

1-1-2010

Fuzzy logic-based image fusion for multi-view through-the-wall radar

Cher Hau Seng

University of Wollongong, aseng@uow.edu.au

Abdesselam Bouzerdoun

University of Wollongong, bouzer@uow.edu.au

Fok Hing Chi Tivive

University of Wollongong, tivive@uow.edu.au

Moeness G. Amin

Villanova University, mamin@uow.edu.au

Follow this and additional works at: <https://ro.uow.edu.au/infopapers>



Part of the [Physical Sciences and Mathematics Commons](#)

Recommended Citation

Seng, Cher Hau; Bouzerdoun, Abdesselam; Tivive, Fok Hing Chi; and Amin, Moeness G.: Fuzzy logic-based image fusion for multi-view through-the-wall radar 2010, 423-428.
<https://ro.uow.edu.au/infopapers/830>

Fuzzy logic-based image fusion for multi-view through-the-wall radar

Abstract

In this paper, we propose a new technique for image fusion in multi-view through-the-wall radar imaging system. As most existing image fusion methods for through-the-wall radar imaging only consider a global fusion operator, it is desirable to consider the differences between each pixel using a local operator. Here, we present a fuzzy logic-based method for pixel-wise image fusion. The performance of the proposed method is evaluated on both simulated and real data from through-the-wall radar imaging system. Experimental results show that the proposed method yields improved performance, compared to existing methods.

Keywords

multi, radar, fusion, wall, image, logic, fuzzy, view

Disciplines

Physical Sciences and Mathematics

Publication Details

Seng, C., Bouzerdoun, A., Tivive, F. & Amin, M. G. (2010). Fuzzy logic-based image fusion for multi-view through-the-wall radar. DICTA 2010: Digital Image Computing: Techniques and Applications (pp. 423-428). USA: IEEE.

Fuzzy Logic-Based Image Fusion for Multi-View Through-the-Wall Radar

C. H. Seng, A. Bouzerdoum and F. H. C. Tivive

School of Electrical, Computer and Telecommunications Engineering

University of Wollongong, Australia

{aseng, a.bouzerdoum, tivive}@uow.edu.au

M. G. Amin

Centre for Advanced Communications

Villanova University, USA

moeness.amin@villanova.edu

Abstract

In this paper, we propose a new technique for image fusion in multi-view through-the-wall radar imaging system. As most existing image fusion methods for through-the-wall radar imaging only consider a global fusion operator, it is desirable to consider the differences between each pixel using a local operator. Here, we present a fuzzy logic-based method for pixel-wise image fusion. The performance of the proposed method is evaluated on both simulated and real data from through-the-wall radar imaging system. Experimental results show that the proposed method yields improved performance, compared to existing methods.

1. Introduction

In remote sensing, image acquisitions from different viewing angles provide very different representations of the same scene. These multi-view images could then be fused to obtain a more informative composite image that maximizes the relevant information, while minimizing uncertainty and redundancy. Although the use of multiple views of the same scene has long been considered an advantage in computer vision, it is only recently that it is being considered for remote sensing approaches [1]. To date, most image fusion techniques for radar imaging are mainly applied to fuse images from different modalities, such as between optical and infra-red images [2, 3, 4, 5]. As a result, there have been very limited studies regarding the fusion of the same scenes, obtained from the same sensor, which is crucial to multi-view through-the-wall radar imaging (TWRI).

Multi-viewing for TWRI was first introduced by Wang and Amin [6] to correct for target displacements, due to the error caused by unknown wall parameters. It was suggested

that the fusion of images obtained from different standoff positions reveals the exact location of the targets. Similarly, Ahmad and Amin [7] suggested that the antenna array be moved around a building to improve indoor target detection and localization, since access is usually available to multiple sides of the enclosed structure under consideration. Hence, with the ability to collect data from multiple vantage points of a scene, fusing a set of multi-view TWRI images and generating a single reference image has become a topic of great interest in recent years.

