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Interferences suppression in data fusion systems

***Abstract**. The paper considers the problem of interferences suppression by means of data fusion in multisensor systems. Main advantages of data fusion systems are presented. Basic architectures are described and practical issues of their use are discussed. Algorithms of data fusion with interferences suppression and simulation results are presented.*

***Streszczenie.** Artykuł dotyczy problematyki estymacji w warunkach zakłóceń. Skupiono się na wykorzystaniu metod fuzji danych w systemach wielosensorowych. Zaprezentowano zalety takiego podejścia oraz podstawowe struktury. W artykule omówiono aspekty praktyczne stosowanych struktur. Przedstawiono również algorytmy fuzji pomiarów i estymat z rozszerzeniem pozwalającym na pracę w warunkach zakłóceń. Efektywność metod pokazano na podstawie wyników badań symulacyjnych. (**Tłumienie zakłóceń w systemach fuzji danych**)*

Keywords: Data fusion, multisensor systems, interferences suppression.
Słowa kluczowe: Systemy wielosensorowe, fuzja danych, estymacja w warunkach zakłóceń.

Introduction

Electromagnetic compatibility and vulnerability to disturbances is essential problem in more and more complex electronic and telecommunication systems [1, 2]. In general, occurrence of interferences causes deterioration of quality of observation and demodulation processes leading to increase of estimation error of the signal value. In telecommunication systems interferences may arise due to such phenomena as electromagnetic disturbances, multipath transmission, compatibility issues, abrupt changes of transmission channel properties, signal fluctuations, intended jamming and others. To overcome the problem, whole range of measures are applied, among which signal processing should also be noticed [1, 3]. The procedures of signal processing in the presence of interferences are based on statistical analysis [4, 5, 6, 7] and nonlinear filtering [8, 9]. Nowadays the number of sensors applied in systems considerably increase, so methods of multisensor data processing should also be introduced to solving interferences suppression problem.

Multisensor systems

Multisensor systems use some number of sensors which are often diverse and dispersed. By the nature, diverse sensors with different construction and relying on different physical phenomenon would be sensitive to environmental disturbances in a different degree. The same holds for dispersed sensors, where local disturbance would influence sensors in different extent. That is why it is worthy to combine information from all sources in order to obtain system less sensitive to interferences.

In comparison with single sensor, multisensor systems bring more qualitative benefits as: improved operational performance, extended spatial coverage, extended temporal coverage, increased confidence (e.g. higher probability of correct inference), improved detection and decreased false alarm rate, enhanced spatial resolution and increased system reliability. Combining information from many sources might be efficiently done by means of data fusion.

Data fusion

Data fusion techniques allow to combine information coming from different sensors [10, 11, 12]. The process should provide more information than obtained by sum of data obtained from individual sensors. A priori information about the system and environment collected in knowledge database may also be used. The aim of data fusion is to improve the system characteristics among which is robustness from disturbances arising in measurement channel. Interferences suppression may be carried out by the functions corresponding to JDL Level 1 processing model, where four tasks are accomplished: data alignment, association, estimation, identification.

Data alignment functions transform data received from multiple sensors into a common spatial and temporal reference frame. Specific alignment functions include coordinate transformation and time transformation. Data association deals with the problem of correlating observations from multiple sensors into groups, with each group representing data related to a single entity. In the estimation process value of the state vector is obtained. Data fusion makes it possible to improve estimation accuracy through the use of redundant measurements from sensors with different space position and taking into consideration a priori information.

In practice, implementation of data fusion system requires development of functionalities as: architecture of the data fusion system, appropriate signal processing algorithms, communication hardware and software and many others. Based on the way information form sensors is processed and fused, three different architectures can be implemented: centralized, distributed, hybrid (mixed).

The distributed fusion architecture is presented in Fig. 1.

