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Robust Detection of Moving Human Target Behind Wall via Impulse Through-Wall Radar

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ABSTRACT

Through-wall human target detection is highly desired in military applications. We have developed an impulse through-wall radar (TWR) to address this problem. In order to obtain a robust detection performance, firstly we adopt the exponential average background subtraction (EABS) method to mitigate clutters and improve the signal-to-clutter ratio (SCR). Then, different from the conventional constant false alarm rate (CFAR) methods that are applied along the fast-time dimension, we propose a new CFAR method along the slow-time dimension to resist the residual clutters in the clutter mitigation output because of timing jitters, based on the presence of a larger relative variation of human target moving in and out in comparison with that of residual clutters in the slow-time dimension. The proposed method effectively solves the false alarm issue caused by residual clutters in the conventional CFAR methods, and obtains robust detection performance. Finally, different through-wall experiments are provided to verify the proposed method.

Keywords: Ultra-wide band, through-wall radar, clutter mitigation, target detection, constant false alarm rate

1. INTRODUCTION

Quick and accurate detection and localization of human target behind wall is an important issue and highly desired in law enforcement and military applications. In antiterrorism and hostage situations, law enforcement officers are often required to determine the location and movement of occupiers inside buildings. Ultra-wide band (UWB) through-wall radar (TWR) has emerged as a promising technique, due to its good penetration and high range resolution, and attracts more and more attention[1,2].

UWB-TWR operates in a low frequency band to obtain good penetration. Data taken by Frazier[3] show that most building materials are relatively transparent for frequencies below 4 GHz. The high range resolution of UWB TWR profits from the large bandwidth usually obtained by transmitting impulse[4] or stepped frequency continuous wave (SFCW) signals[5]. Impulse is inherently short, generally several nanoseconds in width, and requires high-speed A/D converters to support the large bandwidth. By contrast, SFCW systems transmit short CW bursts at progressively higher frequencies, and require higher dynamic ranges and longer acquisition time[5].

Detection and localization can be divided into zero (0-D), one (1-D), two (2-D), or three dimensional (3-D) systems[1]. 0-D system[3] is simply a motion detector and will report any motion in the scene. 1-D systems[6,7] provide a range to a target but not an angle. The extra dimension provides the ability to separate and possibly discriminate multiple targets. 2-D[8,9,10] and 3-D[11] systems provide more information and better localization of targets, at the expense of more complicated design and longer data acquisition time.

To sense through wall effectively and efficiently, we developed a portable real-time mono-static 1-D impulse TWR[12]. As is well known, reliable detection of human target is full of challenges, and usually resorts to signal processing technique. Rovnakova[13] outlined all required phases in through-wall target tracking. There into, clutter mitigation and target detection are the most important two phases, since the low reflectivity of human body, strong environmental clutters and high signal attenuation of walls result in fairly low signal-to-clutter ratio (SCR), which greatly degrades the detectability of human target. Therefore, in this study we focus on the clutter mitigation and target detection in the impulse TWR.

Clutter mitigation methods can be generally categorized into subspace methods, frequency-domain methods and time-domain methods. Subspace methods are widely studied in the 2-D through-wall imaging[14,15], and seem complicated for real-time applications. Frequency-domain methods[16,17,18] fail to deal with running or walking human targets due to the high range resolution of UWB TWR. The basis for the time-domain processing becomes moving target indication (MTI) problem with low SCR[19]. Background subtraction techniques are commonly used and carefully examined[20,21], and exponential average background subtraction (EABS)[21] is believed effective to combat clutters. In EABS, background is estimated first using previous pulses weighted by exponential coefficients and then subtracted from the current pulse to indicate targets. EABS is reasonable since exponential weighting coefficients gradually weaken the previous pulses effect as time increases[22]. Moreover, it can be implemented pulse by pulse. Thus, we consider the EABS method to suppress clutters.

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Conventional constant false alarm rate (CFAR) methods are usually adopted to tackle the clutter mitigation output[13,23] to obtain predictable and robust detection performance. Rovnakova[13] assumed a Gaussian clutter model and applied the CFAR method along the fast-time dimension in a simple scenario with only one moving target. Urdzik[23] further extended the investigation to the case with multiple targets. With an exponential clutter random distribution assumed, different modifications of the CFAR detector were examined along the fast-time dimension, which indicated that order statistics CFAR (OSCFAR) provides more reliable decision than the others. Note that good detection results of the above experiments with the conventional CFAR methods are obtained under the condition that clutters are sufficiently mitigated.

