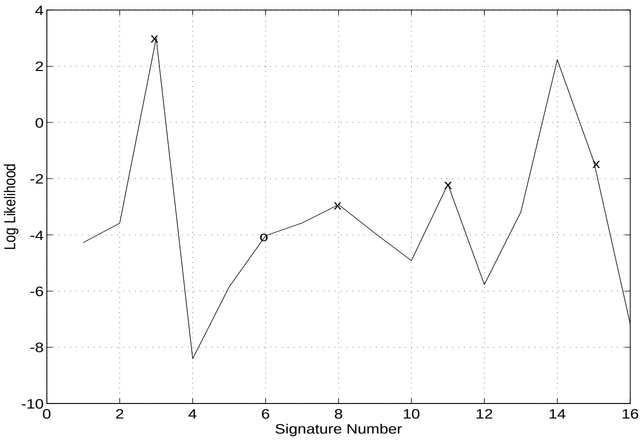

Fig. 5. Log Likelihood for Sensor 1 at Scale j=5.

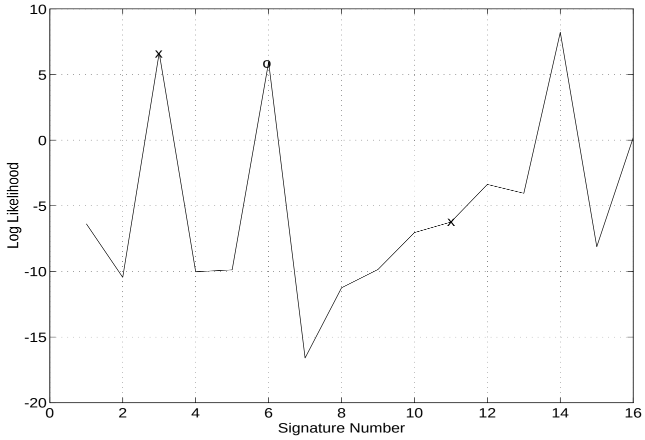

Fig. 6. Log Likelihood for Sensor 1 at Scale j=6.

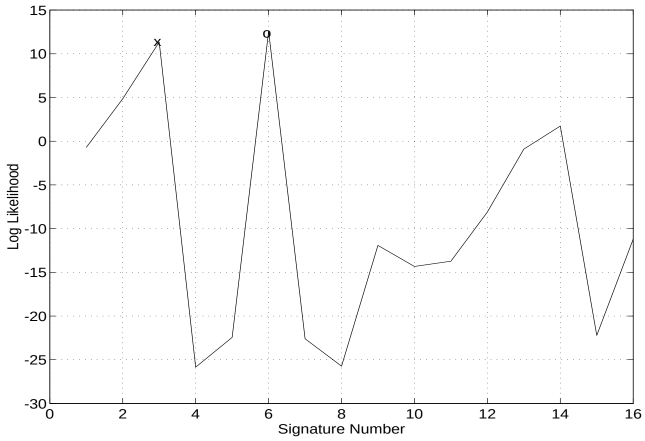

Fig. 7. Log Likelihood for Sensor 1 at Scale j=7.

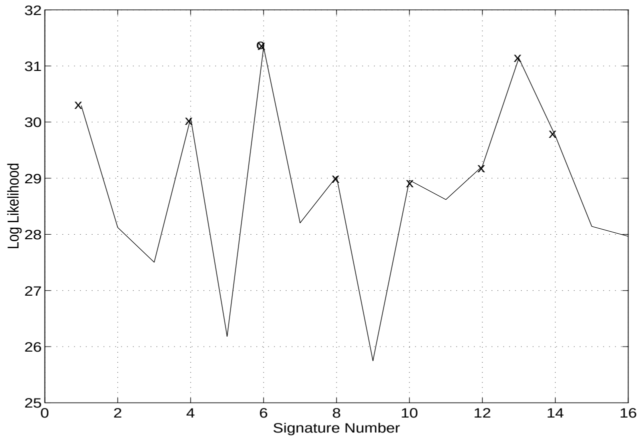

Fig. 8. Log Likelihood for Sensor 2 at Scale j=4.

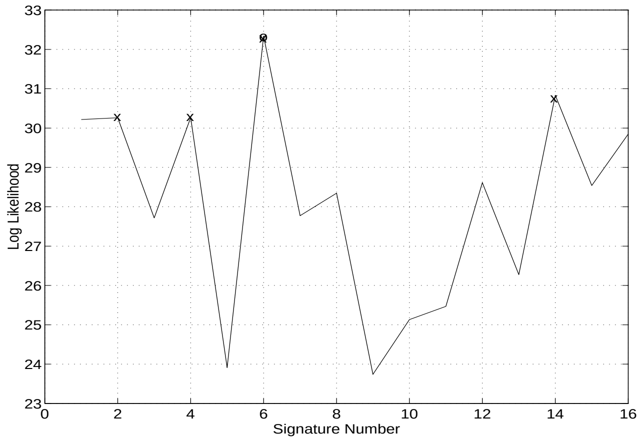

Fig. 9. Log Likelihood for Sensor 2 at Scale j=5.

