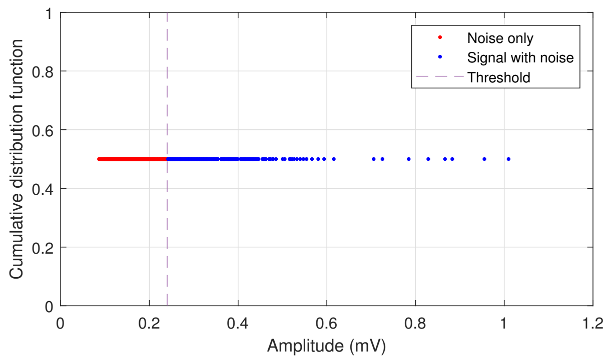

Fig. 6. Assignment of clusters using the K-means method.

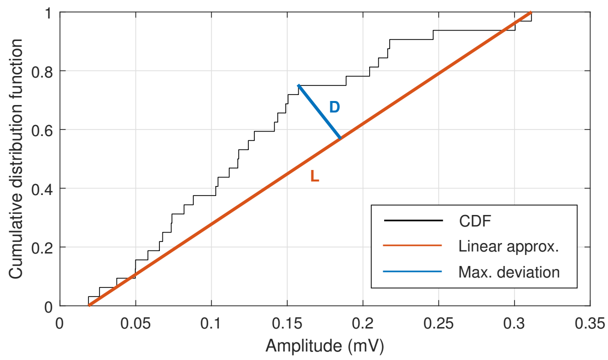

Fig. 8. Conversion of a single CDF into a length-difference (L/D) pair.

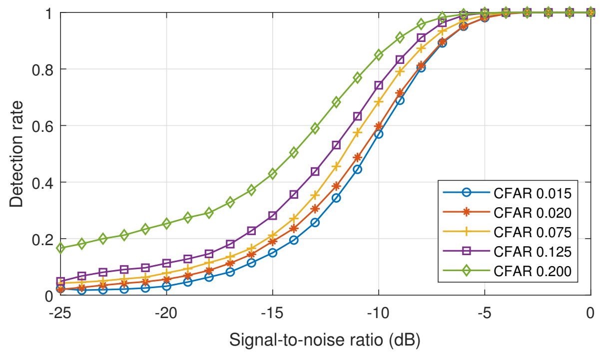

Fig. 7. Detection rate in a CFAR scenario using mean classification.

Fig. 9. Cluster assignment using the DBSCAN method.

B. Mean

One of the most straightforward and intuitive approaches to evaluating the centrality/non-centrality of a distribution is through the assessment of the mean value. This reduces the earlier 2D planeto to a one-dimensional amplitude criterion for a probability of 0.5. The value is easily distinguishable using k-means clustering with Euclidean distance criterion (Fig. 6). In this case, the false alarm probability is adjusted by adopting a threshold value for the observed amplitude. For such a tailored method, the detection efficiency at a 90% level in a scenario analogous to the previous one is -7 dB (Fig. 7).

C. Linear Approximation: Length and Deviation

A more intricate, yet still accessible, evaluation of CDFs focuses on measuring curvature rather than mean-shift. In this regard, the curve undergoes approximation through a linear function, resulting in the length L as the first acquired dimension. Subsequently, the evaluation involves assessing the maximum deviation of the empirical CDF from the approximation, yielding second dimension D (Fig.8). The cloud of points in the D/L plane serves as the basis for clustering in the ML process (Fig.9). The clustering utilizes the DBSCAN algorithm, created on a density-based spatial clustering (control parameters: a minimum of 10 points within a distance of 0.02). The simplified 2D approach produces more promising results than the 1D analysis of the mean, ensuring a 90% detection accuracy at approximately -9 dB (Fig. 10).

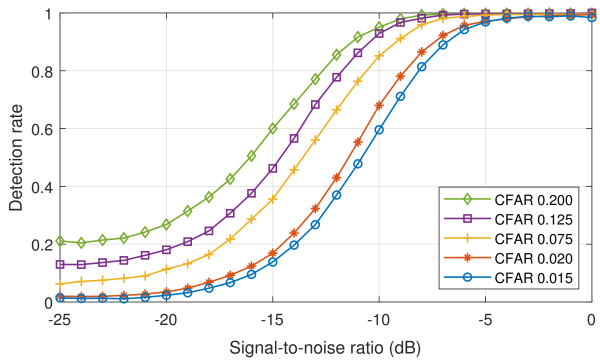

Fig. 10. Detection rate in a CFAR scenario with L/D classification.