Generally, clutter mitigation methods like EABS work well, if the received stationary clutters are stable. However, in real applications, non-ideal sampling clock at the receiver gives room for sampling offsets referred to as timing jitter, which usually is modeled as a Gaussian random process. The fact that impulse TWR employs pulses with very narrow width makes the sensitivity to timing jitter significant. Common timing jitter inaccuracy with jitter root-mean-square between 10 ps and 150 ps[24] is large enough to destroy the amplitude and delay stability of stationary clutters. Consequently, the residual clutters are almost inevitable in the clutter mitigation result. In the fast-time dimension, residual clutters could be strong enough to introduce false alarms with the conventional CFAR methods. However, in the slow-time dimension, for a specified range, the relative variation of residual clutters is generally smaller than that of human target moving in and out. Based on this fact, we assume the samples in each range cell obey a discrete time Gaussian random distribution and propose a new CFAR method along the slow-time dimension for moving target detection (MTD). The method can effectively relieve the false alarms introduced by residual clutters and obtain robust detection.

2. RADAR SYSTEM

The impulse TWR is a portable real-time mono-static 1-D system with two co-located Archimedean spiral antennas. Figure 1 shows its block diagram. The radar consists of antenna module, transmitting and receiving module, and data acquiring, processing and displaying module. Both transmitting and receiving are controlled by frequency synthesizer and timing controller (FSTC). At the transmitter, the TWR transmits a series of first-order Gaussian pulses, about 2 ns in width, as shown in Fig. 2(a). Figure 2(b) plots the frequency spectrum of the transmitting pulse, which ranges in 375~1125 MHz. The pulse transmitting frequency is 1000 Hz. At the receiver, the sampling rate is 8 GHz, and every 500 pulses are averaged to improve the signal-to-noise ratio (SNR) of the received signal[19]. Consequently, the pulse repetition frequency (PRF) equals 20 Hz, corresponding to pulse repetition period (PRP) T_p = 0.05 s.

During working, the impulse TWR remains immobile and the recorded echo pulses are aligned to each other, creating a 2-D matrix as shown in Fig. 3. In the measured data matrix, the fast-time dimension is related to the echo time delay corresponding to the measured range, and the slow-time dimension is related to the measured pulse number.

3. TARGET DETECTION

3.1 Clutter Mitigation

In comparison with the antenna coupling, wall clutters and strong ambient clutters, the echoes reflected by human body are fairly low. In addition, the high signal attenuation of walls

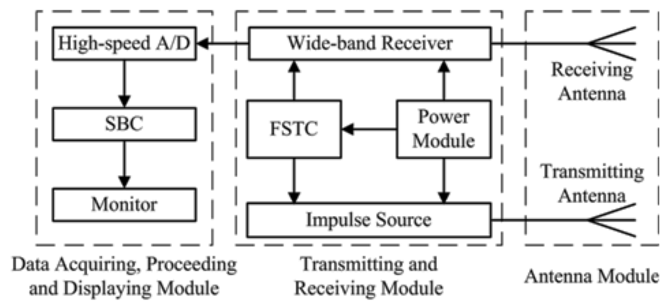
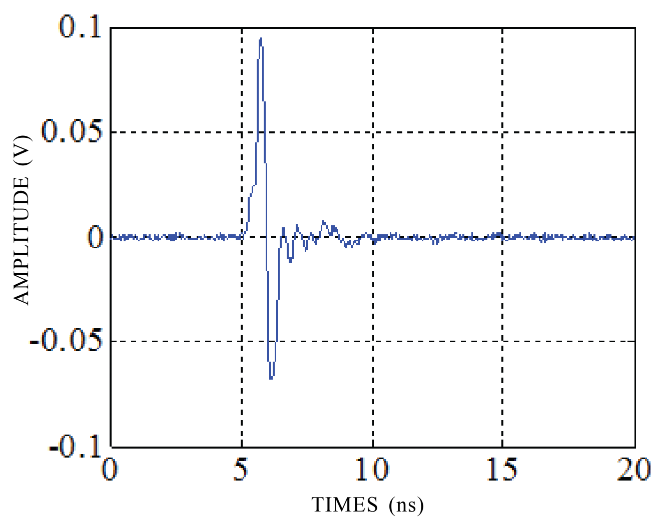
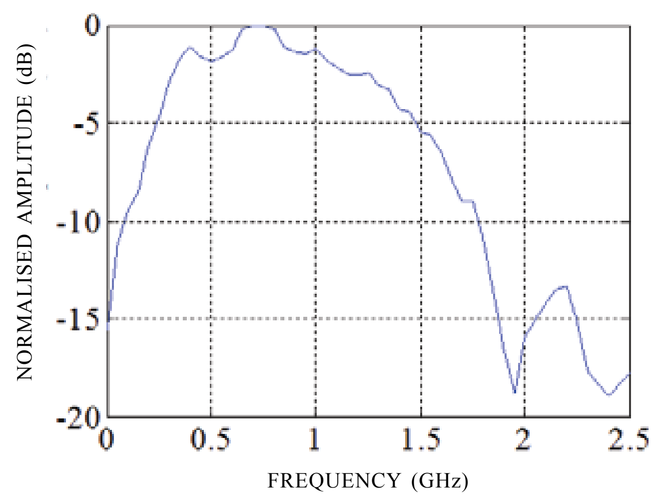


