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Advances in Adaptive Threshold Techniques in Cognitive Radio: A Survey

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Abstract
Cognitive radio technology has emerged as a transformative solution to the growing spectrum scarcity and demand for wireless communication services. At the core of cognitive radio's effectiveness lies spectrum sensing, a fundamental process for dynamically allocating unused spectrum bands. In this context, adaptive thresholding techniques assume a pivotal role, ensuring the precise detection of primary users and, consequently, the efficient use of available spectrum resources. This survey paper delves into recent advancements in adaptive threshold estimation techniques within the domain of cognitive radio. Our aim is to provide a comprehensive, structured, and insightful overview of these techniques, with a primary focus on global thresholding methods. We classify these adaptive threshold estimation techniques into two principal categories: local and global Adaptive Thresholding Techniques (ATTs). Within the realm of local ATTs, we explore notable techniques such as Cell Averaging CFAR (CA-CFAR) and its various iterations, encompassing 'greatest of' (GO-CFAR), 'smallest of' (SO-CFAR), heterogeneous clutter estimating (HCE-CFAR), 'trimmed mean' (TM-CFAR), and ordered statistics (OS-CFAR). Additionally, we captured variants of local ATTs like the maximum likelihood and algebraic product (MLAP-CFAR) and the goodness-of-fit and generalized likelihood test with dual censoring (GGDC-CFAR). On the global front, we further categorize ATTs

into parametric and non-parametric methods. In the parametric domain, we scrutinize techniques such as Recursive One-sided Hypothesis Testing (ROHT) and First Order Statistical Testing (FOST) Algorithm, while in the non-parametric arena, we explore enhancements in approaches like Otsu, Modified Otsu's Algorithm (MOA), Non-parametric Amplitude Quantization Method (NPAQM), and the Autonomous Global Threshold Adjustment Algorithm (AGTAA). Our pilgrimage guides us through each of these techniques, unveiling their underlying principles, tangible applications, and the specific scenarios in which they excel. The paper identifies key challenges, and presenting a taxonomy of global thresholding techniques based on their working principles. This taxonomy provides a holistic view of the landscape, guiding us toward more accurate spectrum sensing and the realization of an ultra-efficient cognitive radio network. Furthermore, we delve into real-world applications and case studies that demonstrate the practical implications of these advancements. As cognitive radio technology continues to evolve, this paper serves as an invaluable resource for researchers, engineers, and practitioners, offering a holistic view of cutting-edge adaptive thresholding techniques. Moreover, it identifies critical challenges and future directions in this dynamic field. Ultimately, the advances in adaptive threshold estimation presented in this paper contribute to improving spectrum sensing accuracy and realizing more efficient cognitive radio networks.

INTRODUCTION

Background to the study

The escalating demand for increased bandwidth in next-generation networks, coupled with the growing number of users, has rendered the wireless spectrum a scarce and invaluable resource (Apostolos & Boulogeorgos, 2018; Barnes et al., 2013). Despite the international allocation charts indicating a diminishing availability of space within the frequency spectrum, its practical allocation remains inefficient (Tarek *et al*., 2020). This inefficiency can be attributed to the dynamic nature of communication systems utilizing the spectrum, such as cellular technologies, which contrasts with the static transmissions employed by television transmitters (Ahmad *et al*., 2020; Hu *et al*.,

2018). In an effort to address the underutilization of the spectrum, the Spectrum Policy Task Force report, published by the Federal Communications Commission, endeavors to delineate spectral efficiency accurately while providing explicit recommendations to achieve uniform throughput (Akyildiz *et al*., 2006).
Consequently, this has spurred the development of various approaches aimed at combating spectrum underutilization, including spectrum refarming, geolocation databases, multiple antennas, and cognitive radio, as depicted in figure 1.1

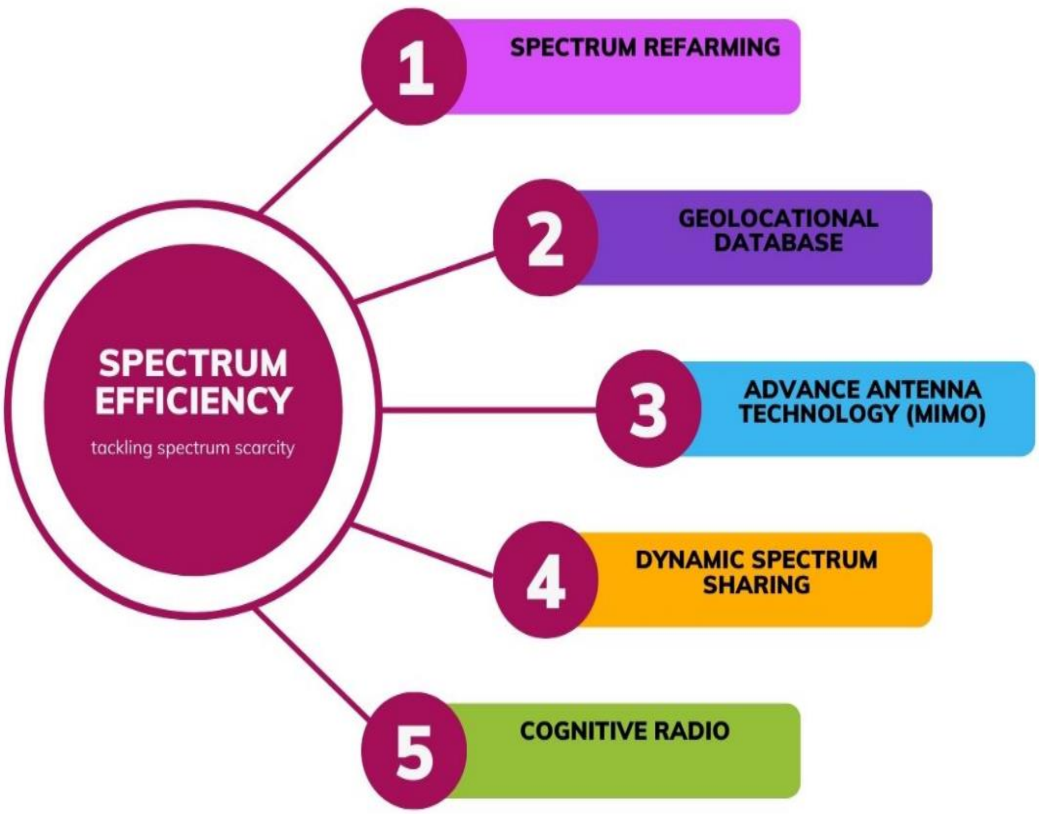

Figure 1: Different Approaches towards spectrum utilization

Cognitive radio (CR) stands out among the aforementioned approaches for several notable reasons. CR exhibits high adaptability and flexibility in spectrum utilization. It possesses the capability to actively sense and analyze the radio frequency environment, thereby identifying available spectrum and dynamically adjusting transmission parameters to enhance efficiency (Ahmad et al., 2020). Moreover, cognitive radio systems can leverage machine learning algorithms to learn from their surroundings, enabling improved decision-making regarding spectrum usage over time. This adaptability empowers cognitive radio to effectively respond to changing network conditions, mitigate interference, and enhance overall spectrum efficiency. Additionally, cognitive radio operates across a wide range of frequency bands and wireless standards, making it a versatile technology applicable to diverse wireless networks (Onumanyi et al., 2018). This versatility enables cognitive radio to efficiently utilize underutilized or unused spectrum. Furthermore, cognitive radio systems are employed to extend the coverage area of modern networks by utilizing lower frequency bands, which facilitate more extensive signal propagation.

