Bibliographic Review on Distributed Kalman Filtering

Magdi S. Mahmoud and Haris M. Khalid

***Abstract*—In recent years, a compelling need has arisen to understand the effects of distributed information structures on estimation and filtering. In this paper, a bibliographical review on Distributed Kalman Filtering (DKF) is provided. The paper contains a classification of different approaches and methods involved to DKF. The applications of DKF are also discussed and explained separately. A comparison of different approaches is briefly carried out. Focuses on the contemporary research are also addressed with emphasis on the practical application of the techniques. An exhaustive list of publications, linked directly or indirectly to DKF in the open literature, is compiled to provide an overall picture of different developing aspects of this area.**

***Index Terms*—Distributed Kalman filtering, Self-tuning distributed fusion Kalman filter, Distributed particle filtering, Distributed consensus-based estimation, Track-to-track fusion, Distributed networks, Multi-sensor data fusion systems, Distributed out-of-sequence measurements, Diffusion-based distributed Kalman filtering.**

I. Introduction

In hi-tech environment, a strict surveillance unit is required for an appropriate supervision. It often utilizes a group of distributed sensors which provide information of the local targets. Comparing with the centralized Kalman filtering (CKF), which can be used in mission critical scenarios, where every local sensor is important with its local information, the distributed fusion architecture has many advantages. There is no second thought that in certain scenarios, centralized kalman filter plays a major role, and it involves minimum information loss. A general structure for the Distributed Kalman Filter (DKF) can seen in figure (see Fig. 1). The distributed system architecture, on the whole, is very powerful since it allows the design of the individual units or components to be much simpler, while not compromising too much on the performance. Additional benefits include increased robustness to component loss, increased flexibility in that the components can be reconfigured for many different tasks and so on. However, the design of such systems challenges various problems of assumptions, handling, fusing the architecture of such systems. Our purpose is to provide a bibliographic survey on DKF and its architectures, comprising of distribution, fusion, filtering and estimation. A classification of such an architecture can be seen in the figure (see Fig. 2), which shows the vision of filtering and estimation under the umbrella of DKF. Therefore, in this paper, we present a bibliographic literature survey and technical review of DKF. The remaining part of the paper is organized as follows: Bibliographic review and technical survey of Distributed Kalman filtering and its applications are presented in Section II, diffusion-based DKF in Section III, followed by Distributed Out-of-Sequence Measurements (OOSM) in Section IV, multi-sensor data fusion (MSDF) systems in section V, followed by distributed networks (DN) in section VI, mathematical design in track-to-track fusion in Section VII, Distributed Consensus-Based estimation in Section VIII, Distributed particle filtering (DKF) in Section IX, self-tuning-Based distributed fusion kalman filter in Section X. Finally some concluding remarks are given in Section XI.

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II. Distributed Kalman Filter Methods and Their Applications

A. DKF methods

DKF can be introduced through different methods promoting to an better filtering approach, also considering various scenarios. A list of publications in DKF is summarized in Table I and Table II. For example, under uncertain observations, method which include measurement with a false alarm probability as a special case is considered in [1], and randomly variant dynamic systems with multiple models are considered in [2]. Optimal centralized and distributed fusers are algebraically equivalent in this case [3]. Looking at mode estimation in power systems, a trust-based distributed Kalman filtering approach to estimate the modes of power systems is presented in [4]. Using standard Kalman filter locally together with a consensus step in order to ensure that the local estimates agree are shown in [5]. Frequency-domain characterization of the distributed estimator's steady-state performance are presented in [96]. Version of Extend Kalman filtering to globally optimal Kalman filtering for the dynamic systems with finite-time correlated noises is shown in [146]. Distributed Kalman-type processing schemes essentially make use of the fact that the sensor measurements do not enter into the update equation for the estimation error covariance matrices, that is, covariance matrices of all sensors calculated at each individual sensor site without any further need of communication is presented in [147]. Also, in distributed fusion Kalman filtering, weighted covariance approach is reported in [153]. Distributed Kalman filtering fusion with passive packet loss or initiative intermittent communications from local estimators to a fusion center while the process noise does exist, is presented in [157]. For each Kalman update, an infinite number of consensus steps, how restricted to one is presented in [197] [198]. For each Kalman update, state estimates additionally exchanged, are presented in [199]. When only the estimates at each Kalman update over-head are exchanged, the results are reported in [200]. Analysis of the number of messages to exchange between successive updates in a distributed Kalman filter is documented in [201]. Global optimality of distributed Kalman filtering fusion exactly equal to the corresponding centralized optimal Kalman filtering fusion, is shown in [271]. A parallel and distributed state estimation structure is developed in the form of hierarchical estimation structure is specified in [292]. A computational procedure to transform a hierarchical Kalman filter into a partially decentralized estimation structure

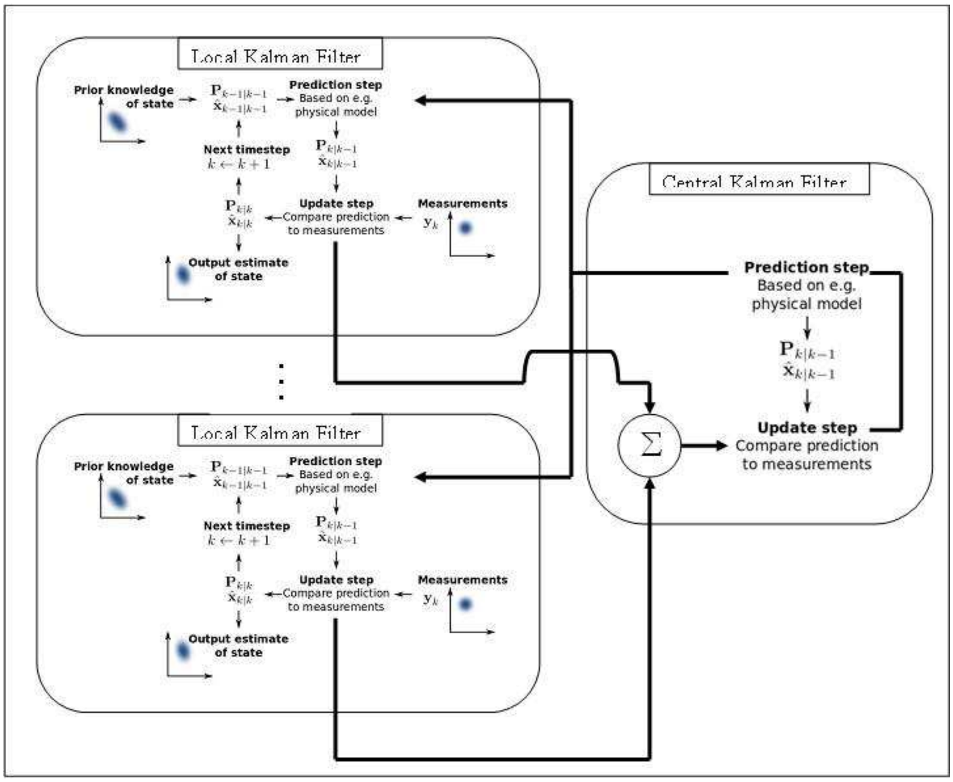

Fig. 1. A general structure of Distributed Kalman Filter

is presented in [293]. Optimal distributed Kalman filter based on a-$priori$ determination of measurements is given in [295].

Estimation of sparsely connected, large scale systems is reported in [20] and an n-th order with multiple sensors presentation is shown in [21]. Data-fusion over arbitrary communication networks is shown in [22]. Iterative consensus protocols are provided in [23]. Using bipartite fusion graphs, the issue of how DKF is performed is the subject of [24]. Local average consensus algorithms for DKF are shown in[25]. Consensus strategies for DKF are reported in [26]. Semi-definite programming based consensus iterations, developed for DKF, are shown in [27]. Converge speed of consensus strategies, is given in [28]. Distributed Kalman filtering, with focus on limiting the required communication bandwidth, is shown in [118]. Distributed Kalman-type processing schemes, which provide optimal track-to-track fusion results at arbitrarily chosen instants of time, are developed in [148]. Distributed architecture of track-to-track fusion for computing the fused estimate from multiple filters tracking a maneuvering target with the simplified maximum likelihood estimator, are presented in [213]. Original batch form of the Maximum Likelihood (ML) estimator, is developed in [214] and modified probabilistic neural network is shown in [215].

Remark II.1: In [157], an ℓ-sensor distributed dynamic system is described by:

$$x_{k+1} = \phi_k x_k + \upsilon_k, k = 0, 1, ... \tag{1}$$

$$y_k^i = H_k^i x_k + w_k^i, i = 1, ..., \ell \tag{2}$$

where ϕ_k is a matrix of order $r \times r$, x_k, $\upsilon_k \in \mathcal{R}^r$, $H_i^k \in \mathcal{R}^{N_i \times r}$, y_k^i , $w_i^k \in \mathcal{R}^{N_i}$. The process noise υ_k and measurement noise w_i^k are both zero-mean random variables independent of each other temporally but w_i^k and w_j^k may be cross-correlated for $i \neq j$ at the same time instant k.

