Optik xxx (2016) xxx–xxx

Contents lists available at ScienceDirect

Optik

journal homepage: www.elsevier.de/ijleo

Original research article

Pulsar profile denoising using kernel regression based on maximum correntropy criterion

Yidi Wang*, Wei Zheng, Dapeng Zhang, Lu Zhang

College of Aerospace Science and Engineering, National University of Defense Technology, Changsha 410073, China

ARTICLE INFO

Article history:
Received 6 September 2016
Accepted 31 October 2016

Keywords:
X-ray pulsar-based navigation
Kernel regression
Correntropy

ABSTRACT

A pulsar profile denoising method using kernel regression based on maximum correntropy criterion is proposed. This method uses the kernel regression to reduce the human visual inspection inescapable in the current profile denoising methods and the reliance of the prior knowledge on the profile of interest. In order to cope with the non-Gaussian case that is common in a real application, the maximum correntropy criterion is introduced into the kernel regression to resist the impact of non-Gaussian noise. The performance of the prosed method is verified via simulation and real data. The results have shown that the proposed method outperforms the current signal denoising methods in a non-Gaussian environment and is readily to be applied.

1. Introduction

Pulsar is a type of rapidly spinning neutron star that emits electromagnetic radiation through its magnetic poles [1]. A measurement device can receive a pulsed signal, when the electromagnetic radiation sweeps across the device. Since the discovery of the pulsar, scientists and scholars have gradually realized that the pulsar can be employed as a ‘perfect’ natural clock as it has a brilliant long-term periodicity stability that can match the current atomic clock. The concept of pulsar-based autonomous navigation was first introduced in 1970s [2]. The concept has experienced a sharp growth, bringing in a nearly-complete framework. Since 1993, the United States has performed a series of programs on pulsar-based navigation method, especially the ongoing SEXTANT program planned to verify the pulsar-based navigation system on the International Space Station (ISS) in 2016 [3]. The European Space Agency (ESA) analyzed the feasibility of pulsar-based navigation method in 2004 [4]. The study on pulsar-based navigation has attracted numbers of researchers in China and arose some heuristic works [5,6].

According to the energy band of electromagnetic radiation, the pulsar can be categorized as X-ray pulsar, radio pulsar, γ-ray pulsar and et al. In order to reduce the size and power consumption of satellite-borne sensor, the X-ray pulsar is recommended to be utilized for navigation. Although the signal of X-ray pulsar is claimed to be a pulse, a spacecraft can merely record a series of discrete photon time of arrivals (TOAs), as the flux of an X-ray pulsar is extremely weak [7]. In order to analyze the character of the pulsar signal and to calculate the pulse TOA, an empirical profile of pulsar must be recovered using the recorded photon TOAs. The predominant method for profile recovery is called epoch folding, which would be renamed direct epoch folding (DEF) in the remainder of the paper [8]. DEF is consisted of the following three steps: 1) fold the photon TOAs recorded over the whole observation period of pulsar back into the first period; 2) divide the first

* Corresponding author.
E-mail address: wangyidi19860609@163.com (Y. Wang).

http://dx.doi.org/10.1016/j.ijleo.2016.10.132

period into N_b bins with equal length and count the photons falling into each bin; and 3) normalize the empirical profile using the number of all recorded photons [9] pointed out that the difference between the empirical and the true profile (i.e. DEF noise), can be modeled as a zero-mean Gaussian noise, the standard deviation of which is a term of N_b. In order to investigate the detailed information within the empirical profile and to have a high-precision pulse TOA, N_b is expected to be as large as possible. However, the growth of N_b increases the DEF noise. Although the DEF noise would be reduced by prolonging the observation period of pulsar in theory, a spacecraft is hardly to observe a specific pulsar for a long time as the spacecraft keeps performing an orbital motion. In this case, it is necessary to develop methods to enhance the signal to noise ratio (SNR) of the recovered empirical profile.

