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Fusion of Through-the-wall Radar Images based on Probabilistic Fuzzy Logic

M.V. Praveen Kumar[1], B.Doss[2]

PG Student, Dept. of ECE, J.N.T.U.A.College of Engineering, Anantapur, AndhraPradesh, India [1]

Lecturer, Dept. of ECE, J.N.T.U.A.College of Engineering, Anantapur, AndhraPradesh, India [2]

ABSTRACT: Through-the-wall Radar Imaging systems are widely used in Remote sensing applications which are used to detect the presence of targets behind the obstacles. This work concentrates on the improvement of the image contrast of those TWR images by combining multiple radar images of the same scene to produce a more informative composite output image. The proposed fusion approach which makes use of the probabilistic fuzzy logic automatically forms the membership functions using the Gaussian-Galton mixture distribution. Galton distribution is also called lognormal distribution. The proposed approach won't use the processes like fuzzification and defuzzification which eliminates the subjective nature of the existing fuzzy logic methods. Experimentally, we can show that the proposed approach gives improved image contrast and enhances the target detection.

KEYWORDS: Through-the-wall Radar, Probailistic Fuzzy Logic, membership function, fuzzification.

I.INTRODUCTION

Through-the-wall Radar Imaging systems are widely used in many defence operations. TWRI systems are used in the Remote Sensing applications to detect the presence of targets behind the obstacles [1], [2]. Due to the unknown wall characteristics, multipath disturbances and various noises, the acquired radar images won't be that much clear which affects the target detection and localization.

During the process of sensing, the scene of interest may be imaged from the same angle but with different polarizations. The TWR images of the same scene with different polarizations are captured and combined to get a much better image which improves the target detection[3], [4]. Multiple TWR images which are differently polarized provide valuable information that a single TWR image can't provide [5], [6].

Till now, simple arithmetic fusion methods have been developed to improve the quality of TWR images [7]. First of all, additive fusion for TWR images is used in [8] to compensate the disturbances caused due to unknown wall characteristics. But the drawback of additive fusion is that it retains most of the clutter and background noise. Later, multiplicative fusion has been introduced in [9], [10] to enhance the polarimetric radar images. This approach also has a drawback that it tends to suppress the targets with weak intensities.

To address these problems and in order to improve target intensities while suppressing clutter, a technique has been proposed in [11], where the fuzzy logic approach has been used. Evaluation of the fusion methods has proven that the fuzzy logic based approach performs better than the already existing arithmetic fusion techniques.
But, like most fuzzy logic based fusion algorithms [12], [13], the method proposed in [11] requires manual selection of fuzzy membership functions calculated from the image intensity distributions. Since, different images are captured in different situations, their intensity distributions vary from image to image. Hence determining the optimal parameters for membership function formulation becomes time consuming.

In this work, we propose to use a method that makes use of both the probability and fuzzy logic. This hybrid technique called probabilistic fuzzy logic overcomes the shortcomings of the existing fusion techniques.
In the proposed approach, the image intensity distributions are modelled with a Gaussian-Galton distribution mixture and the fuzzy membership functions are selected automatically. By estimating he image intensity distributions with the

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Gaussian-Galton mixture, the probability of a pixel value belonging to different regions can be determined from which we can find the respective membership functions automatically.
In contrast with the existing fuzzy logic approach, the proposed approach does not require fuzzification and defuzzification processes. The formulated membership functions in the proposed approach are used as weights in the fusion process, where a weighted sum of arithmetic operators like addition, square root and maximum are applied to the input image pixels for fusion.

The performance of the proposed approach is evaluated using two parameters known as Improvement Factor in the target-to-clutter ratio (IF) and the Target Improvement Factor (TIF). Experimental results show that the proposed approach performs better than the existing methods improving the target intensities, which helps in the better detection of targets. Hence the proposed approach is used to enhance the performance of the target methods [14], [15].

II. EXISTING APPROACH BASED ON FUZZY LOGIC

This section concentrates on how the fuzzy logic based approach works to fuse two differently polarized TWR images. This is a pixel-level operation which makes use of a Fuzzy Inference System (FIS) that formulates the mapping from two inputs to a single output.
According to fuzzy logic, first of all, a set of linguistic variables are assumed and membership functions are to be defined. After that, the inputs are converted in to linguistic variables using a set of predefined membership functions. Fuzzification process is nothing but the determination of the degree of membership to a particular fuzzy set for each input. Then the fuzzy inference engine is invoked which performs the fuzzy operations on the inputs based on a set of predefined fuzzy rules. After that, finally, all the results are aggregated and defuzzified to get the final output. The flowchart of the fuzzy image fusion is shown in the fig.1

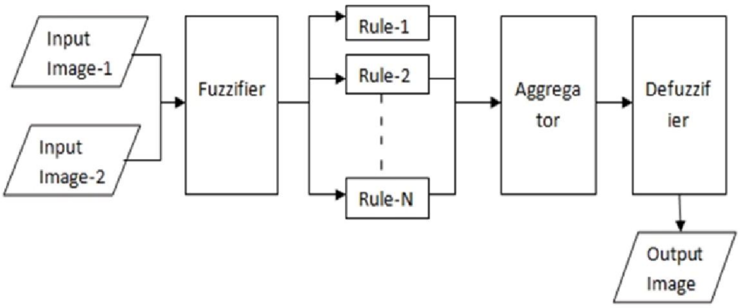

Fig.1. Flowchart of the fuzzy image fusion

A. Formulation of membership functions
In the fuzzification process, membership functions are formulated. A typical TWR image will have the pixel values ranging from 0 to 255 and can be divided into M regions based on our requirement. For the sake of discussion, here we have divided them into four regions namely targets, side lobes, clutter and background noise. Therefore, we can define the linguistic variable as region and fuzzy sets as

