Bibliographic Review on Distributed Kalman Filtering

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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 applications 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.

Keywords: Distributed Kalman filtering (DKF), Self-tuning (ST) distributed fusion Kalman filter, distributed particle filtering (DPF), distributed consensus (DC)-based estimation, track-to-track fusion, distributed networks (DN), multi-sensor data fusion systems (MSDF), distributed out-of-sequence measurements (OOSM), diffusion-based DKF.

1 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 DKF can be seen in figure (see Fig. 1).

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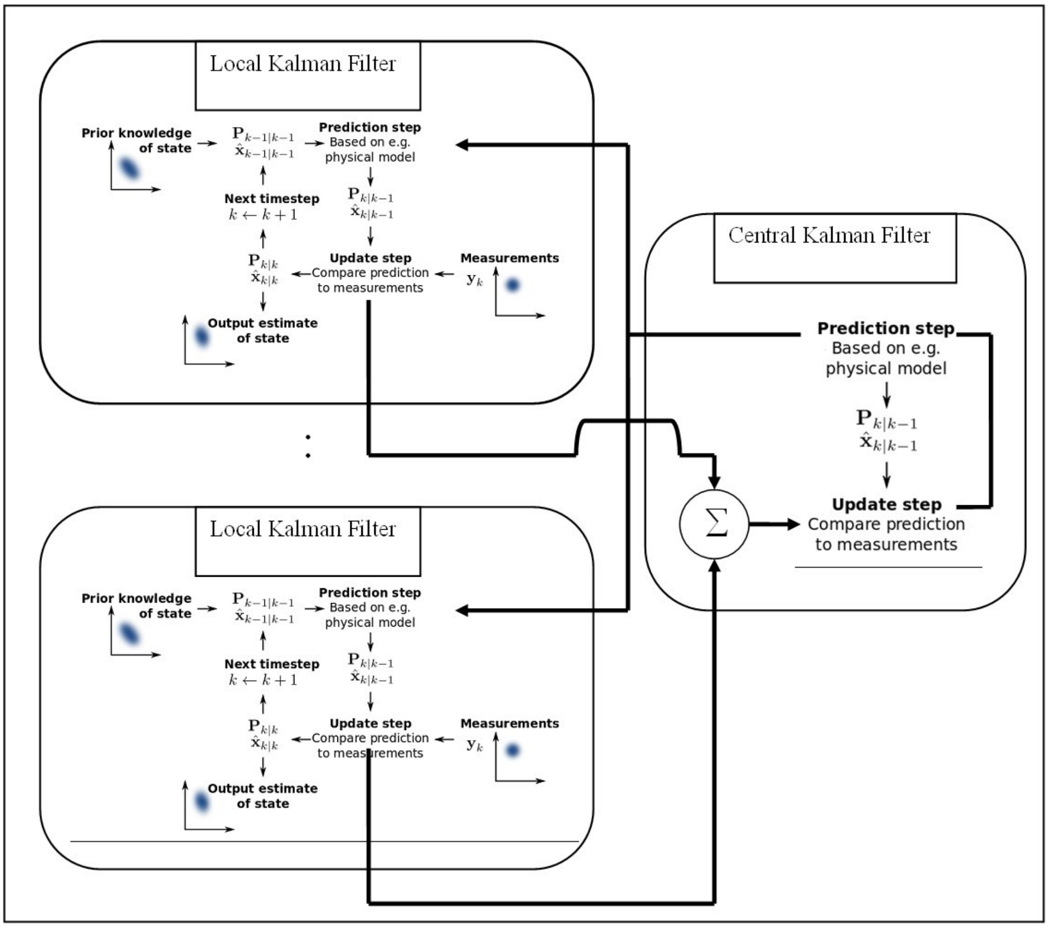

Figure 1: A general structure of DKF

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. DKF methods have been categorized into eight main divisions which are then further categorized into other several subdivisions.

Therefore, in this paper, we present a bibliographic literature survey and an overall technical review of DKF. To meet our goal, the remaining part of the paper is organized as follows: Bibliographic review and technical survey of DKF and its applications are presented in Section 2, diffusion-based DKF in Section 3, followed by Distributed OOSM in Section 4, MSDF systems in section 5, followed by DN in section 6, mathematical design in track-to-track fusion in Section 7, DC-based estimation in Section 8, DPF in Section 9, ST-based distributed fusion Kalman filter in Section 10. Finally some concluding remarks are given in Section 11. It should be noted that remark has been generated at the end of every section, showing the generic formulation generation explanation of a particular approach in that specific section.

2 DKF Methods and their Applications

2.1 DKF methods

DKF can be introduced through different methods promoting to a better filtering approach, also considering various scenarios. A list of publications focusing on DKF methods and their applications is summarized in Table 1 and Table 2. In Table 1, the most recent references are [1] and [2], where in [1], a method is discussed under uncertain observations, including measurement with a false alarm probability as a special case. Moreover, it is proved that under a mild condition the fused state estimate is equivalent to the centralized Kalman filtering. In [2], consensus strategies of DKF are discussed where the problem of estimating the state of a dynamical system from distributed noisy measurements is considered with the help of a two-stage strategy for estimation. Other DKF methods and their applications can be seen in [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19] and

[3]* The Fig. 2 is showing the classification of distributed Kalman filter, where KF stands for Kalman filter, DKF stands for distributed Kalman filter, EKF stands for extended Kalman filter, DC stands for distributed consensus, MSDF stands for multi-sensor data fusion, OOSM stands for out-of-sequence measurements, SN stands for sensor network, ST stands for self tuning, DPF stands for Distributed particle filter, DN stands for distributed networks.