Essentially, cognitive radios are intelligent communication devices that adaptively utilize available channels by detecting their occupancy status. They detect and vacate occupied channels while utilizing unoccupied ones (Yücek and Arslan, 2009). Ongoing research in cognitive radio focuses on several areas, including spectrum sharing, management, handoff, and sensing. Spectrum sensing is a crucial component, allowing secondary users to detect the presence or absence of primary user signals without causing interference. Different detectors, such as the energy detector (ED), cyclostationary detector, matched filter, Eigenvalue detector, or compressed sensing method, are utilized in cognitive radio systems. Among these, the ED is widely considered the most practical option due to its simplicity, speed, affordability, and low computational requirements (Akyildiz *et al*., 2006; Onumanyi *et al*., 2020).

Accurate threshold estimation is crucial for effective spectrum sensing, particularly in Energy Detection (ED) techniques (Benazzouza *et al*., 2019). The selection of an appropriate threshold estimation approach, either fixed or adaptive, plays a vital role in achieving reliable performance. Fixed threshold estimation utilizes a predetermined constant threshold, while adaptive threshold adjustment (ATA) algorithms continuously adjust the threshold based on changing noise levels (Farag and Mohamed, 2017; Mustapha *et al*., 2017; Sabuj and Hamamura, 2017). Both approaches have their advantages and limitations, and the choice depends on the specific application and system requirements. However, due to the random and unpredictable nature of noise, it is essential for cognitive radio (CR) systems to employ effective ATAs to accurately compute and adapt the ED threshold to fluctuating noise levels (Kumar et al., 2021; Ogbodo et al., 2017; Onumanyi et al., 2017, 2019; Vartiainen et al., 2017; Vuohtoniemi et al., 2016)

ATAs can be categorized into two types: local and global. Local methods determine a distinct threshold for each sample in the measured spectra, known as constant false alarm rate (CFAR) detectors such as CA-CFAR, GO-CFAR, SO-CFAR, and HCE-CFAR, commonly used in cognitive radio systems (Lehtomäki *et al*., 2005, 2006, 2007). In contrast, global methods compute a single threshold value over an entire range of samples in a reference window or measured spectra. Examples of these global thresholding techniques include the recursive one-sided hypothesis testing (ROHT) algorithm, first-order statistical technique (FOST), forward consecutive mean excision

(FCME) algorithm, Otsu, and the Modified Otsu methods. The choice of a specific ATA depends on the requirements of the CR system, including noise characteristics, detection sensitivity, and available computational resources. Both local and global thresholding methods have their advantages and limitations, and selecting the appropriate ATA is crucial for achieving accurate and reliable spectrum sensing in CR (Onumanyi *et al*., 2018). However, local thresholding techniques (LTT) may perform poorly under specific conditions, such as closely spaced signal samples with high average power distributed over a wide frequency range (broadband) (Onumanyi *et al*., 2018). This is attributed to the threshold biasing effect caused by contiguous signal samples in the algorithm's computing window. In contrast, global thresholding techniques (GTTs) generally outperform LTTs in detection performance and are more suitable for CR applications compared to LTTs.(Onumanyi et al., 2018). Consequently, in recent years, there has been a notable paradigm shift particularly with a discernible trend towards global thresholding techniques (GTTs). This shift is fueled by the recognition that while local thresholding techniques (LTTs) have their merits, they may exhibit suboptimal performance under specific conditions. For instance, LTTs might face challenges when dealing with closely spaced signal samples exhibiting high average power distributed over a wide frequency range, such as broadband signals. The root cause of this challenge is the threshold biasing effect stemming from the presence of contiguous signal samples within the algorithm's computing window.

As we delve into this conference paper, we aim to provide a comprehensive overview, analysis, and classification of these adaptive threshold estimation techniques, with a primary focus on the paradigm shift towards global thresholding methods. Our journey will traverse through both parametric and non-parametric GTTs, offering insights into their principles, applications, and scenarios of excellence. Additionally, we will address the challenges associated with these methods and explore potential solutions, ultimately contributing to the advancement of spectrum sensing accuracy and the realization of more efficient cognitive radio networks.

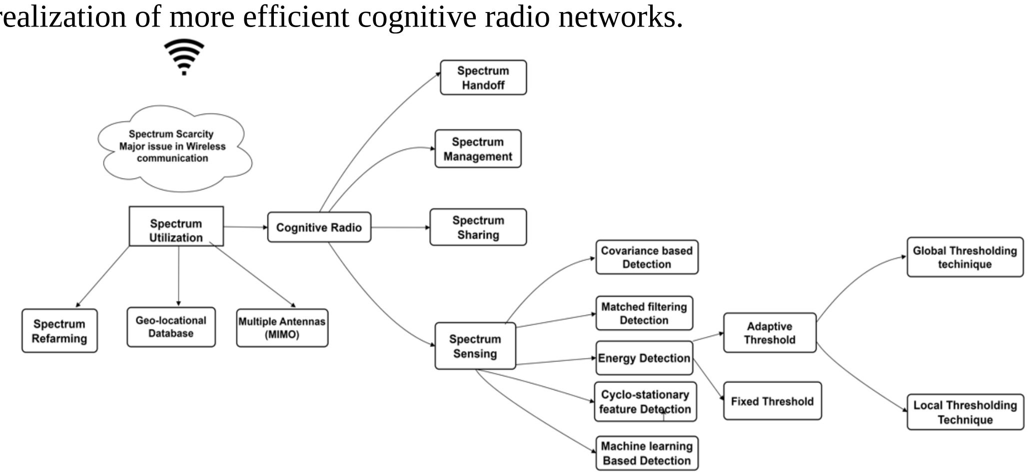

Figure 2: Pathway Leading to Adaptive Thresholding: A Visual Representation.

Review of related work

In the dynamic realm of cognitive radio (CR) systems, the quest for efficient and autonomous global thresholding techniques has led to notable recent advances. These developments are a response to the inherent limitations of conventional methods that rely on fixed parameters, often set by human operators. The inflexibility of these settings can result in suboptimal performance, translating into a significantly diminished Probability of Detection (PD) or an inflated Probability of False Alarm (PFA) for CR systems. The need for more advanced, adaptable techniques has spurred the emergence of Self-Adaptive Threshold Adjustment Algorithms (SATAs).

