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Signal Processing Algorithm for Detection of Two concealed Targets

Sajjad Ahmed[1*], Muhammad Ali Bijarani[2], Imran Khan Keerio[3], Syed Qutaba[4], Muhammed Juman Jhatial[5]
[1]Department of Computer Science, The University of Larkano, (TUL), Larkana, Sindh, Pakistan
[2]Department of Electrical Engineering, Quaid-e-Awam University of Engineering, Science and Technology (QUEST) Nawabshah, Pakistan
[3]Departement of Computer Science, Sindh Madressatul Islam University, Karachi Pakistan
[4]Department of textile Engineering, BUITEMS, 87300, Quetta, Baluchistan, Pakistan
[5]Department of Computer Science, Shah Abdul Latif University, Khairpur Mir's, Sindh, Pakistan

Email: dr.sajjad@uolrk.edu.pk

ABSTRACT:

This study emphasizes the development of a signal processing algorithm for detecting concealed targets behind a wall using Synthetic Aperture Radar (SAR) data. Backscattered signals were generated through a simulation model in CST Studio Suite, where two targets of dimensions 5 × 5 cm² and thickness 1.5 cm were positioned behind a standard wall and scanned with a co-located Ultra-Wideband (UWB) antenna system. These signals were then analyzed using MATLAB which included an algorithm that has been developed to rebuild 2D images. To minimize noise and maximize target visibility, the algorithm will use a combination of the computation of the absolute values and a low-pass Finite Impulse Response (FIR) filter.. Findings indicate that the suggested processing system is able to effectively locate and visualize metallic and non-metallic hidden objects. Through the analysis of improving the signal algorithmically and reconstructing the images, the core contribution of signal processing to the development of through-wall detection technologies is emphasized, and the technology may find use in security, surveillance, and non-invasive imaging.

KEYWORDS: Signal Processing Algorithm, SAR, FIR, CST, UWB, TWI

1. INTRODUCTION

Through-wall imaging (TWI) is a novel research field because of its critical application in security, surveillance, search and rescue as well as military practice [1-3]. The main problem with TWI is not just to transmit electromagnetic (EM) signals across barriers, e.g. concrete, brick or drywall, but also to reconstruct the hidden objects by accurately interpreting distorted and noisy signals obtained as a result of backscattering [4]. Although Synthetic Aperture Radar (SAR) is generally known insofar as its ability to attain high-resolution images [5] with the help of the coherence processing and the formation of a synthetic aperture, the quality of the final image depends primarily on the efficiency of the signal processing algorithm to be used with the processed data. The processing of signals is the main component of TWI systems [6]. Radar echoes of ultra-wideband (UWB) antenna tend to be full of clutter, wall reflections and high levels of noise that hides the weak signals of hidden targets [7]. Noise suppression, clutter removal and target enhancement demand strong algorithms to tackle these issues a variety of modern clutter-suppression methods have been developed to overcome these issues. The data-driven decomposition algorithms like the Robust Principal Component Analysis (RPCA) and low-rank sparse separation have proven to significantly reduce the static wall clutter and rediscover weak target components in TWI

datasets [8]. These methods are particularly effective in cases where there is low-rank structure of the clutter and the targets are sparse As a complement to decomposition, digital filtering is an effective and commonly-used method: it has been shown recently that well-designed digital FIR filters can achieve success in cleaning up low-resolution MIMO radar systems with a carefully designed signal-to-clutter ratio, without filtering away information, before reassembling the image [9]. It is experimentally validated this type of filtering, that your algorithm relies upon, and has been demonstrated to be efficiently implementable in software/FPGA. The conventional methods of back-projection and delay-and-sum have been limited by the sidelobe contention and diminished resolution [10-12], which encourages the combination of the innovative methods like filtering, thresholding, and magnitude-based processing. An example is Finite Impulse Response (FIR) filters, which are often used to suppress undesired wall echoes whilst absolute value computation is employed to boost the magnitude response of the target especially when signal-to-noise is low. Besides the hardware settings and the antenna design, the sophistication of the further processing stage also determines the performance of the TWI systems. The simulation models such as CST Studio Suite make it possible to precisely model EM wave propagation and wall penetration, although the clear images can only be reconstructed with the use of sophisticated processing software. MATLAB offers a generalized system in which such custom algorithms can be implemented with filtering, calculation, and visualization being integrated into the system depending on the detection problem. In comparison, the current paper is concerned with a computationally efficient and lightweight alternative that integrates absolute-value computation (to increase magnitude) with FIR filtering (to eliminate clutter and noise) in digital form. The direct solution to this research gap, in between the abstractive and computation-intensive algorithms and the abstractive and low-resolution algorithms, is this absolute + FIR approach, which offers a balanced approach.