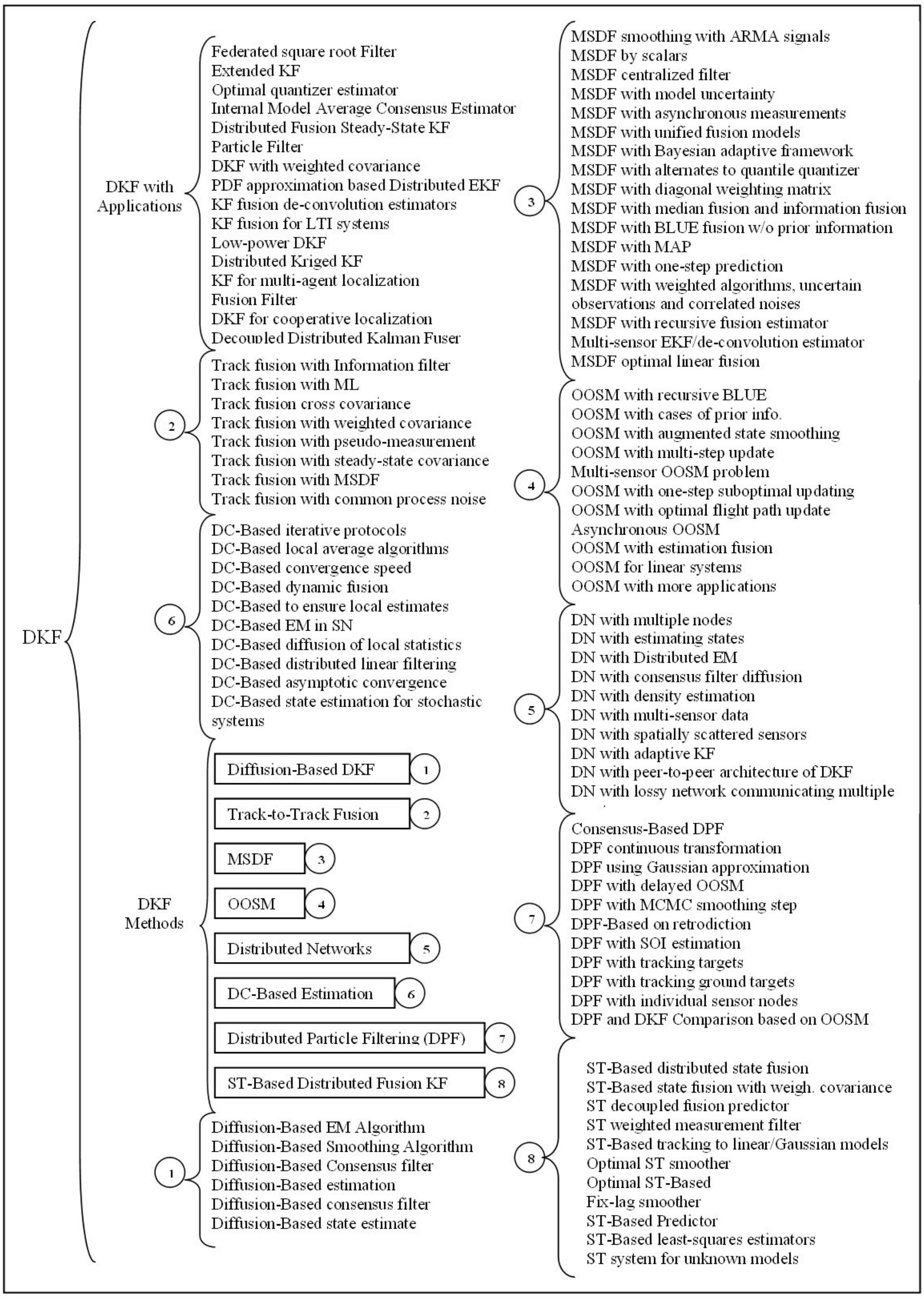

Figure 2: Classification of Distributed Kalman Filter*

[20].

In Table 2, the most recent references are [21] and [22], where in [21], the estimation of sparsely connected, large scale systems is reported, moreover full distribution of Kalman filter is achieved. In [22], a network is modeled as a Bernoulli random topology and establish necessary and sufficient conditions for mean square sense and almost sure convergence of average consensus when network links fail. Other DKF methods and its applications can be seen in [23], [24], [25], [26], [27], [2], [28], [29], [30], [31], [32] and [33].

Remark 2.1 *In [11], an ℓ-sensor distributed dynamic system is described by:*

$$\begin{aligned} x_{k+1} &= \phi_k x_k + \upsilon_k, k = 0, 1, ... \quad (2.1)\\ y_k^i &= H_k^i x_k + w_k^i, i = 1, ..., \ell \quad (2.2) \end{aligned}$$

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:

$$y_k = H_k x_k + w_k \quad (2.3)$$

where

$$\begin{aligned} y_k &= (y_k^{1^t}, ..., y_k^{\ell^t})^t, H_k = (H_k^{1^t}, ..., H_k^{\ell^t})^t,\\ w_k &= (w_k^{1^t}, ..., w_k^{\ell^t})^t \quad (2.4) \end{aligned}$$

and the covariance of the noise w_k is given by:

$$Cov(w_k) = R_k, R_k^i = Cov(w_k^i), \quad i = 1, ..., \ell \quad (2.5)$$

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 at the i-th sensor is expressed as:

$$\widehat{K}_k^i = \widehat{P}_{k/k}^i H_k^{i^t} \widehat{R}_k^{i^{-1}} \quad (2.6)$$

$$\widehat{x}_{k/k}^i = \widehat{x}_{k/k-1}^i + \widehat{K}_k^i (y_k^i - H_k^i \widehat{x}_{k/k-1}^i) \quad (2.7)$$

$$\widehat{P}_{k/k}^i = \widehat{P}_{k/k-1}^i - \widehat{K}_k^i H_k \widehat{P}_{k/k-1}^i \quad (2.8)$$

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

$$\widehat{P}_{k/k}^{i^{-1}} = \widehat{P}_{k/k-1}^{i^{-1}} + H_k^{i^t} \widehat{R}_k^{i^{-1}} H_k^i \quad (2.9)$$

with

$$\begin{aligned}
\widehat{x}^i_{k/k-1} &= \widehat{\Phi}_k \widehat{x}^i_{k-1/k-1}, \\
\widehat{P}^i_{k/k} &= E[(\widehat{x}^i_{k/k} - \widehat{x}_k)(\widehat{x}^i_{k/k-1} - \widehat{x}_k)^t] \\
\widehat{P}^i_{k/k-1} &= E[(\widehat{x}^i_{k/k-1} - \widehat{x}_k)(\widehat{x}^i_{k/k-1} - \widehat{x}_k)^t] \qquad (2.10)
\end{aligned}$$

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

$$\widehat{K}_k = \widehat{P}_{k/k} H^t_k \widehat{R}^{-1}_k \qquad (2.11)$$

$$\widehat{x}_{k/k} = \widehat{x}_{k/k-1} + \widehat{K}_k (y_k - H_k \widehat{x}_{k/k-1}) \qquad (2.12)$$

$$\widehat{P}_{k/k} = \widehat{P}_{k/k-1} - \widehat{K}_k H_k \widehat{P}_{k/k-1} \qquad (2.13)$$

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

$$\widehat{P}^{-1}_{k/k} = \widehat{P}^{-1}_{k/k-1} + {H_k}^t \widehat{R}^{-1}_k H_k \qquad (2.14)$$

with

$$\begin{aligned}
\widehat{x}_{k/k-1} &= \widehat{\Phi}_k \widehat{x}_{k-1/k-1}, \\
\widehat{P}_{k/k} &= E[(\widehat{x}_{k/k} - \widehat{x}_k)(\widehat{x}_{k/k-1} - \widehat{x}_k)^t] \\
\widehat{P}_{k/k-1} &= E[(\widehat{x}_{k/k-1} - \widehat{x}_k)(\widehat{x}_{k/k-1} - \widehat{x}_k)^t] \qquad (2.15)
\end{aligned}$$

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

$$H^t_k \widehat{R}^{-1}_k H_k = \sum_{i=1}^{l} H^{i^t}_k \widehat{R}^{i^{-1}}_k H^i_k \qquad (2.16)$$

