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Power-based pulsed radar detection using wavelet denoising and spectral threshold with pattern analysis

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Research Paper

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EMI (electromagnetic interference); HOS (higher order statistics); LFM (linear frequency modulation); PRF (pulse repetition frequency); PSD (power spectral density); PW (pulse width); RMSE (root mean square error); STFT (short-time Fourier transform); WPD (wavelet packet decomposition); WT (wavelet transform)

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Abstract

In this paper, an algorithm for extracting and localizing a radar pulse in a noisy environment is described. The algorithm combines two powerful tools: wavelet denoising and the short-time Fourier transform (STFT) analysis with statistical-based threshold. We aim to detect radar pulses transmitted by any radar in blind mode regardless of the intra-pulse modulation and parametric features. The use of the proposed technique makes the detection and localization of radar pulses possible under very low signal-to-noise ratio conditions (−18 dB), which leads to a reduction of the required signal power or alternatively extends the detection range of radar systems. Radar classes pattern-based analysis is used in blind mode to decrease the probability of false alarm.

Introduction

The received radar pulses are subject to different levels of noise that may lower the signal-to-noise ratio (SNR), some of which are unavoidable such as the device's thermal noise or electromagnetic interference. Low SNR may cause the receiver to miss and/or falsely detect the received echo signals. One solution is to increase the power of the transmitted signal, but this is not always feasible due to equipment limitations and some isolation issues; besides, increasing the pulse power may be expensive. Moreover, in our case we are not controlling the power because we just act as a receiver in blind mode to detect transmitted radar pulses.

Solving low-SNR issue has been an important goal researchers continue to work on. Signal-processing techniques contribute to provide some solutions to enhance the probability of detection as well as maintaining low probability of false alarm. Time-domain analysis was used in many standards to measure pulse transitions, duration, and amplitude such as IEEE standard 181-2011 [1] and IEEE STD-181-2003 [2]. Although working in the time domain is limited to high received power, its performance degrades dramatically at 0 dB SNR.

Improvements were achieved using the strength of digital signal processing in frequency and in time–frequency domains. Wavelet packet decomposition (WPD) was used to denoise the received signal prior to pulse localization and measurement [3]. However, high complexity of WPD is not preferable; also the Gaussianity test used to make a decision "noise/pulse" is too much computational because they applied the higher order statistics [3] to allow detection at very low SNR (−23 dB).

Short-time Fourier transform (STFT) analysis has been used in the literature [4]; first, the power spectral density (PSD) is calculated in a short time based to obtain the time–frequency distribution, and then spectral envelope [4] is extracted based on the maximum power in each time frame. The result is a simple 1-D time–frequency noisy envelop; this envelop is denoised using wavelet ("Haar" mother wavelet). The denoised envelop is used to check the presence of linear frequency modulated pattern. This algorithm resulted in detection at −18 dB SNR for specific intra-pulse modulated radar pulses (linear frequency modulation (LFM)).

Then, the main challenges to be held in our new algorithm are to build lower computational solution but with accepted low SNR detection. Also, we are searching for independent intra-pulse modulation processing whereas in the literature it is not always the case. Wavelet transform (WT) denoising is used instead of WPD and STFT is used to find statistical-based adaptive threshold. Then, the pattern analysis is used based on the radar parameter's classes (jittered, dwell, switch, and so on).

Proposed solution

First, signal generation is used to set up the waveform to be detected. Remember that we are just generating the transmitted waveform to test the algorithm; however, we are assuming that we have no information about its parameters in the rest of the block diagram shown in Fig. 1. Wavelet denoising is used instead of WPD to decrease the complexity. The denoised signal is