To compare performances between the centralized and distributed filtering fusion, the stacked measurement equation is written as:

$$y_k = H_k x_k + w_k \tag{3}$$

where

$$\begin{aligned} y_k &= (y_k^{1^t}, ..., y_k^{\ell^t})^t, H_k = (H_k^{1^t}, ..., H_k^{\ell^t})^t, \\ w_k &= (w_k^{1^t}, ..., w_k^{\ell^t})^t \end{aligned} \tag{4}$$

and the covariance of the noise w_k is given by:

$$Cov(w_k) = R_k, R_k^i = Cov(w_k^i), \quad i = 1, ..., \ell \tag{5}$$

where R_k and R_k^i are both invertible for all i. According to the standard results of Kalman filtering, the local Kalman filtering

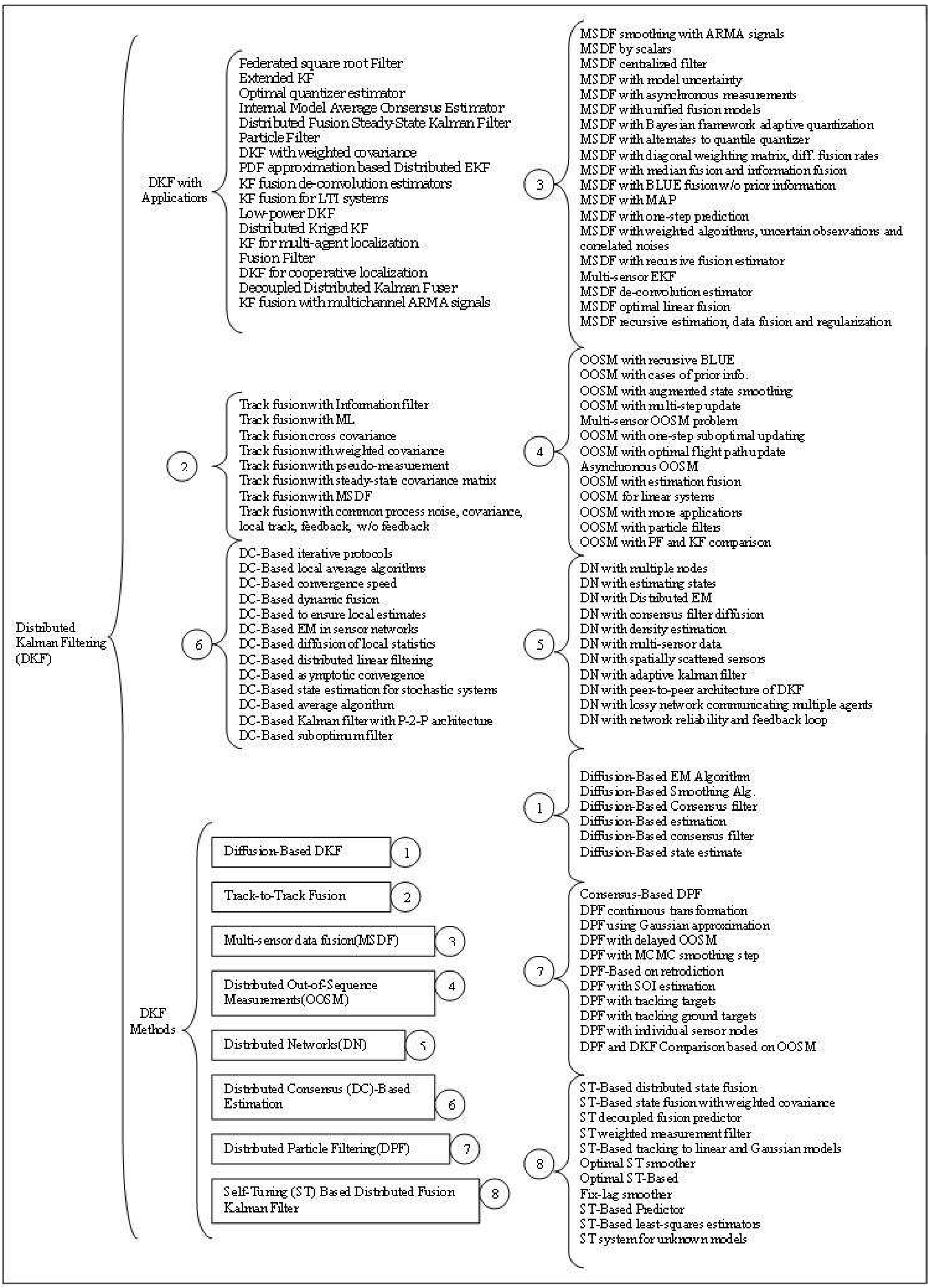

Fig. 2. Classification of Distributed Kalman Filter

at the i-th sensor is expressed as:

$$\widehat{K}_k^i = \widehat{P}_{k/k}^i H_k^{i^t} \widehat{R}_k^{i^{-1}} \tag{6}$$

$$\widehat{x}_{k/k}^i = \widehat{x}_{k/k-1}^i + \widehat{K}_k^i (y_k^i - H_k^i \widehat{x}_{k/k-1}^i) \tag{7}$$

$$\widehat{P}_{k/k}^i = \widehat{P}_{k/k-1}^i - \widehat{K}_k^i H_k \widehat{P}_{k/k-1}^i \tag{8}$$

$$\tag{9}$$

where, the covariance of filtering error can be stated as:

$$\widehat{P}_{k/k}^{i^{-1}} = \widehat{P}_{k/k-1}^{i^{-1}} + H_k^{i^t} \widehat{R}_k^{i^{-1}} H_k^i \tag{10}$$

with

$$\begin{aligned} \widehat{x}_{k/k-1}^i &= \widehat{\Phi}_k \widehat{x}_{k-1/k-1}^i, \\ \widehat{P}_{k/k}^i &= E[(\widehat{x}_{k/k}^i - \widehat{x}_k)(\widehat{x}_{k/k-1}^i - \widehat{x}_k)^t] \\ \widehat{P}_{k/k-1}^i &= E[(\widehat{x}_{k/k-1}^i - \widehat{x}_k)(\widehat{x}_{k/k-1}^i - \widehat{x}_k)^t] \end{aligned}$$

Similarly, the centralized Kalman filtering with all sensor data is given by:

$$\widehat{K}_k = \widehat{P}_{k/k} H_k^t \widehat{R}_k^{-1} \tag{11}$$

$$\widehat{x}_{k/k} = \widehat{x}_{k/k-1} + \widehat{K}_k (y_k - H_k \widehat{x}_{k/k-1}) \tag{12}$$

$$\widehat{P}_{k/k} = \widehat{P}_{k/k-1} - \widehat{K}_k H_k \widehat{P}_{k/k-1} \tag{13}$$

$$\tag{14}$$

where, the covariance of filtering error can be described as:

$$\widehat{P}_{k/k}^{-1} = \widehat{P}_{k/k-1}^{-1} + H_k{}^t \widehat{R}_k^{-1} H_k \tag{15}$$

with

$$\begin{aligned} \widehat{x}_{k/k-1} &= \widehat{\Phi}_k \widehat{x}_{k-1/k-1}, \\ \widehat{P}_{k/k} &= E[(\widehat{x}_{k/k} - \widehat{x}_k)(\widehat{x}_{k/k-1} - \widehat{x}_k)^t] \\ \widehat{P}_{k/k-1} &= E[(\widehat{x}_{k/k-1} - \widehat{x}_k)(\widehat{x}_{k/k-1} - \widehat{x}_k)^t] \end{aligned}$$

It is quite clear when the sensor noises are cross-dependent that

$$H_k^t \widehat{R}_k^{-1} H_k = \sum_{i=1}^{l} H_k^{i^t} \widehat{R}_k^{i^{-1}} H_k^i$$

Likewise, the centralized filtering and error matrix could be explicitly expressed in terms of the local filtering and error matrices as follows:

$$\widehat{P}_{k/k}^{-1} = \widehat{P}_{k/k-1}^{-1} + \sum_{i=1}^{l} (\widehat{P}_{k/k}^{i^{-1}} - \widehat{P}_{k/k-1}^{i^{-1}}) \tag{16}$$

and

$$\begin{aligned} \widehat{P}_{k/k}^{-1} \widehat{x}_{k/k} &= \widehat{P}_{k/k-1}^{-1} \\ &+ \sum_{i=1}^{l} (\widehat{P}_{k/k}^{i^{-1}} \widehat{x}_{k/k}^i - \widehat{P}_{k/k-1}^{i^{-1}} \widehat{x}_{k/k-1}^i) \end{aligned} \tag{17}$$

Also,

$$H_k^{i'} \widehat{R}_k^{i^{-1}} y_k^i = \widehat{P}_{k/k}^{i^{-1}} \widehat{x}_{k/k}^i - \widehat{P}_{k/k-1}^{i^{-1}} \widehat{x}_{k/k-1}^i \tag{18}$$

In what follows, we are going to deal with the practical situation in which the local sensors may fail to send their estimates to the fusion center. In this case, the measurement equation of the corresponding centralized multi-sensor system has to be modified, that is, the original multiple individual observations should be stacked as a modified single observation.