SATAs, like the Non-parametric Amplitude Quantization Method and the Autonomous Global Threshold Adjustment Algorithm (AGTAA), have become pivotal in the ongoing evolution of CR systems. They represent a shift towards self-configuring algorithms that can autonomously recalibrate their parameters during runtime, diminishing the impact of suboptimal settings on system performance (Bouhdjeur et al., 2022; Onumanyi et al., 2017; Onumanyi et al., 2021).

These recent breakthroughs also address the limitations of conventional thresholding methods, particularly those predicated on Gaussian distribution assumptions. For instance, the Recursive One-sided Hypothesis Testing (ROHT) algorithm, while demonstrating an ability to adapt rapidly to changing environments, grapples with limitations such as decreased reliability in dynamic settings, extended decision-making intervals, and potential unsuitability for real-time scenarios. In response, alternatives like the Forward Consecutive Mean Excision (FCME) algorithm and the FOST algorithm have emerged, offering faster decision-making and simplified adaptability (Datla et al., 2009; Barnes et al., 2013; Ali et al., 2010; J. Lehtomäki et al., 2012).

Recent efforts have also ushered in autonomous non-parametric threshold estimation techniques, notably the Modified Otsu's algorithm (MOA), which streamlines threshold value optimization, overcoming computational overhead concerns and enhancing autonomy. Another significant innovation is the Non-parametric Amplitude Quantization Method (NPAQM), which circumvents the need for histogram and grayscale computations, offering enhanced autonomy and reduced PFA rates in noise-only scenarios (Onumanyi et al., 2017; Onumanyi et al., 2021).

Amid these advancements, the Histogram Partition Algorithm (HPA) remains a powerful tool for threshold adjustment. Nevertheless, its reliance on parameters and lack of autonomy are shortcomings that continue to drive innovation in the field (Onumanyi et al., 2019).

These adaptations and enhancements of Otsu's algorithm, such as MOA and NPAQM, address critical issues, including sensing delays and performance variability in diverse environments, making them better suited for CR applications (Datla et al., 2009; Onumanyi et al., 2017, 2021).

Ultimately, the Autonomous Global Threshold Adjustment Algorithm (AGTAA) represents a significant milestone in autonomous threshold adjustment. This algorithm, developed by Bouhdjeur et al. (2022), optimizes Energy Detectors in CR applications, substantially reducing P_FA rates in noise-only scenarios and improving detection rates where signals are present. However, it's important to note that it may exhibit suboptimal performance in scenarios characterized by bimodal or multimodal noise distributions.

Collectively, these recent advancements are poised to significantly enhance the adaptability and overall performance of cognitive radio systems. They hold the promise of fostering more efficient spectrum sensing in the face of dynamic and challenging real-world environments.

Table 1: Summary of Review of related works

Reference	Year	Specific details
(Lehtomäki et al., 2007) (Vuohtoniemi et al., 2016)	2007 2016	• Utilizes the Cell-Averaging (CA) Constant False-Alarm Rate (CFAR) technique for outlier detection.
(Gandhi & Kassam, 1988)	1988	• CFAR processors are essential for detecting radar targets in complex environments with unknown and potentially changing statistical parameters. • Different CFAR processors, like "cell averaging" (CA), "greatest of" (GO), "smallest of" (SO), "ordered statistics" (OS), and "trimmed mean" (Thl), each have strengths and weaknesses in handling various clutter and target scenarios.
(Harold M. Finn, 1986)	1986	• The paper introduces the unbiased version of the HCE-CFAR test. • It presents the single-cell false alarm probability equation along with its corresponding value.
(Verma & Sahu, 2016)	2016	• The paper suggests an approach that takes into account the distance between the secondary transmitter and primary receiver, emphasizing interference-aware threshold selection following the CDR and CFAR principles.
(Kumar et al.,	2021	• The paper evaluates the performance of various

2021)		constant false alarm rate (CFAR) processors in nonhomogeneous background clutter conditions.
(Datla et al., 2009a)	2009	• The paper proposes an automated and standardized spectrum-surveying framework. • It introduces the ROHT techniques for data processing without prior knowledge, addressing signal dynamic range and varying signal-to-noise ratios.
(Lehtomaki et al., 2006)	2006	• FCME: Forward Consecutive Mean Excision for energy-based spectrum sensing with unknown noise power. • Uses a threshold factor to declare signal presence based on the test statistic exceeding the threshold.
(Abdullahi et al., 2020)	2020	• Novel model combines Cuckoo Search Optimization (CSO) with FCME algorithm for adaptive thresholds in cognitive radio (CR) systems.
(Onumanyi et al., 2019)	. 2019	• Introduces two threshold estimation algorithms: histogram partitioning and mean-based histogram partitioning, evaluated using 100 Hz resolution video bandwidth and dBmHz PSD measurements.
(Otsu, 1996) (Datla et al., 2005)	1996 2005	• The paper reviews previous threshold estimation methods, such as Otsu's algorithm, and delves into the ROHT and recursive Otsu's algorithms, emphasizing their autonomous threshold estimation capabilities for spectrum surveying and occupancy characterization.
(Onumanyi et al., 2017)	2017	• The paper introduces a modified Otsu's algorithm for automatic threshold estimation in energy detection-based Cognitive Radio (CR) applications, demonstrating its capability for fully autonomous blind spectrum sensing with an Energy Detector at a 5dB Signal-to-Noise Ratio, in accordance with the IEEE 802.22 draft standard.
(Onumanyi et al., 2021)	2021	• The paper explores an autonomous amplitude quantization method for threshold estimation in self-reconfigurable cognitive radio systems, emphasizing the computation of the total mean to determine the optimal threshold.
(Bouhdjeur et al., 2022)	2022	• The paper introduces an autonomous global threshold adjustment algorithm for energy detection in self-

	reconfigurable cognitive radio systems, utilizing the position of the maximum difference to determine threshold settings and detect signals within spectral bands.