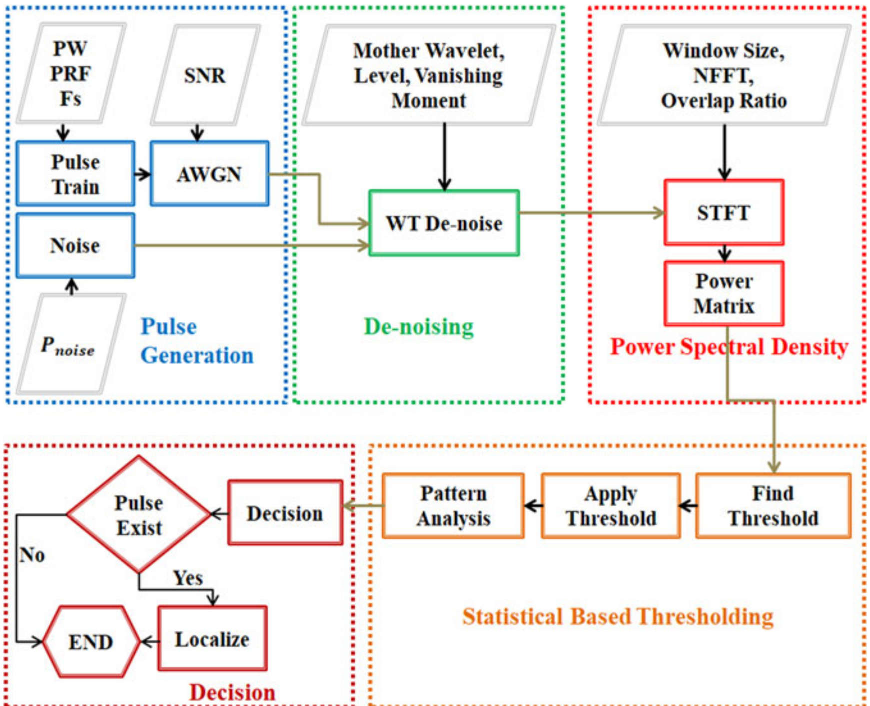

Fig. 1. Flowchart of the algorithm scheme.

transformed to time–frequency distribution using STFT. Then statistical-based threshold is computed and applied prior to pattern analysis. After that, decision is taken if pulses exist or not, if exist the pulses are localized in the time domain.

Pulsed signal generation

The proposed channel model is additive white guassian noise. Train of pulses is generated by taking the LFM as an intra-pulse modulation example. This type of modulation is of great interest in today's radar applications due to its high resolution in range and increasing of maximum range capability. Sweep bandwidth is considered to be 500 kHz sampled at 5 MHz and the duty cycle is 10% (pulse width (PW) = 0.1 ms and PRI (pulse reppitition interval) = 1 ms). Figure 2 shows the pulse train and its noisy version. For the false alarm testing, pure noise is also generated as shown in Fig. 1.

Wavelet denoising

WT is a new technique that maps from $L^2(R)$ to $L^2(R)$ and gives a time–frequency distribution of the input signal. It contributes in high frequency and time resolution that can localize the spectral components in precise time. Making an evolution in digital signal processing, WT is widely used in many applications such as multimedia compression. It decomposes the signal into what is called "approximations" and "details." What makes WT different than WPD is that in WT only approximations are considered in sub-division, whereas in the latter one, both approximation and details are divided which results in a full tree of all parameters.

Equation (1) shows the WT of $f(x) \in L^2(R)$ relative to ($\psi(x)$) wavelet and scaling function "$\phi(x)$", where j_0 is an arbitrary starting scale and "$c_{j0}(k)$'s" are normally called the approximations or scaling coefficients, the "$d_j(k)$'s" are called the details or wavelet coefficients:

$$f(x) = \sum_k c_{j0}(k)\phi_{j0,k}(x) + \sum_{j=j0}^{\infty}\sum_k d_j(k)\psi_{j,k}(x) \tag{1}$$

In this paper, WT is used for denoising; three steps are included to make that: decompose, apply threshold, and signal regeneration. After WT decomposition hard threshold is applied, consisting of establishing the coefficients to zero whose absolute values are less than the threshold, otherwise, the coefficient values are not modified, as shown in equation (2) where $c(n)$ represents the coefficients and "T" the threshold value:

$$f_H = \begin{cases} C(n), & \text{for } |c(n)| > T \\ 0, & \text{Otherwise} \end{cases} \tag{2}$$

Threshold selection rules are derived by mathematical calculations that can provide a representative noise threshold. We propose the use of "Sqtwolog" method which was proposed by "Donoho and Johnstone" [5]. Threshold values are calculated by using the universal method (square root record) given by equations (3) and (4) where σ is the mean absolute deviation (MAD), N_j is the length of the noisy signal, and ω represents the wavelet coefficient to scale j:

$$th_j = \sigma_j\sqrt{2\log(N_j)} \tag{3}$$

$$\sigma_j = \frac{MAD_J}{0.6745} = \frac{\text{median}(|\omega|)}{0.6745} \tag{4}$$

Another essential choice is the mother wavelet. Combining both threshold technique and mother wavelet was subjected to

