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Original Article

A New Method for Detection of Backscattered Signals from Breast Cancer Tumors: Hypothesis Testing Using an Adaptive Entropy-Based Decision Function

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Abstract

Introduction
In recent years methods based on radio frequency waves have been used for detecting breast cancer. Using theses waves leads to better results in early detection of breast cancer comparing with conventional mammography which has been used during several years.
Materials and Methods
In this paper, a new method is introduced for detection of backscattered signals which are received by microwave breast radar. In this method, a decision function is constructed based on noise and signal cross-entropy, using hypothesis testing concept. Then noise and signal are separated using the calculated value for the decision function in each time frame. To estimate value of the decision function, discrete wavelet transform and discrete S transform are used.
Results
Performance of the proposed method was evaluated in two different scenarios, in which the breast was considered homogenous and heterogeneous, respectively. The obtained results showed that the proposed method detected breast backscattered signals 55% and 49% better than existing methods in two above scenarios.
Conclusion
Performance of S transform was 21% better than discrete wavelet transform in detection of weak backscattered signals. So it can be concluded that hypothesis testing method which uses S coefficients of received wave for construction of its decision function may be a suitable choice for detection of backscattered signals in breast radar.

Keywords: Breast Cancer, Heterogeneous Breast Lesions, Hypothesis Testing, S Transform

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1. Introduction

Breast cancer is the most prevalent type of cancer comprising 22.9 percent of cancers in women and is the reason for 13.7 percent of mortalities in women due to cancers [1]. Mammography has been the main method for detecting breast cancer for many years [2]. Nowadays, there are methods based on microwaves1 that have been used for detecting breast cancer. These methods have better results in early detection of breast cancer comparing to conventional mammography. It is of vital value to detect breast cancer in its early stage and RF methods have undergone great advances in recent years for early detection of breast cancer [3-5]. RF methods for detecting breast cancer can be classified into different types. In one method, passive radiometry, RF waves which are radiated from breast are received and processed. Intensities of these waves are proportional to the temperature of breasts which depends on components of this tissue. Consequently, processing of the received waves can separate healthy and cancerous breast tissues [6]. In some other methods, hybrid methods, the combination of RF waves and ultrasonic waves is utilized for detection of breast cancer. In these methods, the breast is heated by controlled RF waves and then changes in tissue due to heating are investigated using an ultrasonic sensor. These changes are different between healthy and cancerous breast tissues which can lead to the detection of probable breast cancer [7].

Another group of methods is based on radiating RF narrow pulses to breast and processing the backscattered signal for detecting cancerous lesions [8-9]. These systems are called wideband radar and work based on the fact that dielectric properties of cancerous breast tissue highly differ from the dielectric properties of the healthy breast. For example, permittivity and conductivity coefficients of a typical cancerous breast may reach up to 6 and 17 times greater than these parameters for a healthy breast [10]. The performance of wideband radars for detecting breast cancer depends on the correct reception of the backscattered signal from the breast. This means that improper reception of the backscattered signal leads to extracting breast dielectric properties with considerable errors and this causes the inability of the wideband radar system to discriminate between healthy and cancerous breasts. Therefore, separating noise and backscattered signal is a vital step for detecting breast cancers using wideband radars [11] and many approaches have been proposed for it.

In energy detection (ED) approaches, signal and noise are separated using their power specifications which are obtained from the received wave amplitude. In these approaches, each time, noise power is estimated by means of its neighbor instances. If power of the received wave is greater than the estimated noise power, it is considered as valid detection; otherwise it is intended as noise and is used for updating noise power estimation [12]. Several approaches based on ED have been presented. The main difference between these methods is the technique they use for estimating the noise power using received wave [13-15]. Whereas the amplitude and the power of backscattered signal are strongly sensitive to noise, ED approaches are more effective when signal to noise ratio (SNR) of received wave is significant. Another group of approaches, which are known as transform domain, utilize features of received wave for separating backscattered signal and noise. In some of the above-mentioned approaches, short-time Fourier transform (STFT) is used [16]. Wavelet transform is used as the extracted feature in some other approaches [17-19]. In these approaches, the estimation of the noise is updated using the transform coefficients which are calculated from the received wave. Afterward, the received wave is assigned to noise or backscattered signal from breast using a threshold proportional to the noise estimation. Results which have been obtained from the above approaches showed

1. Radio Frequency (RF) waves

that although wavelet has been more efficient than STFT because of its time-frequency resolution, but none of them has desirable outcome in the presence of strong noise in received wave [16-19].
In this paper, a new method for separating backscattered signal and noise in breast wideband radar is presented which is based on combination of a new time-frequency feature (S transform which will be mentioned in part II) and stochastic modeling of received wave. In the proposed method, the dependency of each time-frame of the received wave to backscattered signal or noise is modeled using hypothesis testing framework. To assign the received wave to one of above hypotheses, a decision function is constructed using cross-entropy of signal and noise. This function is accordingly updated by means of S coefficients. Therefore, this method has more compatibility with stochastic nature of backscattered signals from breast tissue and therefore separates backscattered signal more precisely than existing methods. Moreover, because of using S coefficients, it extracts instantaneous frequencies more accurately than other methods.
The paper is organized as follows. In part II the combination of S transform and proposed hypothesis testing algorithm for separation of backscattered signal and noise is described. The performance of the proposed method is examined in part III. Two scenarios are simulated based on real situations and the performance of the proposed algorithm is studied in both. In part IV, simulation results are studied and performance of the proposed method is compared with available methods. Part V is the conclusion.