Figure 1. Block diagram of the impulse TWR.



(a)



(b)

Figure 2. (a) Time-domain waveform and (b) frequency spectrum of the transmitting pulse.

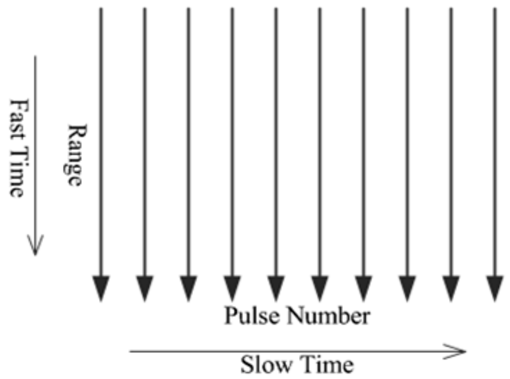


Figure 3. Sketch map of the measured data matrix.

further weakens human target echoes. As a result, the SCR is too low to be applicable for detection. We adopt the EABS method to combat clutters and improve SCR before detection.

In the background subtraction paradigms, background data is estimated first with previous pulses and then subtracted from the current pulse to indicate targets. As to EABS[21], previous pulses are weighted by exponential coefficients to estimate the background data. For a specified mth range cell, let $x(m, n)$ denote the n^{th} sample, and $b(m, n)$ denote the estimated background, then the output of EABS is

$$y(m,n)=x(m,n)-b(m,n)=x(m,n)-\sum_{i=1}^{n-1}\alpha^{i}x(m,n-i) \tag{1}$$

where α $(0 < \alpha < 1)$ is the constant scalar weighing factor. Larger α will retain more low components in the output of EABS[22]. Note that the background estimation in EABS can be rewritten in a recursive form as

$$b(m,n)=\alpha b(m,n-1)+(1-\alpha)x(m,n) \tag{2}$$

Obviously, background can be updated pulse by pulse. EABS makes use of all history information, and weights them by exponentially decreasing coefficients, which allows emphasizing of recent events, and gradually weakening of past data. Thus, EABS permits meaningful control over its clutter-reduction behavior.

3.2 The Proposed Method

Affected by timing jitters, residual clutters are inevitable. Thus, we consider the clutter mitigation output be made up of target echoes and residual clutters, ignoring the noise signals. Although clutter mitigation improves SCR and enhances the detectability, the residual clutters could be still comparable with human target echoes. In the conventional CFAR detection carried out along the fast-time dimension[23], for a tested range cell, the judgment of the target presence or not is made based on the comparison between the tested cell and its background threshold estimated by the tested cell's neighbors. Thereby, strong residual clutters could be easily misinterpreted as targets.

Note that the delay deviation of stationary clutters caused by timing jitters is generally smaller than one range cell. Therefore, in the slow-time dimension the relative variation of the residual clutters is generally smaller than that of human target moving in and out. For the range cell without human target, smooth variation results in a small deviation to the mean. By contrast, with moving human target, sharper variation will generate a larger deviation. This makes it possible to detect moving human target robustly with the CFAR method in the slow-time dimension.