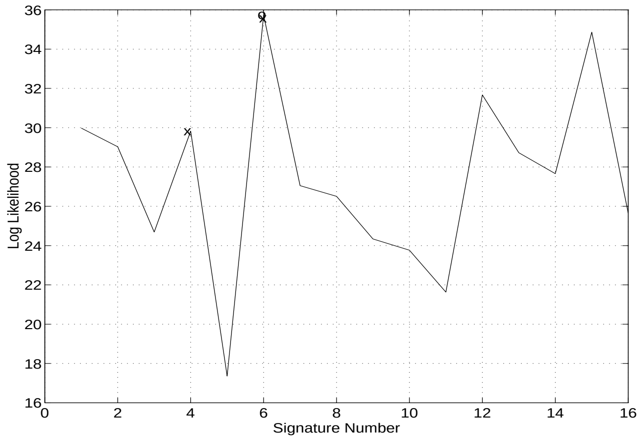

Fig. 10. Log Likelihood for Sensor 2 at Scale j=6.

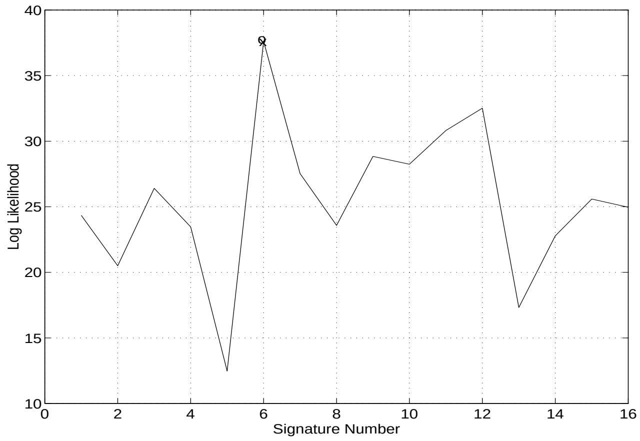

Fig. 11. Log Likelihood for Sensor 2 at Scale j=7.

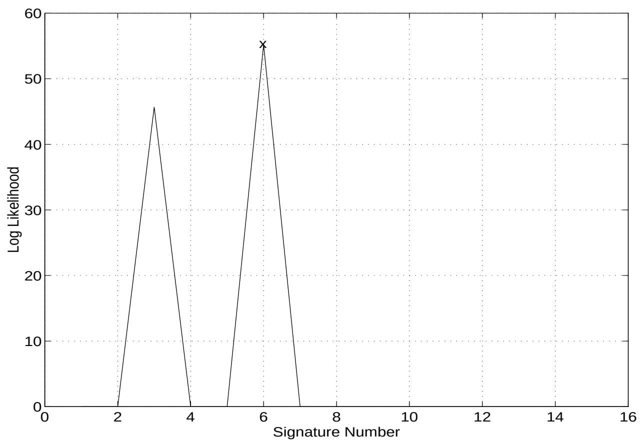

Fig. 12. Log Likelihood for Fused Signal.

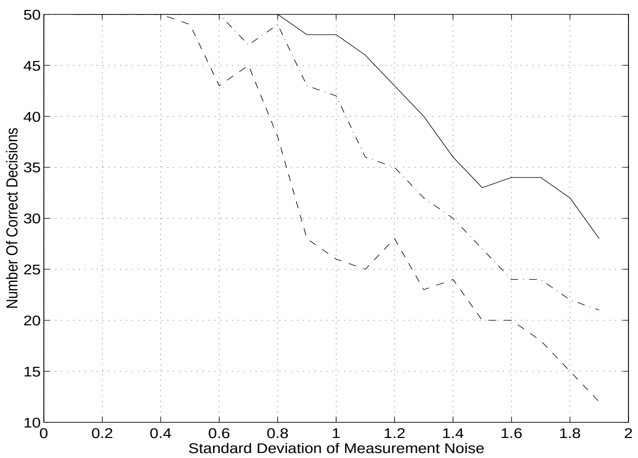

Fig. 13. Comparison of Identification Performance Between the Proposed Multisensor Algorithm and the Algorithm Based on One Sensor.