Existing image fusion techniques for TWRI proposed by Amin *et al.* [6, 7] consist of simple arithmetic operations that perform pixel-wise addition or multiplication. Besides enhancing the overall contrast of the imaged scene [8], these methods proved to be the most practical for TWRI. This is due to the fact that there may be differences in indoor and clutter scattering characteristics between TWRI and other radar imaging paradigms, thus causing existing fusion methods to be invalid for TWRI [7]. While it is practical to consider a global operator for image fusion, it is desirable to have a local operator, which takes into consideration the differences between neighboring pixels.

Hence, in this paper, we investigate and introduce a new image fusion method that is suitable for multi-view TWRI, based on the fuzzy logic approach. The remainder of the paper is organized as follows. Section 2 outlines the proposed fuzzy logic image fusion approach. Section 3 presents its performances on the application to TWRI using both simulated and real data. Section 4 concludes the paper.

2. Fuzzy logic image fusion

Fuzzy logic is an extension of Boolean logic that provides a platform for handling indistinct boundaries of definition [9]. Therefore, fuzzy approaches are mainly used

when there is uncertainty and no mathematical relations are easily available. One of the major advantages of fuzzy logic over other existing fusion methods is that it permits the user to define the encoding directly by using linguistic labels as rules [2]. Since studies of fuzzy image fusion of the same scene and from the same sensor have been limited, we consider the application of fuzzy logic for pixel-level image fusion in multi-view TWRI.

2.1. Fuzzy Inference System

The fuzzy logic approach can be implemented through a Fuzzy Inference System (FIS) that formulates the mapping from multiple inputs to a single output. The inputs are first converted into linguistic variables using a set of predefined membership functions. In this fuzzification process, the degree of belonging of each input to an appropriate fuzzy set is determined. Then, the inference engine is invoked, where fuzzy operators are applied to the fuzzified input images, based on a set of pre-determined fuzzy rules. All the results are then aggregated and defuzzified to produce the final desired output.

Two commonly used FIS are the Mamdani and Sugeno fuzzy models. The main difference between these two models is that Mamdani outputs are constants, while the Sugeno model allows for a polynomial output. Since it is sufficient to obtain a constant as the output in pixel-wise image fusion, we will only consider the Mamdani fuzzy model in this paper. The flow chart of the Mamdani-type FIS with two inputs and one output is shown in Fig. 1.

2.2. Membership function

In order to determine the degree of belonging of each input pixel intensity to the appropriate fuzzy set, a set of membership functions will first need to be defined. A fuzzy membership function for a set of data X , can be defined as a mapping from $X \rightarrow [0, 1]$.

A typical through-the-wall radar image, with pixel values scaled from 0 to 255, could be segmented into four regions, namely the target, the target's sidelobes, the clutter and background noise. Therefore, we define the linguistic

variable as *region* and the linguistic terms or fuzzy sets as

$$U = \{background, clutter, sidelobes, target\}, \quad (1)$$

where each region represents a membership function. Empirical observations of radar images suggest that the pixel intensities generally range from 225 to 255 for the target region (R_t), 165 to 225 for the sidelobes region (R_s), 105 to 165 for the clutter region (R_c), and the remaining 0 to 105 for the background noise region (R_b), as shown in Fig. 2.

Since the image statistics of radar images used for multi-view fusion was adapted under the assumption of Gaussian distribution [10], we model the four regions as Gaussian curves. Hence, using the observed intensity ranges for each region, the membership functions can then be formulated as follows:

$$\mu_1(x) = e^{-\frac{x^2}{2\sigma^2}} \quad (2)$$

$$\mu_2(x) = e^{-\frac{(x-129)^2}{2\sigma^2}} \quad (3)$$

$$\mu_3(x) = e^{-\frac{(x-192)^2}{2\sigma^2}} \quad (4)$$

$$\mu_4(x) = e^{-\frac{(x-255)^2}{2\sigma^2}}, \quad (5)$$

where $\mu_i(x)$ for $i = 1, 2, 3, 4$ represents the membership function of the background, clutter, sidelobes and target regions, respectively. Here, we choose a standard deviation $\sigma = 30$, which is the minimum of R_t, R_s, R_c and R_b . Figure 3 shows the defined membership functions for the four regions, denoted as m_1, m_2, m_3 and m_4 .