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

$$\widehat{P}^{-1}_{k/k} = \widehat{P}^{-1}_{k/k-1} + \sum_{i=1}^{l} (\widehat{P}^{i^{-1}}_{k/k} - \widehat{P}^{i^{-1}}_{k/k-1}) \qquad (2.17)$$

and

$$\widehat{P}^{-1}_{k/k} \widehat{x}_{k/k} = \widehat{P}^{-1}_{k/k-1} + \sum_{i=1}^{l} (\widehat{P}^{i^{-1}}_{k/k} \widehat{x}^i_{k/k} - \widehat{P}^{i^{-1}}_{k/k-1} \widehat{x}^i_{k/k-1}) \qquad (2.18)$$

Also,

$$H^{i'}_k \widehat{R}^{i^{-1}}_k y^i_k = \widehat{P}^{i^{-1}}_{k/k} \widehat{x}^i_{k/k} - \widehat{P}^{i^{-1}}_{k/k-1} \widehat{x}^i_{k/k-1} \qquad (2.19)$$

Table 1: DKF Methods I

DKF Design Approaches Used	References
• Under uncertain observations, including measurement with a false alarm probability	[1]
• Under uncertain observations, randomly variant dynamic systems with multiple models	[3]
• Optimal centralized and distributed fusers are algebraically equivalent in this case	[4]
• Power systems: mode estimation. A trust-based DKF approach to estimate the modes of power systems	[5]
• Using Standard Kalman filter locally, together with a consensus step in order to ensure that the local estimates agree	[6]
• Frequency-domain characterization of the distributed estimator's steady-state performance	[7]
• EKF to globally optimal KF for the dynamic systems with finite-time correlated noises	[8]
• 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	[9]
• DKF fusion with weighted covariance approach	[10]
• DKF fusion with passive packet loss or initiative intermittent communications from local estimators to a fusion center while the process noise does exist	[11]
• For each Kalman update, an infinite number of consensus steps to restricted to one	[12] [13]
• For each Kalman update, state estimates are additionally exchanged	[14]
• Only the estimates at each Kalman update over-head are exchanged	[15]
• Analyzes the number of messages to exchange between successive updates in DKF	[16]
• Global Optimality of DKF fusion exactly equal to the corresponding centralized optimal Kalman filtering fusion	[17]
• A parallel and distributed state estimation structure developed from an hierarchical estimation structure	[18]
• A computational procedure to transform an hierarchical Kalman filter into a partially decentralized estimation structure	[19]
• Optimal DKF based on a-$priori$ determination of measurements	[20]

Table 2: DKF Methods II

DKF	References
• Estimate sparsely connected, large scale systems	[21]
• n-th order with multiple sensors	[23]
• Data-fusion over arbitrary communication networks	[24]
• Iterative consensus protocols	[25]
• Using bipartite fusion graphs	[26]
• Local average consensus algorithms	[27]
• Based on consensus strategies	[2]
• Semi-definite programming -based consensus Iterations	[28]
• Converge Speed of consensus strategies	[22]
• Distributed Kalman filtering, with focus on limiting the required communication bandwidth	[29]
• Distributed Kalman-type processing scheme, which provides optimal track-to-track fusion results at arbitrarily chosen instants of time	[30]
• 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	[31]
• Original batch form of the Maximum Likelihood (ML) estimator	[32]
• Modified Probabilistic Neural Network	[33]

Proposition 2.1 *In what follows, the detailed bibliographic reviews of DKF methods are explained comprehensively in Table 1 and Table 2, respectively. DKF in general shows a scheme or class of schemes which employs interconnected or spatially distributed Kalman filter. If the system under consideration employs sensor network, it can process Kalman filter or its advancements (mass produced). However, to cope with multi-sensor network, multi-sensor data fusion, we need a revised version of Kalman filters. Therefore in some cases, the conditions of standard Kalman filtering are violated and the regular recursive formulation cannot be derived directly from the Kalman filtering theory. We have to develop methods for uncertain observations, passive packet loss, finite-time correlated noises etc. The recent references for these methods have been explained and others have been cited in the tables. Some consideration of the distributed dynamic systems for DKF has been explained in [11] as a particular case.*

2.2 DKF with applications

This section shows the characterization of DKF with various applications. A list of publications in some application-oriented research is summarized in Table 3 and Table 4 respectively. As it can be seen, a large amount of research has been carried out in the framework of modified filters. In Table 3, the most recent ones are as follows. In [34], the synthesis of a distributed algorithm is made to compute weighted least squares estimates with sensor measurements correlated. In [35], distributed object tracking system which employs a cluster-based Kalman filter in a network of wireless cameras is presented. In [36] [37], distributed recursive mean-square error optimal quantizer-estimator based on the quantized observations is presented. Other DKF applications can be seen in [1], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63] , [64] and [65].

In Table 4, the most recent one are as follows. Low-power DKF based on a fast polynomial filter is shown in [66]. Distributed 'Kriged' Kalman filtering is addressed in [67]. Decoupled distributed Kalman fuser presented by using Kalman filtering method and white noise estimation theory is shown in [68]. Decomposition of a linear process model into a cascade of simpler subsystems is given in [69]. Other applications can be seen in [3], [39], [70], [71], [72], [73], [74], [75], [76], [202], [77], [78], [79], [80], [81], [82], [83] and [84]-[90] respectively.

Proposition 2.2 *In what follows is the detailed bibliographic review of DKF methods with applications are presented comprehensively in Table 3 and Table 4 respectively. Nowadays many advanced systems make use of large number of sensors in practical applications. These applications are ranging from aerospace and defense, robotics and automation systems, to the monitoring and control of a process generation plants. An important practical problem in the foregoing systems is to find an optimal state estimator given the observations. Moreover, DKF using applications of sensor fusion filter, federated square root filter, network of wireless cameras, multi-user detection problems, formation*

Table 3: DKF with Applications I

DKF with Applications	References
• Multi-sensor networks amenable to parallel processing	[41]
• Two sensors fusion filter	[42]
• Federated square root filter	[43]
• Fusion filter for LTI systems with correlated noises	[44]
• Fusion filter for multichannel ARMA signals	[45]
• Fusion de-convolution estimators for the input white noise	[46]-[47]
• DKF for cooperative localization by reformulating as a parameter estimation problem	[48]
• DKF techniques for multi-agent localization	[49][50]
• Collaborative processing of information, and gathering scientific data from spatially distributed sources	[51]
• Particle filter implementations use Gaussian approximations	[52]
• Channel estimation method based on the recent methodology of distributed compressed sensing (DCS) and Frequency Domain Kalman Filter	[53]
• Algorithm for DKF, where global information about the state covariances is required	[54]
• The synthesis of a distributed algorithm to compute weighted least squares estimates with sensor measurements correlated	[34]
• Distributive and efficient computation of linear MMSE for the multiuser detection problem	[55]
• A statistical approach derived, calculating the exact PDF approximated by EKF	[56]
• Distributed object tracking system which employs a cluster-based Kalman filter in a network of wireless cameras	[35]
• Distributed recursive MSE optimal quantizer-estimator based on the quantized observations	[36] [37]
• Design a communication access protocol for wireless sensor networks tailored to converge rapidly to the desired estimate and provides scalable error performance	[57][58]
• Decentralized versions of the Kalman filter	[59]
• DKF estimator based on quantized measurement innovations	[60]
• Novel distributed filtering/smoothing approach, flexible to trade-off estimation delay for MSE reduction, while exhibiting robustness	[61]
• Distributed estimation agents designed with a bank of local KFs using consensus method	[62]
• State estimation of dynamical stochastic processes based on severely quantized observations	[63] [64]
• Scheme for approximate DKF based on reaching an average-consensus	[65]