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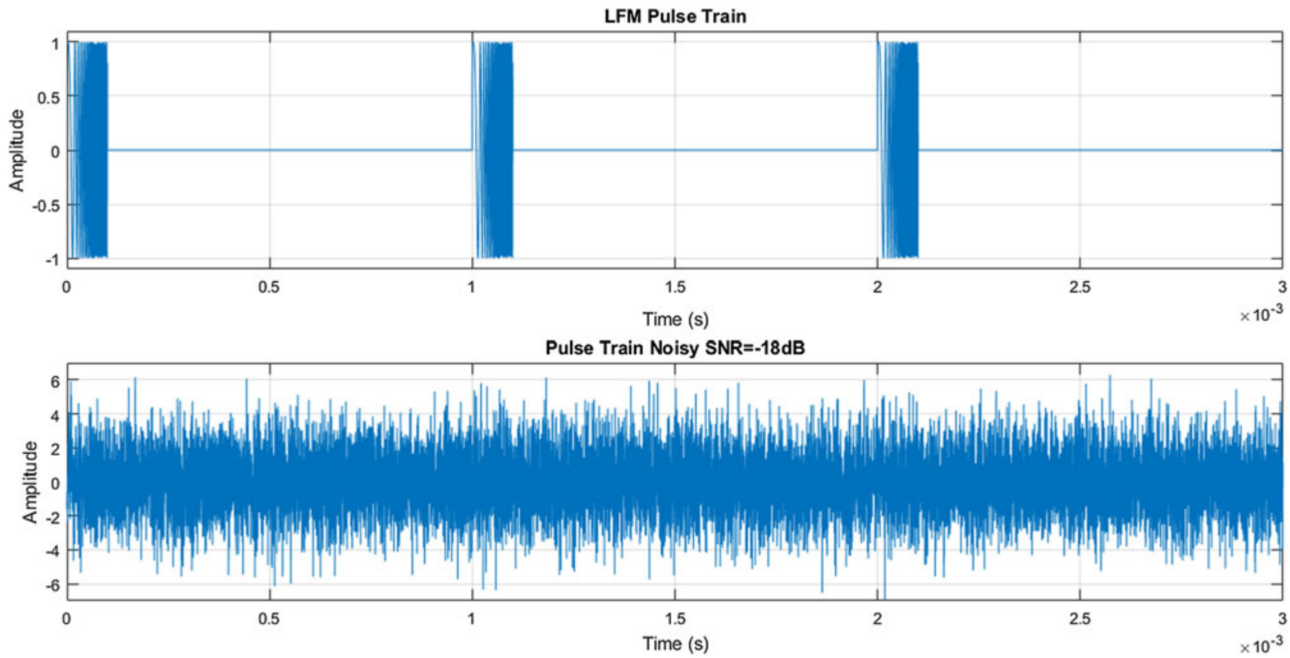

Fig. 2. Pulse-train (top), noisy with SNR −18 dB (bottom).

root mean square error (RMSE) testing, "Daubechies" mother wavelet shows the lowest RMSE with the original signal. Different mother wavelets show close results by this test; no specific condition is required; and hence no dependency between the signal denoising and the required denoising technique. "Daubechies" mother wavelet of order 8 is used with six levels decomposition and after that the threshold is applied and signal is regenerated. Figure 3 shows the signal before and after denoising at SNR −18 dB.

STFT and statistical threshold

These are used to determine the sinusoidal frequency and phase content of local sections of a signal as it changes over time. In a short-time basis STFT creates the time–frequency grid that describes the spectral components in time basis. The signal is divided into shorter frames windowed and overlapped. The window size is an important parameter; it is preferable in our case to be small enough to get high-resolution spectral localization for both short and long

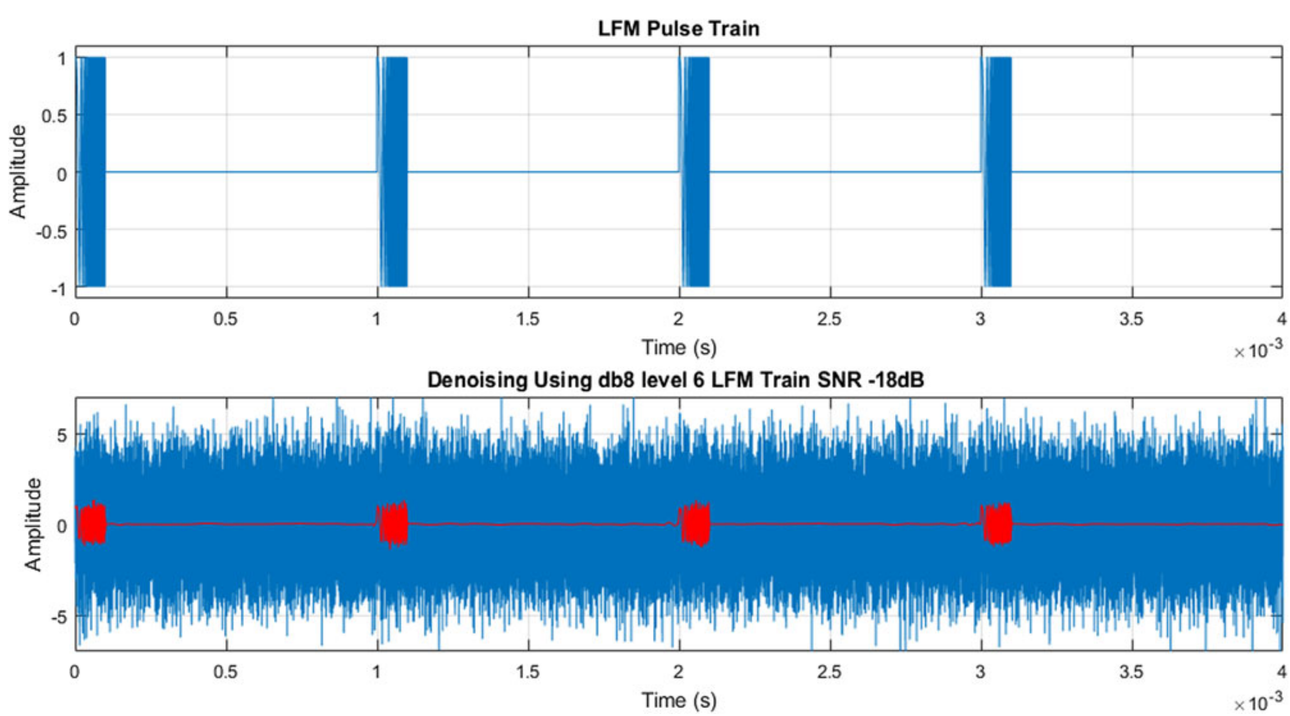

Fig. 3. Pulse train (top), noisy with SNR −18 dB (middle), and denoised (bottom).