2. Materials and Methods

Assume that $x_r(t)$ is the received wave by wideband breast radar and it has been divided to ξ equal parts with time duration t_0. $x(t)$ is a part of $x_r(t)$ as:

$$x(t) = x_r(t) \quad (\eta-1)t_0 \le t \le \eta t_0 \;,\; \eta = 1,2,...,\xi \tag{1}$$

$x(t)$ Consists of signal $a(t)$ and noise $n(t)$:

$$x(t) = a(t) + n(t) \tag{2}$$

Wavelet transform of $x(t)$ is [20]:

$$W(\tau,d) = \int_{-\infty}^{\infty} x(t)\left\{\frac{1}{\sqrt{d}}\, w\left(\frac{\tau - t}{d}\right)\right\}dt \tag{3}$$

Where, $w(t,d)$ is basis function, d is delay parameter and τ is scale parameter. If the basis function depends on both time and frequency [21]:

$$S_x(\tau, f) = \int_{-\infty}^{\infty} x(t) w(\tau - t, f) e^{-j2\pi ft} dt \tag{4}$$

Where $S_x(\tau, f)$ is called S transform of $x(t)$. Similar to STFT, $S_x(\tau, f)$ is time-frequency presentation of received wave, but it hasn't time-frequency resolution problem since it is derived from wavelet transform. Furthermore, because of existing f in $S_x(\tau, f)$, it depends on frequency and received spectrum directly as equation (5). $X(f)$ is spectrum of the received wave $x(t)$ [21-22].

$$S_x(\tau, f) = \int_{-\infty}^{\infty} X(f+\alpha) w(\alpha, f) e^{j2\pi\alpha\tau} d\alpha \tag{5}$$

By replacing Gaussian window [23] of equation (6) in equation (4), Gaussian S transform $S_{xg}(\tau, f)$ is obtained as (7).

$$w_g(t, f) = \frac{|f|}{\sqrt{2\pi}} e^{-\frac{t^2 f^2}{2}} \tag{6}$$

$$S_{xg}(\tau, f) = \int_{-\infty}^{\infty} x(t) \frac{|f|}{\sqrt{2\pi}} e^{-\frac{(\tau - t)^2 f^2}{2}} e^{-j2\pi ft} dt \tag{7}$$

Using equation (6), equation (5) can be rewritten as:

$$S_{xg}(\tau, f) = \int_{-\infty}^{\infty} X(f+\alpha) e^{\frac{-2\pi^2\alpha^2}{f^2}} e^{j2\pi\alpha\tau} d\alpha \tag{8}$$

In discrete form, equation (1) is rewritten as equation (9) with sampling period T:

$$x[lT] = a[lT] + n[lT]$$
$$1 \le l \le M \qquad M = \frac{t_0}{T} \tag{9}$$

Similarly, the discrete form of equation (8) is obtained as:

$$S_{xg}[kT, \frac{m}{MT}] = \sum_{i=0}^{M-1} X(\frac{i+m}{MT}) e^{\frac{-2\pi^2 i^2}{m^2}} e^{\frac{j2\pi ik}{M}}$$
$$1 \le k \le M \quad 1 \le m \le M \tag{10}$$

Where $\frac{m}{MT}$ and kT are discrete versions of f and τ in equation (8). Unlike most bilinear transforms, the S transform has linear property and thus collective noise in time domain doesn't make crossover term in transform domain [21-22]. Therefore, the equivalent of equation (9) in S domain can be written as:

$$S_{xg}[kT, \frac{m}{MT}] = S_{ag}[kT, \frac{m}{MT}] + S_{ng}[kT, \frac{m}{MT}] \tag{11}$$

In above equation, the terms $S_{xg}[kT, \frac{m}{MT}]$, $S_{ag}[kT, \frac{m}{MT}]$ and $S_{ng}[kT, \frac{m}{MT}]$ are S coefficients of $x[lT], a[lT]$, and $n[lT]$ in equation (9) that each of them is obtained by an equation similar to (10). Now, we try to separate signal and noise of equation (9) by equation (11). For this purpose, we show elements of equation (11) in vector form S_{xg}, S_{ag}, and S_{ng} with vector sizes $Q = M^2$.