Table 4: 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	[70]
• Rigorous performance analysis for KF fusion with feedback	[71]
• Low-power DKF based on a fast polynomial filter	[66]
• Consensus Problem and their special cases	[72]
• DKF for sparse large-scale systems monitored by sensor networks	[73]
• DKF to estimate actuator faults for deep space formation flying satellites	[74]
• Internal model average consensus estimator for DKF	[75]
• Distributed Kriged Kalman filtering	[67]
• The behavior of the distributed Kalman filter varies smoothly from a centralized Kalman filter to a local Kalman filter with average consensus update	[76]
• Track fusion formulas with feedback are, like the track fusion without feedback	[202]
• Decoupled distributed Kalman fuser presented by using Kalman filtering method and white noise estimation theory	[68]
• Decomposition of a linear process model into a cascade of simpler subsystems	[69]
• Distributed fusion steady-state Kalman filtering by using the modern time series analysis method	[77]
• Distributed Kalman filtering with weighted covariance transfer function describing the error behavior of the DKF in the case of stationary noise processes	[78] [79]
• DKF approach for distributed parametric systems, for deep space formations, for unreliable information, for false alarms respectively	[80][81] [82][83]
• DKF approach for multi-sensor, consensus based and PF	[84]-[90]

flying satellites, sparse large-scale systems, estimation on quantized observations etc. pave the route to DKF with applications. The recent references have been explained and others have been cited in the tables.

3 Diffusion-Based DKF

The publications of diffusion-based DKF are classified in Table 5. Recent ones in this area are as follows. Diffusion-based distributed expected maximization (EM) algorithm for Gaussian mixtures is shown in [91]. Diffusion-based Kalman filtering and smoothing algorithm is shown in [92]. Diffusion Kalman filtering for every measurement and for every node, a local state estimate using the data from the neighborhood is provided in [93]. Other publications classified with diffusion-based DKF are [94], [95], [96], [97], [98], [99] and [100] respectively.

Remark 3.1 *In the paper [91], 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 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 $\{y_{m,n}\}$, $m = 1, 2, \ldots., M$, $n = 1, 2, \ldots.., N_m$. These observations are drawn from a K Gaussian mixtures with mixture probabilities $\alpha_1, \ldots.., \alpha_k$.*

$$y_{m,n} \sim \sum_{j=1}^{K} \alpha_j . N(\mu_j, \Sigma_j) \tag{3.1}$$

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

Proposition 3.1 *In the sequel, the detailed bibliographic review of diffusion-based DKF methods are documented comprehensively in Table 5. The recent references have been explained and others have been cited in the Table. In order to motivate the diffusion-based DKF, the architecture assumes that every node is able to share data with its*

Table 5: Diffusion-Based DKF

Diffusion Approaches Used	References
• Diffusion-Based Distributed EM algorithm for Gaussian mixtures	[91]
• Diffusion-Based Kalman filtering and smoothing algorithm	[92]
• Distributed EM algorithm over sensor networks, consensus filter used to diffuse local sufficient statistics to neighbors and estimate global sufficient statistics in each node	[94]
• Consensus filter diffusion of local sufficient statistics over the entire network through communication with neighbor nodes	[95]
• Diffusion Kalman filtering , where nodes communicate only with their neighbors, and no fusion center is present	[96]
• DKF proposed in the context of diffusion estimation	[97][98]
• DKF proposed in the context of average consensus	[99][100]
• Diffusion Kalman filtering for every measurement and for every node, a local state estimate using the data from the neighborhood	[93]

neighbors, and uses the data to obtain the optimal state estimate given the data from the neighborhood only. In a diffusion implementation, nodes communicate with their neighbors in an isotropic manner and cooperate to obtain better estimates than they would without cooperation, thus promoting to distributed implementations. The algorithms are easier to implement and also more robust to node and link failure, at the expense of inferior performance compared to incremental or centralized solutions. These diffusion strategies are of more practical use when dealing with dynamic state vectors, where new measurements must be processed in a timely manner instead of waiting for a consensus to be achieved. Diffusion-based DKF can be promoted in scenarios such as estimation, average consensus, EM algorithms for gaussian mixtures, smoothing algorithms etc. The diffusion scheme for Gaussian mixture in wireless sensor network has been explained in [91] as a particular case.

4 Distributed OOSM

This section shows the discussion on distributed OOS. Distributed OOSM-based list of publications are classified in Table 6. The most recent publications in distributed OOSM are [101]-[106], [107], [108] and [109], where efficient incorporation of OOSMs in Kalman filters is developed in [101]-[106]. Counterpart of the OOSM update problem, needed to remove an earlier measurement from the flight path, is analyzed in [107]. Focus on centralized update problem for multiple local sensor systems with asynchronous OOSMs is treated in [108]. 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 [109]. Other publications classified with distributed OOSM are [110], [111], [112], [113], [114], [115], [116], [117], [118], [119], [120], [121], [122], [123], [104], [124], [125], [126], [127], [128], [129], [130], [131], [132], [133], [135], [135]-[139], [140], [141], [143], [144] and [145].

Proposition 4.1 *The bibliographic review of out-of-sequence-measurements (OOSM), a subdivision of DKF, have been explained comprehensively in Table 6. OOSM is an updating problem to update the current state with an older measurement, rather than updating it with a current measurement (a standard estimation problem). This problem arises usually in a distributed environment, where due to different preprocessing and transmission times, measurements received at the fusion center exhibit different delays. This can lead to situations where measurements from the same target arrive out of sequence. OOSM approaches such as cases of prior information, in a cluttered environment, with applications, target tracking etc. are developed in the literature. The recent references have been explained and others have been cited in the Table.*