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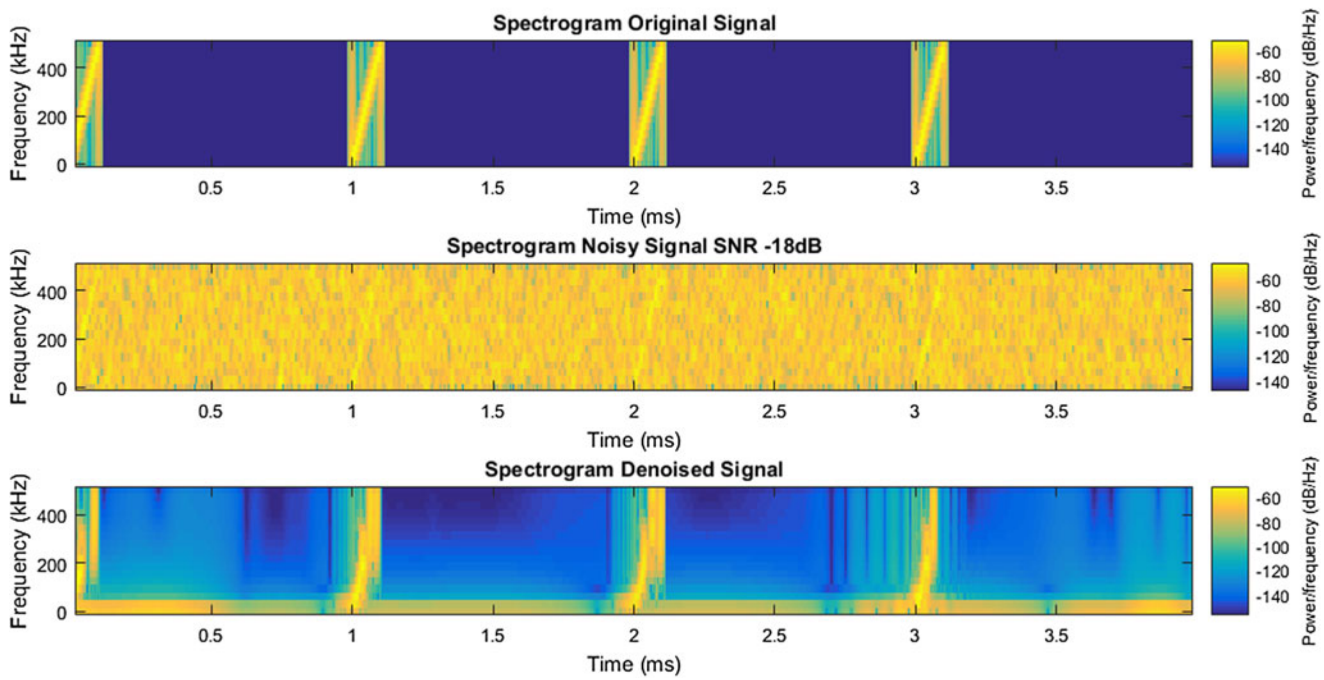

Fig. 4. Spectrogram: pulse train (top), noisy with SNR −18 dB (middle), and denoised (bottom).

pulses. STFT in discrete time is described in equation (5):

$$X_l(k) = \sum_{n=-(N/2)}^{N/2-1} w(n)x(n + lM)e^{-j2\pi kn/N} \tag{5}$$

where l is the frame number, M is the frame length, and w is the analysis window.

It can be seen from Fig. 4 that the denoised signal spectrogram contains the original spectral information. In our solution, we need to automatically calculate a threshold to be applied on the denoised signal on time–frequency basis. The threshold is adaptive; meaning that it is calculated each time the STFT is performed. Because this algorithm is a power-based algorithm, the intra-pulse modulation is an independent condition.

Essential condition earned from the pulsed radar signals is the duty cycle, usually below 5%. In the time domain, this contributes in the ideal case in most probable zeros and least probable values for the signal; therefore in a noisy environment, pure noise exists in all the PRI period and the signal plus noise exist just in the smaller PW time. In the time–frequency domain this gives an important theoretical result, noise spreads all over the band with low power and in all the time bins considered the centers of the frames, but the targeted signal waveform is condensed in fewer time bins corresponds to the transmitting period. The same view can be seen in the frequency band where in most cases the signal in the small time of the frame occupies small band in the entire band $[-f_s/2 \; f_s/2]$. Different scenarios of intra-pulse modulations (LFM with different chirp coefficients, quadrature phase shift keying, and rectangular pulse) and using several duty cycle values implemented in pulsed radar can have the same result, which is an expected result, because calculating the threshold depends on the redundancy of noise in the PSD (spectrogram).