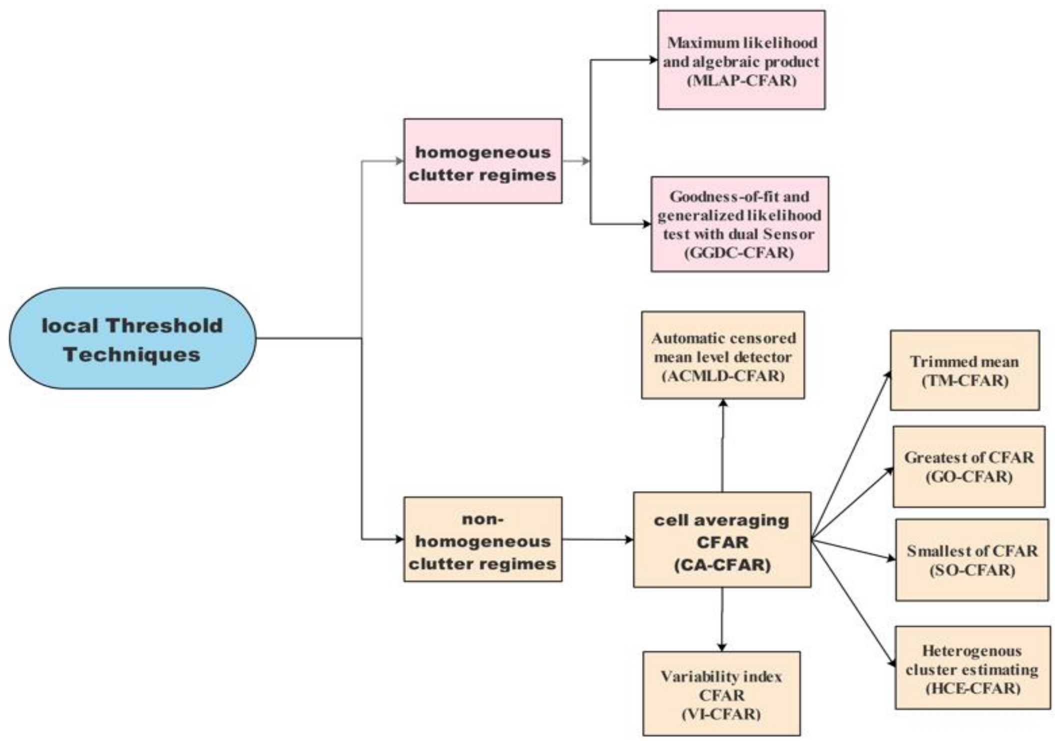

Figure 3: Different local Thresholding Techniques.

General Overview of Global Adaptive Thresholding

Global thresholding techniques (GTTs) are methods that compute a single threshold value over a contiguous number of samples in a specified window or measured spectra, Onumanyi *et al*. (2018). Compared to fixed thresholding which determines the threshold value, keeping it constant throughout the analysis while implying that same threshold value to all data points, irrespective of their characteristics or the analysis context, GTT computes a new threshold value continuously for each newly measured spectrum, adapting to the specific characteristics of the data being analyzed. This approach allows for a more precise classification of data and reduces the likelihood of misclassification, avoiding false positives or false negatives. Onumanyi *et al*. (2021) categorized GTTs into two types: parametric and non-parametric.

Parametric-based GTTs, also known as adaptive-only methods, require manual fine-tuning of parameters before they can be used. Examples of classical GTTs with less than two tunable parameters include the Recursive One-sided Hypothesis Testing

(ROHT) algorithm (Datla *et al*., 2009; Onumanyi *et al*., 2018) and the First Order Statistical Technique (Ali *et al*., 2010). Another approach, such as the Forward Consecutive Mean Excision (FCME) developed by J.J. Lehtomak *et al*. (2006), requires fine-tuning of a few parameters for performance regulation.

However, in cognitive radio (CR) systems, certain parameters that are critical to the system's performance are typically computed and adjusted by a human operator during runtime. Once these parameters are set, they cannot be reconfigured until the next runtime, meaning that any errors or suboptimal settings can severely affect the system's performance. This limitation can cause suboptimal settings that severely affect the system's performance, leading to a very low probability of detection (PD) or a very high probability of false alarm (P_FA) for the CR system. Thus, there is a growing demand for more advanced non-parametric or autonomous methods that can self-reconfigure their parameters at runtime without human intervention, such as self-adaptive threshold adjustment algorithms (SATAs). Examples of non-parametric methods include Otsu, modified Otsu, Non-parametric Amplitude Quantization method, and Autonomous global threshold adjustment (Bouhdjeur et al., 2022; Onumanyi et al., 2017; Otsu, 1996).

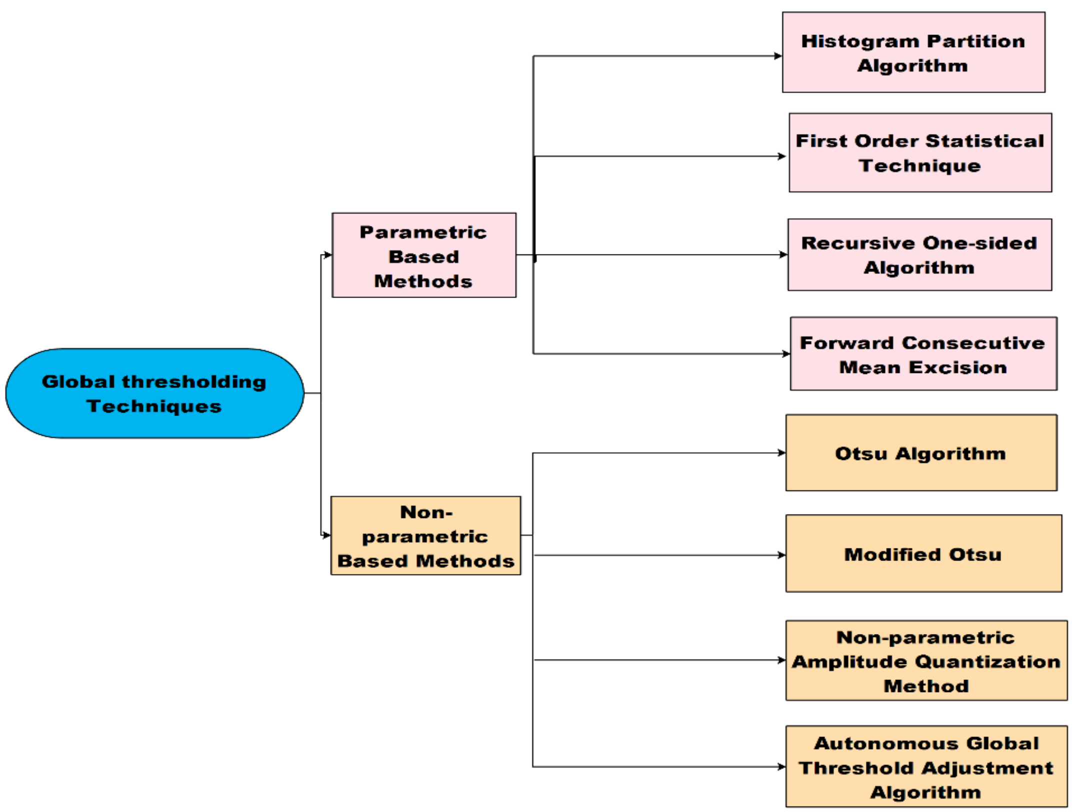

Figure 4: Different Global thresholding techniques as available in the literature

Taxonomy of Global Threshold techniques as available in the literature.