2.3. Fuzzy rules

Instead of using a standard global operator that is similar to pixel-wise addition and multiplication, the fuzzy operator is implemented in the form of IF-THEN rules, for instance, IF variable IS property THEN action. Generally, the rule:

$$\text{IF } x \text{ IS } a \text{ AND IF } y \text{ IS } b \text{ THEN } z \text{ IS } c$$

can be represented as

$$I = a \times b \rightarrow c, \quad (6)$$

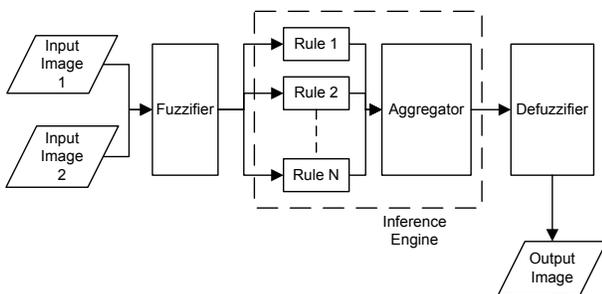


Figure 1. Flow chart of fuzzy fusion system.

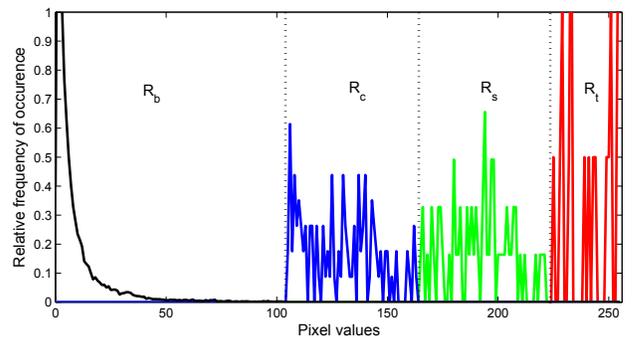


Figure 2. Relative histogram of the four regions.

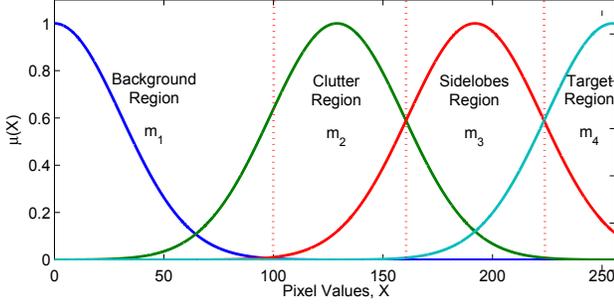


Figure 3. Four regions of a through-the-wall radar image.

where x is input 1, y is input 2, z is the output and a , b and c are the membership values.

Similarly for pixel-wise image fusion, the IF-THEN rules can be logically defined as "IF input pixel 1 IS background AND input pixel 2 IS background, THEN the output pixel IS background" for the background noise region. Correspondingly, the linguistic rule can be written as "IF input pixel 1 IS target AND input pixel 2 IS target, THEN the output pixel IS target" for the target region. Hence, with four membership functions and two input images, we define a set of ten non-overlapping rules, given as follows:

$$I_1 = m_1 \times m_1 \rightarrow m_1 \quad (7)$$

$$I_2 = m_1 \times m_2 \rightarrow m_1 \quad (8)$$

$$I_3 = m_1 \times m_3 \rightarrow m_2 \quad (9)$$

$$I_4 = m_1 \times m_4 \rightarrow m_4 \quad (10)$$

$$I_5 = m_2 \times m_2 \rightarrow m_2 \quad (11)$$

$$I_6 = m_2 \times m_3 \rightarrow m_3 \quad (12)$$

$$I_7 = m_2 \times m_4 \rightarrow m_4 \quad (13)$$

$$I_8 = m_3 \times m_3 \rightarrow m_4 \quad (14)$$

$$I_9 = m_3 \times m_4 \rightarrow m_4 \quad (15)$$

$$I_{10} = m_4 \times m_4 \rightarrow m_4, \quad (16)$$

where I_j for $j = 1, 2, \dots, 10$ is the j -th rule and m_k for $k = 1, 2, 3, 4$ denotes the four defined regions.

