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Enhancement of GPS Signals Acquisition in non-Homogeneous Environment using the OS-CFAR Techniques with Optimization Technique

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Abstract. In this paper, we propose to use metaheuristic optimization techniques to improve the adaptive acquisition of the global navigation satellite system (GNSS) in both homogeneous and non-homogeneous environments, The main objective of this work is to optimize the thresholding of the Constant False Alarm Rate (OS-CFAR) in Rayleigh fading channels we compare the result with the base detector CA-CFAR . In GNSS acquisition, the pilot and data blocks may have different thresholds. Therefore, the optimization will focus on two scaling factors (T and k). Two fusion rules have been used here "AND" and "OR". Due to their performance in different optimization problems, metaheuristics have been chosen as the tool to solve this type of problem. The simulation results show that the optimized thresholds have a significant impact on the performance of the acquisition system.

Access this article online

Keywords: Metaheuristic optimization techniques, GNSS, OS-CFAR.

1. Introduction

The term "Global Navigation Satellite System (GNSS)" broadly refers to satellite navigation systems that provide continuous worldwide coverage under all weather conditions for positioning, navigation, and timing services[1]. Four major global satellite navigation systems have been established : the American Global Positioning System (GPS), the European Galileo system, the Russian GLONASS system, and the Chinese BeiDou (BDS) system. Additionally, the Indian Regional Navigation Satellite System (IRNSS) has been deployed by India, while Japan has developed the Quasi-Zenith Satellite System (QZSS)[2-4].

Satellite navigation systems have become fundamental infrastructures for spatial and temporal referencing. The evolution of navigation technologies significantly impacts various sectors of society, including the economy, cartography, energy, transportation, and military operations. An increasing number of infrastructures rely heavily on satellite navigation systems. A failure in these systems could have severe consequences, highlighting the crucial importance of improving GNSS stability.

Modern GNSS signals generally consist of two distinct components : data channels and pilot channels. The former carries navigation information, while the latter, more compact, facilitates accurate pseudo-range determination. GNSS signal acquisition is a crucial step in ensuring precise and reliable positioning. Monitoring interference in satellite navigation is an essential method for effectively assessing disruptions and ensuring the proper functioning of the Global Navigation Satellite System (GNSS). Once interference is detected, this monitoring process helps identify its type, perform direction-finding and localization operations, evaluate its impact on GNSS, and guide the implementation of effective countermeasures.

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The continuous advancement of signal processing algorithms and optimization techniques enhances the performance of GNSS receivers, even under challenging environmental conditions [5].

Given that our environment is non-homogeneous and our applications require real-time processing, we will use an alternative detector (OS-CFAR) compared to the baseline CA-CFAR detector in our study. This approach will allow us to better adapt to the environment by integrating metaheuristic optimization techniques tailored to our problem.

The remainder of the paper is structured as follows: Section 2 introduces and describes the proposed adaptive acquisition system in a Rayleigh fading channel, based on the OS-CFAR processor, Section 3 analyzes this system and provides expressions for detection and false alarm probabilities as functions of the two parameters (T, k).Section 4 explores metaheuristic optimization methods, Section 5 evaluates the acquisition and detection performance of the proposed models based on simulation results. Finally, the paper concludes in Section 6.

2. System Model

In this study, we focus on signal acquisition phase, which is particularly interesting as it determines the presence or absence of the tested signal while simultaneously providing an estimation of various key parameters, mainly the code delay and Doppler frequency of the incoming signal. GNSS signal acquisition is initially presented as a detection/estimation problem.

The probability density function under hypothesis (H_1) is denoted as $f(x/H_1)$, and is given by[6]:

$$f(x/H_1) = \frac{1}{2\delta_n{}^2(1+\lambda\frac{\delta_m{}^2}{\delta_n{}^2})} exp\left(-\frac{x}{2\delta_n{}^2(1+\lambda\frac{\delta_m{}^2}{\delta_n{}^2})}\right) \quad (1)$$

Using a predetermined threshold β, the detection probability is obtained as follows:

$$P_D = \int_{\beta}^{\infty} f(x/H_1)\, dx \quad (2)$$

$$= exp\left(-\frac{\beta}{2\delta_n{}^2(1+\frac{1}{2}\frac{c}{N_0}T_c)}\right)$$