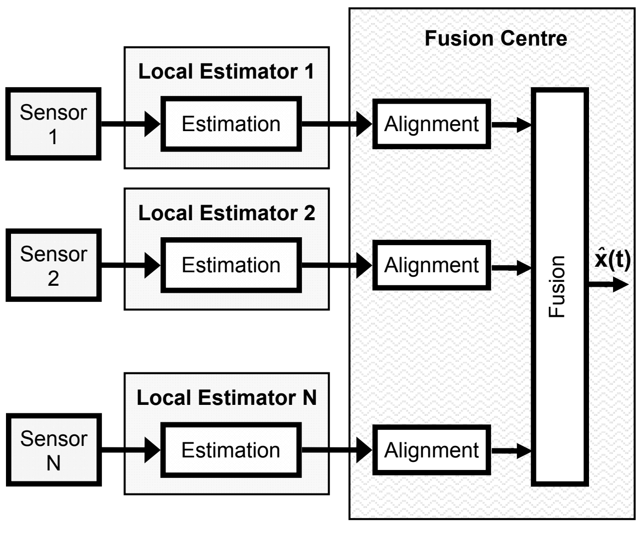

Fig. 1. Distributed fusion architecture

In the case of distributed architecture, the fusion centre receives estimates from local estimators dedicated to each sensor. Thus the method is sometimes called estimates fusion. On that basis, fused estimates are usually obtained by means of selection or weighting. The latter method requires transfer of error covariance matrices from all local estimators. The main advantages of the architecture are: reduced load on data transfer links and the central processor, signal and data processing directly dedicated to particular sensor, the fusion algorithm almost not depended on the number of sensors, robustness with respect to sensor failures. However a distributed architecture fusion centre does not utilize redundant information from all sensors. On the contrary the centralized architecture, which is presented in Fig. 2, allows processing the raw measurements from all sensors in a single centre. That requires fast data transfer links and fast central processor which is needed for realisation of much more complex algorithms comparing to that used in the distributed architecture. The method is referred as measurement fusion.

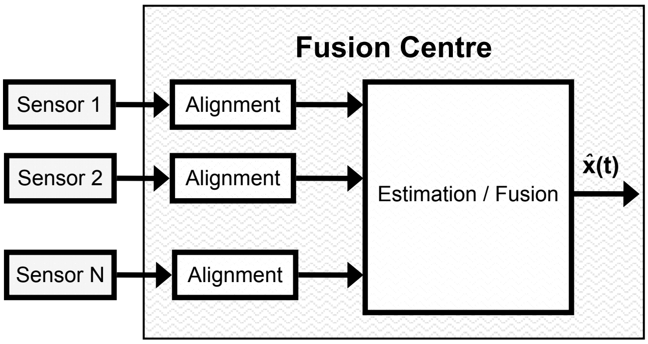

Fig. 2. Centralized fusion architecture

Fusion centre in the hybrid architecture receives both raw measurement data from all sensors and estimates from all local estimators. It keeps all the advantages of the centralized architecture and can take advantage of local estimators merits in distributed architecture.
The algorithms used in centralized hybrid architectures are rather complex but processing raw data from all sensors should potentially achieve the best performance.

Multisensor data fusion in presence of interferences

Interferences may be modelled as additional noise in transmission channel or modified parameters of noise. Using this model, occurrence of interferences may be detected and suppressed using signal processing approach and statistical analysis of measurement data. In the case of distributed fusion architecture, where fusion centre receives estimates and covariance matrixes, the selection or weighted techniques are used. The first method chooses the best of obtained estimates on the basis of error covariance matrixes. When sensors are diverse and dispersed the method may choose estimates originated from interferences free sensor or that less influenced by disturbances. Unfortunately in a case of sensors of the same kind located on the same platform the method would be sensitive to interferences. Moreover this approach looses benefits from redundant information from other sensors. The other (weighted) technique is superior because estimation process incorporates information from estimates obtained by all sensors. However in this case, weighted coefficients are obtained on the basis of error covariance matrixes, which in practical applications may not be accurately determined. That situation may lead to considerable influence of estimate from disturbed sensor and poor overall estimate (fused) quality. Thus distributed fusion architecture should not be chosen when local estimators use typical estimators (for example Kalman filter). When interferences are expected to arise, all local estimators should incorporate assessment procedures of measurement channel state (for instance as in [3, 5]). Centralized and hybrid architectures would also benefit from such procedures. However typical centralized fusion algorithms which take into consideration a priori information on potential interferences would work properly in a case of partially disturbed multisensor system and would be more efficient than distributed fusion architecture.
In the following sections selected algorithms and simulation results of central and distributed fusion systems will be presented. The presence of interferences and their suppression will be considered.