Afterward, below hypotheses are assumed to prescribe nature of S_{xg}:

$$\begin{cases} H_0 : S_{xg} = S_{ng} \\ H_1 : S_{xg} = S_{ag} + S_{ng} \end{cases} \tag{12}$$

The hypothesis H_0 shows that the received wave is only noise and hypothesis H_1 depicts received wave as backscattered signal from breast. Now, for assigning the received wave to the correct hypothesis, a decision function Λ is constructed using the cross entropy of backscattered signal and noise as: [24]

$$\Lambda = \frac{1}{Q} \ln \frac{P(S_{xg} \mid H_1)}{P(S_{xg} \mid H_0)} \tag{13}$$

Yang showed [25] that (13) can be rewritten using noise variance σ_{sng}^2 as:

$$\Lambda = \frac{1}{Q} \sum_{q=0}^{Q-1} \frac{|S_{xg}(q)|^2}{\sigma_{sng}^2(q)} \underset{H_0}{\overset{H_1}{\gtrless}} 1 + \beta \tag{14}$$

Based on above equation, the noise variance should be known in order to separate signal from noise. Therefore, we estimate $\sigma_{sng}^2(q)$ as $\hat{\sigma}_{sng}^2(q)$ using equation (15).

$$\begin{aligned} \hat{\sigma}_{sng}^2(q) &= E(\sigma_{sng}^2(q) \mid S_{xg}(q)) = \\ & E(\sigma_{sng}^2(q) \mid H_0) P(H_0 \mid S_{xg}(q)) \\ & + E(\sigma_{sng}^2(q) \mid H_1) P(H_1 \mid S_{xg}(q)) \end{aligned} \tag{15}$$

Using Bayes theorem, it can be written:

$$\begin{aligned} & P(H_0 \mid S_{xg}(q)) = \\ & \frac{P(S_{xg}(q) \mid H_0) P(H_0)}{P(S_{xg}(q) \mid H_0) P(H_0) + P(S_{xg}(q) \mid H_1) P(H_1)} = \\ & \frac{1}{1 + \varepsilon \Lambda(q)} \end{aligned} \tag{16}$$

$\Lambda(q) = \frac{P(S_{xg}(q) \mid H_1)}{P(S_{xg}(q) \mid H_0)}$ and $\varepsilon = \frac{P(H_1)}{P(H_0)}$. Also $\Lambda(q)$ is decision function of equation (14) where it is calculated from S_{xg} vector. Equation (17) can be obtained by a similar method.

$$\begin{aligned} & P(H_1 \mid S_{xg}(q)) = \\ & \frac{P(S_{xg}(q) \mid H_1) P(H_1)}{P(S_{xg}(q) \mid H_1) P(H_1) + P(S_{xg}(q) \mid H_0) P(H_0)} = \\ & \frac{\varepsilon \Lambda(q)}{1 + \varepsilon \Lambda(q)} \end{aligned} \tag{17}$$

Substituting two latter equations in (15), leads to the estimation of noise power in the form of $\hat{\sigma}_{sng}^2(q)$ as:

$$\begin{aligned} \hat{\sigma}_{sng}^2(q) &= E(\sigma_{sng}^2(q) \mid H_0) \frac{1}{1 + \varepsilon \Lambda(q)} \\ & + E(\sigma_{sng}^2(q) \mid H_1) \frac{\varepsilon \Lambda(q)}{1 + \varepsilon \Lambda(q)} \end{aligned} \tag{18}$$

If the above equation belongs to frame η of the received wave as mentioned in equation

(1), $\left|S_{xg}(q)\right|_{\eta}^{2}$ and $[\hat{\sigma}_{sng}^{2}(q)]_{\eta-1}$ can be used as estimations of $E(\sigma_{sng}^{2}(q) \mid H_0)$ and $E(\sigma_{sng}^{2}(q) \mid H_1)$. We assume that $\Lambda(q)$ is constant and equal to Λ for each frame of received wave and rewrite equation (18) as adaptive equation (19).

$$[\hat{\sigma}_{sng}^{2}(q)]_{\eta} = \left|S_{xg}(q)\right|_{\eta}^{2} \frac{1}{1+\varepsilon[\Lambda]_{\eta-1}(q)} + [\hat{\sigma}_{sng}^{2}(q)]_{\eta-1} \frac{\varepsilon\Lambda(q)}{1+\varepsilon[\Lambda]_{\eta-1}(q)} \quad (19)$$

3. Results

The proposed method was implemented using MATLAB 2009. The software contains two distinct parts. In the first part the received wave was simulated using its main parameters such as frequency, time length, amplitude, and signal to noise ratio. The second part of software dealt with algorithms for separation of backscattered signal from noise. In this part, our proposed method was applied using wavelet coefficients and S coefficients as features distinctly. Additionally, ED algorithm [13-15] was implemented for comparison with the proposed algorithm. Waves returned from the breast were simulated with different scenarios, and detected backscattered signals were obtained by applying above algorithms. Finally, performance of each algorithm was determined by comparing its obtained results with original signals.