The probability density function under hypothesis (H_0) is exponentially distributed with the parameter $1/2\delta_n{}^2$:

$$f(x/H_0) = \frac{1}{2\delta_n{}^2} exp\left(-\frac{x}{2\delta_n{}^2}\right) \quad (3)$$

In the same conditions, the probability of a false alarm is obtained as follows:

$$P_{FA} = \int_{\beta}^{\infty} f\left(\frac{x}{H_0}\right) = exp\left(-\frac{\beta}{2\delta_n{}^2}\right) \quad (4)$$

3. Analysis of the Proposed system

For each local OS-CFAR detector, the reference cells of each local sensor are sorted, and the K-th largest range

sample is selected to estimate the background noise level. This value is then multiplied by a scaling factor T to obtain the local adaptive threshold. The resulting value is compared to the local cell under test to make a local decision as shown in figure 1. Thus, each detector transmits its local determination to the data fusion center to make a global decision based on the fusion rule.

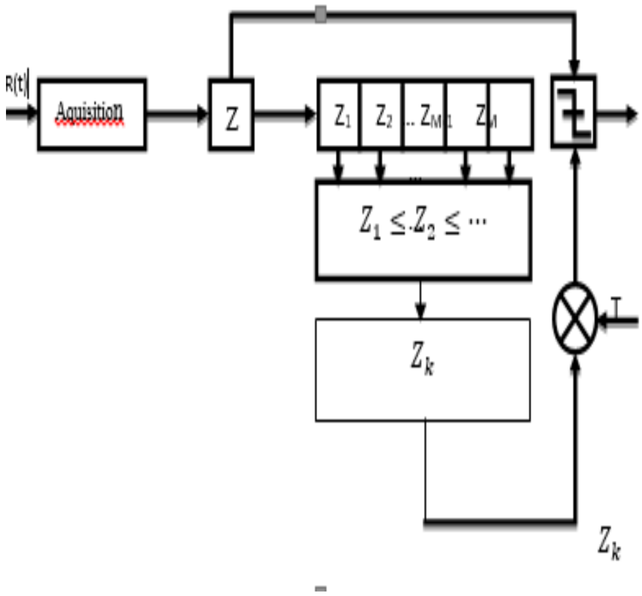


Figure 1. Schéma fonctionnel du détecteur OS-CFAR

In the OS-CFAR detector, the outputs of the M reference cells are recorded in ascending order:

$$Z_1 \leq Z_2 \leq \cdots \leq Z_{M-1} \leq Z_M \quad (5)$$

Instead of calculating the average signal over the cells, the cells are sorted in ascending order of their amplitudes: Z (1), Z (2),… Z (M). The main idea behind the OS-CFAR detector concept is to select a specific value Z (k), where k {1, 2, ..., M}, to estimate the average clutter power in the observed detection window. Then, by multiplying this value by the scalar factor T, obtained by setting the false alarm probability of the OS-CFAR detector [2].

The probability of false alarme is given by [7]:

$$P_{fa} = \prod_{i=1}^{M}(1 - \frac{T}{M-i+1}) \quad \textbf{(6)}$$

The corresponding detection probability of the individual detectors is given by

replacing T with T / (1 + µ) in (6) :

$$P_D = \prod_{i=1}^{M}(1 - \frac{T}{(M-i+1)(1+\mu)}) \quad \textbf{(7)}$$

Detection performance can be improved by combining the results of two or more CFAR detectors, whether they are identical or different. The fusion center merges the results from the two detectors, increasing the detection probability while maintaining a constant false alarm probability. Two fusion methods are used: the AND rule and the OR rule. These two rules are commonly applied in many applications involving data from multiple sources. The proposed structure is illustrated in Figure 2.