D. Linear Approximation: Slope Coefficient and Length

The third considerable factor that captures the distinctiveness of CDFs between 'noise-only' and 'signal-with-noise' states is the slope coefficient of the curve in its linear approximation. In this context, we assess the length of the curve, denoted as L, approximated based on the points where the curve reaches probabilities of 0.1 and 0.9. For the linear approximation, we determine the slope coefficient α (Fig.11). These measurements enable the construction of a two-dimensional space, denoted as α/L, where, once again, a cloud of points undergoes clustering into two groups using the DBSCAN strategy (control parameters: a minimum of 10 points within a distance of 0.01) (Fig.12). It's important to

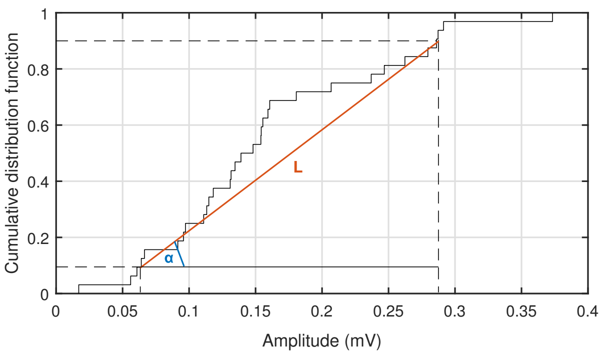

Fig. 11. Conversion of a single CDF into a slope-length (α/L) pair.

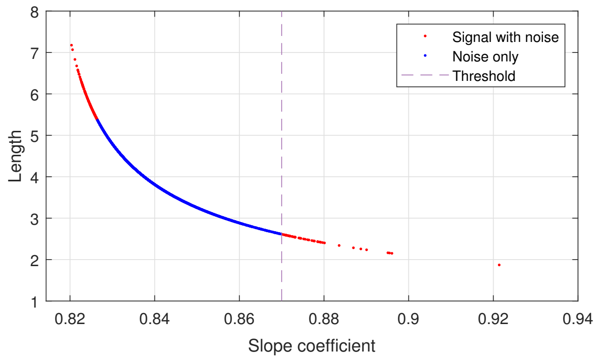

Fig. 12. Assignment of clusters using the DBSCAN method.

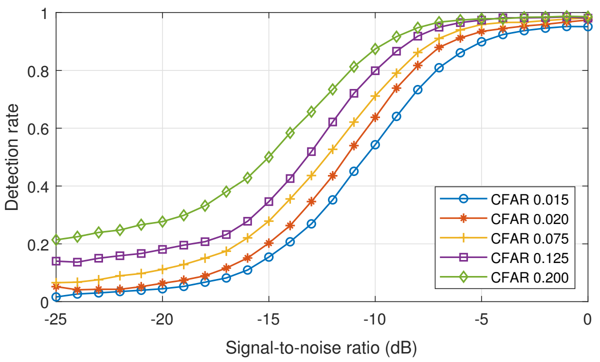

Fig. 13. Detection rate in a CFAR scenario with α/L classification.

highlight that the pivotal factor in partitioning the plane is not the length but rather the determined slope coefficient. This 2D approach yields a detection accuracy of approximately -7 dB for a 90% detection rate when considering a 7.5% false alarm rate (Fig. 13).

E. Complexity

The investigation into time complexity was conducted by averaging the duration of 25,000 detection processes executed serially on a 3 GHz CPU. According to previous considerations, relinquishing the determination of the polyshape in favor of other methods results in a significant decrease in the detection time by order of magnitude (Fig. 14). In the case of

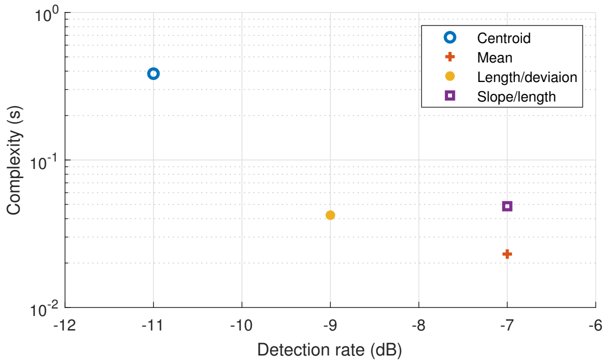

Fig. 14. Time complexity comparison.

the centroid-based method, the total process of single detection took 385 ms, with the shape determination itself accounting for 304 ms. In comparison, for methods based on D/L and α/L, taking 42 ms and 48.5 ms, respectively, the two most complex operations were linear approximation at 16 ms and building CDF matrices at 14.2 ms (common to all methods). The most straightforward approach, i.e., assessing the mean value, took 23 ms.