Statistically, the histogram validates this taking the example of 5% duty cycle, 32 samples window size, and 32 frequency bins in the band. The signal is generated at different low SNR values down to −18 dB, and then the histogram is calculated for the STFT matrix obtained (we take the PSD). Monte-Carlo simulations at different SNRs and duty cycles were performed to validate that. An example at the lowest SNR is shown in Fig. 5.

Applying threshold and localizing pulses were performed prior to ideal known pulse locations comparison. The results lead to an automatically validated threshold that was used.

Apply threshold and localize

The PSD matrix is subjected to the threshold "T," forcing smaller than "T" values to 0 and higher to 1. Then the resulted plot will be

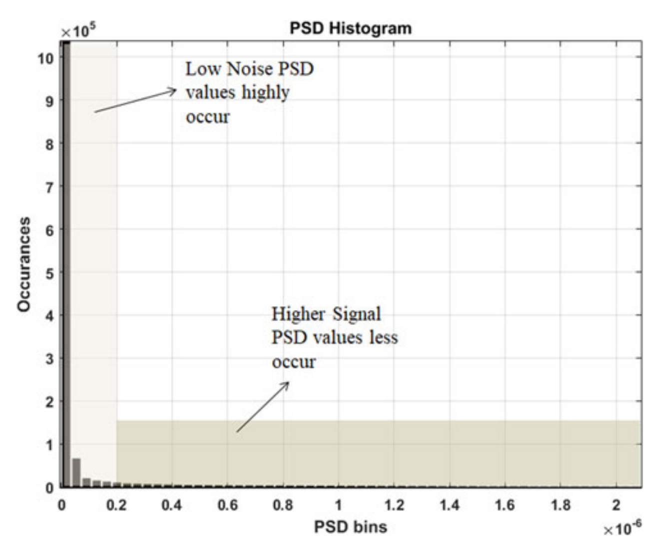

Fig. 5. Histogram of the time-basis PSD showing the statistical aspect of the pulsed radar signal.

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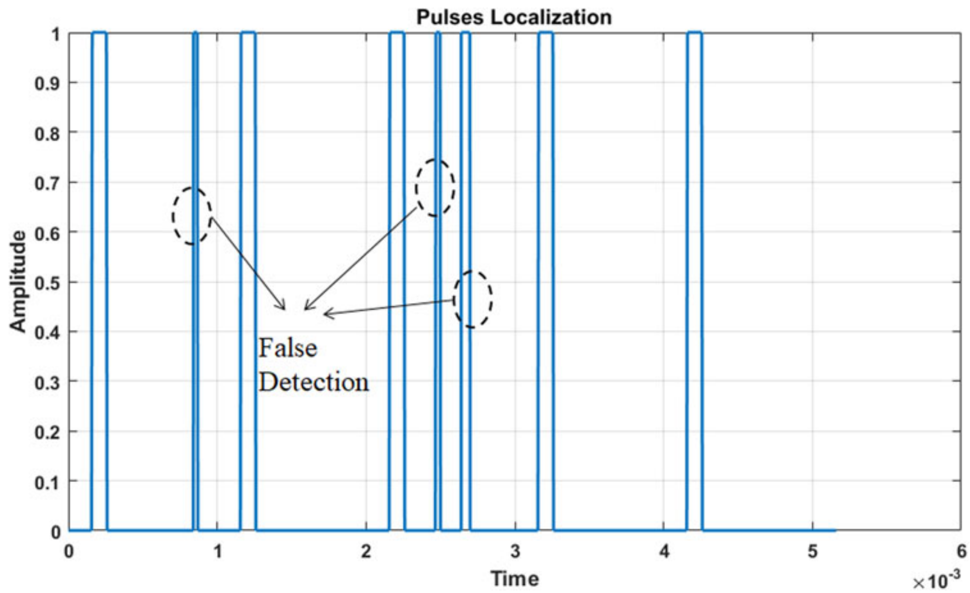

Fig. 6. Applying threshold and localizing pulses in the PSD matrix.

a rectangular waveform representing a decision of signal at a set of time bins and noise at others. Each stream of ones corresponds to pulse with the corresponding width. However, some noise overcomes the "*T*" value to result in a pulse with random PW value and gives a false detection. Simulation of long signal with many pulses results in low probability of false detection. Figure 6 shows an example of two pulses case.