Table 6: OOSM

OOSM Approaches	References
• Recursive BLUE without prior	[110]
• Cases of prior information about the OOSM	[111] [132]
• Dating the state estimate globally optimally	[112][113]
• Minimum storage at the current time to guarantee a globally optimal update	
with three cases of prior information about OOSM	[114] [123][104]
• Updating the state estimate globally optimally with an OOSM within one step time delay for a system	[115]
• Multi-step OOSM updating using augmented state smoothing	[117][118][119]
• Multi-step update in OOSM	[116]
• Multi-sensor OOSM problem in a cluttered environment	[118][120][121]
• one-step suboptimal updating algorithms with a nonsingular state transition matrix	[115][122]
• Efficient incorporation of OOSMs in KFs	[101]-[106]
• A globally optimal flight path update algorithm with OOSMs	[124]
• Counterpart of the OOSM update problem, needed to remove an earlier measurement from flight path	[107]
• One-step solution for the general OOSM problem in tracking presented independently	[125] [126]
• Distributed fusion update for the local sensors with OOSMs	[128]
• OOSM with practical applications	[127]
• Optimal analysis of one-step OOSM filtering algorithms in target tracking	[129]
• Focus on centralized update problem for multiple local sensor systems with asynchronous OOSMs	[108]
• The l step algorithm developed for OOSM	[130]
• Optimal distributed estimation fusion with OOSM at local sensors	[131]
• Two new algorithms for solving the out-of-sequence data problem for the case	
of linear and nonlinear dynamic control systems	[133]
• When the delays and the sequence of arrival of all the information are	
not fixed, constituting the named Out-Of-Sequence Problem (OOSP)	[135]
• Out-Of-Sequence Problem (OOSP) developed for linear systems	[135]-[139]
• OOSP developed for non-linear systems	[140][141]
• A globally optimal state trajectory update algorithm for a sequence	
with arbitrary delayed OOSMs including the case of interlaced OOSMs with less storages	[109]
• OOSM with more applications	[143]
• OOSM processing for tracking ground target using particle filters	[144]
• Comparison of the KF and particle filter based OOSM filtering algorithms	[145]

5 MSDF Systems

This section shows the discussion on another division of DKF with respect to MSDF systems. In Tables 7, 8 and 9, MSDF systems-based list of publications are classified respectively. The most recent of the publications described in these tables are as follows. 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 [38]. Bayesian framework for adaptive quantization, fusion-center feedback, and estimation of a spatial random field and its parameters are treated in [146]. A framework for alternates to quantile quantizer and fusion center is provided in [147]. Median fusion and information fusion, not based on weighted sums of local estimates, are presented in [148]. Optimal distributed estimation fusion algorithm with the transformed data is proposed in [180]. Corresponding distributed fusion problem, proposed based on a unified data model for linear unbiased estimator is presented in [182]. An algorithm, fuses one step predictions at both the fusion center and all current sensor estimates is given in [149]. In multi-sensor linear dynamic system, several efficient algorithms of centralized sensor fusion, distributed sensor fusion, and multi-algorithm fusion to minimize the Euclidean estimation error of the state vector are documented in [150]. Problem of data fusion in a decentralized and distributed network of multi-sensor processing nodes is contained in [151]. Fusion algorithm based on multi-sensor systems and a distributed multi-sensor data fusion algorithm based on Kalman filtering is presented in [152]. Other related publications cited in the Table 7 are [39]-[40], [153], [154], [155, 156], [157], [158], [159], [160], [160], [161], [162, 163], [164], [165], [166], [167], [168], [169]. Other related publications cited in the Table 8 are [170], [171], [172], [173, 174], [175], [176], [177], [178], [179], [180], [181] and [182]. Other related publications cited in the Table 9 are [183], [184, 185], [185, 186, 187], [188], [189], [190], [191], [192], [193], [194], [195], [196], [197, 198, 199], [200], [201], [202], [203], [204], [205] and [206].

Remark 5.1 *In [154], 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 [155] and [156]. 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:*

$$B(q^{-1})s(t) = C(q^{-1})w(t) \tag{5.1}$$

$$y_i(t) = s(t) + \upsilon_i(t),\ i = 1,\ ....,\ L \tag{5.2}$$

where $s(t) \in \Re^m$ is the signal to estimate, $y_i(t) \in \Re^m$ is the measurement of the ith sensor, $w(t) \in \Re^r$ is the process noise, $\upsilon_i(t) \in \Re^m$ is the measurement noise of the ith 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, $q^{-1}x(t) = x(t-1)$, $\quad X_i,\ i = 0, 1,\ , ...,\ n_x$ 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 [39, 40]. 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 [38], 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:

$$x_{k+1} = F_k x_k + \upsilon_k \tag{5.3}$$

$$y_k = H_k x_k + \omega_k, k = 0, 1, 2, 3, ... \tag{5.4}$$

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.

Proposition 5.1 *The detailed bibliographic review of multi-sensor data fusion (MSDF) methods have been explained comprehensively in Table 7, Table 8 and Table 9 respectively. While dealing with MSDF, a general problem arose in all the cases is how to combine, in the best possible manner, diverse and uncertain measurements and other information available in a multi-sensor system. The ultimate aim of such a fusion is to enable the system to estimate or make inference concerning a certain state of nature. The design approaches for MSDF are in the areas of automatic target*

Table 7: MSDF I

MSDF Design Approaches	References
• Sensor noises of converted systems cross-correlated, whilst original system independent	[39]-[40]
• 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	[38]
• No centralized fusion center, but algorithm highly resilient to lose one or more sensing nodes	[153]
• Discrete smoothing fusion with ARMA Signals LMV with information fusion filter	[154][155][156]
• Deconvolution estimation of ARMA signal with multiple sensors	[157]
• Fusion criterion weighted by scalars	[158]
• Functional equivalence of two measurement fusion methods	[159]
• Centralized filter, data processed/communicated centrally	[160]
• New performance bound for sensor fusion with model uncertainty	[160]
• All prior fusion results with Asynchronous Measurements	[161]
• Unified fusion model and unified batch fusion rules	[162][163]
• Unified rules by examples	[164]
• Computing formulation for cross-covariance of the local estimation	[165]
• Conditions for centralized and distributed fusers to be identical	[166]
• Relationships among the various fusion rules	[167]
• Optimal rules for each sensor to compress its measurements	[168]
• Various issues unique to fusion for dynamic systems	[169]
• Bayesian framework for adaptive quantization, fusion-center feedback, and estimation of a spatial random field and its parameters	[146]
• Framework for alternates to quantile quantizer and fusion center	[147]

Table 8: MSDF II

MSDF Design Approaches	References
• Diagonal weighting matrices	[170]
• Different fusion rates for the different states	[171]
• Optimal distributed estimation fusion in the LMV estimation	[172]
• Median fusion and information fusion, not based on weighted sums of local estimates	[148]
• Distributed filtering algorithms, optimal in mean square sense linear combinations of the matrix or scalar weights with derivations	[173][174]
• Closed form analytical solution of steady fused covariance of information matrix fusion with arbitrary number of sensor derived	[175]
• Focus on various issues unique to fusion for dynamic systems, present a general data model for discretized asynchronous multi-sensor systems	[176]
• Recursive BLUE fusion without prior information	[177]
• Statistical interval estimation fusion	[178]
• Fused estimate communicated to a central node to be used for some task	[179]
• Optimal distributed estimation fusion algorithm with the transformed data is proposed, which is actually equivalent to the centralized estimation fusion	[180]
• State estimation fusion algorithm, optimal in the sense of MAP	[181]
• Corresponding distributed fusion problem, proposed based on a unified data model for linear unbiased estimator	[182]
• An algorithm, fuses one step predictions at both the fusion center and all current sensor estimates	[149]
• In multi-sensor linear dynamic system, several efficient algorithms of centralized sensor fusion, distributed sensor fusion, and multi-algorithm fusion to minimize the Euclidean estimation error of the state vector	[150]