A signal processing algorithm that enhances the detection of a target in a through-wall imaging with the SAR data is the area of interest of this study. The CST Studio Suite was developed as a simulation model, that had two hidden objects behind a wall, backscattered signals recorded at a wall at one UWB antenna system. The signals were processed in MATLAB using an algorithm that combines absolute value computation with a low-pass FIR filter to suppress clutter and reconstruct clear two-dimensional (2D) images. By placing emphasis on algorithmic enhancements, this research highlights the central role of signal processing in improving the accuracy and reliability of TWI systems, enabling effective detection of both metallic and non-metallic targets in complex environments.

2. THROUGH WALL SIMULATION MODEL (TWSM)

The signal was done on MATLAB and an algorithm that integrates the absolute value calculation with a low-pass FIR filter took the signal to eliminate clutter and recreate clear two-dimensional (2D) images. Focusing on the algorithmic improvements, this study draws the focus on the central role of signal processing in enhancing accuracy and reliability of TWI systems, which allows detecting both metallic and non-metallic objects in complicated settings.

The TWSM model was designed based on CST Microwave Studio (CST MWS) [13-16] in this study as illustrated in Figure 1. The CST MWS is an effective electromagnetic analyzing instrument that allows the design, analysis and optimization of a wide range of electromagnetic systems. The model is divided into three main layers the first layer will include an Ultra-Wideband (UWB) antenna, namely a Slotted Antipodal Vivaldi Antenna (SAVA), which is reported in [17]. The SAVA has been experimentally demonstrated to be excellent in its electromagnetic (EM) performance and it is therefore quite useful in high-resolution imaging processes. The millimeters were used to optimize the SAVA dimensions as they were summarized in Table 1. The SAVA layouts are of various designs, as depicted in Figure 2 that depicts its geometrical design. Transmission and reception of EM signals in this model is done by the use of SAVA. The second layer is the wall, which is modeled as a dielectric slab with the same thickness dz and relative permittivity εr ε0, and which is a representation of a concrete medium. The third layer is the free space, in which the target objects are put. Two targets were placed behind a concrete wall, 30 x 30 cm2, and the thickness of 25 cm, according to civil standards, in the simulation model, to detect and image them (Fig. 1). The

targets were simulated as dielectric blocks, which had a size of 5 x 5 cm2 and a thickness of 1.5 cm. The targets had a certain distance down-range to the wall which was referred to as dy (distance between the wall and the target). The antenna and the wall were spaced with a distance of 3 cm, which is the optimal distance. The system of the antenna was in the cross-range orientation and was centrally pointed to the targets. Scanning was performed in a Synthetic Aperture Radar (SAR) mode in resolution, in which the SAVA antenna was stepped through a linear direction that parallel the wall. The antenna positions were in the range of -100 (bottom of the wall), 0 (centre of the wall) and 100 (top of the wall).During every scanning step, the antenna sent and received the backscattered electromagnetic signals. The cross-range coordinate (x) was calculated based upon the position of scanning the antenna, and it varied with the movement of the antenna along the wall. The time delay of the received was used to calculate the down-range coordinate (y). The distance that the wave covers between the antenna and the target plus the reverse distance is known as signals. The propagation speed of the electromagnetic wave was used to reduce this time delay to a distance.

Table 1: presents signal processing techniques, their working principles, advantages, limitations, and relevance to the current study.

