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Sensor Fusion for Irregular Sampled Systems

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Chapter 1

Introduction

1.1 Motivation

In nature it is possible to observe data fusion in a variety of phenomenons. Animals combine signals received by different senses, such as sight, hearing, smell, taste and touch to recognize the surroundings. Plants have analogous mechanisms, used to water consumption modulation, leaf-color changes or structure bending towards the light, for instance. Throughout history the sensory systems in living beings have evolved to assimilate multiple information coming from a variety of sources in a highly complex and efficient way, in order to have a better perception of the environment.

Nowadays information fusion is studied in many fields of science, as a way of exploiting data from multiple sources to achieve better outcomes in comparison to those obtained if any of theses sources were used separately (Dasarathy, 2001). Other terms have been used to denote the merge of information in technical literature, e.g. "data fusion", "sensor fusion", "multi-sensor fusion" or "multi-sensor integration". To avoid confusion, the terminology used by (Elmenreich, 2002) will be adopted, whereby information fusion is understood as the overall term and sensor fusion is used in case the sources of information are sensors.

Some research fields have been increasingly exploiting the advantages of sensor fusion techniques, such as robotics, military, biometrics and image processing. The main benefits expected are related to accuracy, due to the use of redundant or complimentary data, to dimensionality, i.e. additional information being created by a group of data, and to robustness against failure and interference. Consequently much effort has been put into the development and investigation of data fusion techniques. The work of (Khaleghi et al., 2013) presents an extensive review of different approaches available, separating them by the way sensor data imperfection is represented, namely probabilistic fusion, evidential belief reasoning, fuzzy reasoning, possibilistic fusion, rough set based fusion and hybrid fusion.

Data fusion techniques based on probability theory are the earliest available and perhaps the most popular ones up until now. They are concerned on estimating the probability distribution functions (pdf) of a system's states by means of the Bayesian approach[1]. If the system is linear and Gaussian, the Kalman filter (KF) guarantees

[1]Bayesian approach to state estimation uses the famous Bayes' rule, i.e. $P(A|B)P(B) = P(B|A)P(A)$, in order to find the posterior *pdf* in terms of the likelihood and the prior *pdf*.

optimal estimation. For nonlinear processes, KF generalizations were proposed, such as the extended Kalman filter (EKF) or the unscented Kalman filter (UKF). Particle filters (PF) on the other hand can be used to deal with both nonlinearities in the dynamics and non-Gaussian distributions.

The most common class of systems studied in state estimation under the probability theory is the sampled-data system, due to the wide use of digital devices. Although described by continuous time differential equations, they can be modeled using discrete state equations, using approximation techniques (Phillips e Nagle, 1995). Usually the sampling period of such systems are constant and known. In other words, the sensors are considered to transmit data at regular intervals. However, for many applications, such consideration is not valid. The use of several redundant sensors, e.g, with different sampling rates or sampled in distinct time intervals leads to data being received at random time instants. Additionally, when data from multiple sensors are transmitted via several subsystems in a network, there might be loss of packets and delays (Schenato et al., 2007) or even multiple information arriving simultaneously (Moayedi et al., 2011). In networked control systems, event-triggered sampling schemes have been proposed to reduce communication resources consumption (Hu et al., 2017), which will also generate variable sampling intervals. Nowadays, because of the ever-growing scientific advances, the technology of microprocessors, sensors and communication has become increasingly accessible, which continues to ensure that multiple sensor networks are more and more common.

Thus, despite improving accuracy and robustness of the estimation process, the fusion of data from multiple sensors might introduce challenges to the state estimation algorithms, due to sampling irregularities. Depending on how they take place, modifications to the KF and its generalizations can be carried out to tackle these abnormalities. In the work of (Fatehi e Huang, 2017), a fusion KF is proposed to estimate the states of a system with multi-rate measurements, whereby one of them is fast, regular and delay-free and the other is slow, irregular and randomly delayed. One application of such system is for industrial process control, where there are on-line instrumentation characterized by the former and data from lab analysis, which are much more accurate, but works as the latter measurement system. For a more general case, when the random delays of the more accurate measurement process is unknown, (Gopalakrishnan et al., 2010) presents a critical analysis of the available methods for data fusion. They are separated into two categories: those that incorporate the delayed measurements upon arrival, and methods that rely in state augmentation, in order to incorporate the delayed information between estimation steps. In general the proposed methods and their performances will depend on particularities of the sampling irregularities and how they are modeled. Time delays, for instance, can be multiple of a base sampling period (Peñarrocha et al., 2012) or continuously random (Yan et al., 2013; Micheli e Jordan, 2002). Some researches treat the variable measurement instants as stochastic processes (Micheli e Jordan, 2002) or as a periodic sampling interval subject to noisy perturbations (Shen et al., 2016).

Parágrafo: *Mencionar que a irregularidade pode ser apenas causada por atrasos, mas de medições feitas regularmente. Para estes casos, há métodos que consideram que os atrasos são conhecidos (referencias) ou não conhecidos, como o método a* Covariance Union *(referencia - julier e uhlman). No entanto, se o modelo de medições permite instantes de tempo aleatório, a maior parte dos métodos considera que, apesar de irregular, o instante é conhecido (duas referencias - obs.: não encontrei alguma pesquisa que trata o instante como totalmente irregular e não conhecido). Dizer que isso pode acontecer quando uma rede de sensores não é sincronizada, por exemplo. Dizer que em várias aplicações práticas isso é desconsiderado (FALTA REFERENCIA) Introduzir o assunto da sincronização como uma solução (referencias)*

Parágrafo: *Mencionar que não há estudos sobre os efeitos de se ignorar a irregularidade amostral e assimilar os dados nas horas em que chegam, considerando apenas que há perdas de pacote. Dizer que por isso, existe uma lacuna em relação ao tradeoff investir em mais sensores para melhorar acurácia e a perda de acurácia introduzida pela amostraegm irregular, caso ela aconteça. Dizer que a proposta deste trabalho é avaliar os efeitos da perda de desempenho em sistemas com amostragem irregular com ou sem timestamp. Jogar luz sobre quando compensa investir em sincronização ou até que ponto mais sensores pode contribuir com a qualidade da estimação*

1.2 Problem Formulation

Apresentação matemática do problema, de forma ampla. Descrever as premissas adotadas.

1.3 Objectives

1 frase para o objetivo geral Objetivos específicos

1.4 Text Outline

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