2.4. Aggregation and defuzzification

Once the results or consequents are determined for each input using the set of fuzzy rules, the individual outputs are then aggregated. Here, the maximum function:

$$\mu_A(x) = \max\{O_1, O_2, \dots, O_{10}\} \quad (17)$$

is used to unify the outputs, where $\mu_A(x)$ is the aggregated curve and O_j for $j = 1, 2, \dots, 10$ is the output of the j -th rule. The aggregated output is then defuzzified using the centroid of area (COA) calculation, given as

$$X_{COA} = \frac{\int \mu_A(x) x dx}{\int \mu_A(x) dx}. \quad (18)$$

The center of the area under the aggregated curve, given by Eq. 18, is the desired final pixel value.

3. Experimental results

The Fuzzy Inference System presented in Section 2 is implemented in MATLAB. Here, we evaluate the performance of the proposed fuzzy logic approach on multi-view through-the-wall radar image fusion, using both synthetic and real data. Three scenarios of multi-view TWRI are investigated and the results are compared with the existing additive and multiplicative fusion methods.

3.1. Synthetic multi-view TWRI data

The synthetic data are obtained by simulating a TWRI system of 57-element antenna array, based on the delay-and-sum beamforming algorithms [11, 12]. The scene of interests consists of three point targets located at $(0, 6)$, $(-2, 4)$ and $(2, 3)$ in an 8×8 m room. Two scenarios are investigated using synthetic data, where in the first scenario, the multi-view scenes are imaged by placing the antenna array at different standoff positions from the wall, as shown in Fig. 4 (a). Next, the antenna array is moved to different sides of the structure for imaging (Fig. 4 (b)).

3.1.1 Scenario 1: antenna arrays located at different standoff positions

The fusion of images of the same scene but obtained from different standoff positions allows the user to correct errors caused by unknown wall parameters. Therefore, in this scenario (Fig. 4 (a)), we simulate two images of the same scene obtained from different standoff distances. The first input image is obtained by placing the antenna array against the wall (0 m), and the second input image is obtained by moving the antenna array 1.5 m away from the wall. Figure 5 shows the simulated images obtained from the two different

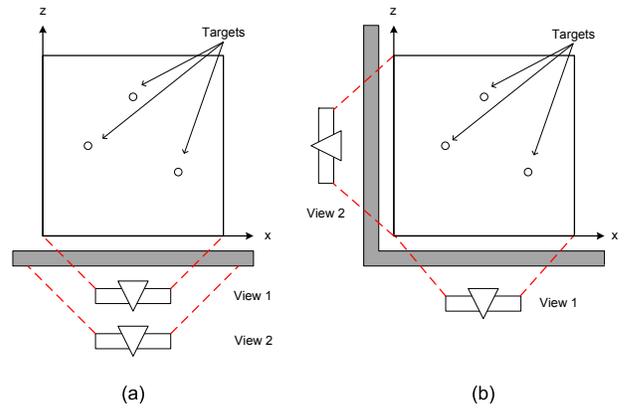


Figure 4. Multi-view scenes with antenna arrays located at (a) different standoff positions, and (b) different sides of the room.

standoff positions and the final fused results using the additive, multiplicative and the proposed fuzzy logic method.