Assume that the EABS output in each range cell obeys a discrete time Gaussian random distribution with time step T_p namely PRP. If the relative deviation between the tested cell and the mean of the Gaussian distribution is larger than a certain threshold, the decision of human target presence will be made, otherwise human target is considered absent. Consider a hypothesis test model as follow: As far as the sample $y(m, n)$ is concerned, if human target is absent (H_0), $y(m, n)$ obeys a Gaussian distribution with mean $\mu(m)$ and variance $\sigma^2(m)$; if present (H_1), $y(m, n)$ obeys a Gaussian distribution with mean $A + \mu(m)$ and variance $\sigma^2(m)$, where A is the amplitude of target echo. Consequently, the detection of the tested sample $y(m, n)$ becomes the problem of mean Gaussian-Gaussian assumption issue based on the Neyman-Pearson criteria[25], i.e.

$$y(m,n)\sim\begin{cases}N(\mu(m),\sigma^{2}(m)), & H_0\\ N(A+\mu(m),\sigma^{2}(m)), & H_1\end{cases} \tag{3}$$

Based on the above hypotheses, the probability of false alarm P_{FA} can be calculated as

$$\begin{aligned}P_{FA}&=P\left\{y(m,n)>T(m,n);H_0\right\}\\&=Q\left(\left(T(m,n)-\mu(m)\right)/\sigma(m)\right)\end{aligned} \tag{4}$$

where Q is the right tail probability function of the standard normal distribution, and $T(m, n)$ is the setup threshold. Let then

$$T(m,n)=\mu(m)+k\sigma(m) \tag{5}$$

$$k=Q^{-1}(P_{FA}) \tag{6}$$

where Q^{-1} is the inverse function of Q. We can find that P_{FA} only depends on the parameter k. If k is constant, the constant false alarm rate can be reached.

In the real processing, $\mu(m)$ and $\sigma^2(m)$ can be estimated and updated in real time by

$$\begin{aligned}\hat{\mu}(m,n)&=\frac{1}{n}\sum_{i=1}^{n}y(m,i)\\&=\frac{n-1}{n}\hat{\mu}(m,n-1)+\frac{1}{n}y(m,n)\end{aligned} \tag{7}$$

$$\begin{aligned}\hat{\sigma}^{2}(m,n)&=\frac{1}{n}\sum_{i=1}^{n}\left(y(m,i)-\hat{\mu}(m,n)\right)^{2}\\&=\frac{n-1}{n}\hat{\sigma}^{2}(m,n-1)+\frac{n-1}{n^{2}}\left(y(m,n)-\hat{\mu}(m,n-1)\right)^{2}\end{aligned} \tag{8}$$

where $\hat{\mu}(m,n)$ and $\hat{\sigma}^2(m,n)$ are the nth estimation of $\mu(m)$ and $\sigma^2(m)$ respectively. Given $\hat{\mu}(m,n)$ and $\hat{\sigma}^2(m,n)$, the threshold of the tested sample $y(m, n)$ can be calculated by

$$\hat{T}(m,n)=k\hat{\sigma}(m,n)+\hat{\mu}(m,n) \tag{9}$$

Then, the decision is made according to

$$C(m,n)=\begin{cases}0, & y(m,n)\le\hat{T}(m,n)\\ 1, & y(m,n)>\hat{T}(m,n)\end{cases} \tag{10}$$

If $y(m, n) > \hat{T}(m,n)$, then the tested sample $y(m, n)$ is considered as a point of interest (POI).

Notice the parameters $\mu(m)$ and $\sigma^2(m)$ are only related to the residual clutters, and have nothing to do with human target. If target echo is used to estimate the two parameters, large errors will be introduced, and the detection performance will be degraded. Thus, target echoes should be excluded when using the newly acquired data to update the estimated parameters. Namely, if target is present in the tested sample, $y(m, n) > \hat{T}(m,n)$, then

$$\hat{\mu}(m,n) = \hat{\mu}(m,n-1) \tag{11}$$

$$\hat{\sigma}(m,n) = \hat{\sigma}(m,n-1) \tag{12}$$

4. EXPERIMENTAL RESULTS

Employing the impulse TWR, we have carried out a series of through-wall experiments. In the experiments, the brick wall to penetrate is 30 cm thick, the exponential coefficient of the EABS is $\alpha = 0.95$, both the conventional OSCFAR method and the proposed method are adopted to process the data, and the desired probability of false alarm P_{FA} is set to 10^{-5}.

