



Probabilistic Association and Fusion for Multi-sensor Tracking Applications

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Abstract

The use of state space techniques to track targets using measurements from multiple sensors is considered. In particular, the operation of the asynchronous fused Kalman filter is investigated and evaluated, using real data collected from a collocated tracking radar and optical tracking system. An analysis of the effect of additional sensors on the filter's sensitivity to model mismatch is carried out.

The performance of the tracking filter is unacceptable in multi-target and/or cluttered environments. This poor performance is attributed to the filter treating all measurements as if they originated from the target of interest. This is often not the case in real environments; therefore some form of data association is required. Two algorithms are developed to overcome this inadequacy, the multi-sensor Probabilistic Multi-Hypothesis Tracking (msPMHT) algorithm and the multi-sensor Probabilistic Least Squares Tracking (msPLST) algorithm. Both these algorithms estimate the measurement to target assignments and the target states simultaneously, the msPMHT using maximum likelihood techniques and the msPLST utilising least squares.

Similarities and differences between the linear Gaussian msPMHT and the msPLST algorithms are discussed. The characteristics and performance of both algorithms are compared using simulated and real data.

A general msPMHT algorithm is introduced with multiple measurement models for each physical sensor. Measurement to sensor assignments, associating individual measurements with selected sensor models, are estimated along with the measurement to target assignments and target states. This allows the algorithm to adapt to varying sensor parameters by changing sensor models.

Declaration

This work contains no material that has been accepted for the award of any other degree or diploma in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text.

I give consent to this copy of my thesis, when deposited in the University Library, being available for loan and photocopying.

Signature

A handwritten signature in black ink, appearing to be 'M. H. ...', written over a horizontal line.

Date

23 January 98

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