Ref.	Method	Principle	Advantages	Limitations	Relevance to Current Work
[19], [20]	Spatial Filtering / Beamforming	Applies spatial-domain weights to suppress wall echoes and enhance target signals (e.g., MVDR, adaptive beamforming).	Effective in suppr-essing coherent wall reflections; enhances angular resolution.	Requires large antenna arrays; sensitive to array calibration.	Provides background for spatial clutter mitigation; complements FIR filtering.
[21]	Subspace Projection / SVD Methods	Decompose signals into dominant (wall) and minor (target) subspaces using SVD or PCA. Wall clutter removed by orthogonal projection.	Strong clutter suppression; no prior wall model needed.	Computationally expensive; performance degrades when wall signature varies.	Benchmark for evaluating clutter removal efficien-cy.
[22]	Time-Gating / Range-Gat-ing	Removes near-range stong wall reflections by discarding early-time samples.	Simple and low-cost; effective for short ranges.	May eliminate near-wall targets; not adaptive.	Can be integrated as a pre-process-ing step before FIR filtering.
[23]	Space–Time Adaptive Processing (STAP)	Jointly processes spatial and temporal data to maximize signal-to-clutter ratio.	Excellent clutter suppression in dynamic scenarios.	High computa-tional cost; requires training data.	Future enhance-ment for adaptive clutter rejection.
[24], [25]	RPCA / Low-Rank + Sparse Decomposi-tion	Separates wall clutter (low-rank) from targets (sparse) using robust PCA or matrix decomposition.	Highly effective against strong static clutter; preserves weak targets.	Iterative, computa-tionally intensive; sensitive to parameter tuning.	Potential hybrid method with FIR pre-filtering for improved suppression.
[27], [28]	Compressed Sensing (CS)	Reconstructs high-resolu-tion images from undersampled data using sparsity priors.	Reduces data requirements; enhances image resolution.	Heavy computa-tion; depends on proper regulariza-tion.	Offers comple-mentary recon-struction strategy for future work.
[29], [30]	Matched Filtering /Delay-and -Sum (DS)	Coherently sums time-de-layed echoes to form an image; often uses windowing or weighting.	Intuitive and widely used; real-time capable.	Limited by sidelobes; sensitive to clutter.	Used as baseline imaging stage in this study
This Work	Digital FIR Filtering (Proposed Study Focus)	Applies low-pass FIR filter to suppress wall clutter and noise, followed by absolute value computation to enhance targets.	Low complexity; efficient; suitable for embedded or MATLAB implementation; effective for both metallic and non-metallic targets.	Fixed filter parameters may limit adaptability to varying walls.	Core technique of this study; validated for short-range TWI applications.

The following table 1 provides a critical analysis of different signal processing methods of through-wall imaging (TWI). Angular resolution is enhanced by spatial filtering and beamforming which needs large portiant arrays that are calibrated. Subspace projection (SVD/PCA) is an efficient clutter-rejection algorithm that does not model walls but requires a lot of computation. Time-gating is a low cost and easy method but it exposes the possibility of missing near-wall targetsSpace-Time Adaptive Processing (STAMP) is a good clutter rejection method but it is very expensive to compute. RPCA methods excel at separating static clutter from targets but demand precise tuning. Compressed Sensing enables high-resolution imaging from limited data but is computationally heavy. Matched Filtering remains a standard baseline for imaging despite clutter sensitivity. The proposed Digital FIR Filtering method combines simplicity and efficiency, offering effective clutter suppression for short-range TWI applications with minimal computational cost.

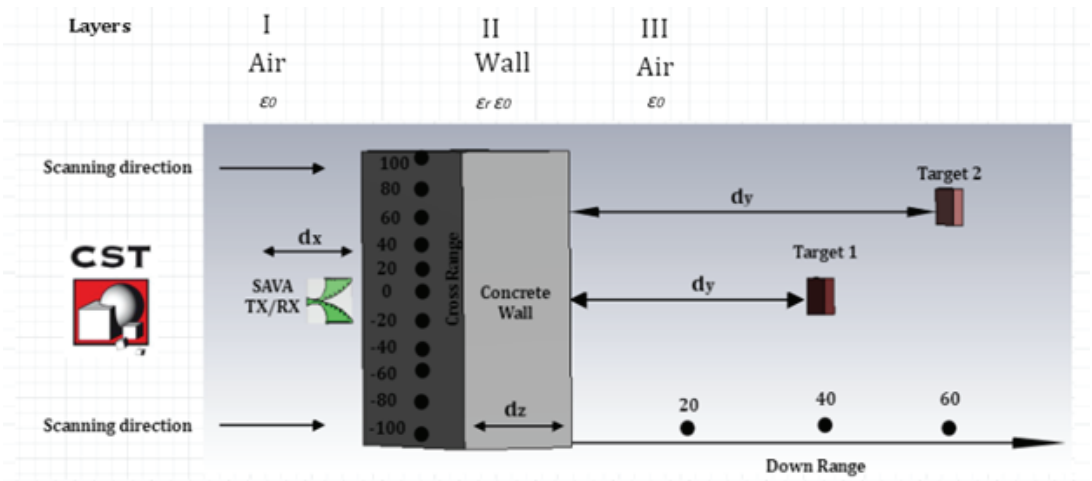


Figure 1: Through Wall Simulation Model

Table 1: Dimensions of SAVA

Parameters	Value (mm)	Parameters	Value (mm)
W	60.70	We	11.80
L	66.20	CS (1-6) (L & W)	2.50
D	27	RS (1-17) (W)	1
Wa	53	RS (1-17) (L)	2.80
Wc	4.60	RS (angle)	45°