F. Comparison to other Methods

Referring to the study [29] is valuable to relate the results obtained to other alternative methods. In a similar impulse transmission scenario, the authors present the effectiveness of detection based on statistical approaches and relate them to the fundamental techniques of energy detection and its modification, utilizing short windows. Table I provides a comparison of methods in two scenarios: S_1) the minimum SNR at which the method achieves 90% detection rate with a CFAR of 10% and 1024 samples per frame (for CDF-based methods decimation coefficient d set to 16); S_2) the detection rate achieved for an SNR cutoff at -6 dB with a CFAR of 10% and 4096 samples per frame.

TABLE I
PERFORMANCE COMPARISON OF DETECTION METHODS IN TWO SIMULATION SCENARIOS

Detection method	SNR in S_1 (DR over 90%)	DR in S_2 (SNR at -6dB)
Conventional energy det.	0 dB	78%
Short windows energy det.	-1 dB	80%
Jarque-Bera normality test	3 dB	81%
Higher-order-statistics test	3 dB	83%
Gaussianity testing	-2 dB	88%
CDF mean-based det.	-2 dB	92%
CDF α/L-based det.	-2 dB	95%
CDF L/D-based det.	-3 dB	99%
CDF centroid-based det.	-5 dB	99%

Comparison with previously studied approaches shows that the proposed solution, even with a short frame of 1024 samples, ensures better detectability than energy detection or direct sample distribution analysis. Reference to results obtained for 4096 samples in the frame indicates that statistical methods significantly benefit from increased frame length used to build the empirical distribution (for details, see [29]).

Nonetheless, the approach based not on predefined patterns but on a learned reference obtained through autonomous clustering occurs superior in both cases, which seems intuitively justified due to the better adaptation to the case achieved for learning methods.

Regarding time complexity, we can draw insights from [30]. The results outlined in subsection V-E surpass the 1 ms threshold observed in energy detection but bring the basic mean-based approach close to 19.2 ms, as seen in normality testing (adjusted for equal input size). It is noteworthy that, from the detectors' standpoint, the entire learning and establishment of the appropriate demarcation function, crucial for detection, occur independently of standalone detection. This process occurs in the background or between detection campaigns.

VI. Conclusions

The presented research builds upon prior investigations into the effective integration of time decomposition and distribution analysis with machine learning. The conducted survey of methods showcases the diversity of solutions achievable through these tools and underscores their practical implementation in an effective and straightforward manner.

The undertaken studies reveal that, despite a relatively modest increment in the complexity of a singular detection process, the utility of detection increases significantly. The adaptability of these methods, enabled by effective learning through autonomous clustering, positions them as efficient solutions for blind signal detection applications, thereby outperforming classical statistical approaches.

Moreover, it is worth noting that even a simple, two-dimensional assessment of CDF curvature proves to enable effective detection. However, exploring additional refinement and optimization of CDF-based detection methods could enhance their efficiency and adaptability in more diverse signal detection scenarios. This avenue of research would contribute to ensuring the robustness and versatility of the proposed methods, making them more applicable across various real-world situations.

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Jakub Nikonowicz received an M.Sc. degree in Electronics and Telecommunication and a Ph.D. degree (with honors) in Telecommunication from Poznan University of Technology, Poznan, Poland, in 2014 and 2019, respectively. He has authored or co-authored over a dozen scientific publications in refereed journals and international conference proceedings. He also served as a project manager for grants supporting young scientists and as a co-principal investigator in an international research consortium, contributing significantly to collaborative research efforts. His current research interests encompass innovations in statistical signal processing for next-generation communication and security technologies.

Mieczyslaw Jessa received the M.Sc. degree with honors from Poznan University of Technology in 1985 and the Ph.D. degree in 1992 from the same University. Initially, his research interest included phase-locked loops and PDH/SDH network synchronization. In the years 1995-1997 he was an expert of the Polish Ministry of Communications in the field of digital network synchronization. His current research concerns the mathematical models of randomness and pseudo-randomness. He is the author or co-author of over one hundred journal and conference papers and fifteen patents.

Łukasz Matuszewski graduated from the Faculty of Electronics and Telecommunications of the Poznań University of Technology in 2010. In 2011, he was employed at the Department of Telecommunications Systems and Optoelectronics at the Faculty of Electronics and Telecommunications of the Poznań University of Technology. In 2019 he defended his Ph.D. thesis and since 2020 he has been an assistant professor at the Institute of Multimedia Telecommunications at the Faculty of Computing and Telecommunications at the Poznań University of Technology. He was a project manager for grants for young scientists, as well as a contractor in projects for a Polish telecommunications operator. He is the author and co-author of 25 scientific publications in peer-reviewed journals and materials from national and international conferences. His research interests include designing devices with the use of reprogrammable circuits, in particular cryptographic circuits, random number generators, and synchronization circuits.