Pattern analysis

Recognition and identification of pulsed radar parameters aims to blindly estimate first the radar class and second calculate its parameters (PW, pulse repetition frequency (PRF), bandwidth, etc.). Classes such as jittered, dwell and switch, staggered and others, each has special PW and PRF mode of variation, or it could be simply constant values. It is a wide range domain of R&D to solve these objectives accurately but in less complicated solutions. In the literature, algorithms exist based on neural network [6], radar signature database analysis [7], energy cumulate STFT [8], and many others.

In this paper, pattern analysis is used to enhance the localization and decrease the false decisions. In this perspective we are going to implement all the cases of radar parameter classes. However, for simplicity and to prove the concept we are going to show the results of the considered example. The generated signal is considered to be dwell and switch mode, the values of PW and PRF are fixed for a train of pulses and switch to other values for another train.

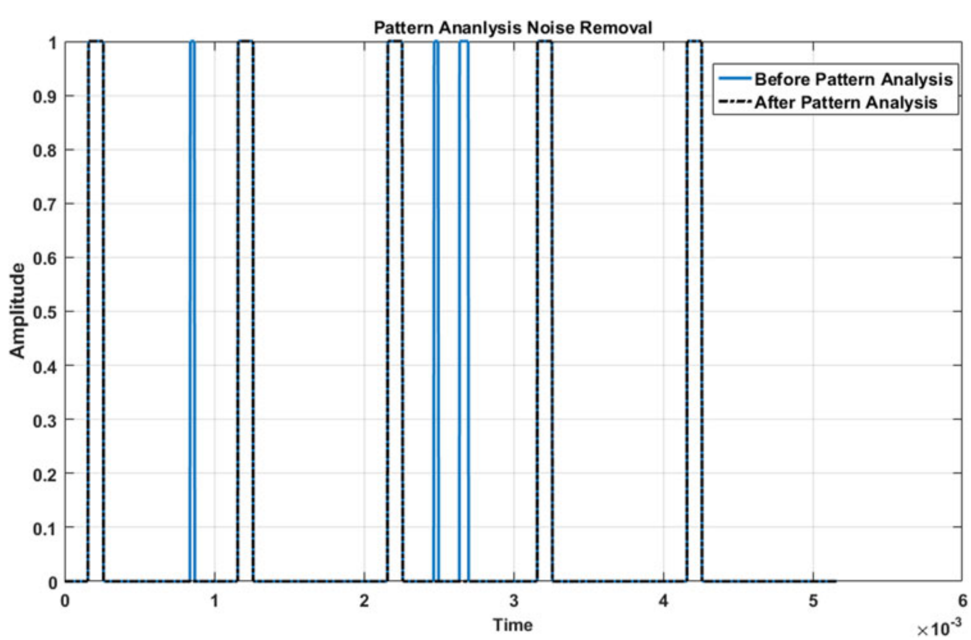

Fig. 7. False detection removal by pattern analysis.

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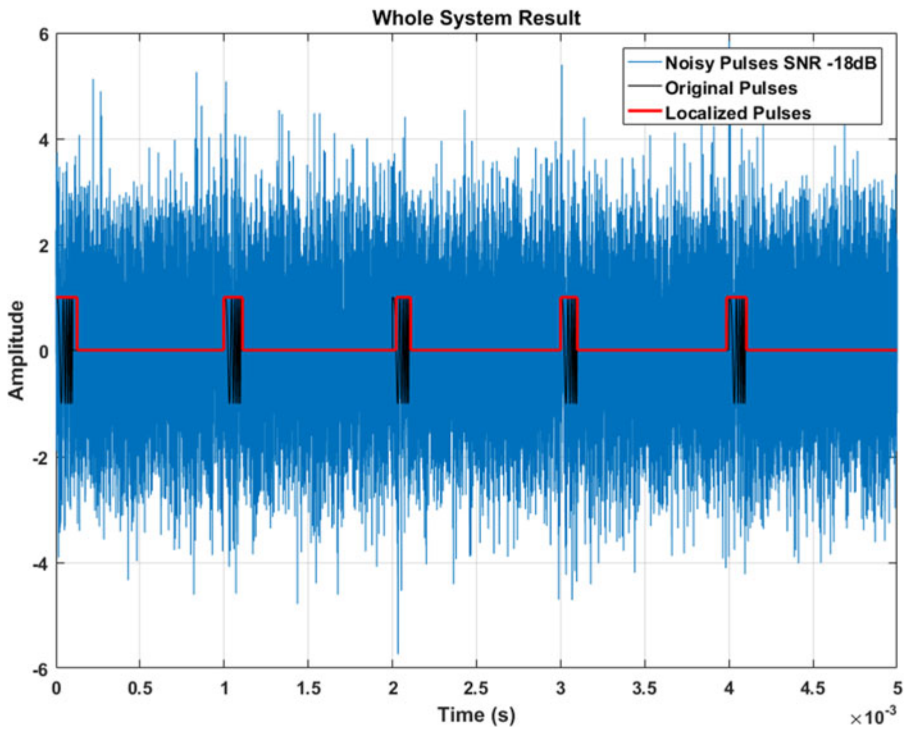

Fig. 8. Original pulse train (black), noisy at SNR −18 dB (blue), localization after denoising and pattern analysis (red).