Data fusion algorithms

In practice, data fusion for measurement systems are based on Bayesian or Dempster - Shafer approaches. As the illustration for the aforementioned fusion systems, the methods based on Kalman filter will be presented, which belong to Bayesian group of methods. In this case observed system is described with means of state equations:

$$\mathbf{x}(k+1) = \boldsymbol{\Phi}(k+1,k)\mathbf{x}(k) + w(k) \tag{1}$$

where $\mathbf{x}(k)$ is n dimensional state vector, $\boldsymbol{\Phi}(k+1,k)$ is the transition matrix, $w(k)$ is white Gaussian sequence with zero mean and covariance matrix $\mathbf{Q}(k)$.
The n-th sensor measurement process influenced by interferences can be described using the following form of the observation equation:

$$\mathbf{y}_n(k) = \mathbf{H}_n(k)\mathbf{x}(k) + \gamma_n(k)v_n(k) \tag{2}$$

where $\mathbf{y}_n(k)$ is s dimensional observation vector of the n-th sensor and $\mathbf{H}_n(k)$ is the observation matrix, $v_n(k)$ is white Gaussian sequence with zero mean and covariance matrix $\mathbf{R}_n(k)$, $\gamma_n(k)$ is a coefficient which takes the value $\gamma_n(k)=1$ under normal measurement conditions (interferences are absent) and $\gamma_n(k)=\gamma_a(k)>1$ under the abnormal measurement conditions.
Changing statistical properties of $\gamma_n(k)$ and random factor $\gamma_a(k)$, such issues as outliers, signal fluctuations, jamming and others can be modelled.
The optimal state vector estimate in n-th local estimator can be calculated using the Kalman filter algorithm [6, 9] described by equations (3) - (8). In this case the estimation equation has a form:

$$\hat{\mathbf{x}}_n(k/k) = \hat{\mathbf{x}}_n(k/k-1) + \mathbf{K}_n(k)[\mathbf{y}_n(k) - \mathbf{H}_n(k)\hat{\mathbf{x}}_n(k/k-1)] \tag{3}$$

with prediction equation:

$$\hat{\mathbf{x}}_n(k/k-1) = \boldsymbol{\Phi}(k,k-1)\,\hat{\mathbf{x}}_n(k-1/k-1) \tag{4}$$

and gain matrix:

$$\mathbf{K}_n(k) = \mathbf{P}_n(k/k-1)\,\mathbf{H}_n^T(k) \times [\mathbf{H}_n(k)\mathbf{P}_n(k/k-1)\,\mathbf{H}_n^T(k) + \mathbf{R}_n(k)]^{-1} \tag{5}$$

Covariance matrix of prediction error:

$$\mathbf{P}_n(k/k-1) = \boldsymbol{\Phi}(k,k-1)\,\mathbf{P}_n(k-1/k-1)\boldsymbol{\Phi}^T(k,k-1) + \mathbf{Q}(k) \tag{6}$$

Covariance matrix of filtering error:

$$P_n(k/k) = P_n(k/k-1)-K_n(k)\, H_n(k)\, P_n(k/k-1) \tag{7}$$

The issue of estimate fusion can be formulated as problem of finding the best fused estimate $\hat{x}_{fd}(k/k)$ and the error covariance matrix $\hat{P}_{fd}(k/k)$ on the basis of sensors' local estimates $\hat{x}_n(k/k)$ and their covariance matrices $\hat{P}_n(k/k)$. When the fused estimate is designed as a linear combination of the N component sensors, the fusion algorithm can be presented as follows [10]:

$$\hat{x}_{fd}(k/k) = \hat{P}_{fd}(k/k)\sum_{n=1}^{N}[\hat{P}_n(k/k)]^{-1}\hat{x}_n(k/k) \tag{8}$$

$$\hat{P}_{fd}(k/k) = \{\sum_{n=1}^{N}[\hat{P}_n(k/k)]^{-1}\}^{-1} \tag{9}$$

Centralized fusion centre obtains raw measurements $y_n(k)$ from all N sensors and combines them in single estimation process. The recursive estimation algorithm can be derived on the basis of multichannel Kalman filter. In this case the fused estimate $\hat{x}_{fc}(k/k)$ takes the form [13]:

$$\begin{aligned}\hat{x}_{fc}(k/k) = {} & \hat{x}_{fc}(k/k-1) + \sum_{n=1}^{N}P_n(k/k)H_n^T(k)R_n^{-1}(k)\times \\ & \times[y_n(k)-H_n(k)\hat{x}_{fc}(k/k-1)]\end{aligned} \tag{10}$$

with covariance matrix $P_{fc}(k/k)$:

$$P_{fc}^{-1}(k/k) = P_{fc}^{-1}(k/k-1) + \sum_{n=1}^{N}H_n^T(k)R_n^{-1}(k)\, H_n(k) \tag{11}$$

