

Laboratório de Modelagem, Análise e Controle de Sistemas Não-Lineares

Departamento de Engenharia Eletrônica

Universidade Federal de Minas Gerais

Av. Antônio Carlos 6627, 31270-901 Belo Horizonte, MG Brasil

Fone: +55 3499-4866 - Fax: +55 3499-4850



Sensor Fusion for Irregular Sampled Systems

Taiguara Melo Tupinambás

Dissertação submetida à banca examinadora designada pelo Colegiado do Programa de Pós-Graduação em Engenharia Elétrica da Universidade Federal de Minas Gerais, como parte dos requisitos necessários à obtenção do grau de Mestre em Engenharia Elétrica.

Orientadores: Prof. Bruno Otávio Soares Teixeira, Dr.
Prof. Leonardo Antônio Borges Tôrres, Dr.

Belo Horizonte, Maio de 2018

Contents

1	Introduction	1
1.1	Motivation	1
1.2	Problem Formulation	3
1.3	Objectives	3
1.4	Text Outline	3
	References	6

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 numerous 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 these 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 complementary 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 approach¹. If the system is linear and Gaussian, the Kalman filter (KF) guarantees

¹Bayesian 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 (Moayed 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 amostragem 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

Bibliography

- Dasarathy, B. (2001). Information Fusion - what, where, why, when, and how? *Information Fusion*, 2(2):75–76.
- Elmenreich, W. (2002). An introduction to sensor fusion. Research report, Vienna University of Technology.
- Fatehi, A. e Huang, B. (2017). Kalman filtering approach to multi-rate information fusion in the presence of irregular sampling rate and variable measurement delay. *Journal of Process Control*, 53:15–25.
- Gopalakrishnan, A., Kaisare, N. S., e Narasimhan, S. (2010). Incorporating delayed and infrequent measurements in Extended Kalman Filter based nonlinear state estimation. *Journal of Process Control*, 21:119–129.
- Hu, R. J., Wang, Z., Alsaadi, F. E., e Hayat, T. (2017). Event-based filtering for time-varying nonlinear systems subject to multiple missing measurements with uncertain missing probabilities. *Information Fusion*, 38:74–83.
- Khaleghi, B., Khamis, A., Karray, F. O., e Razavi, S. N. (2013). Multisensor data fusion: A review of the state-of-the-art. *Information Fusion*, 14(1):28–44.
- Micheli, M. e Jordan, M. I. (2002). Random sampling of a continuous-time stochastic dynamical system. In *in Proc. of the 15th International Symposium on the Mathematical Theory of Networks and Systems (MTNS 2002)*, (University of Notre Dame, South).
- Moayed, M., Foo, Y. K., e Soh, Y. C. (2011). Filtering for networked control systems with single/multiple measurement packets subject to multiple-step measurement delays and multiple packet dropouts. *International Journal of Systems Science*, 42(3):335–348.
- Peñarrocha, I., Sanchis, R., e Romero, J. A. (2012). State estimator for multisensor systems with irregular sampling and time-varying delays. *International Journal of Systems Science*, 43(8):1441–1453.
- Phillips, C. L. e Nagle, H. T. (1995). *Digital control system analysis and design*. Prentice-Hall, Inc.

- Schenato, L., Sinopoli, B., Franceschetti, M., Poolla, K., e Sastry, S. S. (2007). Foundations of Control and Estimation Over Lossy Networks. *Proceedings of the IEEE*, 95(1):163–187.
- Shen, B., Wang, Z., e Huang, T. (2016). Stabilization for sampled-data systems under noisy sampling interval. *Automatica*, 63:162–166.
- Yan, L., Xiao, B., Xia, Y., e Fu, M. (2013). State estimation for a kind of non-uniform sampling dynamic system. *International Journal of Systems Science*, 44(10):1913–1924.