B. DKF with applications

A list of publications in some application-oriented research is summarized in Table III and Table IV. As it can be seen, a large amount of research has been carried out in the framework of modified filters. Multi-sensor networks are developed that are amenable to parallel processing in [33]. Then, a two sensors fusion filter system has been applied in [34], followed by federated square root filter in [35]. Fusion filters are developed for linear time-invariant (LTI) systems with correlated noises and multi-channel ARMA signals, respectively in [36] and [37]. Fusion de-convolution estimators for the input white noise are worked out in [38]-[39]. Distributed Kalman filtering for cooperative localization is re-formulated as a parameter estimation problem in [100]. DKF techniques for multi-agent localization is dealt with in [101], [104]. Collaborative processing of information, and gathering scientific data from spatially distributed sources is described in [109]. Particle filter implementations using Gaussian approximations are documented in [114]. Channel estimation method based on the recent methodology of distributed compressed sensing (DCS) and frequency domain Kalman filter is worked out in [151]. Algorithms for distributed Kalman filtering, where global information about the state covariances is required in order to compute the estimates are shown in [174]. The synthesis of a distributed algorithm to compute weighted least squares estimates with sensor measurements correlated is presented in [181]. Distributive and efficient computation of linear minimum mean square error (MMSE) for the multiuser detection problem is presented in [186]. A statistical approach for calculating the exact PDF approximated by well-placed Extended Kalman Filter is presented in [192]. Distributed object tracking system which employs a cluster-based Kalman filter in a network of wireless cameras is presented in [194]. Distributed recursive mean-square error (MSE) optimal quantizer-estimator based on the quantized observations is presented in [206] [207]. Design a communication access protocol for wireless sensor networks tailored to converge rapidly to the desired estimate and provides scalable error performance is presented in [208], [209]. Decentralized versions of the Kalman filter is presented in [210]. Distributed Kalman filter based on quantized measurement innovations is presented in [211]. Novel distributed filtering/smoothing approach, flexible to trade-off estimation delay for MSE reduction, while enhancing robustness is presented in [216]. In distributed estimation agents, where a bank of local Kalman filters is embedded into each sensor and diagnosis decision is performed by a distributed hypothesis testing consensus method is presented in [228]. State estimation of dynamical stochastic processes based on severely quantized observations is reported in [232], [233]. Scheme for approximate DKF and is based on reaching an average-consensus is presented in [237]

In the multi-sensor random parameter matrices case [1], sometimes, even if the original sensor noises are mutually independent, the sensor noises of the converted system are still cross-correlated. Hence, such multi-sensor system seems not satisfying the conditions for the distributed Kalman filtering fusion given in [8]-[9]. It was proved that when the sensor noises or the random measurement matrices of the original system are correlated across sensors, the sensor noises of the converted sys-

TABLE I
DISTRIBUTED KALMAN FILTERING (DKF) METHODS I

Distributed Kalman Filtering(DKF) Design Approaches Used	References
• Under uncertain observations, including measurement with a false alarm probability as a special case	[1]
• Under uncertain observations, randomly variant dynamic systems with multiple models	[2]
• Optimal centralized and distributed fusers are algebraically equivalent in this case	[3]
• Power systems: mode estimation. A trust-based distributed Kalman filtering approach to estimate the modes of power systems	[4]
• Using Standard Kalman filter locally, together with a consensus step in order to ensure that the local estimates agree	[5]
• Frequency-domain characterization of the distributed estimator's steady-state performance	[96]
• Extend Kalman filtering to globally optimal Kalman filtering for the dynamic systems with finite-time correlated noises	[146]
• Distributed Kalman-type processing scheme essentially makes use of the fact that the sensor measurements do not enter into the update equation for the estimation error covariance matrices i.e. covariance matrices of all sensors calculated at each individual sensor site without any further need of communication	[147]
• In Distributed fusion Kalman filtering, weighted covariance approach	[153]
• Distributed Kalman filtering fusion with passive packet loss or initiative intermittent communications from local estimators to a fusion center while the process noise does exist	[157]
• For each Kalman update, an infinite number of consensus steps to restricted to one	[197] [198]
• For each Kalman update, state estimates are additionally exchanged	[199]
• Only the estimates at each Kalman update over-head are exchanged	[200]
• Analyzes the number of messages to exchange between successive updates in a distributed Kalman filter	[201]
• Global Optimality of distributed Kalman filtering fusion exactly equal to the corresponding centralized optimal Kalman filtering fusion	[271]
• A parallel and distributed state estimation structure developed from an hierarchical estimation structure	[292]
• A computational procedure to transform an hierarchical Kalman filter into a partially decentralized estimation structure [293]	
• Optimal Distributed Kalman filter based on a-$priori$ determination of measurements	[295]

tem are cross-correlated. Even if so, similarly with [6], centralized random parameter matrices Kalman filtering, where the fusion center can receive all sensor measurements, can still be expressed by a linear combination of the local estimates. Therefore, the performance of the distributed filtering fusion is the same as that of the centralized fusion under the assumption that the expectations of all sensor measurement matrices are of full row rank. When there is no feedback from the fusion center to local sensors, a distributed Kalman filtering fusion formula under a mild condition is presented as [242]. A rigorous performance analysis for Kalman filtering fusion with feedback is presented in [243].

Low-power DKF based on a fast polynomial filter is shown in [262]. Consensus Problem and their special cases are reported in [263]. DKF for sparse large-scale systems monitored by sensor networks is treated in [264]. DKF to estimate actuator faults for deep space formation flying satellites are developed in [265]. Internal model average consensus estimator for distributed Kalman filtering is worked out in [266]. Distributed 'Kriged' Kalman filtering is addressed in [267]. The behavior of the distributed Kalman filter that varies smoothly from a centralized Kalman filter to a local Kalman filter with average consensus update is presented in [268]. Both track fusion formulas with feedback and without feedback are analysed in [270]. Decoupled distributed Kalman fuser presented by using Kalman filtering method and white noise estimation theory is shown in [276]. Decomposition of a linear process model into a cascade of simpler subsystems is given in [277]. Distributed fusion steady-state Kalman filtering by using the modern time series analysis method is shown as [278]. Distributed Kalman

TABLE II
DISTRIBUTED KALMAN FILTERING (DKF) METHODS II

Distributed Kalman Filter	References
• Estimate sparsely connected, large scale systems	[20]
• n-th order with multiple sensors	[21]
• Data-fusion over arbitrary communication networks	[22]
• Iterative consensus protocols	[23]
• Using bipartite fusion graphs	[24]
• Local average consensus algorithms	[25]
• Based on consensus strategies	[26]
• Semi-definite programming based consensus Iterations	[27]
• Converge Speed of consensus strategies	[28]
• Distributed Kalman filtering, with focus on limiting the required communication bandwidth	[118]
• Distributed Kalman-type processing scheme, which provides optimal track-to-track fusion results at arbitrarily chosen instants of time	[148]
• Distributed architecture of track-to-track fusion for computing the fused estimate from multiple filters tracking a maneuvering target with the simplified maximum likelihood estimator	[213]
• Original batch form of the Maximum Likelihood (ML) estimator	[214]
• Modified Probabilistic Neural Network	[215]

filtering with weighted covariance is reported in [279]. Transfer function describing the error behavior of the distributed Kalman filter in the case of stationary noise processes is shown in [294]. The paper [2] shows that this result can be applied to Kalman filtering with uncertain observations, as well as randomly variant dynamic systems with multiple models.

Under some regularity conditions as shown in [8], in particular the assumption of independent sensor noises, an optimal Kalman filtering fusion was proposed in [8], which is proved to be equivalent to the centralized Kalman filtering using all sensor measurements; therefore such fusion is globally optimal. In the multi-sensor random parameter matrices case, sometimes, even if the original sensor noises are mutually independent, the sensor noises of the converted system are still cross-correlated. Hence, such multi-sensor system seems to be not satisfying the conditions for the distributed Kalman filtering fusion given in [8].

III. DIFFUSION-BASED DISTRIBUTED KALMAN FILTERING

The publications of diffusion-based DKF are classified in Table V. Diffusion-based distributed expected maximization (EM) algorithm for Gaussian mixtures is shown in [45]. Diffusion-based Kalman filtering and smoothing algorithm is shown in [46]. Distributed EM algorithm over sensor networks, consensus filter used to diffuse local sufficient statistics to neighbors and estimate global sufficient statistics in each node is shown in [92]. Consensus filter diffusion of local sufficient statistics over the entire network through communication with neighbor nodes is presented in [94]. Diffusion Kalman filtering, where nodes communicate only with their neighbors, and no fusion center is worked in [168]. Distributed Kalman filtering proposed in the context of diffusion estimation is treated in [169], [170]. Distributed Kalman filtering proposed in the context of average consensus [171][172]. Diffusion Kalman filtering for every measurement and for every node, a local state estimate using the data from the neighborhood is provided in [173].

Remark III.1: In the paper [45], a diffusion scheme of EM (DEM) algorithm for Gaussian mixtures in Wireless Sensor Networks (WSNs) is proposed. At each iteration, the time-varying communication network is modeled as a random graph. A diffusion-step (D-step) is implemented between the E-step and the M-step. In the E-step, sensor nodes compute the local statistics by using local observation data and parameters estimated at the last iteration. In the D-step, each node exchanges local information only with its current neighbors and updates the local statistics with exchanged information. In the M-step, the sensor nodes compute the estimation of parameter using the updated local statistics by the D-step at this iteration. Compared with the existing distributed EM algorithms, the proposed approach can extensively save communication for each sensor node while maintain the estimation performance. Different from the linear estimation methods such as the least-squares and the least-mean squares estimation algorithms, each iteration of EM algorithm is a nonlinear transform of measurements. The steady-state performance of the proposed DEM algorithm can not be analyzed by linear way. Instead, we show that the DEM algorithm can be considered as a stochastic approximation method to find the maximum likelihood estimation