Table 9: MSDF III

MSDF Design Approaches	References
• Derivation of approximation technique for arbitrary probability densities, providing distributable fusion structure as the linear information filter	[183]
• Multi-sensor distributed fusion filters based on three weighted algorithms, applied to the systems with uncertain observations and correlated noises	[184] [185]
• MSDF in state estimation fields, and easy fault detection, isolation and more reliability	[185][186][187]
• CKF algorithm, obtained by combining all measurement data	[188]
• Design of general and optimal asynchronous recursive fusion estimator for a kind of multi-sensor asynchronous sampling system	[189]
• Problem of data fusion in a decentralized and DN of multi-sensor processing nodes	[151]
• To assure the validity of data fusion, a centralized trust rating system	[190]
• white noise filter weighted by scalars based on Kalman predictor	[191]
• White noise de-convolution estimators	[192]
• Optimal information fusion distributed Kalman smoother given for discrete time ARMA signals	[193]
• Optimal dimensionality reduction of sensor data by using the matrix decomposition, pseudo-inverse, and eigenvalue techniques	[194]
• Multi-sensor Information fusion distributed KF and applications	[195]
• Based on analysis of the fused state estimate covariances of the two measurement fusion methods	[196]
• MSDF approaches to resolve problem of obtaining a joint state-vector estimate	[197][198][199]
• Decentralized multi-sensor EKF which has been divided up into modules	[200]
• A distributed reduced-order fusion Kalman filter (DRFKF)	[201]
• Fusion algorithm based on multi-sensor systems and a distributed MSDF algorithm based on KF	[152]
• Track fusion formulas with feedback are, like the track fusion without feedback	[202]
• The optimal distributed KF fusion algorithms for the various cases	[203]
• General optimal linear fusion	[204]
• Information fusion in distributed SN	[205]
• Multi-scale Recursive Estimation, Data Fusion, and Regularization	[206]

recognition, remote sensing, automated manufacturing, monitoring problems such as fault detection and diagnosis, safety of complex systems (aircrafts, rockets, nuclear power plants), quality control, plant monitoring and monitoring in biomedicine. These problems result from the increasing complexity of most technological processes, the availability of sophisticated sensors and the existence of sophisticated information processing systems. The recent references promoting to the solutions to MSDF problems with different situations have been explained and others have been cited in the Tables. The optimal information fusion distributed Kalman smoother has been explained in [154] as a particular case.

6 DNs

This section describes the area of DNs in DKF. The list of publications on DNs is classified in Table 10. Some recent publications in this area are as follows. 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 [94]. Modified adaptive Kalman filter for sensor-less current control of a three-phase inverter based distributed generation system is proposed in [207]. 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 [208]. A message-passing version of the Kalman consensus filter (KCF) is considered in [134]. 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 [209]. Other publications cited in Table 10 are [210], [211], [212, 213], [95], [214], [215], [216], [217], [218], [219], [142], [220], [221]-[227] and [228].

Remark 6.1 *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 [210]. A DNCS extends an NCS to model a distributed multi-agent system such as the Vicsek model. The best examples 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 [210]. 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 [211], 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 [229], [230]. 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:*

$$x_j(k+1) \quad = \quad \sum_{i=1}^{N} A_{ij} x_i(k) + G_j w_j(k) \tag{6.1}$$

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 $G_j \in \mathbf{R}^{n_x \times nW}$. 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 $i \neq j$.

Proposition 6.1 *The detailed bibliographic review of distributed networks (DN) methods have been explained comprehensively in Table 10. In a general sense, a DN consists of spatially distributed or interconnected multiple systems or agents equipped with sensors, actuators, and computing and communication devices. The operation of each agent is coordinated over a medium of communication that can be wired or wireless. The examples of an DN include sensor networks, formation control systems, arrays of micro or micro-electromechanical sensors (MEMS) devices, a network of mobile robots etc. Design approaches of DN have considered cases with multiple nodes, estimation against false data detection, communicating over a lossy communication channel, estimation/filtering for time-varying class etc. The recent references have been explained and others have been cited in the Table. Using distributed networked control system over a lossy communication has been considered in [210] as a particular case.*

7 Mathematical Design in Track-to-Track Fusion

Track fusion (TF)-based list of publications are classified in Table 11. Some recent publications in this area are as follows. Track fusion measurement is given in [231]. Performance of various track-to-track fusion algorithms from aspects of fusion accuracy, feedback and process noises are treated in [232]. Perform track fusion optimally for a multiple-sensor system with a specific processing architecture is treated in [233]. Other work cited in Table 11 are [39], [234, 235, 236, 237], [238], [239], [240], [241], [242], [243], [244], [245]-[246], [247]-[248], [249], [250]-[251], [179], [252], [253], [254, 255], [256, 257], [258], [259], [260], [261] and [262].

Proposition 7.1 *The detailed bibliographic review of track-to-track fusion-based methods which have been explained comprehensively in Table 11. The structure of distributed fusion consists of sensor-based filtering algorithms, local processors, and a global processor, where the main agenda is that several sensors execute surveillance over a certain area. For the local processors, each sensor acts as a tracking system, where each track-to-track fusion algorithm is used to merge two tracks representing the same target. In such a scenario estimating the fusion, the track estimation*

Table 10: DNs

Design Approaches Used in DN	References
• Distributed networked control system (DNCS) with multiple nodes	[210]
• Two approximate filtering algorithms for estimating states of a DNCS	[211]
• Distributed EM algorithm over sensor networks, consensus filter used to	
diffuse local sufficient statistics to neighbors and estimate global sufficient statistics	[94]
• Density estimation and unsupervised clustering, first step in exploratory data analysis	[212][213]
• Consensus filter diffusion of local sufficient statistics over the entire network	[95]
• Distributed fusion of multiple sensor data to networks	[214]
• Robust distributed state estimation against false data injection	[215]
• Distributed SN, consisting of a set of spatially scattered sensors	[216]
• SN with noisy fading wireless channels	[217]
• Modified adaptive KF for sensor-less current control of a three-phase inverter	[207]
• Distributed estimation scheme for tracking the state of a Gauss-Markov	
model by means of observations at sensors connected in a network	[208]
• A message-passing version of the Kalman-Consensus Filter (KCF)	[134]
• A peer-to-peer (P2P) architecture of DKF that rely on reaching a consensus	
on estimates of local KFs	[218]
• For decentralized tracking applications, DKF and smoothing algorithms are derived	
for any-time MMSE optimal consensus-based state estimation using WSN	[209]
• Trade-off between the estimation performance and the number of communicating nodes	[219]
• DNCS consisting of multiple agents communicating over a lossy communication channel	[142]
• Impact of the network reliability on the performance of the feedback loop	[220]
• SN-based distributed H_∞ state estimation, filtering for time-varying class, state estimation	
for uncertain Markov, H_∞ stochasitc sampled-data approach and non-linear systems, discrete	[221]-[227]
time, robust fault detection and modeling and analysis respectively.	[228]