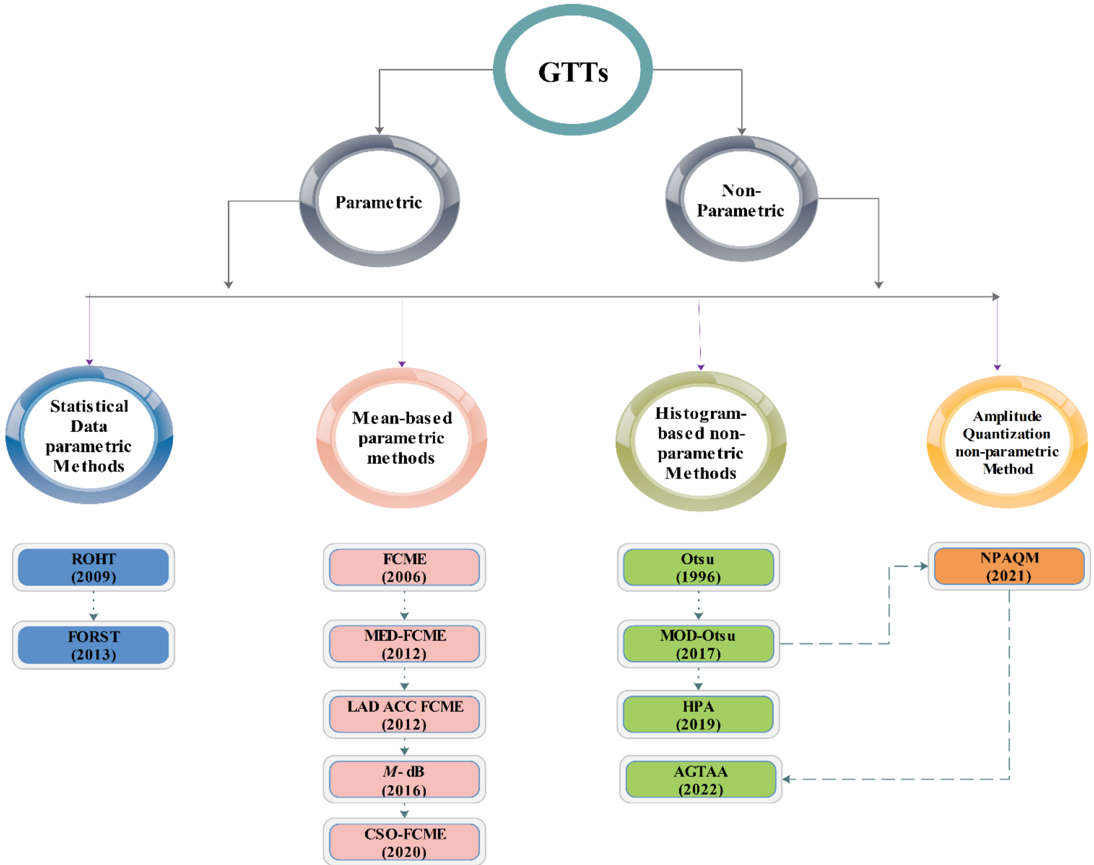

Figure 5: Taxonomy of Global Threshold techniques as available in the literature.

Statistical Data-Based Parametric Method

Recursive One-Sided Hypotesis Testing Technique

The ROHT algorithm is based on one-sided hypothesis testing, assuming that the measurement data conforms to a Gaussian distribution and that there are a sufficient number of measurement samples available to obtain accurate estimates of the mean and standard deviation (Datla *et al*., 2009). At each iteration, a specified percentage of the measurements on the far right of the Gaussian distribution are identified as signals and discarded, with the remaining unclassified measurements subjected to further iteration. The standard deviation is progressively reduced after each iteration until the change in standard deviation between consecutive iterations becomes less than or equal to a predetermined arbitrary positive value, denoted by ϵ. This process is graphically illustrated in (Datla et al., 2009a). While the ROHT algorithm offers the cutting-edge advantage of rapidly adapting to changes in the environment and making accurate decisions about channel availability, it has limitations such as reduced reliability in rapidly changing environments, longer decision-making periods, and potential unsuitability for real-time decision-making scenarios. These limitations should be considered when using this testing method, and alternative approaches should be explored if necessary. Threats to the algorithm's success include the emergence of more accurate algorithms and the shift toward machine learning-based approaches.

First-Order Statistical Technique

Conceptually identical work, utilizing a similar method, was proposed by Barnes *et al*.(2013) called the FOST algorithm which is similar to the ROHT algorithm but faster since it does not use a recursive mechanism (Barnes *et al*., 2013). It is essentially a simplified version of the ROHT algorithm that produces the same result when iterated only once. Ali *et al*. (2010) evaluated the performance of the FOST algorithm in the one-tier CRN model and proposed an adaptive threshold method for detecting unused frequency bands in cognitive radio systems. The method estimates the threshold as a function of first and second-order statistics of recorded signals, without requiring estimation of noise variance or signal-to-noise ratio. The simulation results show that the proposed method has low false alarm and missed detection rates, and can be used for narrow or wideband spectrum sensing. While the FOST algorithm has several strengths such as not requiring estimation of noise variance or signal-to-noise ratio and demonstrating low false alarm and missed detection rates, its effectiveness depends on the proper selection of the standard deviation coefficient and may not generalize to other scenarios. Further evaluation and testing in diverse environments are necessary.

Mean- based Parametric Method

Forward Cosecutive Mean Excision (FCME)

The Forward Consecutive Mean Excision (FCME) algorithm is a widely used and effective technique for detecting and removing outliers in datasets (J. Lehtomäki *et al*., 2012; J. J. Lehtomäki *et al*., 2006). This algorithm is popular due to its simplicity and efficiency, and it has been applied in cognitive radio networks, wireless sensor networks, and signal processing applications. The FCME algorithm computes an initial threshold value λ_i , given estimated energy samples γ_n, using the mean of the first Q samples, N_e, and a manually pre-calculated parameter T_{cme}. It then iterates over the remaining samples, updating the threshold value λ in each iteration until an outlier is found. The algorithm terminates when the threshold value converges to a final value λ.

A study by Onumanyi *et al*. (2018) compared the performance of the FCME algorithm to other global thresholding techniques (GTTs) in various frequency bands. The authors found that the FCME algorithm outperformed the other methods in several scenarios, including real-life noise only (132–133 MHz), crowded FM band (88–108 MHz), digital TV signals (720–732 MHz), analog TV signals (174–181 MHz), single FM radio station signal (90.2–90.3 MHz), two closely spaced signals (90–94 MHz), and a wide sparse spectrum with a single signal source (4240–454 MHz). However, the FCME method assumes that the smallest I samples are caused only by noise (J. J. Lehtomäki *et al*., 2006), which may not always hold true, particularly when the signal is weak or the noise is non-Gaussian. Additionally, the FCME method's performance may be affected by the choice of scaling factors or threshold factors that define its properties. Therefore, the FCME method may not be optimal for all scenarios and may require further optimization like the use of machine learning algorithms to modify and improve its performance.