It can be observed that the additive fusion method simply adds both images together. As a result, it tends to retain most of the background noise from both input images. While the multiplicative fusion method managed to reduce the background noise, the target intensities were also reduced. This is due to the fact that, when the pixels co-exist in the same location in both input images, these overlapping pixels will be enhanced through multiplication, while those non-overlapping pixels will be suppressed. In this scenario, it can be observed that the proposed method performed better than the two existing methods by producing a balanced output image that has the least amount of clutter, while maintaining strong target intensities.

3.1.2 Scenario 2: antenna arrays located at different sides of the room

In this scenario (Fig. 4 (b)), simulated radar images from different sides of the room are used as input images. This

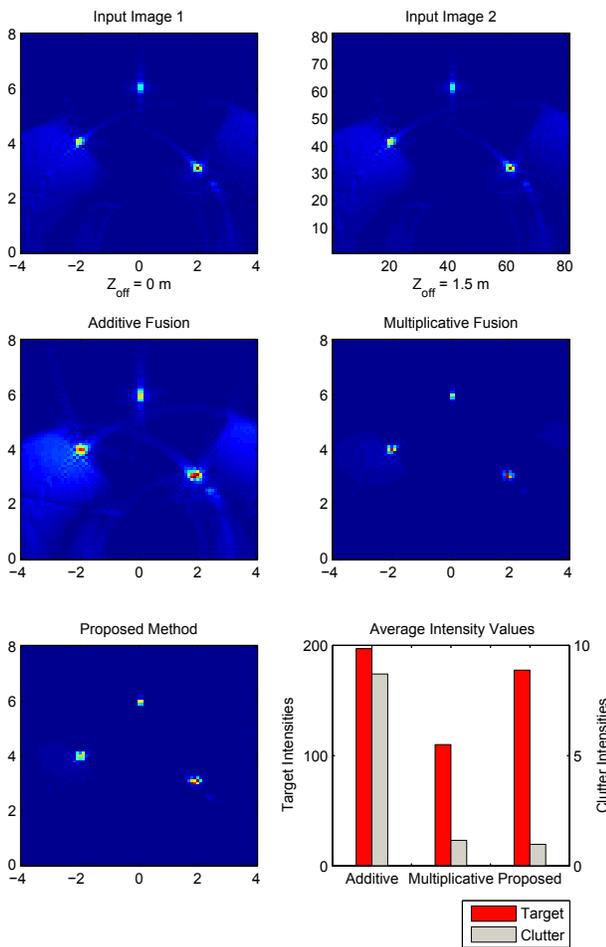


Figure 5. Experimental results using synthetic data for scenario 1.

is due to the fact that access is usually available to another side of the room or structure in typical TWRI cases. Therefore, the scene is first imaged from the front of the structure, followed by the movement of the antenna array to the side of the structure for imaging. Image registration is then performed on the input image obtained from the side of the structure. The simulated images after image registration and the final fusion results for the additive, multiplicative and proposed method are shown in Fig. 6.

Similarly, it can be observed that the additive method retained most of the clutter, while the multiplicative method reduced the intensities of both clutter and target in the final image. Again, it can be observed that the proposed method performed the best since it reduces the clutters while maintaining the target intensities.

3.2. Real multi-view TWRI data

With the successful application of the proposed method to synthetic data, the last scenario, as shown in Fig. 7, is experimented using real data, which was collected in a semi-controlled laboratory environment, based on the