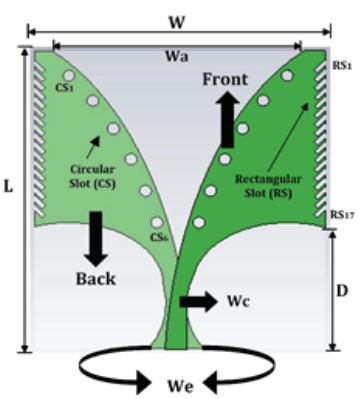


Figure 2: SAVA design

3. SIGNAL PROCESSING ALGORITHM

Once the received signals are obtained from the through-wall simulation model, the following signal processing algorithm is applied for target imaging. The overall block diagram of Signal processing algorithm is shown in Figure 3.The step-wise pseudocode of the signal processing algorithm has been provided.

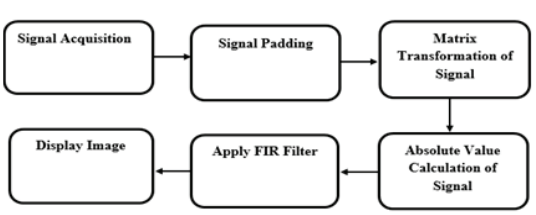


Figure 3: Block diagram of Signal Processing Algorithm

Signal Processing Algorithm

Input:
r_i[k] // Raw received signals, i = 1...M scans, k = 1...N samples
N_p // Padded length
h_f[n] // FIR low-pass filter coefficients
N_f // Final truncated length (e.g., 5500)
Output:
I(x, z) // 2D reconstructed image

Steps:

i. Signal Acquisition

The signal is calculated in an absolute sense. This transforms negative values into positive values and the signal magnitude becomes more important and the further treatment is simplified.
For each element (i, k): A[i][k] = |R[i][k]|

ii. Signal Padding

Padding is done to increase the length of scanning signals. This guarantees the uniformity in the data length which is prerequisite in the generation of uniform 2D images.
For each scan position i = 1 to M:
For k = 1 to N_p:
If k ≤ N:
r_pad[i][k] = r_i[k]
Else:
r_pad[i][k] = 0

iii. Matrix Formation

The padded signals are organized and put in a matrix format. With the help of this transformation, it is possible to generate a structured 2D picture of the target scene.
Construct matrix R of size M × N_p:
R[i][k] = r_pad[i][k]

iv. Absolute Value Computation

The absolute value of the signal is computed. This converts negative values into positive, emphasizing signal magnitude and simplifying further processing.
For each element (i, k):
A[i][k] = |R[i][k]|

v. Low-Pass FIR Filtering

A low-pass filter is used, a finite impulse response (FIR) filter. This minimizes noise, increases signal-to-noise ratio (SNR) and increases target detection accuracy. Signal length has been cut down to 5500 samples as opposed to 8000 samples. This eliminates undesirable reflections of the antenna. and the wall, and the clarity of the received signal is increased.
For each scan position i = 1 to M:
For k = 1 to N_p:
y[i][k] = 0
For n = 0 to (L - 1): // L = filter length
If (k - n) ≥ 1:
y[i][k] = y[i][k] + h_f[n] *A[i][k - n]

vi. Signal Length Reduction

For each scan position i = 1 to M:
For k = 1 to N_f:
Y[i][k] = y[i][k]

vii. Image Formation

The processed data is displayed as a 2D image of the targets at the back of the wall which makes the detection and interpretation clearer. Apply imaging operator: I(x, z) = ImagingOperator(Y)

viii. Return reconstructed image I(x, z)