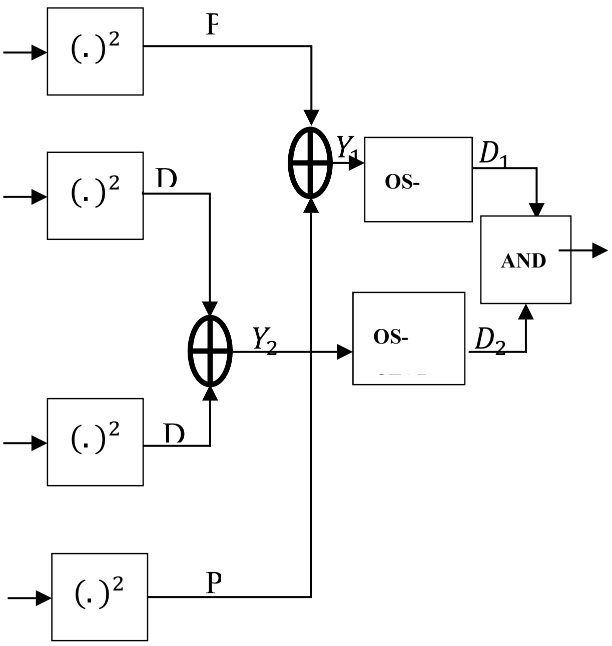


Figure 2. Distributed CFAR Processor System.

from separate CFAR detectors; this increases the probability of detection while keeping the false alarm probability constant[8].

In this architecture, as shown in figure 2, each CFAR detector makes a local decision based on its own observations, which is then transmitted to the fusion center. There, a global decision is typically made using the AND fusion rule or the OR fusion rule, ensuring that the channels remain independent. In this case, only two detectors are used one for data channel and the other for pilot channel.

4. Optimization Techniques

4.1 Firefly algorithm (FA)

The Firefly Algorithm (FA) was developed by Yang for continuous optimization. It is based on the flashing patterns and behavior of fireflies. The FA algorithm follows three idealized rules:

Fireflies are unisex; therefore, regardless of their gender, any firefly can attract others.

Fireflies are attracted to each other in proportion to their brightness, and their attraction decreases as the distance increases. Thus, between two flashing fireflies, the less bright one will be attracted to the brighter one.

If no brighter firefly is visible, a firefly will move in a random direction. The brightness of fireflies shapes the objective function landscape. The attraction between fireflies is proportional to the perceived light intensity of adjacent fireflies. The variation of attraction β with distance r can be defined as:

$$\beta = \beta_0 e^{-\gamma r^2} \quad \textbf{(8)}$$

Where β is the attraction at r = 0.

The movement of firefly I toward a brighter firefly j is determined by:

$$x_i^{t+1} = x_i^t + \beta_0 e^{-\gamma r^2}(x_j^t - x_i^t) + \alpha_t \epsilon_i^t \quad \textbf{(9)}$$

The second term represents attraction.

The third term introduces randomization, where α_t is the randomization parameter, and ϵ_i^t is a random vector that can follow a uniform or Gaussian distribution [9].

5. Simulations and Results

In this section, we present the simulation results aimed at comparing and analyzing the performance of the OS-CFAR algorithm. These results are compared with those of the baseline CA-CFAR detector in both homogeneous and non-homogeneous environments, with a fixed false alarm rate of Pfa= $10^{-4}$and a reference window size of M=32 cells.

The study is divided into two scenarios: one without interference (homogeneous environment) and the other with interference (non-homogeneous environment), each analyzed with and without optimization.

In figures 3 (a and b) illustrate the detection probability of the OS-CFAR detector with a constant false alarm rate, for M=32 reference cells. It is clearly observed that the CA-CFAR detector, whether optimized or not, outperforms OS-CFAR in homogeneous environments.

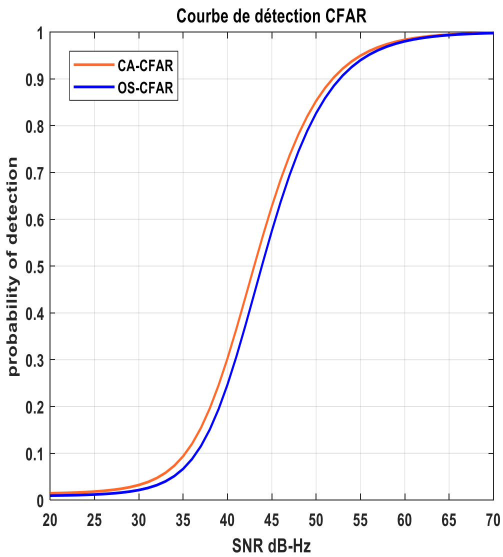
However, in non-homogeneous conditions, OS-CFAR demonstrates better performance than CA-CFAR, as highlighted in Figure 4. Therefore, OS-CFAR proves to be more suitable for non-homogeneous environments.