TABLE III
DISTRIBUTED KALMAN FILTERING(DKF) WITH APPLICATIONS I

DKF with Applications	References
• Multi-sensor networks amenable to parallel processing	[33]
• Two sensors fusion filter	[34]
• Federated square root filter	[35]
• Fusion filter for LTI systems with correlated noises	[36]
• Fusion filter for multichannel ARMA signals	[37]
• Fusion de-convolution estimators for the input white noise	[38]-[39]
• Distributed Kalman filtering for cooperative localization by reformulating as a parameter estimation problem	[100]
• Distributed Kalman filtering techniques for multi-agent localization	[101][104]
• Collaborative processing of information, and gathering scientific data from spatially distributed sources	[109]
• Particle filter implementations use Gaussian approximations	[114]
• Channel estimation method based on the recent methodology of distributed compressed sensing (DCS) and Frequency Domain Kalman Filter	[151]
• Algorithm for distributed Kalman filtering, where global information about the state covariances is required in order to compute the estimates	[174]
• The synthesis of a distributed algorithm to compute weighted least squares estimates with sensor measurements correlated	[181]
• Distributive and efficient computation of linear MMSE for the multiuser detection problem	[186]
• A statistical approach derived, calculating the exact PDF approximated by well-placed Extended Kalman Filter	[192]
• Distributed object tracking system which employs a cluster-based Kalman filter in a network of wireless cameras	[194]
• Distributed recursive mean-square error (MSE) optimal quantizer-estimator based on the quantized observations	[206] [207]
• Design a communication access protocol for wireless sensor networks tailored to converge rapidly to the desired estimate and provides scalable error performance	[208][209]
• Decentralized versions of the Kalman filter	[210]
• Distributed Kalman Filter estimator based on quantized measurement innovations	[211]
• Novel distributed filtering/smoothing approach, flexible to trade-off estimation delay for MSE reduction, while exhibiting robustness	[216]
• Distributed estimation agents designed, where a bank of local Kalman filters embedded into each sensor, where, diagnosis decision performed by a distributed hypothesis testing consensus method	[228]
• State estimation of dynamical stochastic processes based on severely quantized observations	[232] [233]
• Scheme for approximate distributed Kalman filtering (DKF) based on reaching an average-consensus	[237]

for Gaussian Mixtures. In this regard, we have in mind a network of M sensor nodes is considered, each of which has N_m data observations $\{y_{m,n}\}$, $m = 1, 2, ..., M$, $n = 1, 2, ..., N_m$. These observations are drawn from a K Gaussian mixtures with mixture probabilities α_1, ..., α_k.

$$y_{m,n} \sim \sum_{j=1}^{K} \alpha_j . N(\mu_j, \Sigma_j) \tag{19}$$

where $N(\mu, \Sigma)$ denote the Gaussian density function with mean μ and covariance Σ. Let $z \in \{1, 2, ..., K\}$ denote the missing data where Gaussian y comes from.

IV. DISTRIBUTED OUT-OF-SEQUENCE MEASUREMENTS (OOSM)

Distributed out-of-sequence measurements-based list of publications are classified in Table VI. Recursive 'BLUE' without prior is given in [56]. Cases of prior information about the OOSM are presented in [57] [203]. Dating the state estimate globally optimal is worked out in [58][59]. Minimum storage at the current time to guarantee a globally optimal update with three cases of prior information about OOSM are treated in [76], [85], [136]. Updating the state estimate globally optimally with an OOSM within one step time delay for a system with a non-

TABLE IV
DISTRIBUTED KALMAN FILTERING(DKF) WITH APPLICATIONS II

DKF with Applications	References
• When no feedback from the fusion center to local sensors, a distributed Kalman filtering fusion formula under a mild condition	[242]
• Rigorous performance analysis for Kalman filtering fusion with feedback	[243]
• Low-power DKF based on a fast polynomial filter	[262]
• Consensus Problem and their special cases	[263]
• DKF for sparse large-scale systems monitored by sensor networks	[264]
• DKF to estimate actuator faults for deep space formation flying satellites	[265]
• Internal model average consensus estimator for distributed Kalman filtering	[266]
• Distributed Kriged Kalman filtering	[267]
• The behavior of the distributed Kalman filter varies smoothly from a centralized Kalman filter to a local Kalman filter with average consensus update	[268]
• Track fusion formulas with feedback are, like the track fusion without feedback	[270]
• Decoupled distributed Kalman fuser presented by using Kalman filtering method and white noise estimation theory	[276]
• Decomposition of a linear process model into a cascade of simpler subsystems	[277]
• Distributed fusion steady-state Kalman filtering by using the modern time series analysis method	[278]
• Distributed Kalman filtering with weighted covariance	[279]
Transfer function describing the error behavior of the distributed Kalman filter in the case of stationary noise processes	[294]

TABLE V
DIFFUSION-BASED DISTRIBUTED KALMAN FILTERING

Diffusion Approaches Used	References
• Diffusion-Based Distributed EM algorithm for Gaussian mixtures	[45]
• Diffusion-Based Kalman filtering and smoothing algorithm	[46]
• Distributed EM algorithm over sensor networks, consensus filter used to diffuse local sufficient statistics to neighbors and estimate global sufficient statistics in each node	[92]
• Consensus filter diffusion of local sufficient statistics over the entire network through communication with neighbor nodes	[94]
• Diffusion Kalman filtering , where nodes communicate only with their neighbors, and no fusion center is present	[168]
• Distributed Kalman filtering proposed in the context of diffusion estimation	[169][170]
• Distributed Kalman filtering proposed in the context of average consensus	[171][172]
• Diffusion Kalman filtering for every measurement and for every node, a local state estimate using the data from the neighborhood	[173]

TABLE VI
DISTRIBUTED OUT-OF-SEQUENCE MEASUREMENTS(OOSM)

Out-of-Sequence Measurements(OOSM) Approaches	References
• Recursive BLUE without prior	[56]
• Cases of prior information about the OOSM	[57] [203]
• Dating the state estimate globally optimally	[58][59]
• Minimum storage at the current time to guarantee a globally optimal update with three cases of prior information about OOSM	[76] [85][136]
• Updating the state estimate globally optimally with an OOSM within one step time delay for a system with a nonsingular state transition matrix	[77]
• Multi-step OOSM updating using augmented state smoothing	[79][80][81]
• Multi-step update in OOSM	[78]
• Multi-sensor OOSM problem in a cluttered environment	[80][82][83]
• one-step suboptimal updating algorithms using stored information for systems with a nonsingular state transition matrix	[77][84]
• Efficient incorporation of OOSMs in Kalman filters	[133]-[138]
• A globally optimal flight path update algorithm with OOSMs, i.e. a globally optimal algorithm which not only updates the current estimate but also updates the past estimates with using a received OOSM	[158]
• Counterpart of the OOSM update problem, needed to remove an earlier measurement from the flight path	[159]
• One-step solution for the general OOSM problem in tracking presented independently	[160] [161]
• Distributed fusion update for the local sensors with OOSMs	[163]
OOSM with practical applications	[162]
• Optimal analysis of one-step OOSM filtering algorithms in target tracking	[183]
• Focus on centralized update problem for multiple local sensor systems with asynchronous OOSMs	[189]
• The l step algorithm developed for OOSM	[190]
• Optimal distributed estimation fusion with out-of-sequence measurements (OOSM) at local sensors	[202]
• Two new algorithms for solving the out-of-sequence data problem for the case of linear and nonlinear dynamic control systems	[219]
• When the delays and the sequence of arrival of all the information are not fixed, constituting the named Out-Of-Sequence Problem (OOSP) [220]	
• Out-Of-Sequence Problem (OOSP) developed for linear systems	[220]-[224]
• OOSP developed for non-linear systems	[225][226]
• A globally optimal state trajectory update algorithm for a sequence with arbitrary delayed OOSMs including the case of interlaced OOSMs with less storages	[274]
• OOSM with more applications	[275]
• OOSM processing for tracking ground target using particle filters	[296]
• Comparison of the KF and particle flter based out-of-sequence measurement fltering algorithms	[297]

singular state transition matrix is developed in [77]. Multi-step OOSM updating using augmented state smoothing is presented in [79], [80], [81]. Multi-step update in OOSM is described in [78]. Multi-sensor OOSM problem in a cluttered environment is the subject in [80], [82], [83]. One-step suboptimal updating algorithms using stored information for systems with a nonsingular state transition matrix is shown in [77], [84]. Efficient incorporation of OOSMs in Kalman filters is developed in [133]-[138]. A globally optimal flight path update algorithm with OOSMs, that is, a globally optimal algorithm which not only updates the current estimate but also updates the past estimates using a received OOSM is documented in [158]. Counterpart of the OOSM update problem, needed to remove an earlier measurement from the flight path, is analysed in [159]. One-step solution for the general OOSM problem in tracking is presented independently in [160] and [161]. Distributed fusion update for the local sensors with OOSMs is shown in [163]. OOSM with practical applications are the subject in [162]. Optimal analysis of one-step OOSM filtering algorithms in target tracking is presented in [183]. Focus on centralized update problem for multiple local sensor systems with asynchronous OOSMs is treated in [189]. The ℓ step algorithm developed for OOSM is given in [190]. Optimal distributed estimation fusion with out-of-sequence measurements (OOSM) at local sensors can be found in [202]. New algorithms for solving the out-of-sequence data problem for the case of linear and nonlinear dynamic control systems are developed in [219]. When the delays and the sequence of arrival of all the information are not fixed, constituting the named out-of-sequence problem (OOSP) can be traced to [220]. Out-of-sequence problem developed for linear systems is described in [220]-[224]. OOSP developed for nonlinear systems are presented in [225][226]. A globally optimal state trajectory update algorithm for a sequence with arbitrary delayed OOSMs including the case of interlaced OOSMs with less storages is given in [274]. More applications of OOSM can be found in [275]. OOSM processing for tracking ground target using particle filters is included in [296]. A comparison of the KF and particle filter-based out-of-sequence measurement fltering algorithms is included in [297].