The geometry of the first experiment is shown in Fig. 4(a). The radar is setup close to the wall, one person is walking from 2 m to 30 m, and a metal cabinet is placed in range 15 m. Figure 5(a) shows the raw range profiles before processing. Both the human target and metal cabinet are invisible. As the range increases, the echo energy gradually decreases and obviously the antenna coupling and wall clutters are the strongest. Clutter mitigation result using the EABS method is displayed in Fig. 5(b). As we can see, clutters are greatly mitigated and human target is clearly visible. But with the presence of timing jitters, the residual antenna coupling and wall clutters are still considerable in the near range, and in the far range the residual cabinet clutters are comparable with the target echoes. Fig. 5(c) depicts the results processed by the conventional OSCFAR method along the fast-time dimension. Fortunately, the residual antenna coupling and wall clutters are not strong enough to cause false alarms in the conventional OSCFAR detection output, compared with the echoes in their

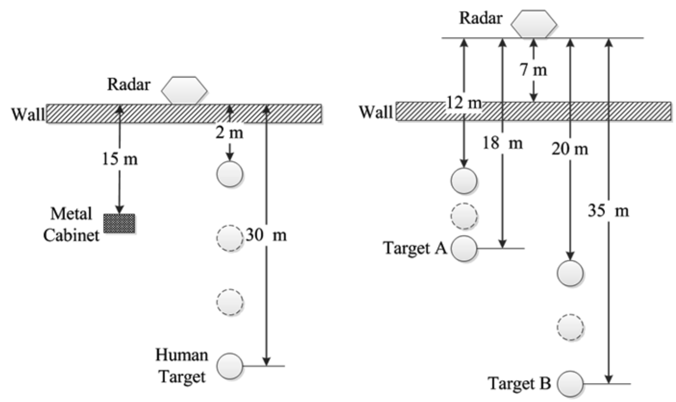


Figure 4. Geometry of (a) the first experiment and (b) the second experiment.