3.1. First scenario

In the first simulation scenario, the breast was supposed as a homogeneous tissue [10, 26, 27]. Specifications of this scenario were as follows in Table 1.

Figure 1 shows one of the results in this scenario. As shown in this figure, original backscattered signal from the breast has had 20 pulses (1.a) and the noisy frame of figure (1.b) with 5dB SNR has been obtained from it. Figures (1.c), (1.d), and (1.e) show results of ED, hypothesis testing with wavelet feature, and hypothesis testing with S coefficients on noisy wave (1.b), respectively. It is obvious that the proposed method with the S coefficients has extracted 20 pulses from original pulses. ED method has extracted only 14 pulses, and hypothesis testing method with wavelet feature has extracted 19 pulses. Additionally, each of ED and wavelet-based hypothesis testing has extracted one false pulse, whereas S transform- based hypothesis testing hasn’t had any false detection.

3.2. Second scenario

In this scenario, simulations were carried out for breast containing heterogeneous cancerous lesions [10, 26-28]. Contrary to the former scenario, backscattered pulses had up to 20 dB difference in their amplitude. General properties of these pulses were similar as shown in Table 1 to enable us to compare scenarios. Figure 2 shows one of the results which had been obtained in the second scenario. As shown in this figure, the original frame has had 20 pulses and their occurrence positions were similar as shown in Figure (1.a). However, amplitudes of pulses in Figure 2 aren’t identical. For example, in Figure (2.a) amplitude of occurred pulse at $t = 38\mu s$ has been smaller than occurred pulse in $t = 4.4\mu s$ about 20 dB. Figures (2.c), (2.d), and (2.e) show the results of ED, hypothesis testing with wavelet feature, and hypothesis testing with S feature on noisy received wave from Figure (2.b). As shown, the proposed method with the S coefficients has extracted 17 pulses of original backscattered pulses. ED has extracted only 13 pulses, and wavelet-based hypothesis testing has extracted 14 pulses. Moreover, each of ED and wavelet-based hypothesis testing has extracted one false pulse, whereas hypothesis testing with S coefficients has had no false detection.

Table 1. Common simulation parameters in both of scenarios

Simulation parameter	Value	Simulation parameter	Value
Frequency	3 GHz	Pulse width	100 nano-seconds
Frame length	50 micro seconds	Number of frames	1400
Total number of pulses	21543	SNR Range	5-30 dB

4. Discussion

Two kinds of returning waves were simulated based on real situations of the breast tissue. In the former scenario, the simulated wave has been considered as backscattering of the homogenous breast. In the latter, since the breast had been considered with heterogeneous cancerous lesions, backscattered pulse amplitudes were highly different. In this case, the weak backscattered pulses may be masked by the greater pulses.

Results showed that, though surveyed algorithms could detect pulses in both scenarios, but their performances have been different in various situations. In order to evaluate performance of each algorithm, its detected pulses were compared with original pulses. Since in wideband radar both detection and fully extraction of pulses are important, detected pulses by examined algorithms were considered acceptable, only when distance of start points of detected and original pulses was less than one pulse width. By using this criterion, we had two kinds of errors. The first type was due to pulses that had been existed in original simulated sequence but the detection algorithms couldn't detect them. Theses pulses were named as lost pulses.