In figure 5 shows the evolution of the overall detection probability as a function of the signal-to-noise ratio (SNR) in dB, using the "AND" fusion rule. A significant drop in detection performance is observed as the Pfa decreases, even though the number of reference cells remains fixed at M=32.

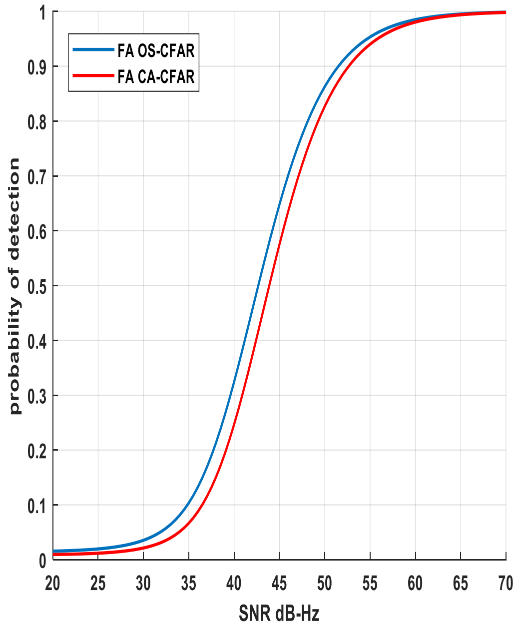
For clearer insight, Figure 6 illustrates how the detection probability varies with SNR using the "AND" fusion rule.

The results show that increasing the number of reference cells enhances the overall system performance.

Finally, Figure 7 also compares the "AND" and "OR" fusion rules. The findings indicate that the "OR" rule offers better detection performance. The best results are achieved using the OS-CFAR detector optimized with the FA method. It is also worth noting that under the conditions M= and Pfa= 10^{-4}, OS-CFAR significantly outperforms the CA-CFAR detector.



(a)



(b)

Figure 3. Detection probability versus signal-to-noise ratio (SNR) for the OS-CFAR and CA-CFAR a) in a homogeneous environment without optimization, b) with optimization method in a homogeneous environment.

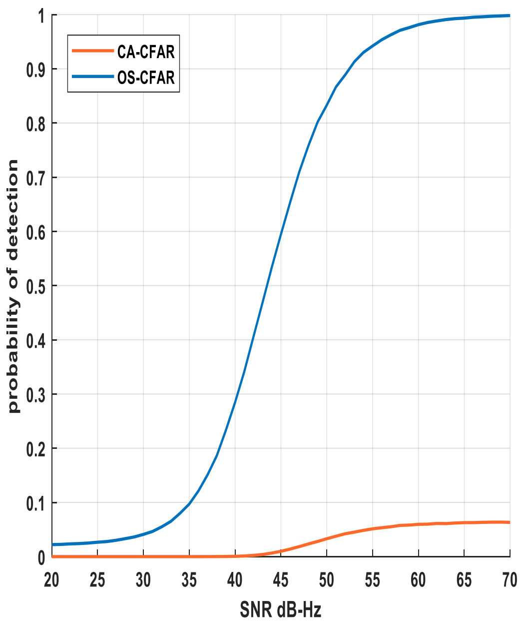


Fig4: Detection probability versus signal-to-noise ratio (SNR) for the OS-CFAR and CA-CFAR in a non-homogeneous environment.

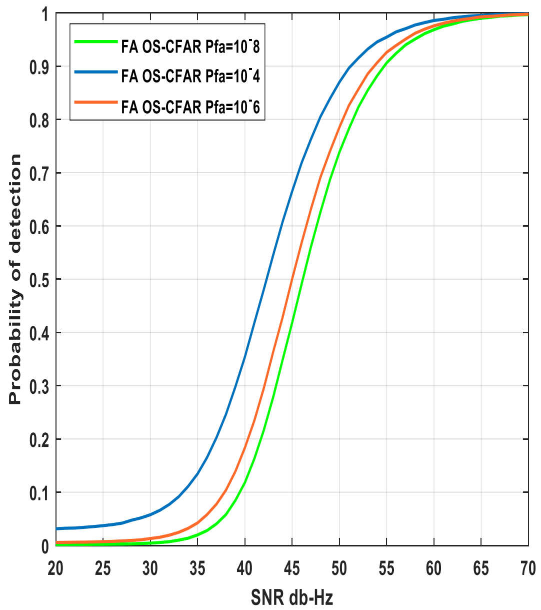


Fig 5: Detection probability versus signal-to-noise ratio (SNR) of the OS-CFAR with different values of Pfa, in the case of M=32.