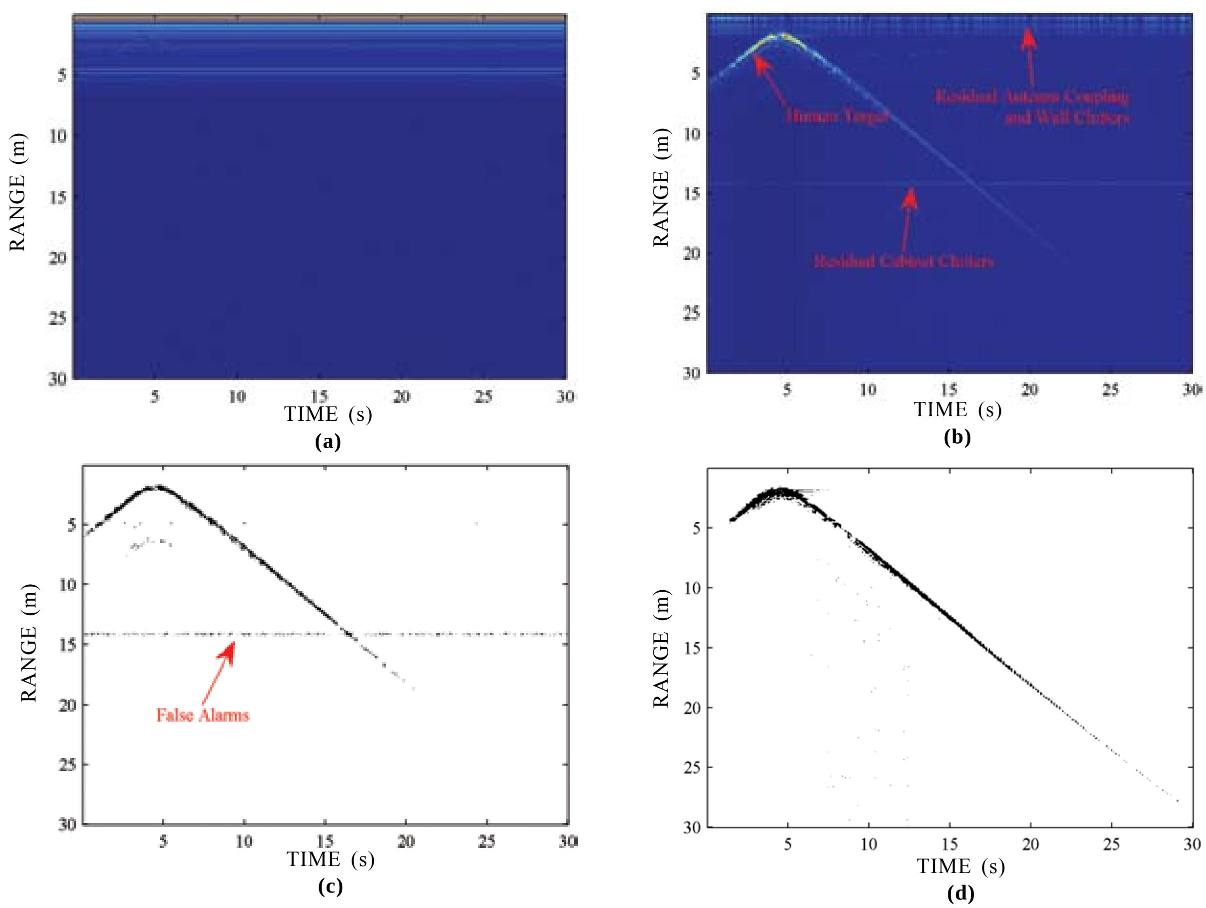


Figure 5. Exponential results of one person moving behind wall. Range profiles of (a) raw data and (b) EABS processing result. Detection results using (c) the conventional OSCFAR method and (d) the proposed method.

ambient range cells. On the contrary, in range 15 m, the weak residual cabinet clutters are strong enough to cause false alarms in the conventional OSCFAR detection output, in comparison with the even weaker echoes in their ambient range cells. Besides, in the range of 20-30 m, the conventional OSCFAR fails to detect the human target, due to the extremely low SNR, and the human target is lost. However, inspection of the processing result obtained by the proposed method in Fig. 5(d) shows that, both the residual clutters appearing in the near and far range are well mitigated, making the processing result free from false alarms. Simultaneously, the human target is robustly detected by the proposed method, even if the target moves in the range further than 20 m with extremely low SNR.

In the second experiment, two moving persons are considered, and the geometry is depicted in Fig. 4(b). The radar is setup 7 m away from the wall, Target A is walking in the range of 12-18 m, and Target B is in the range of 20-35 m. For the sake of better display of the results, the echoes in the range between the wall and the radar are discarded and only the range behind wall is shown. The raw range profiles are provided in Fig. 6(a). The two targets are masked by strong clutters. Fig. 6 (b) displays the EABS clutter mitigation result. The two targets are visible, but the residual wall clutters are more considerable than the echoes in their ambient range cells. As a result, the conventional OSCFAR method misinterprets the residual wall clutters to be a target and introduces false alarms in Fig. 6(c). Moreover, the conventional OSCFAR method fails to detect Target B in the range of 25-30 m because of the fairly low SNR. By contrast, as we can observe in Fig. 6(d), the proposed method not only gets rid of the residual wall clutters in the near range, but also robustly detects the two targets.

From the above two experiments, we can find that the conventional OSCFAR method has a poor performance on resistance of the residual stationary clutters caused by timing jitters and introduces too much false alarms. In addition, the detection performance degrades seriously in the far range with a low SNR. But with exploiting the information along the slow-time dimension, the proposed method achieves great improvement on the detection performance. It is able to effectively eliminate false alarms arising from the strong residual stationary clutters in different scenes. Moreover, even with a fairly low SNR in the far range, it can still obtain robust detection performance.

Note that the proposed method suffers from poor detection performance in the initial phase. This is because of few data available in this period, which results in serious errors in the parameter estimation. As the number of the collected echo pulse increases, the detection performance becomes robust. Besides, the proposed method seems more sensitive to noise signals than the conventional OSCFAR method, and introduces more speckles in the processing result. These speckles can be effectively removed by the median filter.