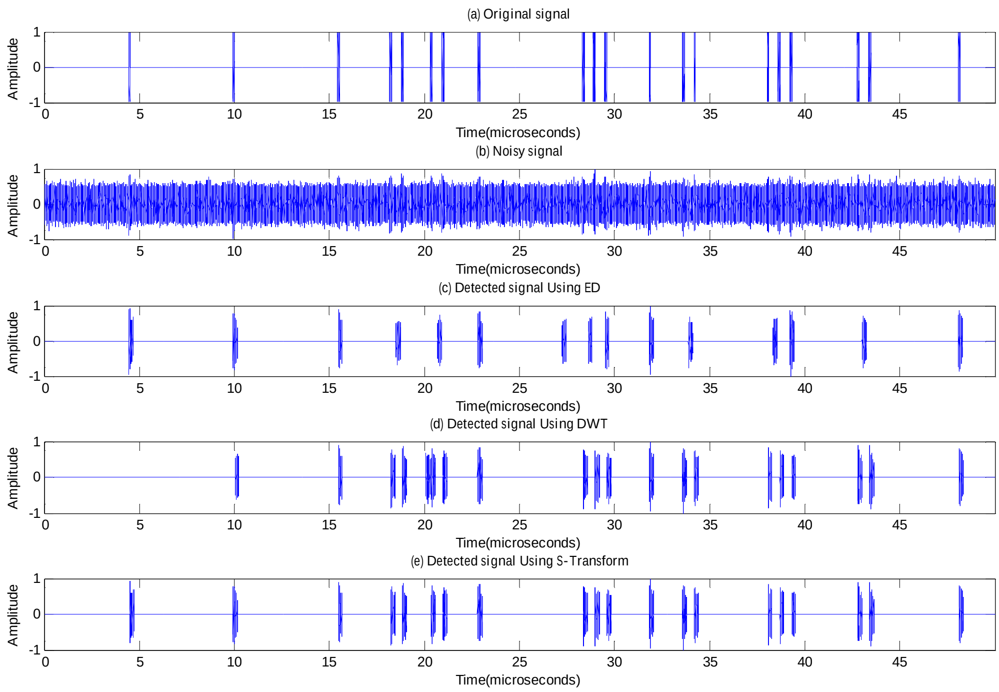

Figure 1. A sample result of the first scenario: a) Original pulse train with equal pulse amplitudes, b) Noisy pulse train with 5dB SNR as input for detection algorithms, c) Pulse train detected using ED, d) Pulse train detected using the proposed algorithm with wavelet coefficients, and e) Pulse train detected using the proposed algorithm with S coefficients

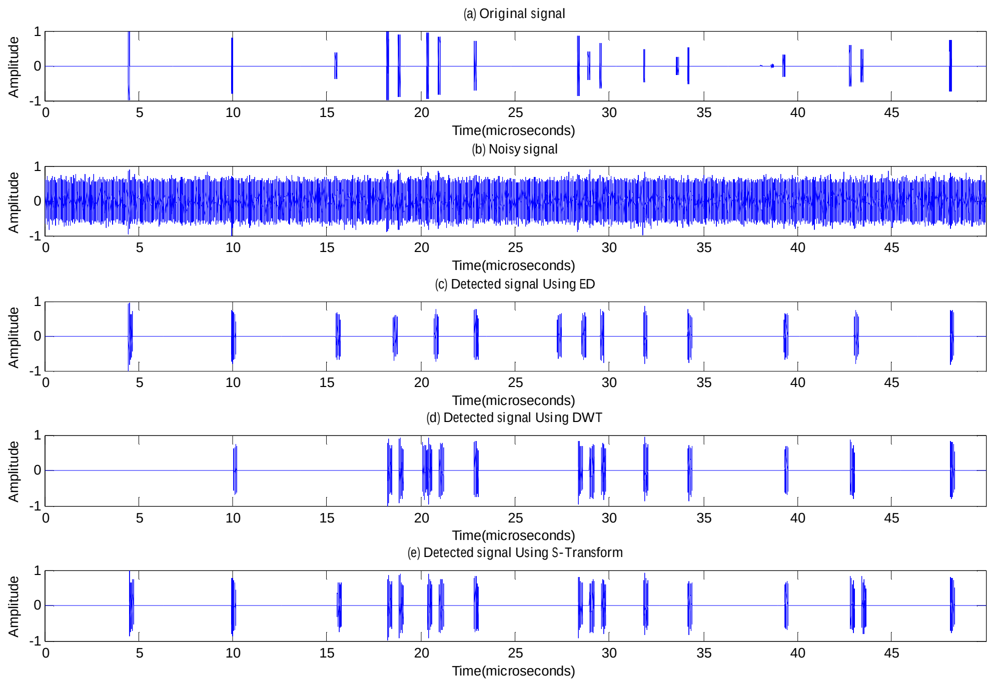

Figure 2. A sample result of the second scenario: a) Original pulse train with different pulse amplitudes, b) Noisy pulse train with 5dB SNR as input for detection algorithms, c) Pulse train detected using ED, d) Pulse train detected using the proposed algorithm with wavelet coefficients, and e) Pulse train detected using the proposed algorithm with S coefficients

The second error belonged to false pulses obtained by detection algorithms, which were called extra pulses. Performance of algorithms was evaluated by comparing their lost and extra pulses. Figure 3 shows distribution of lost pulses in first scenario with 15 dB SNR. It can be shown that ED has detected 49% of whole frames with ratio of lost pulses less than 30%. Whereas, two other methods have detected 100% of whole frames with ratio of lost pulses less than 30%. Moreover, Figure 4 shows distribution of lost pulses in second scenario with 15 dB SNR. It can be shown that ED has detected 33% of whole examined frames with ratio of lost pulses less than 30%. Figure (4.b) and (4.c) show that wavelet-based and S transform-based hypothesis testing have detected 100% of whole frames with ratio of lost pulses less than 30%. By comparing the results of Figures 3 and 4, using their lost pulses parameters, it can be concluded that the hypothesis testing method has had more accurate results than ED algorithm.