Prediction estimate and covariance matrix of prediction error have typical form:

$$\hat{x}_{fc}(k/k-1) = \Phi(k,k-1)\, \hat{x}_{fc}(k-1/k-1) \tag{12}$$

$$P_{fc}(k/k-1) = \Phi(k,k-1)\, P_{fc}(k-1/k-1)\Phi^T(k,k-1) + Q(k) \tag{13}$$

Interferences suppression

When one or small number of all sensors are influenced by rather small or moderate level interferences, the typical multisensor estimation system would suppress them by means of averaging. However when interferences are severe or influence most of sensors, a special means of measurement channels state control should be undertaken. The a posteriori probability of the measurement channel state can be determined taking into consideration unknown changes of the observation noise variance sequence $\gamma_n^2(k)R_n(k)$ modelling certain level of the interferences and using the Gaussian approximation approach for calculating the probability density function. As presented in author's paper [5], the suboptimal state vector estimate $\hat{x}_n(k/k)$ of single local estimator can be expressed as the weighted sum of M partial estimates (for M different observation noise variances considered) with weights equal to a posteriori probabilities $p_{nj}(k)$ of the n-th observation channel state:

$$\begin{aligned}\hat{x}_n(k/k) = {} & \hat{x}_n(k/k-1) + \sum_{j=1}^{M}p_{nj}(k)K_{nj}(k)\times \\ & \times[y_n(k)-H_n(k)\hat{x}_n(k/k-1)]\end{aligned} \tag{14}$$

where the partial filter matrix gain $K_{nj}(k)$ is calculated with taking into consideration observation noise variance:

$$\begin{aligned}K_{nj}(k) = {} & P_n(k/k-1)H_n^T(k)\times \\ & \times[H_n(k)P_n(k/k-1)H_n^T(k)+\gamma_{nj}^2R_n(k)]^{-1}\end{aligned} \tag{15}$$

Covariance matrix of prediction error $P_n(k/k-1)$ is calculated as in (6).

In uncorrelated case a posteriori probabilities $p_{nj}(k)$ [8, 13] can be found with constant a priori probabilities $q_j(k)$ as following:

$$p_{nj}(k) = \frac{f(y(k)/\gamma(k)=\gamma_j, Y_{n1}^{k-1})\, q_j(k)}{\sum_{i=1}^{M}f(y(k)/\gamma(k)=\gamma_i, Y_{n1}^{k-1})q_i(k)} \tag{16}$$

where $j = 1,\ldots,M$ and

$Y_{n1}^{k-1} = \{y_n(1), y_n(2),\ldots y_n(k-1)\}$ is the sequence of measurements and the Gaussian density function of the predicted measurement is denoted:

$$f(y_n(k)/\gamma(k)=\gamma_i, Y_1^{k-1}) = N[H_n(k)\hat{x}_n(k/k-1), \\ H_n(k)P_n(k/k-1)H_n^T(k)+\gamma_{ni}^2R_n(k)]\ .$$

Covariance matrix of filtering error:

$$\begin{aligned}P_n(k/k) = {} & P_n(k/k-1)-K_\Sigma(k)H_n(k)P_n(k/k-1)+ \\ & +\sum_{j=1}^{N}p_{nj}(k)K_{n\Sigma}(k)S_n(k)K_{n\Sigma}^T(k)\end{aligned} \tag{17}$$

where $K_{n\Sigma}(k) = [K_{nj}(k) - \sum_{j=1}^{M}p_{nj}(k)K_{nj}(k)]$,

$S_n(k) = z_n(k/k-1)\cdot z_n^T(k/k-1)$ and $z_n(k/k-1)$ is the innovation process.

Simulation results

The performance of the proposed methods was investigated by using 1000 Monte Carlo runs. The first-order system with the parameters: $\Phi(k+1/k)=1$, $H(k)=1$, $Q(k)=1$, $R(k)=100$, $x(0)=N[10^4, 30^2]$, was simulated. The interferences level was modelled through modification of the observation channel noise variance by means of $\gamma(k)$. As a performance measure the root mean square error (RMSE) was calculated.