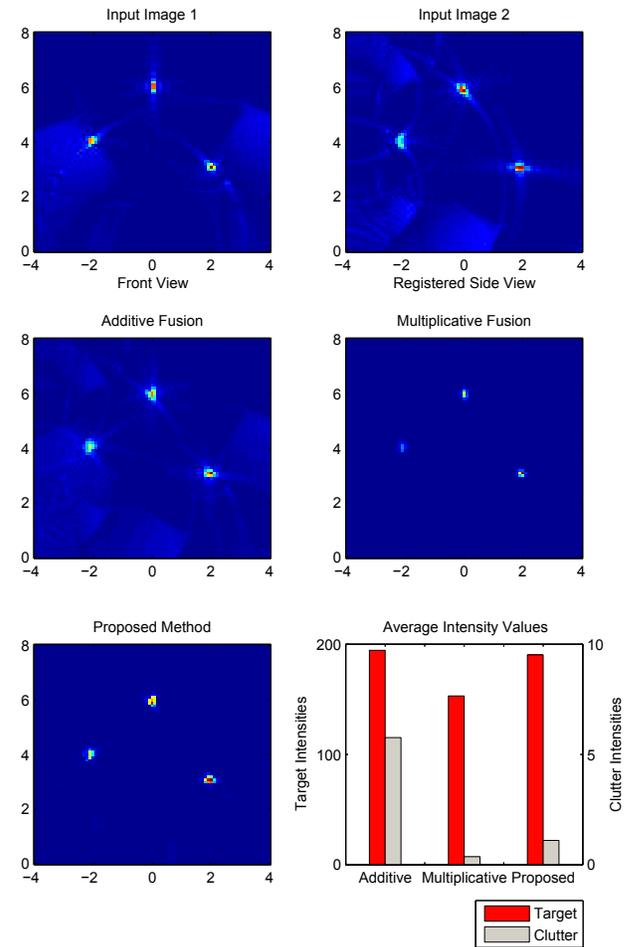


Figure 6. Experimental results using synthetic data for scenario 2.

TWRI methods presented by Ahmad and Amin [13]. Using a stepped-frequency radar system with waveforms of 2-3 GHz frequency range and a step size of 5 MHz, the data was collected from a populated scene, which consists of a jug of water, metal table, computer, file cabinet and several trihedrals, as shown in Fig. 8.

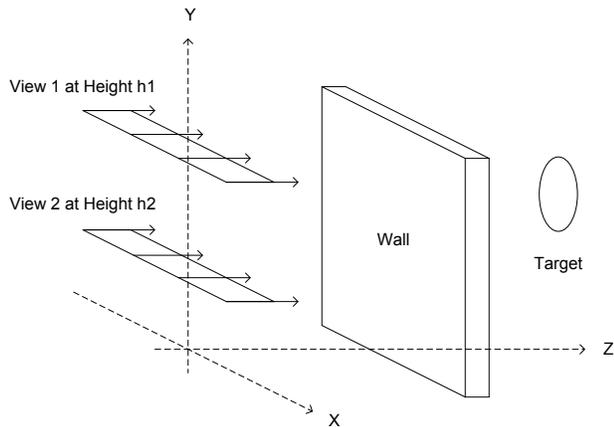


Figure 7. Multi-view scenes with antenna arrays located at different elevations.

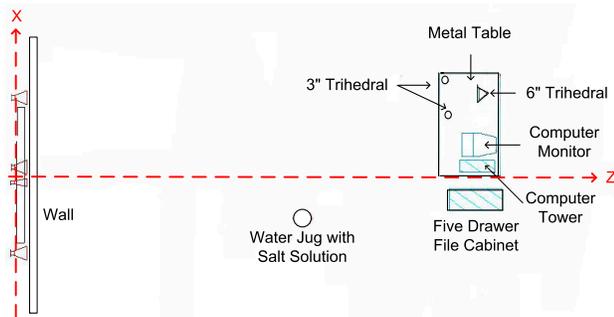


Figure 8. A populated scene (top view).

Since most objects, such as file cabinets, computer monitors and chairs, are usually higher than several centimeters in a general TWRI scenario, we investigate the fusion of images obtained from the same scene, but at two different elevations. Therefore, in this experiment, two views imaged at different elevations are fused, where the top view is approximately 2 cm higher than the bottom view.

Figure 9 shows the results of the experiment. Similar to the synthetic data experiments, it can be observed that the additive fusion method did not manage to remove the background noise. While the multiplicative fusion method managed to reduce most of the background noise, it is also obvious that the target intensities were degraded. For instance, the jug of water, which has a lower target return than the other metallic objects, is now less visible.