V. Multi-sensor Data Fusion Systems (MSDF)

In Tables VII, VIII and IX, multi-sensor data fusion systems (MSDF)-based list of publications are classified . Sensor noises of converted systems cross-correlated but independent of the original system is covered in [8]-[9]. Sensor noises of converted system cross-correlated, and also correlated with the original system is treated in [1]. Centralized fusion center, expressed by a linear combination of the local estimates is presented in [6]. Without centralized fusion center, algorithms tend to be highly resilient to lose one or more sensing nodes is treated in [7]. Discrete smoothing fusion with ARMA signals is presented in [29]. Linear minimum variance (LMV) with information fusion filter is developed in [30], [31]. Deconvolution estimation of ARMA signal with multiple sensors is presented in [32]. Fusion criterion weighted by scalars is proposed in [41]. Functional equivalence of two measurement fusion methods is provided in [42]. Centralized filter where data processed/communicated centrally is discussed in [43]. New performance bound for sensor fusion with model uncertainty is developed in [43]. All prior fusion results with asynchronous measurements is provided in [55]. Unified fusion model and unified batch fusion rules is presented in [54], [53]. Unified rules by examples are found in [52]. Computing formulation for cross-covariance of the local estimation is presented in [51]. Conditions for centralized and distributed fusers to be identical is developed in [50]. Relationships among the various fusion rules is given in [49]. Optimal rules for each sensor to compress its measurements is considered in [48]. Various issues unique to fusion for dynamic systems is developed in [47]. Bayesian framework for adaptive quantization, fusion-center feedback, and estimation of a spatial random field and its parameters are treated in [60]. A framework for alternates to quantile quantizer and fusion center is provided in [61].

Diagonal weighting matrices are presented in [62]. Different fusion rates for the different states are contained in [63]. Optimal distributed estimation fusion in the linear minimum variance (LMV) estimation is presented in [86]. Median fusion and information fusion, not based on weighted sums of local estimates, are presented in [87]. Distributed filtering algorithms, optimal in mean square sense linear combinations of the matrix or scalar weights with derivations are developed in [88], [89]. Closed-form analytical solution of steady fused covariance of information matrix fusion with arbitrary number of sensor derived is developed in [90]. Focus on various issues unique to fusion for dynamic systems, present a general data model for discretized asynchronous multi-sensor systems, are treated in [110]. Recursive BLUE fusion without prior information is worked out in [111]. Statistical interval estimation fusion is contained in [112]. Fused estimate communicated to a central node to be used for some task is presented in [119]. Optimal distributed estimation fusion algorithm with the transformed data is proposed in [120], which is actually equivalent to the centralized estimation fusion. State estimation fusion algorithm, optimal in the sense of maximum a posteriori (MAP) is developed in [122]. Corresponding distributed fusion problem, proposed based on a unified data model for linear unbiased estimator is presented in [123]. An algorithm, fuses one step predictions at both the fusion center and all current sensor estimates is given in [124]. In multi-sensor linear dynamic system, several efficient algorithms of centralized sensor fusion, distributed sensor fusion, and multi-algorithm fusion to minimize the Euclidian estimation error of the state vector are documented in [125].

Derivation of approximation technique for arbitrary probability densities, providing the same distributive fusion structure as the linear information filter is presented in [126]. Multi-sensor distributed fusion filters based on three weighted algorithms, applied to the systems with uncertain observations and correlated noises are detailed in [164], [165]. Multi-sensor distributed fusion in state estimation fields, and easy fault detection, isolation and more reliability is developed in [165], [166], [167]. Centralized fusion Kalman filtering algorithm, obtained by combining all measurement data is developed in [178]. Design of general and optimal asynchronous recursive fusion estimator for a kind of multi-sensor asynchronous sampling system is presented in [182]. Problem of data fusion in a decentralized and distributed network of multi-sensor processing nodes is contained in [188]. To assure the validity of data fusion, a centralized trust rating system is presented in [195]. White noise filter weighted by scalars based on Kalman predictor is developed in [235]. White noise deconvolution estimators are desvcribed in [236]. Optimal information fusion distributed Kalman smoother given for discrete time multi-channel autoregressive moving average (ARMA) signals with correlated noise is presented in [239]. Optimal dimensional reduction of sensor data by using the matrix decomposition, pseudo-inverse, and eigenvalue techniques is contained in [244]. Multi-sensor Information fusion distributed Kalman filter and applications is presented in [247]. Based on analysis of the fused state estimate covariances of the two measurement fusion methods is described in [248]. Multi-sensor data fusion approaches to resolve problem of obtaining a joint state-vector estimate, better than the individual sensor-based estimates is documented in [249], [250], [251]. Decentralized multi-sensor extended Kalman filter (EKF) which is divided up into modules, one associated with each sensor is developed in [252].

A distributed reduced-order fusion Kalman filter (DRFKF) is treated in [254]. Fusion algorithm based on multi-sensor systems and a distributed multi-sensor data fusion algorithm based on Kalman filtering is presented in [269]. Track fusion formulas with feedback are, like the track fusion without feedback are contained in [270]. The optimal DKF fusion algorithms for the case with feedback and cross-uncorrelated sensor measurement noises are presented in [272]. General optimal linear fusion is worked out in [273]. Information fusion in distributed sensor networks is shown in [299]. Multi-scale recursive estimation, data fusion, and regularization are proposed in [302].

Remark V.1: In [29], using estimators of white measurement noise, an optimal information fusion distributed Kalman smoother is given for multichannel ARMA signals with correlated noise. The work on ARMA signal and information fusion is also done in [30] and [31]. Basically it has a three-layer fusion structure with fault tolerant, and robust properties. The first fusion layer and the second fusion layer both have nested parallel structures to determine the prediction error cross-covariance of the state and the smoothing error cross-covariance of the ARMA signal between any two faultless sensors at each time step. And the third fusion layer is the fusion centre to determine the optimal matrix weights and obtain the optimal fusion distributed smoother for ARMA signals. The computation formula of smoothing error cross-covariance matrix between any two sensors is given for white measurement noise. The computation formula of smoothing error cross-covariance matrix between any two sensors is given for white measurement noise. The discrete time multi-channel ARMA signal system considered here with L *sensors is:*

$$B(q^{-1})s(t) = C(q^{-1})w(t) \tag{20}$$

$$y_i(t) = s(t) + \upsilon_i(t),\, i = 1, ..., L \tag{21}$$

where $s(t) \in \Re^m$ *is the signal to estimate,* $y_i(t) \in \Re^m$ *is the measurement of the* i*th sensor,* $w(t) \in \Re^r$ *is the process noise,* $\upsilon_i(t) \in \Re^m$ *is the measurement noise of the* i*th sensor,* L *is the number of sensors, and* $B(q^{-1})$*,* $C(q^{-1})$ *are polynomial matrices having the form*

$$X(q^{-1}) = X_0 \;+\; X_1(q^{-1}) + \;..... \;+ X_{n_x}q^{-n_x}$$

where the argument q^{-1} *is the back shift operator, that is,* $q^{-1}x(t) = x(t-1)$*,* $X_i,\, i = 0, 1, ,....., n_x$ *are the coefficient matrices, the degree of* $X(q^{-1})$ *is denoted by* n_x*.*

In the multi-sensor random parameter matrices case, sometimes, even if the original sensor noises are mutually independent, the sensor noises of the converted system are still cross-correlated. Hence, such multi-sensor system seems not satisfying the conditions for the distributed Kalman filtering fusion as given in [8], [9]. In the paper [1], it was proved that when the sensor noises or the random measurement matrices of the original system are correlated across sensors, the sensor noises of the converted system are cross-correlated. Even if so, similarly with [6], centralized random parameter matrices Kalman filtering, where the fusion center can receive all sensor measurements, can still be expressed by a linear combination of the local estimates. Therefore, the performance of the distributed filtering fusion is the same as that of the centralized fusion under the assumption that the expectations of all sensor measurement matrices are of full row rank. Numerical examples are given which support our analysis and show significant performance loss of ignoring the randomness of the parameter matrices. The following discrete time dynamic system is considered:

$$x_{k+1} = F_k x_k + \upsilon_k \tag{22}$$

$$y_k = H_k x_k + \omega_k, k = 0, 1, 2, 3, ... \tag{23}$$

where $x_k \in \Re^r$ *is the system state,* $y_k \in \Re^N$ *is the measurement matrix,* $\upsilon_k \in \Re^r$ *is the process noise, and* $\omega_k \in \Re^N$ *is the measurement noise. The subscript* k *is the time index.* $F_k \in \Re^{r\times r}$ *and* $H_k \in \Re^{N\times r}$ *are random matrices.*

VI. Distributed Networks (DN)

The list of publications on distributed networks (DN) is classified in Table X. Distributed networked control system (DNCS) with multiple nodes is presented in [64]. Two approximate filtering algorithms for estimating states of a DNCS is presented in [65]. Distributed expectation maximization (EM) algorithm over sensor networks, consensus filter used to diffuse local sufficient statistics to neighbors and estimate global sufficient statistics in each node are developed in [92]. Density estimation and unsupervised clustering, first step in exploratory data analysis is treated in [93], [95]. Consensus filter diffusion of local sufficient statistics over the entire network through communication with neighbor nodes, is provided in [94]. Distributed fusion of multiple sensor data to networks is considered in [127]. Robust distributed state estimation against false data injection is treated in [149]. Distributed sensor network, consisting of a set of spatially scattered sensors that can measure various properties of the environment, formulate local and distributed inferences, and make responses to events or queries are developed in [150]. Sensor network where single or multiple sensors amplify and forward their measurements of a common linear dynamical system to a remote fusion center via noisy fading wireless channels is given in [187]. Modified adaptive Kalman filter for sensor-less current control of a three-phase inverter based distributed generation system is proposed in [191]. Distributed estimation scheme for tracking the state of a Gauss-Markov model by means of observations at sensors connected in a network is the subject of [196]. A message-passing version of the Kalman consensus filter (KCF) is considered in [204]. A peer-to-peer (P2P) architecture of DKF that rely on reaching a consensus on estimates of local Kalman filters is analysed in [205]. For decentralized tracking applications, DKF and smoothing algorithms are derived for any-time MMSE optimal consensus-based state estimation using Wireless Sensor Networks are considered in [212]. Trade-off between the estimation performance and the number of communicating nodes with respect to the major MAC protocols used in wireless sensor networks is developed in [218]. Distributed networked control system (DNCS) consisting of multiple agents communicating over a lossy communication channel is presented in [227]. Impact of the network reliability on the performance of the feedback loop is considered in [229].