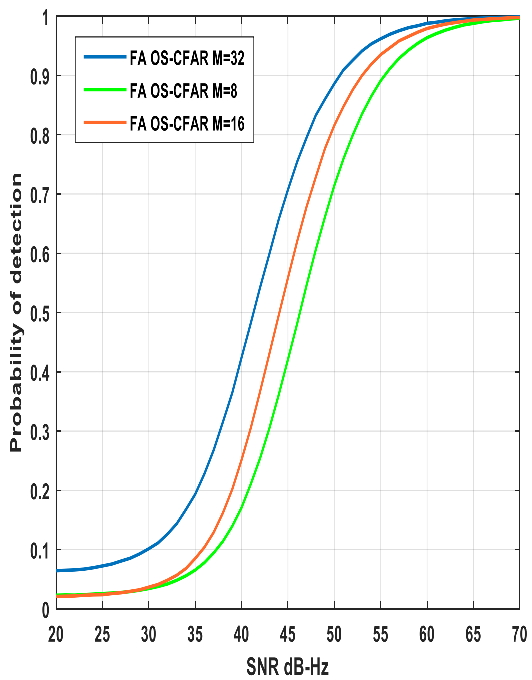


Figure 6: Detection probability versus signal to-noise ratio (SNR) of the OS-CFAR with different values of M, in the case of Pfa= 10^-4

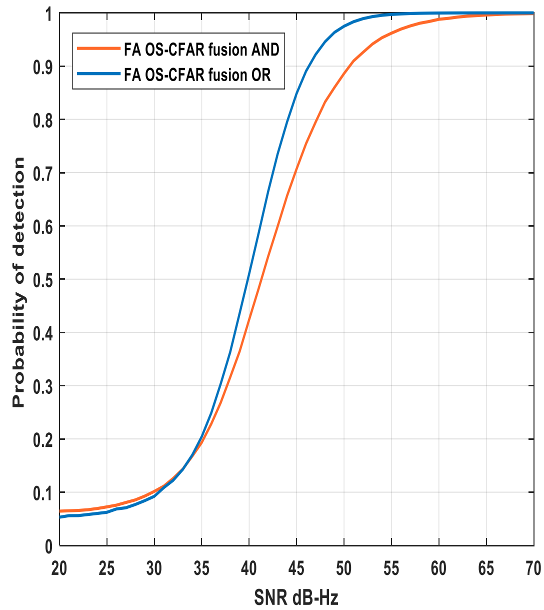


Figure 7: Detection probability versus signal-to-noise ratio (SNR) of the OS-CFAR detector using firefly algorithm (FA) for "AND" and "OR" fusion rules when M = 32 and different detectors are employed.

6. Conclusion

In this work, we present an attempt to improve the efficiency of an approach based on metaheuristic optimization algorithms to optimize the detection threshold in distributed OS-CFAR systems. In this context, various simulations were conducted, and the results obtained for the studied cases were compared and analyzed. All results are presented and validated.

To enhance the acquisition sensitivity of the GNSS receiver in a variable noise environment, we applied adaptive thresholding with an OS-CFAR detector during the acquisition phase.

The results obtained show that applying optimization methods improves the performance of the OS-CFAR detector in non-homogeneous environments, allowing for better estimation of scaling factors. The choice of the fusion rule has a significant impact on the performance of the acquisition system. The optimization method demonstrated that the Firefly Algorithm (FA) provided the best results. Furthermore, the OR fusion rule outperformed the AND rule as well as the standard CA-CFAR detector. These conclusions validate the usefulness of the proposed techniques for optimizing the performance of the OS-CFAR detector in a non-homogeneous environment.

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