There are two main types of ways to realize the above objective: 1) fitting the empirical profile using a Gaussian mixture model [10]; and 2) signal denoising such as wavelet-based method and empirical model decomposition (EMD) [11]. In essence, the two ways belong to parametric regression that presets the empirical profile as a sum of a series of base functions weighted by coefficients needed to be fitted. The performance of the methods heavily relies on whether the presumed models are accurate enough to describe the empirical profile. In addition, the signal denoising methods needs to empirically set the signal decomposition level that determines whether the high-frequency noise can be removed. Thus, the aforementioned methods are more suitable for off-line analysis rather than for on-orbit autonomous operation of spacecraft, as they are interactive or need human visual inspection.

On the other hand, the assumption that DEF noise is Gaussian holds only when the X-ray detector works well over the whole observation period. If some problems, such as the atomic clock cannot provide accurate time sampling caused by the clock drift or color noise, occur in the X-ray detector, it would cause a pseudo-photon case, where the detector would record not only the photons from the pulsar as well as the pseudo-photons produced by the detector itself. In other words, the detector would record photons more than the ordinary case. In this case, the DEF noise becomes a non-Gaussian noise. Although, based on the central limit theorem, the noise could be approximated as a Gaussian one when the observation period is long enough, a spacecraft cannot observe a specific pulsar for a long time as described before. In a non-Gaussian environment, the performance of aforementioned methods would fall, as the weights in the methods are calculated out using least square that is vulnerable to the presence of non-Gaussian noise.

Thus, for X-ray pulsar-based navigation, it is necessary to propose a signal denoising method that can autonomously perform and resist to the impact of non-Gaussian noise. In this paper, we propose a kernel regression based on maximum correntropy criterion to accomplish the above objective. Kernel regression is a typical non-parameteric regression method that expresses the measurement at an arbitrary epoch as a sum of the measurements at the past epochs weighted by kernel functions [12]. However, the kernel regression is also easily affected by non-Gaussian noise, as the kernel regression works based on the minimum mean square error criterion (MMSEC). To cope with the non-Gaussian noise, we modify the MMSEC to be the maximum correntropy criterion (MCC), as the correntropy is a generalized correlation function that has been documented to perform better than correlation function in a non-Gaussian noise environment [13]. Compared with Gaussian mixture model and current signal denoising method, the proposed method requires little prior knowledge of the investigated signal and does not need to set decomposition level in advance.

The remainder of this paper proceeds as follows. Section 2 introduces the related works. Section 3 shows how to embed the MCC into the kernel regression. Section 4 analyzes the performance of proposed method via simulation, and Section 5 investigates the performance via the experiment data from Rossi X-ray Timing Explorer (RXTE).

2. Related works

2.1. Kernel regression

Assuming a nonlinear model is

$$\boldsymbol{y} = \boldsymbol{s}(\boldsymbol{X}) + \boldsymbol{\omega}, \tag{1}$$

where $\mathbf{y} \in \mathbb{R}^{n\times 1}$ is the measurement, $\mathbf{X} \in \mathbb{R}^{n\times 1}$ is the vector of measurement epoch, and $\boldsymbol{\omega}$ is the measurement noise.

Then, using the kernel regression, the estimate of $\mathbf{y}$ at x, $\hat{\boldsymbol{y}}$, can be obtained by solving the minimizing problem of [12]

$$\hat{\boldsymbol{y}} = arg\min \sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2 w_i(x), \tag{2}$$

where $\hat{y}_i$ is the ith component of $\hat{\boldsymbol{y}}$ and $w_i(x)$ is the weight with the expression of

$$w_i(x) = \kappa\left(\frac{x - X_i}{h}\right) \Big/ \sum_{i=1}^{n} \kappa\left(\frac{x - X_i}{h}\right). \tag{3}$$

In Eq. (3), $\kappa(\bullet)$ is the kernel function with a kernel width of h that can be autonomously calculated via Leave One Out Cross Validation.