In the same manner, Figures 5 and 6 show distribution of extra pulses in the first and the second scenarios in SNR equal to 15 dB. Figure (5.a) shows that ED has detected 53% of all examined frames in the first scenario with ratio of extra pulses less than 30%. Figures (5.b) and (5.c) show this parameter for hypothesis testing algorithm with wavelet feature and hypothesis testing with S coefficients in the first scenario when has been equal to 97% and 93%, respectively. The results from the second scenario have been shown in Figure 6. Figure (6.a) shows that ED has detected 58% of all examined frames in the second scenario with ratio of extra pulses less than 30%. Hypothesis testing with wavelet and S features has detected 96% and 94% of examined frames with ratio of extra pulses less than 30% in this scenario. Therefore, it is obvious that the proposed algorithm have had higher capability to extract backscattered pulses in contrast with ED method. Moreover, this greater capability is independent from homogeneity or heterogeneity of the breast tissue.

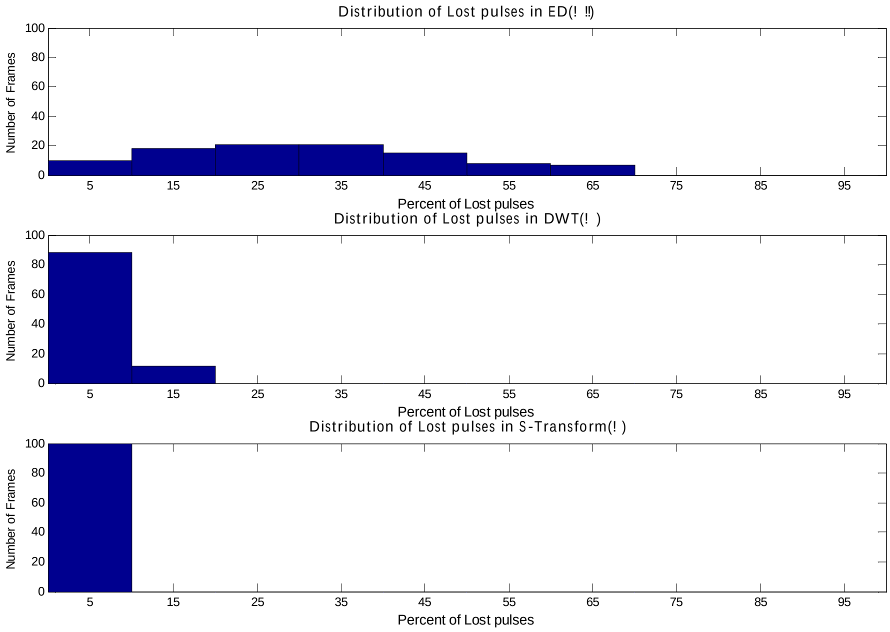

Figure 3. Distribution of lost pulses in first scenario with 15 dB SNR using methods: a) ED, b) Hypothises test with wavelet feature and c) Hypothises test with S feature

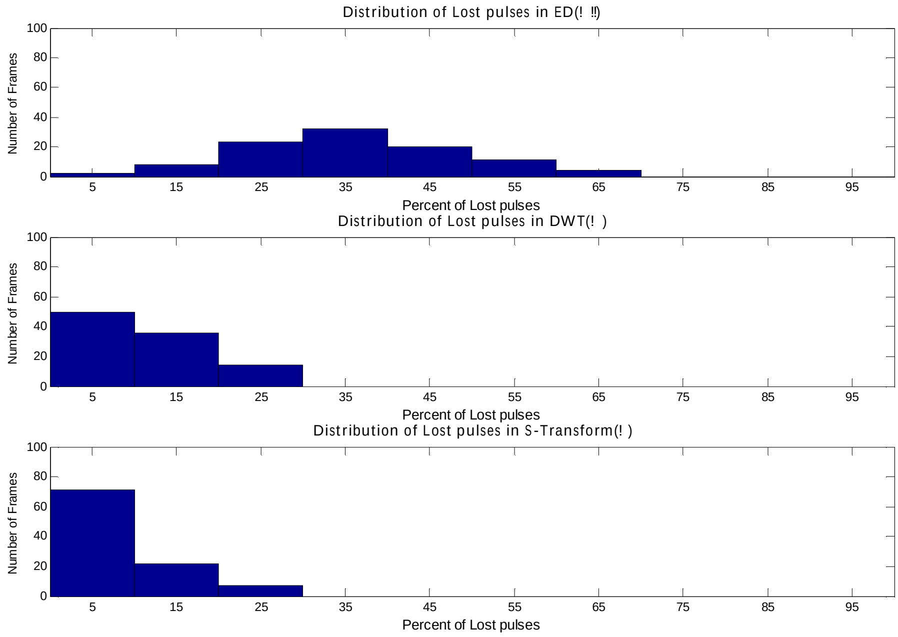

Figure 4. Distribution of lost pulses in second scenario with 15 dB SNR using methods: a) ED, b) Hypothises test with wavelet feature, and c) Hypothises test with S feature