Influence of moderate level interferences ($\gamma_a(k)=4$) on the estimate and measurement fusion systems (algorithms (3) – (13)) was investigated. Fig. 3 and Fig. 4 present influence of such interference on one of the measurement channels in the fusion system with 2 or 5 sensors. As can be seen, such interferences are suppressed by means of averaging in the typical fusion system. The interference influence on fused estimate diminishes with growing number of sensors. Moreover Fig. 3. And Fig. 4. show that the measurement fusion reveals slightly smaller RMS error than estimate fusion.

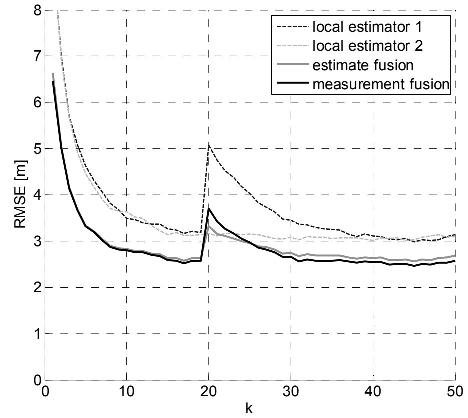

Fig. 3. Influence of moderate level interference on one of two measurement channels of the estimate fusion system

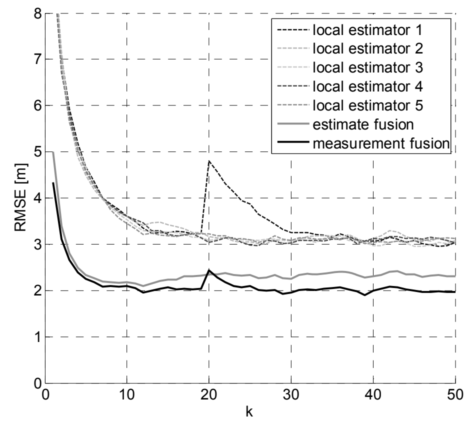

Fig. 4. Influence of moderate level interference on one of five measurement channels of the estimate fusion system

Next, the performance of the estimate fusion system with the interference suppression filters was investigated. It was assumed $M=10$ equiprobable, evenly distributed outlier levels (for $1<\gamma_{nj}<\gamma_a$) of approximating Gaussian pdfs. Pulsed interferences $\gamma_a(k)=10$ for $k=\{15, 16, 30, 31\}$ in sensor 1 measurement channel and for $k=\{20, 21, 30, 31, 39, 40\}$ in sensor 2 measurement channel were simulated. The RMS errors are presented in Fig. 5. Solid lines represent estimate fusion and local estimates with the interference suppression while thin dashed lines represent results for typical Kalman filter estimates and their fusion.

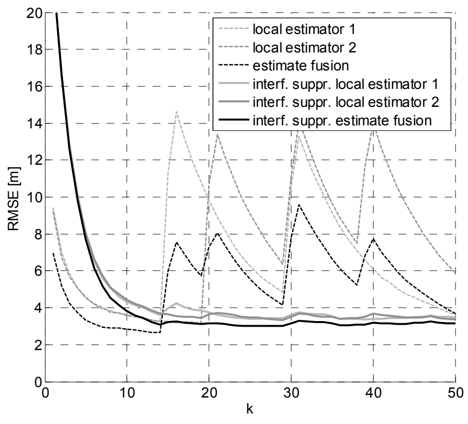

Fig. 5. The estimate fusion system with the interference suppression filters

As it follows from Fig. 5., estimate fusion with use of the proposed algorithm reveals better performance than with use of traditional Kalman filter under high interference conditions.

The performance of the methods for second and third order system was similar, leading to the same conclusions as for results presented above obtained for first-order system.

Conclusions

Occurrence of interferences causes deterioration of quality of observation and demodulation processes leading to increase of estimation error of the signal value.

The paper considers the use of data fusion in multisensor systems to solve the problem of interferences suppression. Multisensor systems use some number of sensors which are often diverse and dispersed. Fusion of data coming from set of such sensors bring some qualitative benefits. Data fusion systems, depending on architecture, are vulnerable to disturbances in different extent. Usually processing procedures should be equipped with measurement channel state assessment procedures or should consider a priori information on potential interferences. Such measures enable disturbances detection and suppression of interferences influence on the estimated value.

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