Median Filter FCME (MED-FCME) Algorithm

The Median Filter FCME (MED-FCME) algorithm represents a crucial enhancement to the conventional Forward Consecutive Mean Excision (FCME) approach. The MED-FCME algorithm initiates with the pre-filtering of the input signal through a defined-length median filter. This pre-processing step substantially reduces the variance associated with noise, which, in turn, paves the way for the more accurate estimation of threshold values (Abdullahi et al., 2020). Furthermore, it elaborates on how the MED-FCME algorithm acts as a safeguard against potential inaccuracies that may arise in estimating the Tcme parameter, an inherent aspect of the FCME algorithm.

Location Algorithm based on Double Thresholding with Adjacent Cluster Combining (LAD ACC FCME)

The Location Algorithm based on Double Thresholding with Adjacent Cluster Combining (LAD ACC FCME) offers a comprehensive insight into this innovative algorithm and its implications in the domain of signal localization. Unlike algorithmic modifications, LAD ACC FCME primarily relies on the core FCME algorithm. It is designed to address issues pertaining to signal localization, with a keen focus on the accurate estimation of channel occupancy and duty cycle rates(Abdullahi *et al*., 2020). J. Lehtomäki *et al*., (2012) explains how the LAD ACC FCME algorithm achieves this by employing the baseline FCME algorithm to estimate double threshold values, ultimately enhancing the probability of signal detection in cognitive radio systems.

The m − dB Model

The m − dB model, presented as a distinct section, explores this particular variant of the FCME algorithm in detail. Vuohtoniemi et al., (2016) elucidates the concept of introducing a tolerance value, "m," to the threshold value computed by the FCME algorithm. The m − dB model serves the purpose of maintaining a specific target Probability of False Alarm (PFA) rate for the baseline FCME algorithm. It highlights the practical advantages of incorporating this tolerance value, and how it contributes to the overall performance optimization of the FCME algorithm, particularly in scenarios where controlling the PF A rate is paramount (Vuohtoniemi *et al*., 2016).

Histogram/ Gray Image Based Method

Otsu Technique

Otsu's algorithm is a technique used to find an optimal threshold for separating the signal and noise classes in a grayscale image (Datla *et a*l., 2009b; Otsu, 1996). The algorithm uses the histogram of the image data to determine the threshold that maximizes the separation between the two classes. This threshold is selected based on the probability distribution of the data, which is quantized into L levels with values ranging from 1 to L. The algorithm calculates the between-class variance for each possible threshold value and then selects the threshold that maximizes a measure of class separability, which is defined as the ratio of the between-class variance to the total variance.

To apply Otsu's algorithm, the image data is first converted to a grayscale image and then quantized into L levels with scaling factor as obtained in the equations seen by Datla *et al*. (2009) and Onumanyi *et al*. (2017). The mean of the distribution is then calculated, and a threshold value is selected to separate the probability distribution into the noise class and the signal class. The between-class variance is then calculated for each possible threshold value, and the threshold that maximizes the measure of class separability is selected.

Datla *et al.* (2009b) approach for spectrum sensing has some limitations, including introducing sensing delay due to requiring multiple spectral sweeps before applying Otsu's algorithm, resulting in wastage of computational resources, and having no mechanism to identify measurements containing only noise samples, leading to a high false alarm rate (Onumanyi *et al*., 2017). These limitations are especially noticeable when sensing TV bands that do not vary much over time.

Modified Otsu Technique

To address these limitations, Modified Otsu’s algorithm (MOA) was proposed by Onumanyi *et al*. (2017) as an adaptive and autonomous threshold estimation technique for CR application. Essentially, the MOA achieves an average lower false alarm rate as compared to the original version proposed by Datla et al. (2009b). It is independent of the bandwidth size and has a total complexity of O(N) where N is the total sample size. The MOA provides complete and automatic blind spectrum sensing for CR applications. For these reasons, the author considered the MOA in the investigation.

The modification of Otsu, which makes threshold values estimable for a single sweep, solves the redundancy problem and eliminates the need for multiple sweeps and computation of gray levels using Doane's formula (Onumanyi *et al*., 2017), thereby addressing the need for a faster sensing and thresholding process in the algorithm. The weakness of the modified Otsu is that it is not suitable for situations involving multiple modes or overlapping intensities. Additionally, its performance is poor in scenarios where noise is the only factor, as this often results in a unimodal distribution that both the modified Otsu and algorithms from the GTT class underperform. As a result, in these cases, these purely autonomous algorithms do not meet the required standard. For further details of its function, the reader is kindly referred to Onumanyi *et al*. (2017).

Histogram Partition Techniique

While the Histogram Partition Algorithm (HPA) can be categorized under parametric-based methods, it utilizes the histogram-based approach used by Datla *et al*. (2009b) and Onumanyi *et al*. (2017). The Histogram Partition Algorithm (HPA) is an adaptable and effective method for optimizing the performance of an Energy Detector (ED) in various scenarios. The algorithm was designed to adjust the threshold of an ED by utilizing a sample histogram to separate the multimodal distributions of an input signal (Onumanyi *et al*., 2019). The histogram is analyzed to determine the region representing the noise spread and the peak of the noise floor, which is assumed to correspond to the mean noise floor (or noise mode). To obtain a useful threshold for separating noise from signal samples, the algorithm searches for a point along the negative slope of the noise distribution that corresponds to this threshold. The search is performed by examining the frequency values along this slope, starting from the peak of the noise floor and moving toward higher energy values. The chosen stopping point along this slope determines the threshold value, which is associated with specific PD and P_FA rates that depend on the chosen search parameters.

Despite the fact the HPA algorithm has demonstrated superior performance compared to other parametric algorithms (Onumanyi *et al*., 2019), it remains subject to the inherent limitations associated with parameterized approaches. Specifically, these limitations arise from suboptimal settings or performance errors that result from human operator involvement. Unfortunately, once these parameters are set, they cannot be reconfigured until the next runtime. Consequently, any errors or suboptimal settings can lead to a significant reduction in the probability of detection (PD) or an increase in the probability of false alarm (PFA) for the cognitive radio (CR) system.