4. RESULT AND DISCUSSION

Figure 4 illustrates the transmit signal of SAVA applied in the TWSM is a Gaussian pulse signal. This kind of pulse is widely applied in UWB systems because of its good characteristics, including the low energy dispersion in time and frequency. An incident wave in the CST MWS software that simulates and analyses the electromagnetic structures and behaviour of antennas uses the Gaussian pulse as the source of the incident wave. The pulse is defined by its brief pulse and wide frequency content making it cover the full UWB spectrum of 3 GHz up to 10 GHz. The first Gaussian pulse plays a critical role in making sure that the SAVA would be able to harness the broad frequency range. A good transmission has minimal distortion with a well-formed Gaussian pulse. Figure 5 illustrates the received signal of SAVA, which was measured in TWSM response in the air in the frequency range of 3 GHz to 10 GHz with the aid of time domain solver. In TWSM, after being transmitted, the Gaussian pulse spreads in the free space and the antenna then collects the pulse. The received signal has a number of different components, which include the direct signal, reflections, and potential multipath effects. The highest value was found in the range of 0.4-1.3 ns, which is the reflection caused by the emission of the radiations produced by the antenna in the free space. This reflection is a major property in the study of the behaviour of the UWB SAVA in the sense that it reflects to the interactions between the transmitted

EM wave energy and the surrounding environment and back to the antenna.

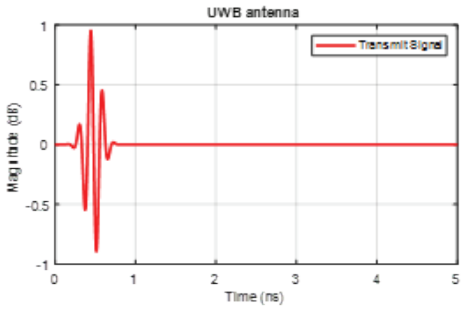


Figure 4: Transmit signal of SAVA in TWSM

The reflection and scattering effects can be understood with the help of the analysis of the received signal, especially the peak of the signal between 0.4ns and 1.3ns. This data is vital to the optimization of the design of the antennas, the enhancement of the signal clarity, and the reduction of interference. The time domain analysis of both transmit and receive signal gives useful information on the performance of the UWB antenna. Information on the radiation pattern of the antenna, its efficiency, and existence of any distortions or losses may be determined by the form and timing of the obtained pulse.

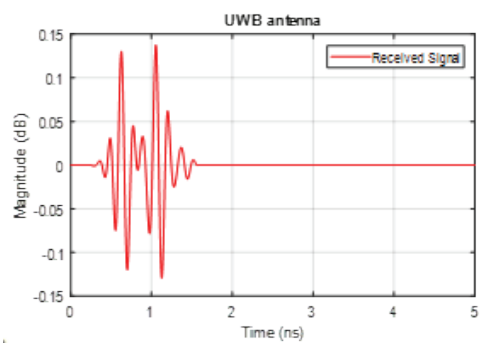


Figure 5: Received signal of UWB antenna in TWSM

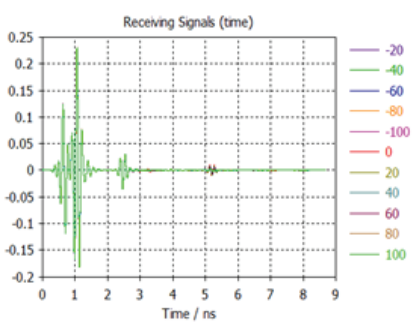


Figure 6: Benchmark of received UWB antenna signals in TWSM

The benchmark of the received UWB antenna signals as shown in Figure 6 is in the Through Wall Simulation Model (TWSM). The antenna response, (seen between 0.6 Ns and 1.1Ns) is the direct signal of the antenna, which can consist of reflections, emissions, calibration signals, or natural system noise. This reaction is significant in distinguishing between the signals that the antenna produces and those bounced back by the environment or other objects around the place. The wall response which is seen between 2.4ns and 2.5ns is due to reflection of the electromagnetic wave by the wall, which is sharp and narrow which has a time window. This response is critical to be accurately detected in order to remove reflections of the wall and improve objects detection behind the wall.. Lastly is the object detection response that lies between 5.15 and 5.28 ns and it refers to reflections of an object nearby and it will give a substantial information concerning the presence of the object, the distance and properties of the object. On the whole, the UWB antenna signals show distinctly separated response with antenna, wall, and object response, which proves that TWSM system is properly calibrated and can sense objects in high-resolution mode. This precise temporal differentiation ensures reliable through-wall imaging and effective object identification. In this study, imaging of both metallic and non-metallic targets behind a wall was performed using the developed signal processing algorithm. Figure 07 illustrates a 2D image of two metallic targets, where the y-axis (cross range) represents the distance of the targets with reference to the wall height, and the x-axis (down range) represents the position of the targets relative to the wall position. The figure shows two metallic targets located in the same plane at a down range of 60 cm, separated vertically by 6 cm. Figure 08 shows the imaging results of two non-metallic rubber targets positioned at down ranges of 20 cm and 40 cm, respectively. The vertical spacing between these targets is 10 cm. The imaging results confirm that the developed algorithm is capable of imaging of targets of different material compositions as well as at different down ranges. The clearer separation and visibility of both metallic and non-metallic targets demonstrate the algorithm's effectiveness for reliable through-wall target imaging. The developed Through-Wall Simulation Model (TWSM), in combination with the proposed signal processing algorithm, has demonstrated significant effectiveness in detecting and imaging

