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Modified likelihood probabilistic data association filter for tracking systems with delayed and lost measurements

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ABSTRACT

In this note, a new probabilistic data association filter (PDAF) is developed for single object tracking, where observations are encountered with random delays and losses. When data are transmitted to the filter with latency and dropout, the common likelihood function which extracts information about the state of the intended object from the measurements, cannot obtain accurately the relationship between received observations and the object's state. So, the likelihood function of the PDAF is modified here to cope with delayed and lost measurements. The introduced idea can be used in other filtering methods to prepare them for application in networked tracking systems. Simulation results of two-dimensional scenarios are presented to verify the considerable improvement in the performance of the proposed PDAF.

1. Introduction

Real world object tracking problems such as radar tracking of aircraft, encounter many challenges such as clutter (non-object originated measurements) and sensor noise which cause uncertainty in the origin of observation data. Using spurious measurements in the filter leads to track loss; so, data association is carried out to select the measurements to be used in updating the state of the object of interest [1,2]. The probabilistic data association filter (PDAF) is a well-known tool to execute data association and state estimation in clutter. In the PDAF the association probabilities are calculated for each validated measurement. This probabilistic information which accounts for the measurement origin uncertainty is used in the tracking algorithm [3].

Additionally, due to increased reliance on networked sensors in recent tracking systems, observation information is exposed to random delays and losses because of unreliability in transmission medium from a sensor to filter [4–8]. Moreover, propagation delay [9], latency in sensor signal processing [10], object hiding [11], low sensor detection capability [12], unsynchronized clocks among sensor and central processor [13], and faults in sensor and communication structure [14] lead to data delays and drop-outs. Therefore, a lot of researches have been conducted and many different methods have been proposed to tracking problems [15–18]. To the best of authors' knowledge only a few papers have been addressed this issue in cluttered environments [19,20,15,21,22].

In [9], a particle filter that compensates the signal propagation delays in the tracking problem was developed by augmenting the state vector with the physical model of delay. In [15], target tracking problem was investigated in Bayesian context for the case that the sensor data do not arrive in the temporal order, known as out of sequence measurements (OOSM). In [22], the problem of multi-target data association in the presence of OOSM, was considered and a common Bayesian framework was proposed for multi-target tracking algorithms with delayed measurements. A recursive algorithm was proposed to find the parameters of joint probability density function of state vectors, called accumulated state density (ASD) by its marginalization. In [16,17], algorithms were developed to handle multiple OOSMs, which arrive at the filtering center in arbitrary orders. In [18], an online parameter estimation method was embedded in the kernel particle filter which mainly used for motion analysis to recursively estimate the target state with delayed measurements. In [23], [24] and [15], the multiple hypothesis tracking (MHT) filter was modified to cope with OOSMs. In [21] and [25], the probability hypothesis density (PHD) filter was generalized for scenarios involving OOSMs. Most relevant works in the literature to one of this paper are [19], [26] and [27], wherein Bayesian solution was presented to target tracking problem through delayed, out-of-sequence measurements for cluttered scenarios involving multiple time-delayed measurements by calculating joint probability density of current and past target states.

This paper aims to compensate the destructive effects of data latency and dropout in the performance of tracking algorithms in

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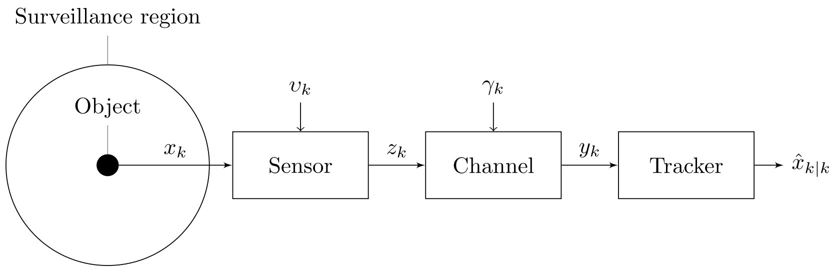

Fig. 1. Schematic diagram of the considered object tracking system.