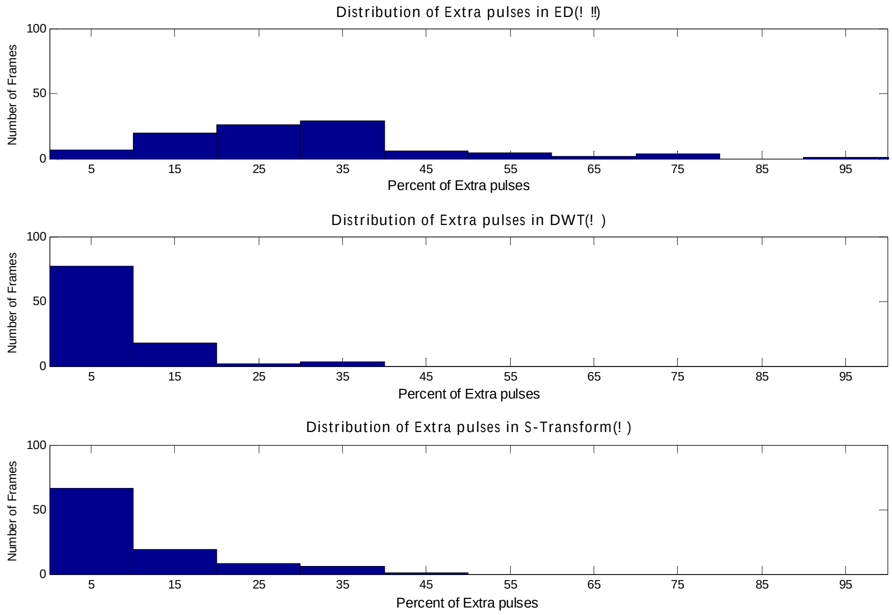

Figure 5. Distribution of extra pulses in first scenario with 15 dB SNR using methods: a) ED, b) Hypothises test with wavelet feature and c) Hypothises test with S feature

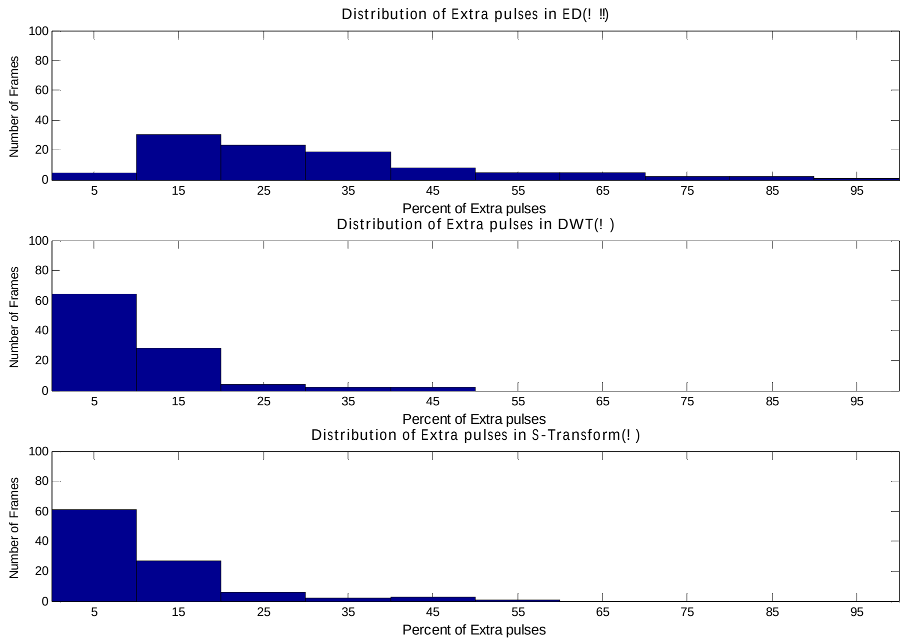

Figure 6. Distribution of extra pulses in second scenario with 15 dB SNR and methods: a) ED, b) Hypothises test with wavelet feature, and c) Hypothises test with S feature

In order to investigate that better performance of the hypothesis algorithm is not dependent on the amount of noise, pulse detection was carried out under several SNRs. For this purpose, all simulations were carried out under SNRs between 5 and 30 dB and the results were compared using their lost and extra pulses. The above procedure was applied to both scenarios and results have been shown in Table 2.

