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RECEDING HORIZON FILTERING FOR MULTISENSOR LINEAR DYNAMICS SYSTEMS

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Abstract. *Distributed receding horizon discrete-time filtering is presented here, which combines a Kalman filter and receding horizon strategy. Distributed fusion with the weighted sum structure is then applied to local receding horizon Kalman filters (LRHKFs) having non-equal horizon time intervals. The proposed distributed algorithm has a parallel structure that allows for the parallel processing of observations, thereby making it more reliable than the centralized version if some sensors become faulty. Moreover, the choice of receding horizon strategy makes the proposed algorithm robust against dynamic model uncertainties. Note that the derivation of the error cross-covariances between the LRHKFs is the key contribution in this distributed algorithm. The subsequent application of the proposed distributed filter to linear discrete-time dynamic systems within a multisensor environment demonstrates and confirms its effectiveness.*
Keywords: Distribution fusion, Kalman filter, Multisensor, Receding horizon

1. **Introduction.** There is growing anticipation about the potential application of multisensor data fusion in a diverse range of applications, including guidance, robotics, aerospace, target tracking, signal processing and control systems [1,2]. Swift progress in communications, low-power computing and sensing hardware have resulted in an abundance of commercially available sensor nodes, and the colossal challenge is now to develop efficient methods for the automatic fusion and interpretation of the information generated by multisensor data fusion. As such, it is expected that the success of future applications could indeed be predicted on the ability to find solutions to this challenge. In general, two basic fusion methods have been commonly used to process measured sensor data; these methods are discussed below [3,4].

The first approach is called centralized fusion estimation, in which the measurement data from all local sensors is directly received and processed in real time. One advantage of this method is that it involves minimal information loss; however, this approach has serious disadvantages, including low reliability and survivability, as well as heavy communication and computational burdens. In addition, there needs to be an ideal assumption of the environment.

The second approach is referred to as distributed fusion estimation, in which every local sensor is attached to a local processor. In this method, the processor optimally estimates a system parameter or state based on its own local measurements, and then transmits its local estimate to the fusion center where the received information is suitably associated to yield a global inference [1-5]. Recently, to avoid the disadvantages associated with centralized estimation, various distributed and parallel versions of standard Kalman filters have been proposed for linear dynamic systems that operate in a multisensor environment