Conversely, it can be observed that the proposed method provides better result compared to the two existing methods

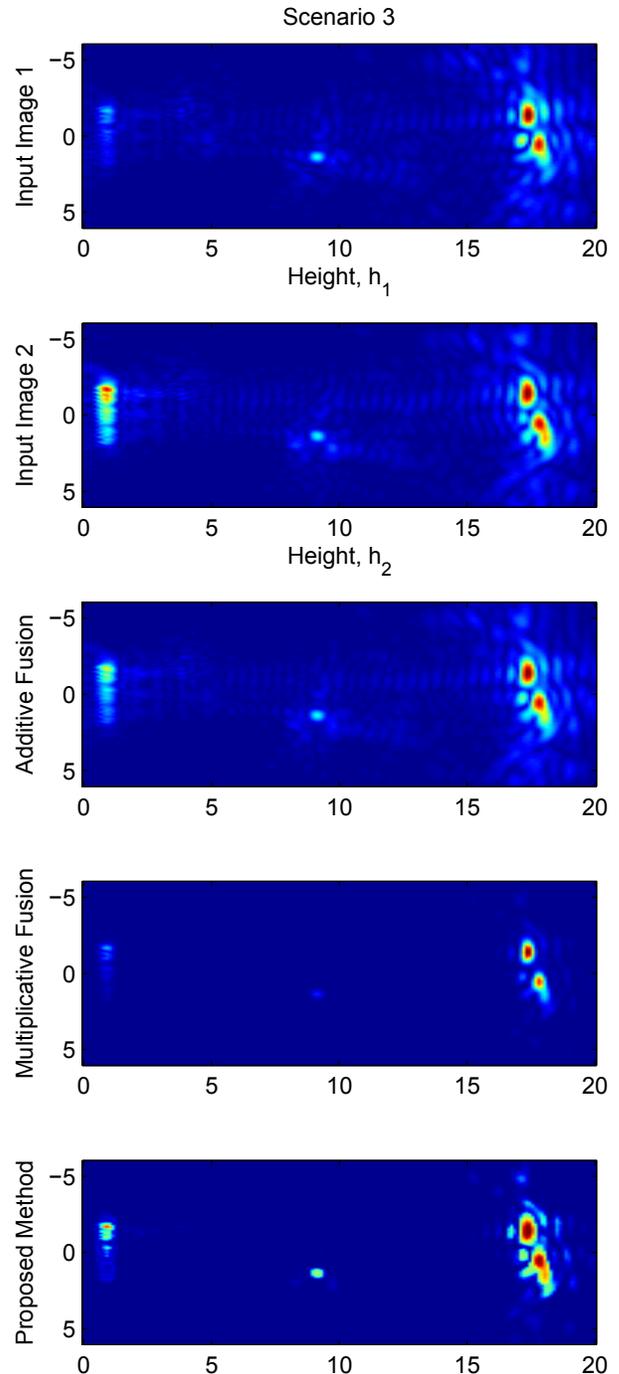


Figure 9. Experimental results using real data.

by removing all the background noise, while at the same time, enhancing the target intensities. A receiver operating characteristic curve for the additive fusion, multiplicative fusion and the proposed method, as shown in Fig. 10, further supports this observation, where the proposed method has a higher probability of detection rate, compared to both existing methods when the probability of false alarm rate is

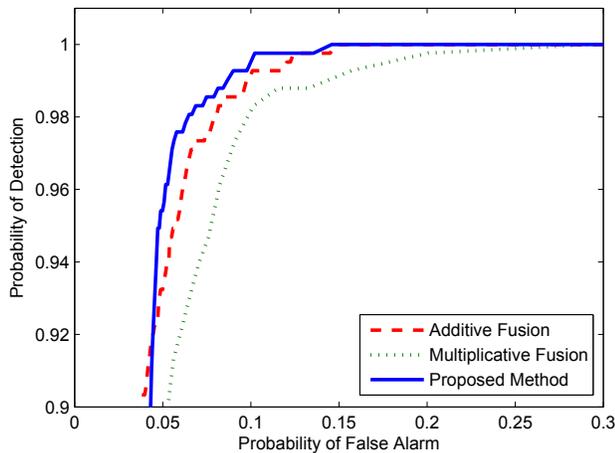


Figure 10. Receiver operating characteristic curve.

greater than 0.04.