Table 2. Performance of the examined algorithms versus SNR

SNR (dB)	Method	Scenario 1 Homogenous Breast		Scenario 2 Heterogeneous Breast	
		Lost Pulse Index	Extra Pulse Index	Lost Pulse Index	Extra Pulse Index
30	ED	44	52	41	61
	DWT	100	99	100	99
	S-T	100	98	100	96
25	ED	42	48	45	63
	DWT	100	100	100	97
	S-T	100	96	100	98
20	ED	44	54	44	59
	DWT	100	97	100	100
	S-T	100	96	100	96
15	ED	49	53	33	58
	DWT	100	97	100	96
	S-T	100	93	100	94
10	ED	43	50	38	60
	DWT	100	98	88	98
	S-T	100	98	95	93
7.5	ED	43	58	29	56
	DWT	100	96	68	96
	S-T	100	96	82	95
5	ED	46	46	23	54
	DWT	100	98	43	98
	S-T	100	95	64	96

*DWT: Discrete Wavelet, S-T: S Transforms

This table shows the sensitivity of ED and hypothesis testing algorithms versus SNR using two following parameters: First, the percent of frames with ratio of lost pulses less than 30%, which is called lost pulses indicator, and second, the percent of frames with ratio of extra pulses less than 30%, which is called extra pulses indicator. This table shows that in the first scenario using the hypothesis testing algorithm (irrespective of extracted feature which can be wavelet or S) has lead to 55% improvement on average in lost pulses indicator comparing to ED. Furthermore, hypothesis testing algorithm has detected backscattered pulses with extra pulses indicator on average 44% better than ED. Therefore, it is clear that the performance of the proposed algorithm (irrespective of its extracted feature) is considerably better than ED in examined range of SNR.

In the second scenario, i.e., breast with heterogeneous cancerous tissue, the table still shows higher performance of the hypothesis testing algorithm comparing to ED irrespective of extracted feature. It can be shown that in this scenario the proposed algorithm has lead to 49% and 36% improvement on average in lost pulses indicator and extra pulses indicator comparing to ED. Additionally, it can be shown that in SNRs higher than 15 dB, the performance of the proposed algorithm is similar in the first and the second scenarios. By reducing SNR bellow 15 dB, a great number of pulses which had been detected in the first scenario may not be detected in heterogeneous breast scenario. Therefore, the lost pulses indicators in this scenario and SNRs bellow 15 dB have been considerably less than the first scenario (see rows 5-7 of Table 2). The main reason for this reduction is that weak pulses have been drowned in noise in such SNRs (for example the pulse which has been happened in $t = 38\mu s$ in Figure 2.a).

Finally, the comparison between the effect of the extracted features, wavelet, and S coefficients, in performance of hypothesis testing algorithm is important. As seen in the first column of Table 2, the performance of the proposed algorithm using wavelet coefficients has been similar to its performance using S coefficients in the first scenario. This similarity has been kept in higher SNRs of the second scenario (four first SNRs of the second scenario in table 2). However, decreasing SNR in the second scenario has caused considerable differences between performances of these features in detecting backscattered signal. In this scenario, the lost pulses indicator for hypothesis testing with S coefficients in SNRs equal with 5, 7.5 and 10 dB has been 21, 14 and 7 percent greater than its values with wavelet coefficients. Based on results in Table 2, it is notable that these improvements have caused no meaningful differences between extra pulses indicator obtained by utilizing two of these features. That means according to decreasing SNR in cancerous breast, the S coefficients can be used as a more effective feature for detecting backscattered signal in wideband breast radars.

5. Conclusion

In this paper, a new method was introduced for separating backscattered signal and noise in received wave using breast wideband radars. For evaluation of the proposed algorithm, two scenarios were simulated based on real situations of human breast. In the first scenario, the breast was considered homogenous and in the second scenario it was considered heterogeneous containing cancerous lesions. In both of scenarios, the performance of the proposed algorithm was studied in several SNRs besides one of energy detection based existing methods using the percent of lost pulses and the percent of extra pulses. The results showed higher performance of the proposed algorithm in separating the backscattered signal from noise. It was shown that in the first scenario, the proposed algorithm detected all of examined frames with ratio of lost pulses bellow 30%. The above result was on average 55% better than the one obtained using ED. Furthermore, this result was regardless of the utilized feature. Moreover, for the proposed algorithm, the number of the detected frames with ratio of extra pulses less than 30% was 44% more than that of which had been detected by ED algorithm.

In the second scenario, the backscattered pulses had different amplitudes, up to 20 dB, because of existing heterogeneous cancerous lesion in breast. Therefore, weaker pulses were drowned in noise in low SNRs which caused degrading of detection performance of all examined algorithms compared to the first scenario. However, it was shown in these simulations that the hypothesis testing method detected backscattered signals with lost pulse and extra pulse indicators on average 49% and 36% better than which had been obtained for ED irrespective of extracted feature. Finally, it was interesting that although wavelet and S coefficients have had the same effects in all homogenous breast simulations and high SNR heterogeneous cancerous breast simulations, but in low SNR tests of the second scenario, the S coefficients has been more effective than the wavelet transform. It was shown that in low SNR tests of heterogeneous cancerous breast, utilizing S coefficients for construction of hypothesis testing decision function has led to maximally 21% improvement versus using wavelet coefficients. Therefore, it can be concluded that hypothesis testing method which uses S coefficients of received wave for construction of its decision function may be a suitable choice for detection of backscattered signals in wideband breast radar.

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