Remark VI.1: In literature, a single plant is usually assumed for an NCS and the links between the plant and the estimator or controller channel. This notion is extended by a distributed networked control system (DNCS) in which there are multiple agents communicating over a lossy communication channel [64]. A DNCS extends an NCS to model a distributed multi-agent system such as the Vicsek model. The best examples

TABLE VII
MULTI-SENSOR DATA FUSION SYSTEMS(MSDF) I

Multi-sensor Data Fusion(MSDF) Design Approaches	References
• Sensor noises of converted systems cross-correlated, whilst original system independent	[8]-[9]
• Sensor noises of converted system cross-correlated, whilst original system also correlated	[1]
• Centralized fusion center, expressed by a linear combination of the local estimates	[6]
• No centralized fusion center, but algorithm highly resilient to lose one or more sensing nodes	[7]
• Discrete smoothing fusion with ARMA Signals	[29]
linear minimum variance(LMV) with information fusion filter	[30][31]
• Deconvolution estimation of ARMA signal with multiple sensors	[32]
• Fusion criterion weighted by scalars	[41]
• Functional equivalence of two measurement fusion methods	[42]
• Centralized filter, data processed/communicated centrally	[43]
• New performance bound for sensor fusion with model uncertainty	[43]
• All prior fusion results with Asynchronous Measurements	[55]
• Unified fusion model and unified batch fusion rules	[54][53]
• Unified rules by examples	[52]
• Computing formulation for cross-covariance of the local estimation	[51]
• Conditions for centralized and distributed fusers to be identical	[50]
• Relationships among the various fusion rules	[49]
• Optimal rules for each sensor to compress its measurements	[48]
• Various issues unique to fusion for dynamic systems	[47]
• Bayesian framework for adaptive quantization, fusion-center feedback, and estimation of a spatial random field and its parameters	[60]
• Framework for alternates to quantile quantizer and fusion center	[61]

of such system include ad-hoc wireless sensor networks and a network of mobile agents. The exact state estimation method based on the Kalman filter is introduced in [64]. However, the time complexity of the exact method can be exponential in the number of communication links.are closed by a common (unreliable) communication In the paper [65], this issue is addressed by developing two approximate filtering algorithms for estimating states of a DNCS. The approximate filtering algorithms bound the state estimation error of the exact filtering algorithm and the time complexity of approximate methods is not dependent on the number of communication links. The stability of estimators under a lossy communication channel is studied in [304], [305]. However, the extension of the result to the general case with an arbitrary number of lossy communication links is unknown. While computing the exact communication link probabilities required for stable state estimation is non-trivial, the general conditions for stable state estimation using jump linear system theory are described. The following first distributed control system consisting of N agents is considered, in which there is no communication loss. The discrete-time linear dynamic model of the agent j can be described as following:

$$x_j(k+1) = \sum_{i=1}^{N} A_{ij} x_i(k) + G_j w_j(k) \tag{24}$$

where $k \in \mathbf{Z}^+$, $x_j(k) \in \mathbf{R}^{n_x}$ is the state of the agent j at time k, $w_j(k) \in \mathbf{R}^{n_w}$ is a white noise process, $A_{ij} \in \mathbf{R}^{n_x \times n_x}$, and $G_j \in \mathbf{R}^{n_x \times n_W}$. Hence, the state of the agent j is governed by the previous states of all N agents. It can also be considered that $A_{ij}x_i(k)$ as a control input from the agent i to the agent j for $i \neq j$.

VII. MATHEMATICAL DESIGN IN TRACK-TO-TRACK FUSION

Track fusion (TF)-based list of publications are classified in Table XI. Track fusion with information filter is presented in [8]. Track fusion optimality with ML is presented in [10], [17], [18], [19]. Two track estimates cross-covariance are presented in [11]. Track fusion local estimate dependency is described in [12]. Track fusion measurement is given in [13]. Track fusion multi-sensor algorithm is proposed in [14] and track fusion cross-covariance with independent noises is presented in [16]. Steady-state fusing problem is analysed in [15] whereas steady

TABLE VIII
MULTI-SENSOR DATA FUSION SYSTEMS(MSDF) II

Multi-sensor Data Fusion(MSDF) Design Approaches	References
• Diagonal weighting matrices	[62]
• Different fusion rates for the different states	[63]
• Optimal distributed estimation fusion in the linear minimum variance (LMV) estimation	[86]
• Median fusion and information fusion, not based on weighted sums of local estimates	[87]
• Distributed filtering algorithms, optimal in mean square sense linear combinations of the matrix or scalar weights with derivations	[88][89]
• Closed form analytical solution of steady fused covariance of information matrix fusion with arbitrary number of sensor derived	[90]
• Focus on various issues unique to fusion for dynamic systems, present a general data model for discretized asynchronous multi-sensor systems	[110]
• Recursive BLUE fusion without prior information	[111]
• Statistical interval estimation fusion	[112]
• Fused estimate communicated to a central node to be used for some task	[119]
• Optimal distributed estimation fusion algorithm with the transformed data is proposed, which is actually equivalent to the centralized estimation fusion	[120]
• State estimation fusion algorithm, optimal in the sense of maximum a posteriori (MAP)	[122]
• Corresponding distributed fusion problem, proposed based on a unified data model for linear unbiased estimator	[123]
• An algorithm, fuses one step predictions at both the fusion center and all current sensor estimates	[124]
• In multi-sensor linear dynamic system, several efficient algorithms of centralized sensor fusion, distributed sensor fusion, and multi-algorithm fusion to minimize the Euclidian estimation error of the state vector	[125]

state fused covariance for hierarchical track fusion architecture with feedback is provided in [66]. Cross-covariance of the local track is developed in [67]. Weighted covariance state-vector Track fusion is analysed in [68]-[69]. Pseudo-measurement state-vector track fusion is presented in [70]-[71]. Steady state fused covariance matrix is the subject of [72]. Various architectures for track association and fusion is contained in [73]-[74]. Fused estimate communicated to a central node to be used for some task is shown in [119]. Track-to-track fusion algorithm, optimal in the sense of ML for more than two sensors is treated in [121]. Measurement fusion and state vector track fusion is considered in [255]. State vector track fusion with pseudo-measurement is presented in [256], [257]. Performance of various track-to-track fusion algorithms from aspects of fusion accuracy, feedback and process noises are treated in [258]. Fuse state vectors using Weighted Covariance (WC) is presented in [259], [260]. Weighted covariance algorithm turns out to be a xaximum likelihood estimate is proposed in [261]. Perform track fusion optimally for a multiple-sensor system with a specific processing architecture is treated in [290]. Track-to-track fusion for multi-sensor data fusion is contained in [291]. Common process noise on the two-sensor fused-track covariance is shown in [298]. Track association and track fusion with non-deterministic target dynamics is presented in [300]. Comparison of two-sensor tracking methods based on state vector fusion and measurement fusion is considered in [301].

VIII. DISTRIBUTED CONSENSUS-BASED ESTIMATION

Distributed Consensus-Based Estimation list of publications are classified in Table XII. Iterative consensus protocols is proposed in [23]. Local average consensus algorithms is treated in [25]. Similar reults are reported in [26], [175] based on consensus strategies and in [27] based on consensus Iterations. The issue of converge speed of consensus strategies is shown in [28]. Dynamic consensus problems regarding fusion of the measurements and covariance information with consensus filters are treated in [75]. Results on using standard Kalman filter locally, together with a consensus step in order to ensure that the local estimates agree are developed in [5]. Distributed expectation-maximization (EM) algorithm over sensor networks, consensus filter used to diffuse local sufficient statistics to neighbors and estimate global sufficient statistics in each node are the subject of [92]. Consensus filter diffusion of local sufficient statistics over the entire network through communication with neighbor

