Fusion of data from different sources

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Abstract: The use of data from different, often complementary sources in order to obtain a better estimate of the state of the system under consideration has recently become very popular within many scientific areas. We will in this talk provide a framework, including the popular Kalman and particle filters for fusing data from different, complementary sources. The theory will be illustrated using several application examples from the automotive and the aerospace industry. Possible applications for 3D analysis of human motion will be discussed.

1. EXTENDED ABSTRACT

Sensor fusion is the process of using information from *several different sources* (sensors) to compute an *overall estimate* of the state of a *dynamic system*. It is the aim of this talk to describe the basic components of a sensor fusion framework. Besides the underlying theory we will also discuss several successful sensor fusion projects from the automotive and the aerospace industry.

The first thing to realize is that we are dealing with *dynamical systems*, that is systems where the output depends on all the previous inputs. In other words a system with a memory. The state contains all information about the past that is worth knowing to be able to predict the future behaviour of the system. In order to be able to produce an overall estimate for the state of the system we need a model of the system. We will make use of standard state-space models for this purpose,

$$x_{t+1} = f(x_t, u_t) + v_t, \tag{1a}$$

$$y_t = h(x_t, u_t) + e_t, \tag{1b}$$

where x_t denotes the state, u_t known control inputs, y_t the measurements, v_t and e_t stochastic process noise and measurement noise, respectively. The function $f(\cdot)$ describes the dynamic equations of the system and hence (1a) is typically referred to as the system model. Furthermore, the function $h(\cdot)$ describes how the measurements are related to the state variables and (1b) is hence referred to as the measurement model.

To illustrate the terms introduced above we can mention one of the examples that will be discussed in the talk, the problem of integrated road geometry estimation and vehicle tracking. Here, the task is to use information from a forward looking camera and radar, together with inertial sensors, wheel speed sensors and a steering wheel sensor in order to compute an overall estimate of the road geometry and the position and velocity of the leading vehicles. Hence, the system model (1a) includes dynamical models describing the motion of the host vehicle, the leading vehicles and the road. Each sensor gives rise to one or more measurement equations (1b).

The *overall estimate* of the state is computed by a state estimator of some kind. The state estimator makes use of the measurements from the *different sensors* to produce an estimate of the filtering probability density function $p(x_t|y_{1:t})$, where $y_{1:t} = \{y_i\}_{i=1}^t$ is all the past measurements. This density function contains all there is to know about the state x_t, given all the information in the measurements $y_{1:t}$. Based on $p(x_t|y_{1:t})$ we can compute for instance an estimate of the state. The are several different algorithms available for estimating the filtering density, but the two most commonly used are

- The *Kalman filter* introduced by Kalman in 1960 [2]. If the model (1) is linear and Gaussian, the filtering density is also Gaussian and hence completely parameterized by the mean and the covariance. The Kalman filter explains how the mean and the covariance are recursively updated based on the measurements y_t and the control signals u_t. For nonlinear systems it is common to linearize the model and then apply the Kalman filter to the approximated model. This gives rise to the popular Extended Kalman Filter (EKF).
- The *particle filter* is capable of dealing with nonlinear systems. It was introduced by Gordon *et al.* in 1993 [1] and has since then become increasingly popular. The key idea here is to approximate the filtering density using an empirical density function consisting of many samples (particles). In this way linearization can be avoided and the full nonlinear model can be exploited. Furthermore, there is no need for the noise to be Gaussian. The downside is that the particle filter is computationally much more demanding than the EKF.

A successful framework for sensor fusion will, besides the modelling and the filtering parts briefly introduced above, rely on a certain “surrounding infrastructure”. By this we mean solutions to issues such as time synchronization between the different sensors, calibration of the various coordinate systems involved, sensor-near signal processing etc. This part of the framework should not be overlooked.

REFERENCES

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[2] R. E. Kalman. A new approach to linear filtering and prediction problems. *Transactions of the ASME, Journal of Basic Engineering*, 82:35–45, 1960.