

Mutual information strategies for sensor registration

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Certificate

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Abstract

This thesis is concerned with relating information originating from disparate sensors by exploring the statistical dependence between multiple time domain signals that occur as a result of a common cause influencing outputs of the sensors. Relating the signals without any attempt to model the environment or the behaviour of any particular object within it is the main focus of this work as scenarios where sufficient a-priori knowledge is not available is of primary interest. Mutual Information (MI) is selected as a suitable metric for determining statistical dependence mainly due to its ability to identify nonlinear high order effects, and due to its ability to deal with multi-dimensional input signals with relative ease.

Inspired by human perception, the focus will be on observing objects moving in space using sensors that operate based on different physical principles and the fact that motion has in principle, greater power to specify properties of an object than purely spatial information captured as a single observation in time. Our first intention is to utilise the dependence between variables to aid active sensing. The second objective is that of multi-sensor, multi-object tracking which is a challenging problem in large part because of the need to solve the embedded problem of data association, which is the task of relating the measurements from different sensors that correspond to the same object.

The contribution of this thesis include the development of a novel strategy for detecting the set of signals that are statistically dependent and correspond to each other from two large multi-dimensional signal streams. The technique is based on deriving a linear mapping that maximises MI between the signal streams in two-dimensional space. The mapping is obtained by an iterative process that maximises MI through using analytical expressions of the gradients of three measures equivalent to two individual entropies and one joint entropy of the signal streams, while at the same time regularising the coefficients of the mapping using L_1 and L_2 norms. Thus a sparse linear mapping that makes it possible to identify the most mutually informative signal pairings, without the need for

exhaustive pair-wise comparisons is obtained. This results in a common multimodal data association methodology, which could be extended to a wide range of sensors with different modalities. The techniques developed are extensively analysed through a series of simulations and experiments. The approach is demonstrated on registration of sensors with disparate modalities, registration of sensors on moving observers and target grouping.