TABLE IX
MULTI-SENSOR DATA FUSION SYSTEMS(MSDF) III

Multi-sensor Data Fusion(MSDF) Design Approaches	References
• Derivation of approximation technique for arbitrary probability densities, providing the same distributable fusion structure as the linear information filter	[126]
• Multi-sensor distributed fusion filters based on three weighted algorithms, applied to the systems with uncertain observations and correlated noises	[164] [165]
• Multi-sensor distributed fusion in state estimation fields, and easy fault detection, isolation and more reliability	[165][166][167]
• Centralized fusion Kalman filtering algorithm, obtained by combining all measurement data	[178]
• Design of general and optimal asynchronous recursive fusion estimator for a kind of multi-sensor asynchronous sampling system	[182]
• Problem of data fusion in a decentralized and distributed network of multi-sensor processing nodes	[188]
• To assure the validity of data fusion, a centralized trust rating system	[195]
• white noise filter weighted by scalars based on Kalman predictor	[235]
• White noise de-convolution estimators	[236]
• Optimal information fusion distributed Kalman smoother given for discrete time multichannel autoregressive moving average (ARMA) signals with correlated noise	[239]
• Optimal dimensionality reduction of Sensor Data by using the matrix decomposition, pseudo-inverse, and eigenvalue techniques	[244]
• Multi-sensor Information fusion distributed Kalman filter and applications	[247]
• Based on analysis of the fused state estimate covariances of the two measurement fusion methods	[248]
• Multi-sensor data fusion approaches to resolve problem of obtaining a joint state-vector estimate, better than the individual sensor-based estimates	[249][250][251]
• Decentralized multi-sensor EKF which has been divided up into modules, one associated with each sensor	[252]
• A distributed reduced-order fusion Kalman filter (DRFKF)	[254]
• Fusion algorithm based on multi-sensor systems and a distributed multi-sensor data fusion algorithm based on Kalman filtering	[269]
• Track fusion formulas with feedback are, like the track fusion without feedback	[270]
• The optimal distributed Kalman Filtering fusion algorithms for the case with feedback and cross-uncorrelated sensor measurement noises	[272]
• General optimal linear fusion	[273]
• Information fusion in distributed sensor networks	[299]
• Multi-scale Recursive Estimation, Data Fusion, and Regularization	[302]

nodes is presented in in[94]. Consensus-based distributed linear filtering problem is developed in [97]. The interaction between the consensus matrix, the number of messages exchanged per sampling time, and the Kalman gain for scalar systems are analysed in [98]. Kalman filter coupled with a consensus filter, ensuring estimates asymptotically converge to the same value are presented in [99]. A novel state estimation algorithm for linear stochastic systems, proposed on the basis of overlapping system decomposition, implementation of local state estimators by intelligent agents, application of a consensus strategy providing the global state estimates are detailed in [105]. Average-consensus algorithm for n measurements of noisy signals obtained from n sensors in the form of a distributed low-pass filter is described in [106] and average-consensus algorithm for n constant values is given in [107], [108]. Consensus-Based distributed implementation of the unscented particle is developed in filter [113]. Consensus-based distributed approached Kalman filters for linear systems [116], [117]. A message-passing version of the Kalman consensus filter (KCF) is proposed in [204]. A peer-to-peer (P2P) architecture of DKF that rely on reaching a consensus on estimates of local Kalman filters is shown in [205]. Consensus-based suboptimum Kalman filtering scheme

TABLE X
DISTRIBUTED NETWORKS(DN)

Design Approaches Used in DN	References
• Distributed networked control system (DNCS) with multiple nodes	[64]
• Two approximate filtering algorithms for estimating states of a DNCS	[65]
• Distributed expectationmaximization (EM) algorithm over sensor networks, consensus filter used to diffuse local sufficient statistics to neighbors and estimate global sufficient statistics in each node	[92]
• Density estimation and unsupervised clustering, first step in exploratory data analysis	[93][95]
• Consensus filter diffusion of local sufficient statistics over the entire network through communication with neighbor nodes	[94]
• Distributed fusion of multiple sensor data to networks	[127]
• Robust distributed state estimation against false data injection	[149]
• Distributed sensor network, consisting of a set of spatially scattered sensors that can measure various properties of the environment, formulate local and distributed inferences, and make responses to events or queries	[150]
• Sensor network where single or multiple sensors amplify and forward their measurements of a common linear dynamical system to a remote fusion center via noisy fading wireless channels	[187]
• Modified adaptive Kalman filter for sensor-less current control of a three-phase inverter based distributed generation system	[191]
• Distributed estimation scheme for tracking the state of a Gauss-Markov model by means of observations at sensors connected in a network	[196]
• A message-passing version of the Kalman-Consensus Filter (KCF)	[204]
• A peer-to-peer (P2P) architecture of DKF that rely on reaching a consensus on estimates of local Kalman filters	[205]
• For decentralized tracking applications, distributed Kalman filtering and smoothing algorithms are derived for any-time MMSE optimal consensus-based state estimation using Wireless Sensor Networks	[212]
• Trade-off between the estimation performance and the number of communicating nodes with respect to the major MAC protocols used in wireless sensor networks	[218]
• Distributed networked control system (DNCS) consisting of multiple agents communicating over a lossy communication channel	[227]
• Impact of the network reliability on the performance of the feedback loop	[229]

is developed in [217]. Finally, distributed filter that allows the nodes of a sensor network to track the average of n sensor measurements using an average consensus based distributed filter is documented in [238].

Remark VIII.1: In the paper [92], the number of Gaussian components is given. In the next step, distributed unsupervised clustering approach is used to select the number of Gaussian components, or it can use a distributed algorithm to estimate this number and run expectation maximization (EM) algorithm simultaneously. A well-fitted approach to this integration is the one proposed in [306]. The proposed distributed EM algorithm in the paper [92] handles this difficulty through estimating the global sufficient statistics using local information and neighbors local information. It calculates the local sufficient statistics in the E-step as usual first. Then, it estimates the global sufficient statistics. Finally, it updates the parameters in the M-step using the estimated global sufficient statistics. The estimation of global sufficient statistics is achieved by using an average consensus filter. The consensus filter can diffuse the local sufficient statistics over the entire network through communication with neighbor nodes [22], [23], [307] and estimate the global sufficient statistics using local information and neighbors local information. By using the estimated global sufficient statistics, each node updates the parameters in the M-step in the same way as in the standard EM algorithm. Because the consensus filter only requires local communication, that is, each node only needs to communicate with its neighbors and gradually gains global information, this distributed algorithm is scalable. It is shown that the equations of parameter estimation in this algorithm are not related to the number of sensor nodes. Thus, it is also robust. Failures of any nodes do not affect the algorithm performance given the network is still connected. Eventually, the estimated parameters can be accessed from any nodes in the network. In this paper, section, we a network of M sen-

TABLE XI
MATHEMATICAL DESIGN IN TRACK-TO-TRACK FUSION

Track-to-Track Fusion Approaches	References
• Track fusion with information filter	[8]
• Track fusion optimality with ML	[10][17][18][19]
• Two track estimates cross-covariance	[11]
• Track fusion local estimate dependency	[12]
• Track fusion measurement	[13]
• Track fusion multi-sensor algorithm	[14]
• Track fusion cross-covariance with independent noises	[16]
• Steady-state fusing problem	[15]
• Steady state fused covariance for hierarchical track fusion architecture with feedback	[66]
• Cross-covariance of the local track	[67]
• Weighted covariance state-vector Track fusion	[68]-[69]
• Pseudo-measurement state-vector Track fusion	[70]-[71]
• Steady state fused covariance matrix	[72]
• Various architectures for track association and fusion	[73]-[74]
• Fused estimate communicated to a central node to be used for some task	[119]
• Track-to-track fusion algorithm, optimal in the sense of ML for more than 2 sensors	[121]
• Measurement Fusion and State vector track fusion	[255]
• State vector track fusion with pseudo-measurement	[256] [257]
• Performance of various track-to-track fusion algorithms from aspects of fusion accuracy, feedback and process noises	[258]
• Fuse state vectors using Weighted Covariance (WC)	[259][260]
• Weighted covariance algorithm turns out to be a Maximum likelihood estimate	[261]
• Perform track fusion optimally for a multiple-sensor system with a specific processing architecture	[290]
• Track-to-track fusion for multi-sensor data fusion	[291]
• Common process noise on the two-sensor fused-track covariance	[298]
• Track association and track fusion with non-deterministic target dynamics	[300]
• Comparison of two-sensor tracking methods based on state vector fusion and measurement fusion	[301]

sors is considered, each of which has N_m data observations $y_{m,n}(m = 1, ..., M, n = 1, ..., N_m$. The environment is assumed to be a Gaussian mixture setting with K mixture probabilities $\alpha_{m,k}, (k = 1, ..., K)$. The unobserved state is denoted as z and z_k represents $z = k$. For each unobserved state z_k, observation $y_{m,n}$ follows a Gaussian distribution with mean μ_k and variance Σ_k:

$$p(y_{m,n}|\mu_k, \Sigma_k) = \frac{1}{\sqrt{2\pi}\|\Sigma_k\|^{\frac{1}{2}}} e^{-\frac{1}{2}(y_{m,n}-\mu_k)^T \Sigma_k^{-1} (y_{m,n}-\mu_k)} \quad (25)$$

The Gaussian mixture distribution for observation $y_{m,n}$ is:

$$p(y_{m,n}|\theta) = \sum_{k=1}^{K} \alpha_{m,k} p(y_{m,n}|\mu_k, \Sigma_k) \quad (26)$$

where θ is the set of the distribution parameters to be estimated $\theta = \{\alpha_{m,k}, \mu_k, \Sigma_k; k = 1, ..., K, m = 1, ..., M\}$.