Autonomous Global Threshold Adjustment Technique

Autonomous Global Threshold Adjustment Algorithm (AGTAA), though a histogram-based algorithm proposed by Bouhdjeur *et al*. (2022), seeks to handle the limitations afore mentioned by Onumanyi *et al*. (2021). The AGTAA detects the presence of a signal in a spectral band Firstly by estimating the power spectral density (PSD) of the signal, Next, an L-bin histogram is generated using the PSD as input and normalized. The histogram is then divided into two equal parts, and the maximum difference between the two parts is found. Depending on the position of the maximum, the methodology distinguishes between the presence of the signal in the spectral band and the unimodality of the distribution. The effectiveness of this methodology is dependent on several factors, such as the accuracy of the PSD estimation the appropriate selection of L, and the predefined threshold. The AGTAA method as proposed by Bouhdjeur *et al*. (2022) has been shown to perform better than other adaptive thresholding methods, with a significant reduction of 96% in the probability of false alarm when there is only noise(unimodal). Additionally, it has improved the detection rate by over 45% in scenarios where signals are present. This method has also significantly increased the sensitivity of the energy detector, particularly for narrow bandwidth spectrums, meeting the IEEE 802.22 standard specification (Liang *et al*., 2011). However, it is worth noting that one of the major drawbacks of this method is that it tends to underperform where the noise distribution is bimodal or multimodal. Additionally, the lack of experimental validation on an FPGA platform is also a weakness of the proposed method. For more information, readers can refer to Bouhdjeur *et al*. (2022) where this methodology was proposed.

Amplitude Quantization Based Non-Parametric Method

Non-Parametric Amplitude Quantization Technique

The same author, in a later publication (Onumanyi *et al*., 2021) proposed a new algorithm for tackling the limitation in Onumanyi *et al.* (2017). This is done by circumventing the need to compute gray-scale levels albeit the need to compute histograms, which further limits the algorithm's performance (Onumanyi *et al*., 2020). Thus, different from these approaches, we seek to alleviate the aforementioned limitations by circumventing the need for both gray-scale and histogram computations. In this regard, a new method by Onumanyi *et al*. (2021) called the Non-parametric Amplitude Quantization Method (NPAQM) as well as a heuristic algorithm that maintains a low false alarm rate for the method under noise-only regimes was proposed. The NPAQM method is a fully autonomous approach for estimating dynamic thresholds. It functions similarly to the MOA method, but does not require histogram and grayscale computations as mentioned by Datla *et al.* (2009a) and Onumanyi *et al*.(2017). Instead, the NPAQM employs the first-order difference of the between-class variance calculated from the input dataset to determine the optimal threshold value for effective signal detection. Additionally, the NPAQM includes a built-in heuristic algorithm to identify cases where the input dataset only contains noise samples. This feature ensures that the NPAQM maintains low PFA rates under such noise-only conditions, making it a significant improvement over other ATTs. The NPAQ method suffers from a weakness that results in a low probability of detection in certain scenarios (Bouhdjeur *et al*., 2022). Specifically, the presence of a valley between video and audio peaks in the analog TV signal spectrum causes high estimated thresholds, leading to a low detection rate for most non-parametric global thresholding techniques, especially the NPAQ. This issue is further compounded by the existence of side lobes in the spectrum, which are often experienced in FM bands. Therefore, it is important to carefully consider the limitations of the NPAQ when applying it in scenarios that involve analog TV signal spectrum or FM bands.

Table 2: Summary of Global Thresholding techniques, Strengths and weaknesses

S/N	AUTHOR	YEAR	APPROACH	STRENGTH	WEAKNESSES
1	Datla *et al*., 2009	2009	Recursive One-sided Hypothesis	• It quickly adapts to changes in the environment and makes accurate decisions about channel availability • Implemented using simple maths calculations making it computationally efficient	• It may require a longer period of time to make a decision (multiple tests) • May not be suitable for applications that require real-time decision-making • suitable for non-Gaussian distributions or small sample sizes only
2	Barnes *et al*., 2013	2013	First Order Statistical Technique	• Used to accurately characterize the statistical properties of a signal such as mean and variance. • Computationally efficient and can be implemented using simple math calculations • a faster version of the ROHT algorithm	• Maybe not be able to accurately characterize signals that have complex or non-Gaussian statistical properties • May not be able to capture higher-order statistical properties
4	J. Lehtomäki *et al*., 2012; 2006	2006, 2012	Forward Consecutive Mean Excision Algorithm	• It is Robust to interferences and noise	• Involve manual input of parameters
5	Onumanyi *et al*., 2019	2019	Histogram Partition Algorithm	• It is Simple and separate multimodal distributions	• Peak value assumption
6	Datla *et al*, Otsu and N., 1996	1996	Otsu Algorithm	• It is Simple, efficient and non-parametric.	• Latency and redundancy

				• Automatic Threshold selection therefore Robust to noise and variations in Intensity	
7	Onumanyi *et al.*, 2017	2017	Modified Otsu Algorithm	• It Solves redundancy and latency problems	• Not suitable for multiple modes or overlapping intensities.
8	Onumanyi *et al.*, 2021	2021	Non-parametric Amplitude Quantization Method	• Does not require histogram and grayscale computations therefore it has a faster processing time • The heuristic algorithm maintains a low false alarm rate for our method under noise-only regimes	• the presence of a valley between video and audio peaks in the n analog TV signal spectrum causes high estimated thresholds
9	Bouhdjeur *et al.*, 2022	2022	Autonomous Global Threshold Adjustment Algorithm	• Increased Sensitivity particularly for narrow bandwidth spectrums, meeting the IEEE 802.22 standard specification	• not suitable for cases where the noise distribution is bimodal or multimodal and low Pd in TV band

Performance Analysis

A comprehensive analysis was conducted, comparing various GTT algorithms as shown in Table 3 and employing empirically estimated probabilities of detection and false alarm. The probabilities were statistically defined as follows:

Probability of Detection ($\boldsymbol{P_D}$): The likelihood of Y(k) being greater than or equal to γ given the presence of a signal ($\boldsymbol{H_1}$), where k represents the signal index ranging from 1 to V.

$$\boldsymbol{P_D = P_r\ \mathrm{Y(k)} > \gamma \mid H_1), \mathrm{k} = 1, 2, \ldots, \mathrm{N}} \quad \textbf{(1)}$$

Probability of False Alarm ($\boldsymbol{P_{FA}}$): The likelihood of Y(k) being less than γ given the absence of a signal $\boldsymbol{H_0}$), where k represents the signal index ranging from 1 to V.

$$\boldsymbol{P_{FA} = P_r\ (\mathrm{Y(k)} > \gamma \mid H_0), \mathrm{k} = 1, 2, \ldots, \mathrm{N}} \quad \textbf{(2)}$$

To calculate the $\boldsymbol{P_D}$ and $\boldsymbol{P_{FA}}$ rates, Fawcett's approach (Fawcett, 2006) was utilized, which involves obtaining and labeling the ground truths of different input signals. For simulated signals, actual signal samples were labeled as "1" (representing true signal samples), while noise samples were labeled as "0" (representing true noise samples). The true threshold of the simulated detector, based on the actual thermal noise level, was used to obtain the ground truths. Real-life signals were also included in our experiments, and each corresponding signal set was labeled in a similar binary manner. The maximum true noise value of each dataset served as the true threshold for classifying the ground truths, ensuring they are obtained from the true dynamic range of each dataset.