The algorithm is built in a way that all the values of PW before pattern analysis (noise and pulses; Fig. 6) are taken each alone (consider no knowledge about the parameters of the generated signal PW and PRF). For each, the values of the time period between the equal PWs are calculated. Clearly, the glitches resulted from noise is randomly spread between the real pulses, therefore the time periods between these glitches are random and hence discarded. This procedure is repeated for all the possible values output from the rectangular plot of Fig. 6. The result outcome is a pure rectangular shape forming the time envelope of the pulses localized in the signal. Figure 7 shows an envelope example before and after the pattern analysis where three glitches are removed. Figure 8 shows the final result of the whole system suggested with pattern analysis at SNR −18 dB.

False alarm testing by pure noise signal

False alarm in radar may happen if decision is taken for target exists in the case of purely noise received signal. Now suppose that the input was pure noise. Referring to the flow chart, all the steps are executed normally; the signal is denoised, the PSD curves are extracted, a threshold is chosen, and localization is done. Figure 9 shows the result after the final step; pattern analysis. The results show the importance of the pattern analysis block. Taking advantage of the fact that it is impossible for a stochastic signal (pure noise) to produce random pulses with PW and PRF that coincides with any radar system pattern; the pattern analysis block will eliminate all the pulses that disagree with the rules. In fact, denoising and thresholding eliminates most of the noise glitches (the narrow one) that looks like pulses and

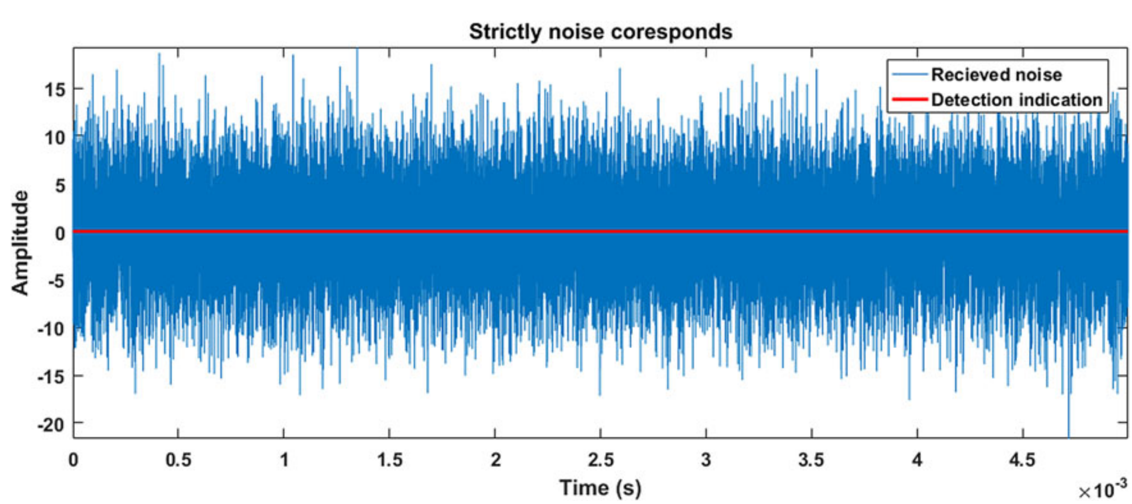

Fig. 9. Testing the case of pure noise.

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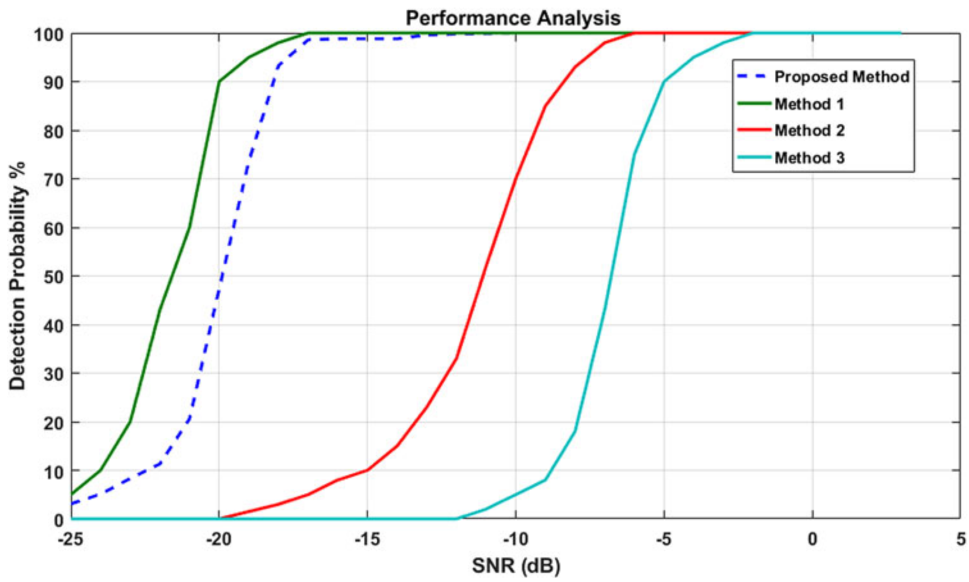

Fig. 10. Performance analysis of the proposed work.

efficiently decrease the false detection, but, pattern analysis improves strongly that by discarding the possible wider glitches that still exist as described.