Table 11: Mathematical Design in Track-to-Track Fusion

Track-to-Track Fusion Approaches	References
• Track fusion with information filter	[39]
• Track fusion optimality with ML	[234][235][236][237]
• Two track estimates cross-covariance	[238]
• Track fusion local estimate dependency	[239]
• Track fusion measurement	[231]
• Track fusion multi-sensor algorithm	[240]
• Track fusion cross-covariance with independent noises	[241]
• Steady-state fusing problem	[242]
• Steady state fused covariance for hierarchical track fusion architecture with feedback	[243]
• Cross-covariance of the local track	[244]
• Weighted covariance state-vector Track fusion	[245]-[246]
• Pseudo-measurement state-vector Track fusion	[247]-[248]
• Steady state fused covariance matrix	[249]
• Various architectures for track association and fusion	[250]-[251]
• Fused estimate communicated to a central node to be used for some task	[179]
• Track-to-track fusion algorithm, optimal in the sense of ML for more than 2 sensors	[252]
• Measurement Fusion and State vector track fusion	[253]
• State vector track fusion with pseudo-measurement	[254] [255]
• Performance of various track-to-track fusion algorithms from aspects of	
fusion accuracy, feedback and process noises	[232]
• Fuse state vectors using Weighted Covariance (WC)	[256][257]
• Weighted covariance algorithm turns out to be a Maximum likelihood estimate	[258]
• Perform track fusion optimally for a multiple-sensor system with a specific processing architecture	[233]
• Track-to-track fusion for multi-sensor data fusion	[259]
• Common process noise on the two-sensor fused-track covariance	[260]
• Track association and track fusion with non-deterministic target dynamics	[261]
• Comparison of two-sensor tracking methods based on state vector fusion and measurement fusion	[262]

errors from different sensors are not necessarily independent due to the common process noise. For this reason, an optimal track-to-track association and fusion is a complicated problem. To handle such a problem, different approaches have been used such as track-to-track fusion with information filter, ML, independent noises, feedback architectures, pseudo measurement, weighted covariance etc. The recent references have been explained and others have been cited in the Table.

8 DC-Based Estimation

DC-based estimation list of publications are classified in Table 12. Some recent work in this area is as follows. Recent work [28] is based on consensus Iterations. Distributed 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 [94]. 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 [263]. Consensus-based distributed approached Kalman filters for linear systems [264, 265]. Other publications cited in Table 12 are [25], [27], [2, 266], [22], [267], [6], [95], [268], [269], [270], [271], [272, 273], [274], [134], [218], [275], [276], [277], [278], [279] and [280] respectively.

Remark 8.1 *In the paper [94], 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 EM algorithm simultaneously. A well-fitted approach to this integration is the one proposed in [281]. The proposed distributed EM algorithm in the paper [94] 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 [24, 25, 282] 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 *sensors is considered, each* *of which has N_m data observations $y_{m,n}(m = 1, \ldots, M, \ n = 1, \ldots, N_m$. The environment is assumed to be a Gaussian mixture setting with K mixture probabilities $\alpha_{m,k}, (k = 1, \ldots, K)$. 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:*

$$p(y_{m,n}|\mu_k, \Sigma_k) = \frac{1}{\sqrt{2\pi}\|\Sigma_k\|^{\frac{1}{2}}} e^{-\frac{1}{2}(y_{m,n}-\mu_k)^T \Sigma_k^{-1}(y_{m,n}-\mu_k)} \tag{8.1}$$

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

$$p(y_{m,n}|\theta) = \sum_{k=1}^{K} \alpha_{m,k} p(y_{m,n}|\mu_k, \Sigma_k) \tag{8.2}$$

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

Proposition 8.1 *The detailed bibliographic review of distributed consensus-based estimation methods have been provided comprehensively in Table 12. In some cases, distributed estimation can be solved as an average consensus problem. The main idea of consensus algorithms is to average measurements or local estimates among all network nodes, based on the intuition that averaging reduces the noise and therefore the parameter estimation error. However, this is not always the case, since local estimates are correlated and a simple average might not be the optimal strategy, in particular when sensors have different accuracy. So, in a consensus problem, a group of agents or network nodes try to reach agreement on a given quantity of interest that depends on their states or variables. To solve this problem, various approaches such as iterative protocols, distributed linear filter, distributed low-pass filter, unscented particle filter, Kalman consensus filter, jump Markov systems have been proposed in the literature. The recent references have been explained and others have been cited in the Table. Distributed consensus using Gaussian components has been considered in [94].*

9 DPF

A DPF list of publications are classified in Table 13. Some recent work in this area is described as follows. A novel framework for delay-tolerant particle filtering, with delayed OOSM is treated in [283]. A number of heuristic metrics to estimate the utility of delayed measurements is proposed in [284]. Other recent publication in this area cited in Table 13 are [274], [285], [286], [287, 288], [289], [290], [291], [291], [292], [293], [294], [295], [296], [297], [298], [299], [144] and [145].

Proposition 9.1 *The detailed bibliographic review of distributed particle filtering (DPF) methods have been explained comprehensively in Table 13. Particle filter is a standard technique for target tracking. The DPF is a distributed*

Table 12: DC-Based Estimation

Design Approaches used in DC	References
• Iterative consensus protocols	[25]
• Local average consensus algorithms	[27]
• Based on consensus strategies	[2][266]
• Based consensus Iterations	[28]
• Converge Speed of consensus strategies	[22]
• Dynamic consensus problems regarding fusion of the measurements and covariance information with consensus filters	[267]
• Using Standard KF locally with a consensus step	[6]
• Distributed EM algorithm over sensor networks, consensus filter used to diffuse local sufficient statistics to neighbors and estimate global sufficient statistics in each node	[94]
• Distributed EM algorithm over SNs, consensus filter used to diffuse local sufficient statistics	[94]
• Consensus filter diffusion of local sufficient statistics over the entire network through communication with neighbor nodes	[95]
• Consensus-based distributed linear filtering problem	[268]
• The interaction between the consensus matrix and the Kalman gain for scalar systems	[269]
• KF with a consensus filter, ensuring estimates asymptotically converge to the same value	[270]
• 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	[263]
• Average-consensus algorithm for n measurements of noisy signals obtained from n sensors in the form of a distributed low-pass filter	[271]
• Average-consensus algorithm for n constant values	[272][273]
• Consensus-Based distributed implementation of the unscented particle filter	[274]
• Consensus-based distributed approached KFs for linear systems	[264][265]
• A message-passing version of the Kalman-Consensus Filter (KCF)	[134]
• A peer-to-peer (P2P) architecture of DKF that rely on reaching a consensus on estimates of local KFs	[218]
• Consensus-based suboptimal KF scheme	[275]
• Distributed filter that allows the nodes of a SN to track the average of n sensor measurements	[276]
• DC-Based estimation for networks of agents, uncertain systems, jump Markov Systems and SN with delay	[277][278] [279][280]