cluttered environments. To demonstrate the merits of the proposed idea, a well-known traditional tracking algorithm, PDAF is chosen to be improved to cope with delayed and lost measurements. In the derivation of traditional PDAF, the likelihood function extracts information about the object from measurements which represent its current state. But, when the measurements are delayed or lost, the likelihood function of the filter needs to be corrected to match with these imperfections in the observation data. The main novelty of this paper is to modify the likelihood function of the common PDAF to take into account the effects of measurement delays and dropouts. It is shown that the resulting modified likelihood PDA filter (MLPDAF) is in the form of Gaussian sum filter-smoother (GSFS) [28]. It should be noted that differently from [19], the suggested MLPDAF does not need any information about the exact value of the data delay. Simulation results of a simple two-dimensional tracking scenario in clutter are presented to illustrate that the proposed MLPDAF has better performance compared to AS-PDAF [19]. The likelihood modification method can be applied to other filters in tracking systems to handle the situations that the measurements may be delayed or lost. The main feature of this method compared to some other ones such as as [4], [6] and [7] is its ability to be easily embedded in other traditional Bayesian filtering and tracking methods to enhance their performance in the presence of data delay and dropout.

The remainder of this paper is organized as follows. Section 2 explains the models of system and measurements. Section 3, presents the main results of the paper wherein MLPDAF relations are derived. In Section 4, merits of the suggested MLPDAF are illustrated in comparison to some existing approaches. Section 5 concludes the paper.

Notations: Throughout the paper, the notations used are standard. $\mathbb{R}^n$ represents the n-dimensional Euclidean space. $|\circ|$ is the determinant of the matrix $\circ$. $p(*)$ stands for the occurrence probability of the event $*$. $\circ^T$ symbolizes the transpose of the matrix $\circ$. $p(*|\circ)$ represents the conditional probability of the event $*$ given the event $\circ$. I_n shows an identity matrix of size $n \times n$.

2. Problem statement and preliminaries

Common assumptions about the trajectory tracking problem are adopted from [29]. Only one object exists in the surveillance region and its trajectory state $x_k \in \mathbb{R}^n$ propagates by

$$x_k = A x_{k-1} + B \omega_{k-1}, \tag{1}$$

where $\omega_k \in \mathbb{R}^r$ is a zero mean white Gaussian noise with covariance Q_k. A and B are known matrices with appropriate dimensions. Clutter's density is assumed to be known a priori or estimated using measurements. It is also assumed that the resolution of the sensor is infinite. As a result, the observation of sensor at each sampling time k is in the form of a measurement set

$$z_k = \{z_k(1), z_k(2), \cdots, z_k(l_k)\}, \tag{2}$$

where $z_k(i) \in \mathbb{R}^m$ is a measurement at time k, and $l_k \geq 0$ is the number of measurements z_k at sampling time k. Object originated measurements has the following relation with the object trajectory state

$$z_k(j) = C x_k + \upsilon_k, \tag{3}$$

where $\upsilon_k \in \mathbb{R}^m$ is a zero mean white Gaussian noise with covariance matrix R_k. C is the measurement matrix with appropriate dimension.

In the considered tracking system, measurement (2) is sent only once by the sensor through the communication channel to the processing center as depicted in Fig. 1. The measurement set y_k received by the tracker will be different from z_k. Some of the effects of the communication link on data which is denoted by γ_k are as follows:

- data might be received in sequence with a random delay,
- data might be received out of sequence,
- data might be dropped out.

So, the measurement set y_k received by the tracker might be one of the following sets:

$$y_k = \phi,$$
$$y_k = z_{k-i}, \quad i = 0, 1, \cdots, d, \tag{4}$$

where $y_k = \phi$ corresponds to the measurement drop-out case. In other words, it means that the measurement set has been lost during the transmission and there is not any information about the intended object. In other cases, measurements are received with/without delays. The maximum delay of the channel is known and indicated by $d \geq 0$. In general, the relation of y_k can be represented as

$$y_k = f(z_k, \gamma_k), \tag{5}$$

where f is a function that depends on channel characteristics.

Remark 1. Main sources of data delay and loss in tracking systems are reported in [13]; like communication channel delay due to congestion and insufficient bandwidth, varying preprocessing time at sensor platforms, lack of sampling time synchronization among sensor and the central processor, and propagation delay. It is worth noting that unsynchronized clocks and propagation delay exist despite using time stamps [9].

Remark 2. In practical object tracking, there may be some situations that the sensor does not detect the object. The case $y_k = \phi$, (measurement loss) can represent this situation, too. Because in both cases, there is no object originated measurement. Moreover, it is possible to receive multiple measurements set at a time.