Performance analysis and comparison

Monte-Carlo simulation is considered a basic procedure to deduce the efficiency of any estimator because the estimation is probabilistic (we cannot suppose an algorithm is successful based on a single try), mainly the generated radar signal parameters are changed and the generated noise is a stochastic process that give each time different random values.

The total input pulses to Monte-Carlo simulation was 1000 pulses and the simulation was repeated. We count the number of detected pulses, the false pulses, and the missed pulses. The result of the simulation leads to calculate the probability of detection, probability of missed pulses. In this simulation, the probability of false pulses was zero along different SNR's greater than −19 dB. We compared the results of the probability of detection with the three methods mentioned in [4] which are: method 1 (STFT 1-D envelope and wavelet denoising [4]), method 2 (Wigner–Ville–Hough [9]), and method 3 (time-domain). The results are shown in Fig. 10 where the blue curve corresponds to our work. Figure 10 with the results of the three methods is based on the result curves in [4].

It is difficult to compare our method with the method that depends on WPD (considered the strongest method in the literature) because they did not show the probability of detection or the false alarm they achieved. However, the less complexity of the WT (used by the proposed method) compared to WPD (used by

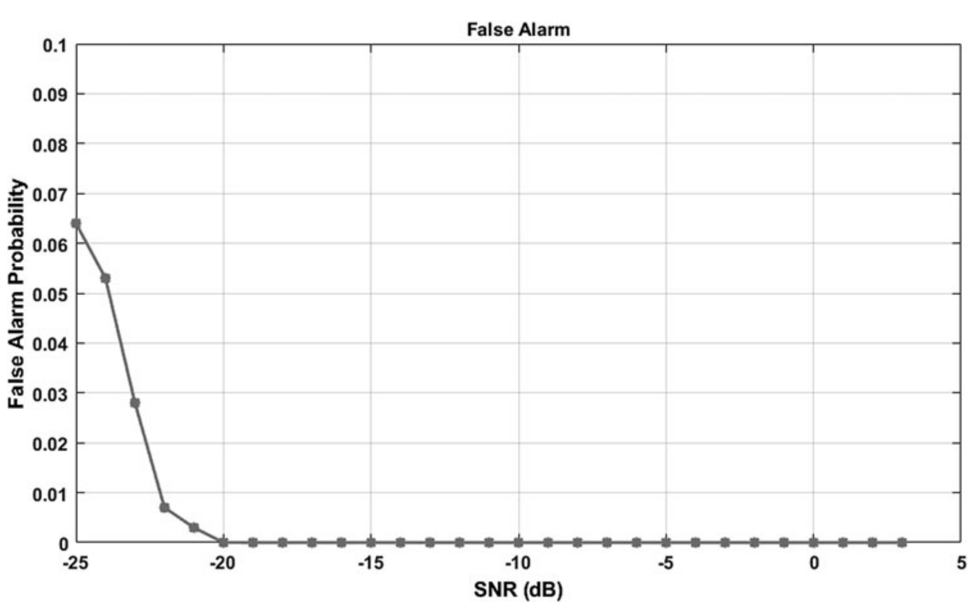

Fig. 11. False detection probability of the proposed work.

method 1) and the threshold calculated from STFT instead of the full WPD tree of parameters makes our method clearly simpler. Concerning method 1, the proposed algorithm is a little bit less in performance concerning the probability of detection at SNR less than −18 dB, but starts to match the same curve of detection probability for SNR ≥−18 dB. Also, the proposed solution is independent of intra-pulse modulation. The probability of false detection is calculated after performing the Monte-Carlo simulation; the results are shown in Fig. 11 versus different SNRs. Figures 10 and 11 are the only results that can be presented based on what the literature presents.

Conclusion and perspectives

Retrieving a radar echo signal in a low-SNR environment is considered a hot topic from the very beginning of advanced radar systems up to these days. We introduced a new algorithm to extract and localize radar echo-pulsed signals in a low SNR (−18 dB) by using STFT and wavelet denoising. The choice of threshold is meant to be automatic and based on the statistical study of the received signal's power. This study makes our algorithm independent of intra-pulse modulation because it is a power-based analysis. We introduced pattern analysis in order to enhance the dynamicity of dealing with any radar class; this feature makes our system independent of PW and PRF changes. Complexity optimization can be done in order to reduce computation time to be compatible with hardware implementation. We can claim that our algorithm is a simple one compared to other algorithms [3, 4] (functioning at very low SNR) but any further simplification can lead to an optimized algorithm suitable for hardware implementation.

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