Table 13: DPF

Design Approaches used in DPF	References
• Consensus-Based distributed implementation of the unscented particle filter(UPF)	[274]
• Particle filtering transformation into continuous representations	[285]
• Consensus-based, distributed implementation of the UPF	[286]
• Particle filter implementations using Gaussian approximations for the local posteriors	[287][288]
• A novel framework for delay-tolerant particle filtering, with delayed OOSM	[283]
• An approach that stores sets of particles for the last l	
time steps, where l is the predetermined maximum delay	[289]
• Markov chain Monte Carlo (MCMC) smoothing step for OOSM	[290]
• Approximate OOSM particle filter based on retrodiction (predicts backward)	[291]
• Also uses retrodiction (predicts backward), but employs the Gaussian particle filter	[291]
• Recent advances in particle smoothing, storage-efficient particle filter	[292]
• Proposed a number of heuristic metrics to estimate the utility of delayed measurements	[284]
• Proposed a threshold based procedure to discard uninformative	
delayed measurements, calculating their informativeness	[293]
• Optimal estimation using quantized innovations, with application to distributed	
estimation over SNs using Kalman-like particle filter	[294]
• SOl-Particle-Filter (SOI-PF) derived to enhance the performance of the distributed estimation procedure	[295]
• Problem of tracking a moving target in a multi-sensor environment DPFs	[296]
• Optimal fusion method, introduced to fuse the collected GMMs	
with different number of components	[297]
• Two distributed particle filters to estimate and track the moving targets in a WSN	[298]
• Updating the complete particle filter on each individual sensor nodes	[299]
• Out-of-sequence measurement processing for tracking ground target using PFs	[144]
• Comparison of the KF and PF based OOSM filtering algorithms	[145]

realization of particle filter. Specifically, centralized particle filters introduce the following problems: 1) collecting data consumes significant energy; 2) converge cast communication introduces a long delay, as the computational center has to receive messages in a sequential order; and 3) centralized implementation is vulnerable as a single point of failure [300]. Distributed particle filters [299] were studied as a response to these problems, in particular, to offload the computation from the central unit as well as to reduce converge cast communication [301]. However, few existing efforts on DPF were implemented in a completely distributed manner [302], because the aggregation of weights is inevitable. For efficiently transmitting the particle data to the computational center, there exist several DPF efforts that focus on reducing the communication cost by compressing messages, such as Gaussian mixture approximation [303], non-parametric particle compression based on support vector machine [300], and adaptive encoding [299], [304]. The recent references have been explained and others have been cited in the Table.

10 ST-Based Distributed Fusion Kalman Filter

This section explains the ST-based distributed fusion Kalman filter, another categorization for DKF. A list of publications is this regard is classified in Table 14. Some of the recent work in this area is as follows. Self-tuning decoupled fusion Kalman predictor is proposed in [305] and self-tuning weighted measurement Kalman filter is included in [306]. Self-tuning measurement system using the correlation method, can be viewed as the least-squares (LS) fused estimator and found in [307]. Self-tuning distributed (weighed) measurement fusion Kalman filters is shown in [308, 309, 310]. Other recent publication in this area cited in Table 14 are [311], [312], [313], [314, 315], [316], [317], [318], [319], [320], [321], [322]-[325], [326] and [327].

Remark 10.1 *For self-tuning decoupled fusion Kalman predictor, the following multi-sensor linear discrete time-invariant stochastic system is considered in the paper [328]:*

$$x(t+1) = \Phi x(t) + \Gamma w(t) \tag{10.1}$$

$$y_i(t) = H_i x(t) + v_i(t)\ ,\ i = 1,\ .....,\ L \tag{10.2}$$

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

The detailed bibliographic review of self-tuning (ST)-based distributed KF methods have been presented comprehensively in Table 14. ST-based estimation is presented usually for the state or signals with unknown model parameters and/or noise statistics. Their basic principle is that the optimal filter with a recursive identifier of a weighted innovation model will yield a self-tuning filter. But, so far, the convergence of self-tuning filter has not been proved strictly, and the strict convergence analysis approach has not been presented. ST-based distributed estimation has been designed

Table 14: ST-Based Distributed Fusion Kalman Filter

ST Design Approaches	References
• Multi-sensor systems with unknown model parameters and noise variances, by the information matrix approach, the ST distributed state fusion information filter is presented	[311]
• ST distributed state fusion Kalman filter with weighted covariance approach	[312]
• ST decoupled fusion Kalman predictor	[305]
• ST weighted measurement Kalman filter	[306]
• Multi-sensor systems with unknown noise variances, a new ST weighted measurement fusion Kalman filter is presented, which has asymptotic global optimality	[313]
• Weighted ST state fusion filters	[314][315]
• Sign of Innovation- Particle Filter (SOI-PF) improves the tracking performance when the target moves according to a linear and a Gaussian model	[316]
• Efficiency of the SOI-PF in a nonlinear and a non Gaussian case, considering a jump-state Markov model for the target trajectory	[317]
• ST information fusion reduced-order Kalman predictor with a two-stage fusion structure based on linear minimum variance	[318]
• Optimal ST smoother	[319]
• Optimal ST fix-lag smoother	[320]
• A new convergence analysis method for ST Kalman Predictor	[321]
• ST measurement system using the correlation method, can be viewed as the least-squares (LS) fused estimator	[307]
• ST filtering for systems with unknown model and/or noise variances	[322]-[325]
• ST distributed state fusion Kalman estimators	[326][327]
• ST distributed (weighed) measurement fusion Kalman filters	[308][309][310]

with approaches for unknown model parameters, weighted covariance approach, two-stage fusion structure, smoother, fix lag-smoother, predictor etc. The recent references have been explained and others have been cited in the Table. In the end, [328] has been considered using decoupled fusion Kalman predictor.

Proposition 10.1 *In what follows is the detailed bibliographic review of ST-based distributed KF methods which have been explained comprehensively in Table 14. ST-based estimation is presented usually for the state or signals with unknown model parameters and/or noise statistics. Their basic principle is that the optimal filter with a recursive identifier of a weighted innovation model will yield a self-tuning filter. But, so far, the convergence of self-tuning filter has not been proved strictly, and the strict convergence analysis approach has not been presented. ST-based distributed estimation has been designed with approaches for unknown model parameters, weighted covariance approach, two-stage fusion structure, smoother, fix lag-smoother, predictor etc. The recent references have been explained and others have been cited in the Table. Using decoupled fusion Kalman predictor has been considered in [328].*

11 Conclusions

The distributed system architecture, as a 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 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, ST designs and various applications of DKF have been classified. Some open problems and current research activities have been discussed and around 328 references have been categorized. We apologize in advance for any omission of publications, in spite of our best effort.

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