IX. DISTRIBUTED PARTICLE FILTERING(DPF)

A Distributed Particle Filtering(DPF) list of publications are classified in Table XIII. Consensus-Based distributed implementation of the unscented particle filter is shown in [113]. Particle filtering transformation into continuous representations is presented in [128]. Consensus-based, distributed implementation of the unscented particle filter is shown in [129]. Particle filter implementations using Gaussian approximations for the local posteriors are proposed in [130], [131]. A novel framework for delay-tolerant particle filtering, with delayed (out-of-sequence) measurements is treated in [132]. An approach that stores sets of particles for the last l time steps, where ℓ is the predetermined maximum delay is reported in [139]. Markov chain Monte Carlo (MCMC) smoothing step for (out-of-sequence) measurements is presented in [140]. Approximate OOSM particle filter based on retrodiction(predicts backward) is given in [141]. Also uses retrodiction (predicts backward), but employs the Gaussian particle filter is found in [141]. Recent advances in particle smoothing, storage-efficient particle filter are doc-

TABLE XII
DISTRIBUTED CONSENSUS-BASED ESTIMATION

Design Approaches used in Distributed Consensus	References
• Iterative consensus protocols	[23]
• Local average consensus algorithms	[25]
• Based on consensus strategies	[26][175]
• Based consensus Iterations	[27]
• Converge Speed of consensus strategies	[28]
• Dynamic consensus problems regarding fusion of the measurements and covariance information with consensus filters	[75]
• Using Standard Kalman filter locally, together with a consensus step in order to ensure that the local estimates agree	[5]
• Distributed expectationmaximization (EM) algorithm over sensor networks, consensus filter used to diffuse local sufficient statistics to neighbors and estimate global sufficient statistics in each node	[92]
• Distributed expectationmaximization (EM) algorithm over sensor networks, consensus filter used to diffuse local sufficient statistics to neighbors and estimate global sufficient statistics in each node	[92]
• Consensus filter diffusion of local sufficient statistics over the entire network through communication with neighbor nodes	[94]
• Consensus-based distributed linear filtering problem	[97]
• The interaction between the consensus matrix, the number of messages exchanged per sampling time, and the Kalman gain for scalar systems	[98]
• Kalman filter with a consensus filter, ensuring estimates asymptotically converge to the same value	[99]
• Novel state estimation algorithm for linear stochastic systems, proposed on the basis of overlapping system decomposition, implementation of local state estimators by intelligent agents, application of a consensus strategy providing the global state estimates	[105]
• Average-consensus algorithm for n measurements of noisy signals obtained from n sensors in the form of a distributed low-pass filter	[106]
• Average-consensus algorithm for n constant values	[107][108]
• Consensus-Based distributed implementation of the unscented particle filter	[113]
• Consensus-based distributed approached Kalman filters for linear systems	[116][117]
• A message-passing version of the Kalman-Consensus Filter (KCF)	[204]
• A peer-to-peer (P2P) architecture of DKF that rely on reaching a consensus on estimates of local Kalman filters	[205]
• Consensus-based suboptimum Kalman filtering scheme	[217]
• Distributed filter that allows the nodes of a sensor network to track the average of n sensor measurements using an average consensus based distributed filter	[238]

umented in [143]. A number of heuristic metrics to estimate the utility of delayed measurements is proposed in [144] and a threshold based procedure to discard uninformative delayed measurements, calculating their informativeness is reported in [145]. Optimal estimation using quantized innovations, with application to distributed estimation over sensor networks using Kalman-like particle filter is the subject of [176]. SOI-Particle-Filter (SOI-PF) derived to enhance the performance of the distributed estimation procedure is presented in [193]. Problem of tracking a moving target in a multi-sensor environment using distributed particle filters (DPFs) is described in [230]. Optimal fusion method, introduced to fuse the collected GMMs with different number of components, is presented in [231]. Two distributed particle filters to estimate and track the moving targets in a wireless sensor network are provided in [245]. Updating the complete particle filter on each individual sensor nodes is given in [246]. Out-of-sequence measurement processing for tracking ground target using particle filters is presented in [296]. A comparison of the KF and particle flter based out-of-sequence measurement fltering algorithms is documented in [297].

X. Self-Tuning Based Distributed Fusion Kalman Filter

A Distributed particle filtering (DPF) list of publications are classified in Table XIV. Multi-sensor systems with unknown model parameters and noise variances, by the information matrix approach, the self-tuning distributed state fusion information filter are presented in [152]. Self-tuning distributed state

TABLE XIII
DISTRIBUTED PARTICLE FILTERING(DPF)

Design Approaches used in DPF	References
• Consensus-Based distributed implementation of the unscented particle filter	[113]
• Particle filtering transformation into continuous representations	[128]
• Consensus-based, distributed implementation of the unscented particle filter	[129]
• Particle filter implementations using Gaussian approximations for the local posteriors	[130][131]
• A novel framework for delay-tolerant particle filtering, with delayed (out-of-sequence) measurements	[132]
• An approach that stores sets of particles for the last l time steps, where l is the predetermined maximum delay	[139]
• Markov chain Monte Carlo (MCMC) smoothing step for (out-of-sequence) measurements	[140]
Approximate OOSM particle filter based on retrodiction(predicts backward)	[141]
• Also uses retrodiction (predicts backward), but employs the Gaussian particle filter	[141]
• Recent advances in particle smoothing, storage-efficient particle filter	[143]
• Proposed a number of heuristic metrics to estimate the utility of delayed measurements	[144]
• Proposed a threshold based procedure to discard uninformative delayed measurements, calculating their informativeness	[145]
• Optimal estimation using quantized innovations, with application to distributed estimation over sensor networks using Kalman-like particle filter	[176]
• SOl-Particle-Filter (SOI-PF) derived to enhance the performance of the distributed estimation procedure	[193]
• Problem of tracking a moving target in a multi-sensor environment using distributed particle filters (DPFs)	[230]
• Optimal fusion method, introduced to fuse the collected GMMs with different number of components [231]	
• Two distributed particle filters to estimate and track the moving targets in a wireless sensor network	[245]
• Updating the complete particle filter on each individual sensor nodes	[246]
• Out-of-sequence measurement processing for tracking ground target using particle filters	[296]
• Comparison of the KF and particle flter based out-of-sequence measurement fltering algorithms	[297]

fusion Kalman filter with weighted covariance approach is reported in [154]. Self-tuning decoupled fusion Kalman predictor is proposed in [155] and self-tuning weighted measurement Kalman filter is included in [156]. Multi-sensor systems with unknown noise variances, a new self-tuning weighted measurement fusion Kalman filter is presented in [177], which has asymptotic global optimality. Weighted self-tuning state fusion filters is given in [179], [180]. Sign of innovation-particle filter (SOI-PF) improves the tracking performance when the target moves according to a linear and a gaussian model as presented in [184]. Efficiency of the SOI-PF in a nonlinear and a non gaussian case, considering a jump-state Markov model for the target trajectory is derived in [185]. Self-tuning information fusion reduced-order Kalman predictor with a two-stage fusion structure based on linear minimum variance is reported in [234]. Optimal self-tuning smoother is proposed in [240]. Optimal self-tuning fix-lag smoother is developed in [241]. A new convergence analysis method for self-tuning Kalman predictor is presented in [253]. Self-tuning measurement system using the correlation method, can be viewed as the least-squares (LS) fused estimator and found in [280]. Self-tuning filtering for systems with unknown model and/or noise variances is presented in [281]-[284]. Self-tuning distributed state fusion Kalman estimators is reported in [285][286] Self-tuning distributed (weighed) measurement fusion Kalman filters is shown in [287], [288], [289].

Remark X.1: For self-tuning decoupled fusion Kalman predictor, the following multi-sensor linear discrete time-invariant *stochastic system is considered in the paper [303]:*

$$x(t+1) = \Phi x(t) + \Gamma w(t) \tag{27}$$

$$y_i(t) = H_i x(t) + \upsilon_i(t)\,,\, i = 1, \ldots.., L \tag{28}$$

where $x(t) \in \Re^n$,$y_i(t) \in \Re^{m_i}$, $w(t) \in \Re^r$ *and* $\upsilon_i(t) \in \Re^{m_i}$ *are the state, measurement, process and measurement noises of the* i*th sensor subsystem, respectively, and* Φ, Γ *and* H_i *are constant matrices with compatible dimensions.*

XI. Conclusions

The distributed system architecture, on the whole, is very powerful since it allows the design of the individual units or components to be much simpler, while not compromising too much on the performance. A brief technical review and bibliography listing on the advances in distributed Kalman filtering (DKF) have been presented in this paper. The current and previous approaches have been reported in this paper. DKF comprising of OOSM approaches, Diffusion-Based approaches, Consensus Based Estimation, Self-Tuning designs and various applications of DKF have been classified. Some open problems and current research activities have been discussed and around 300 references have been categorized. We apologize in advance for any omission of publications, in spite of our best effort.

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TABLE XIV
SELF-TUNING BASED DISTRIBUTED FUSION KALMAN FILTER

Self-Tuning Design Approaches	References
• Multi-sensor systems with unknown model parameters and noise variances, by the information matrix approach, the self-tuning distributed state fusion information filter is presented	[152]
• Self-tuning distributed state fusion Kalman filter with weighted covariance approach	[154]
• Self-tuning decoupled fusion Kalman predictor	[155]
• Self-tuning weighted measurement Kalman filter	[156]
• Multi-sensor systems with unknown noise variances, a new self-tuning weighted measurement fusion Kalman filter is presented, which has asymptotic global optimality	[177]
• Weighted self-tuning state fusion filters	[179][180]
• Sign of Innovation- Particle Filter (SOI-PF) improves the tracking performance when the target moves according to a linear and a gaussian model	[184]
• Efficiency of the SOI-PF in a nonlinear and a non gaussian case, considering a jump-state Markov model for the target trajectory	[185]
• Self-tuning information fusion reduced-order Kalman predictor with a two-stage fusion structure based on linear minimum variance	[234]
• Optimal self-tuning smoother	[240]
• Optimal self-tuning fix-lag smoother	[241]
• A new convergence analysis method for Self-Tuning Kalman Predictor	[253]
• Self-Tuning measurement system using the correlation method, can be viewed as the least-squares (LS) fused estimator	[280]
• Self-tuning filtering for systems with unknown model and/or noise variances	[281]-[284]
• Self-tuning distributed state fusion Kalman estimators	[285][286]
• Self-tuning distributed (weighed) measurement fusion Kalman filters	[287][288][289]

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