In summary, the above experimental results show that the proposed fuzzy logic approach to pixel-wise image fusion for multi-view TWRI provided a balanced solution that further improves indoor target detection and localization.

4. Conclusion

In this paper, we have presented a new method for pixel-wise image fusion for multi-view TWRI that is based on fuzzy logic. Experimental results based on both simulated and real TWRI data are also presented, which demonstrate the effectiveness of the proposed method on pixel-level image fusion. In conclusion, the proposed method offers a balanced solution that enhances target intensities and reduces the clutter during the image fusion process.

Acknowledgments

Real TWRI data used in the experiments was provided by the Centre of Advanced Communications at Villanova University, USA. This work has been supported in part by a grant from the Australian Research Council.

References

- [1] P. Gamba, F. Dell'Acqua, and B. Dasarathy, "Urban remote sensing using multiple data sets: Past, present, and future," *Information Fusion*, vol. 6, pp. 319–326, 2005.
- [2] T. Meitzler, D. Bednarz, E. Sohn, K. Lane, D. Bryk, G. Kaur, H. Singh, S. Ebenstein, G. Smith, Y. Rodin, and J. Rankin II, "Fuzzy logic based image fusion," US Army TACON, Tech. Rep. 13818, 2002.
- [3] T. Meitzler, D. Bryk, E. Sohn, K. Lane, J. Raj, and H. Singh, "Fuzzy logic based sensor fusion for mine and concealed weapon detection," *Proceedings of SPIE*, vol. 5089, pp. 1353–1362, 2003.
- [4] Z. Mengyu and Y. Yuliang, "A new image fusion algorithm based on fuzzy logic," in *Proceedings of the International Conference on Intelligent Computation Technology and Automation*, 2008, pp. 83–86.
- [5] J. Saeedi and K. Faez, "The new segmentation and fuzzy logic based multi-sensor image fusion," in *Proceedings of the 24th International Conference in Image and Vision Computing New Zealand*, 2009, pp. 328–333.
- [6] G. Wang and M. Amin, "Imaging through unknown walls using different standoff distances," *IEEE Transactions on Signal Processing*, vol. 54, no. 10, pp. 4015–4025, 2006.
- [7] F. Ahmad and M. Amin, "Multi-location wideband synthetic aperture imaging for urban sensing applications," *Journal of the Franklin Institute*, vol. 345, pp. 618–639, 2008.
- [8] C. Pohl and J. Van Genderen, "Multisensor image fusion in remote sensing: Concepts, methods and applications," *International Journal of Remote Sensing*, vol. 19, no. 5, pp. 823–854, 1998.
- [9] A. Filippidis, L. Jain, and N. Martin, "Fuzzy rule based fusion technique to automatically detect aircraft in sar images," in *Proceedings of the First International Conference on Knowledge-Based Intelligent Electronic Systems*, 1997, pp. 435–441.
- [10] S. Papson and R. Narayanan, "Multiple location sar/isar image fusion for enhanced characterization of targets," in *Proceedings of SPIE*, 2005, pp. 128–139.
- [11] F. Ahmad, G. Frazer, S. Kassam, and M. Amin, "Design and implementation of near-field, wideband synthetic aperture beamformers," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 40, no. 1, pp. 206–220, 2004.
- [12] F. Ahmad, M. Amin, and S. Kassam, "Synthetic aperture beamformer for imaging through a dielectric wall," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 41, no. 1, pp. 271–283, 2005.
- [13] F. Ahmad and M. Amin, "Through-the-wall radar imaging experiments," in *IEEE Workshop on Signal Processing Applications for Public Security and Forensics*, 2007, pp. 1–5.