Subsequently, the $\boldsymbol{P_D}$ and $\boldsymbol{P_{FA}}$ rates were computed per dataset using the following formulas:

$$\boldsymbol{P_D} = \frac{\boldsymbol{\phi}}{\boldsymbol{P}} \tag{3}$$

where ϕ represents the number of true positives (signal samples correctly detected) given that Y(k) ≥ γ|H1, and P is the total number of actual true signal samples.

$$\boldsymbol{P_{FA}} = \frac{\boldsymbol{\varphi}}{\boldsymbol{N_0}} \tag{4}$$

where φ represents the number of false positives (signal samples falsely detected) given that Y(k) < γ|H0, $\boldsymbol{N_0}$ and is the total number of noise samples.

By plotting receiver operating characteristic curves per dataset based on the computed $\boldsymbol{P_D}$ and $\boldsymbol{P_{FA}}$ values were derived for the point performance values for each threshold estimation algorithm. The results that the different GTTs produced is shown in table 3 that shows detailed summary of comparative analysis of the different GTTs as captured in literature, real world application and future direction.

Table 3: Summary of comparative analysis of GTTs, real world application and future directions

Technique	Method	Adaptability	Time complexity	Fully Auto	• Noise only Band (Real Threshold) ✓ ATV Bnd (Real Threshold) ▪ FM band (Real Threshold)			Real world Application	Future direction
					Threshold	PFA (%)	PD (%)		
Recursive One-sided Hypothesis	Statistical Data based Parametric Method	Parametric	0(N)	No	• -75.34	• 5	• -	- Dynamic spectrum access	-Enhancing computational efficiency
					✓ -74.20	✓ 0	✓ 31	- Wireless security	-Adapting to non-stationary environments
					▪ -49.40	▪ 0	▪ 19	- Industrial automation	-Improving stopping criteria
								- Environmental monitoring	
First Order Statistical Technique			0(N)	No	• -75.34	• 5	• -	Key applications are in spectrum sensing and wireless communication systems where precise signal detection is critical.	Future directions for FOST may include optimizing the coefficient (**h**) and enhancing its adaptability.
					✓ 56.81	✓ 0	✓ 10		
					▪ -45.41	▪ 0	▪ 12		
Forward Consecutive Mean Excision Algorithm	Mean based Parametric Method		0(N)	No	• -74.14	• 0	• -	Applications of the FOST method include spectrum sensing in cognitive radios and signal quality improvement in wireless networks.	Future developments may focus on parameter optimization and enhancing adaptability.
					✓ -99.06	✓ 22	✓ 100		
					▪ -65.75	▪ 58	▪ 100		
Otsu Algorithm			0(N)	yes	• -77.06	• 55	• -	Image processing, biomedical imaging (including facial and fingerprint recognition), medical imaging, document analysis, and quality control are some of the key real-world applications of Otsu's algorithm in various fields.	- Optimize computational efficiency of Otsu's algorithm
					✓ -75.90	✓ 00	✓ 34		- Apply Otsu's algorithm for noise source classification and noise reduction
					▪ -54.01	▪ 00	▪ 45		- Explore integration with machine learning to enhance adaptability across applications

Modified Otsu Algorithm	Histogram Based non Non-parametric Parametric method		0(N)	yes	• -77.00	• 55	• -	- Image processing	- Develop adaptive signal detection and classification mechanisms for multi-modal environments
					✓ -75.34	✓ 00	✓ 33	- Biomedical imaging	- Enhance MOA performance in noise-dominated scenarios
					▪ -53.86	▪ 00	▪ 39	- Facial recognition	- Investigate hybrid approaches with machine learning integration to expand MOA's capabilities
								- Fingerprint recognition	
Autonomous Global Threshold Adjustment Algorithm			0(N)	yes	• -74.95	• 02	• -	- Cognitive Radio Spectrum Sensing	AGTAA algorithm is only tested in Three band (noise only, Fm and ATV band).
					✓ -92.98	✓ 00	✓ 85	- Wireless Communication Systems	Future research can focus on extending AGTAA's to other bands like DTV etc handle scenarios with bimodal or multimodal noise distributions
					▪ -62.75	▪ 00	▪ 96	- Dynamic Spectrum Access	
Non-parametric Amplitude Quantization Method			0(N)	yes	• 73.89	• 00	• 00	- Cognitive Radio Spectrum Sensing	- Addressing challenges related to analog TV signal spectra and FM bands
					✓ -80.34	✓ 00	✓ 46	- Wireless Communication Systems	- Exploring the integration of machine learning approaches with NPAQM for improved adaptability and robustness in signal detection
					▪ 54.20	▪ 00	▪ 41	- Dynamic Spectrum Access	

Future Directions and Real-World Applications of Global Thresholding Techniques (GTTs)

Future Directions:

Future directions for Global Thresholding Techniques (GTTs) encompass enhancing their adaptability to non-stationary environments, addressing their limitations in scenarios dominated by noise, exploring hybrid methods that integrate machine learning algorithms to extend their functionality, and optimizing their computational efficiency. Researchers aim to develop mechanisms that allow GTTs to adaptively detect and classify signals in complex, multi-modal environments, potentially making them more robust and reliable. GTTs show promise in improving their performance in scenarios where noise prevails, and researchers seek continuous refinements and hybrid methods, possibly incorporating machine learning, to enhance their accuracy in signal detection and noise reduction. Optimizing computational efficiency is crucial, especially in applications like cognitive radio, as fine-tuning algorithms and reducing computational resource wastage can lead to faster and more efficient thresholding processes. These future directions aim to make GTTs more versatile, accurate, and efficient in a wide range of applications, ensuring their continued relevance in various domains.

Real-World Applications:

Global Thresholding Techniques (GTTs) find practical applications in fields such as cognitive radio spectrum sensing, wireless communication systems, dynamic spectrum access, image processing, biomedical imaging (including facial recognition and fingerprint recognition), and document analysis, with potential to contribute to advanced noise reduction techniques, signal quality improvement, and various quality control scenarios.

Conclusion

In conclusion, Global Thresholding Techniques (GTTs) are essential tools in spectrum sensing, wireless communication, image processing, and various other applications. Future research directions should focus on improving adaptability, performance in noise-dominated scenarios, and computational efficiency. Real-world applications span cognitive radio, wireless communication, dynamic spectrum access, image processing, biomedical imaging, and document analysis. By addressing these research directions and applying GTTs in practical scenarios, we can advance the capabilities of these techniques and contribute to more efficient and reliable systems.

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