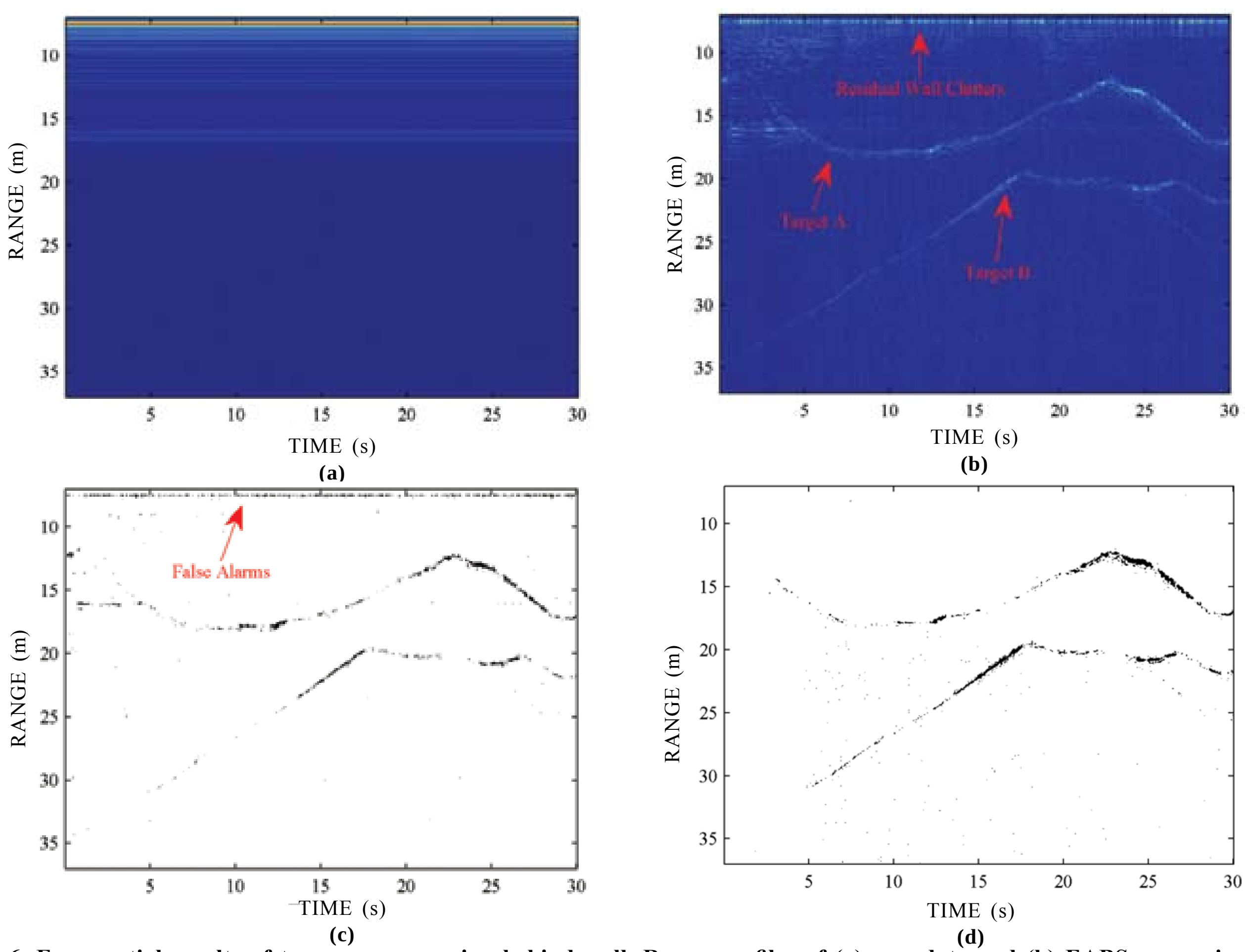


Figure 6. Exponential results of two persons moving behind wall. Range profiles of (a) raw data and (b) EABS processing result. Detection results using (c) the conventional OSCFAR method and (d) the proposed method.

5. CONCLUSION

In this paper, we concentrate on the through-wall moving human target detection. We developed a real-time 1-D impulse TWR. In order to obtain predictable and robust detection efficiently, firstly we consider the EABS method to improve the SCR. However, timing jitters make the residual clutters in the clutter mitigation output inevitable. This problem cannot be solved by the conventional CFAR methods implemented along the fast-time dimension, and false alarms occur. Fortunately, in the slow-time dimension the relative variation of residual clutters is smaller than that of human target moving in and out. Then, based on this fact, we assume the samples in each range cell obey a Gaussian random distribution and propose a new CFAR detection method which is implemented along the slow-time dimension pulse by pulse efficiently. Finally, different experiments are conducted and comparisons show that the proposed method is able to effectively resist the residual clutters, and obtain a robust MTD performance.

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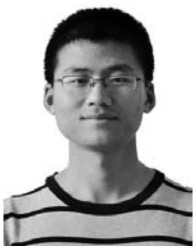

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