concealed targets. The key strength of the system lies in the algorithm's ability to enhance weak backscattered signals, suppress wall clutter, and reconstruct high-quality images. By integrating absolute value computation and a low-pass Finite Impulse Response (FIR) filter, the algorithm successfully reduced noise and wall echoes, thereby improving the visibility of concealed objects. The algorithm proved capable of detecting metallic targets located up to 60 cm behind a standard wall, confirming its robustness in handling attenuation effects caused by wall materials.

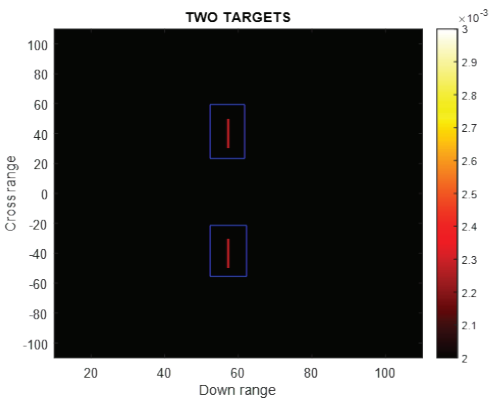


Figure 7: Two metallic targets at down range of 60 cm

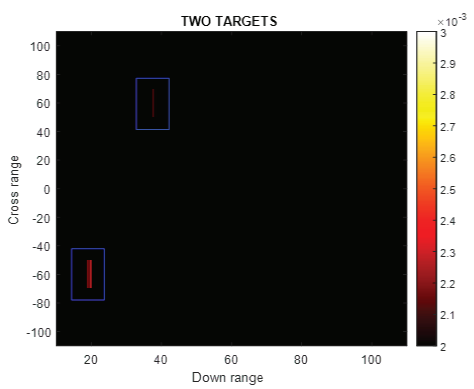


Figure 8: Two non-metallic targets at down range 20 cm and 40 cm

More importantly, the ability to resolve two closely spaced targets with a separation of only 6 cm highlights the fine cross-range resolution achieved through algorithmic processing. This shows that the algorithm is accurate in distinguishing between the close scatterers, which is also a widespread issue in through-wall imaging. In addition to metallic objects, the algorithm was also capable of detecting low-reflectivity non-metallic objects, including a rubber object, which is at a down-range of 40 cm. The obtained result suggests that the algorithm designed can be applied to a band of different concealed objects rather than exclusively to high-reflective objects, which increases the range of applicability.

5. CONCLUSION AND FUTURE WORK

This paper has introduced the design of a signal processing algorithm used in concealed target detection. The algorithm was written using MATLAB, and the absolute value calculation and low-pass Finite Impulse Response (FIR) filter were used to achieve the suppression of wall clutter, enhancement of target echoes, and reconstruction of 2D images. The findings establish that the decisive factor toward success in detecting the targets and the image clarity was the signal processing stage. Significantly, the algorithm was found to be able to detect metallic targets 60 cm behind a wall and with a fine cross-range resolution of 6-10 cm, pointing to the adaptability of the algorithm to non-high-reflectiveness targets, making the algorithm useful to a broader range of concealed targets. In general, the results indicate that the proposed signal processing algorithm is the major facilitator of a trustworthy short-range through-wall imaging, which is robust and precise. These findings are similar to those found by Arumugam et al. (2021), who have shown that digital FIR filtering is an effective method to prevent static clutter in MIMO radarThrough this, the current research further expands on this by demonstrating effective detection of metallic and non-metallic targets with enhanced spatial resolution, which extends the research of through-wall sensing technologies. The current task is to work on the future and improve the algorithm to achieve better penetration and faster processing, including adaptive filtering and machine learning algorithms to enhance target detection and clutter suppression. Also, the practical application on embedded systems and testing on various wall materials and environments will further make this research more important and useful.

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