$$A = \{background, clutter, sidelobes, target\}$$

Here, each region represents a membership function. Based on empirical observations, the pixel intensities generally range from 225 to 255 for target region, 165 to 225 for sidelobe region, 105 to 165 for clutter region and the remaining 0 to 105 for the background region. The division of regions in a TWR image is shown in the fig.2.Each region is then formulated as a fuzzy set $\mu_i(x)$ using the Gaussian distribution as follows

$$f_m(x) = \mu_m(x) = \exp\{\frac{-(x-C_m)^2}{2\sigma_m{}^2}\}$$

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Where m = 1,2,3,4 corresponds to different regions
C_m is the mean value of the respective region
σ_m is the standard deviation and here we have chosen it to be 30
x is the pixel intensity value

Here $\mu_m(x_i)$ is the degree of membership to the fuzzy set $F_m(x)$. The value $\mu_i(x_i) = 1$ means that the intensity value x_i is fully a member of the ith fuzzy set, where as $0 < \mu_i(x_i) < 1$ indicates that x_n partially belongs to the fuzzy set F_i.

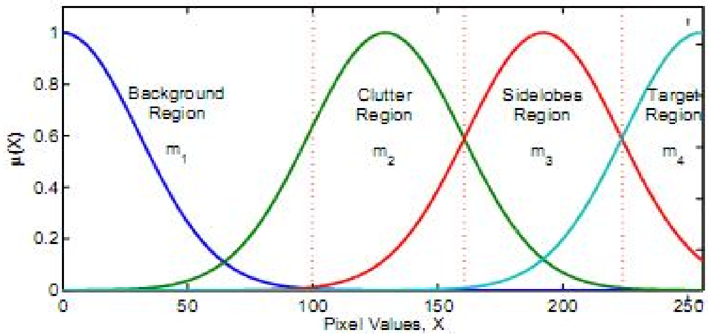

Fig.2. Four regions of a Through-the-wall Radar Image

B. Fuzzy Rules

Fuzzy rules are applied after fuzzifying the input images. In the previous methods like additive and multiplicative fusion, they have used a global operator for the entire fusion process. But here operators in the form of IF-THEN statements are applied to the fuzzified images based on a set of predefined rules. Consider two differently polarized input images X_1 and X_2 and our target is to get the fused output image Y. Let x_1 , x_2 and y denote the intensity values of a given pixel in X_1, X_2 and Y respectively. Then, the statement

(IF x_1 IS F_i) AND (IF x_2 IS F_j) THEN (y IS G_K)

TABLE I

An example of Fuzzy Rules for M Fuzzy sets and N Images, where M=4 and N=2

F_i \ F_j	F_1	F_2	F_3	F_4
F_1	G_1	G_1	G_3	G_4
F_2	G_1	G_2	G_3	G_4
F_3	G_3	G_3	G_3	G_4
F_4	G_4	G_4	G_4	G_4

In the fuzzy fusion operation, the aim is to maintain or enhance target regions and to suppress others. To achieve this, we define the output fuzzy sets as follows

$$G_k = \begin{cases} G_{\max\{i,j\}}, & if \max\{i,j\} > M/2 \\ G_{\min\{i,j\}}, & otherwise \end{cases}$$

Where M is the no. of membership functions, i.e., 4

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N is the no. of input images considered
And k=1,2,…….M
In such a case, there will be M^N fuzzy rules possible. The possible fuzzy rules in this situation are given in Table. I

C. Aggregation and Defuzzification

The consequent results are determined for each input using the set of fuzzy rules and the individual outputs are then aggregated. Here the max-min operator is employed to calculate the aggregate output membership function. Firstly, the consequent membership function for each rule is computed using the min operator $f_q(x)$ = min $\{\eta_q, f_k(x)\}$ where η_q is the firing strength given as

$$\eta_q = \mu_i(x_1) \wedge \mu_j(x_2), \quad q = 1,2,3\ldots\ldots M^N$$

and $f_k(x)$ is the MF of the output fuzzy set G_k
Then the overall output membership function is obtained by aggregating the consequent MFs using the max operator

$$f_A(x) = \max\{f_1(x), f_2(x), \ldots\ldots\ldots f_{M^N}(x)\}$$

Finally, the aggregated output is then defuzzified using the centroid of area (COA) rule given as

$$y = \frac{\int_{-\infty}^{\infty} f_A(x).x \ dx}{\int_{-\infty}^{\infty} f_A(x) \ dx}$$

Since, the fuzzy logic based fusion is a pixel level operation, the fusion process is repeated for each and every pixel in the input images.
Although, the existing fuzzy logic approach is successful, it requires manual formulation of membership functions by observing the pixel intensity distributions. Since the acquired images depends on different situations like unknown wall characteristics and environmental disturbances, determining the optimum membership functions for each and every different image becomes time consuming.

III.PROPOSED APPROACH BASED ON PROBABILISTIC FUZZY LOGIC

This section introduces a hybrid probability based approach for the fuzzy logic fusion that is intended to overcome the drawbacks of the existing approaches.
In this approach, the membership functions are automatically learned and the pixel intensity values are modelled with a Gaussian-Galton mixture. The degrees of membership to different regions are then used as weights in the fusion process and finally, a weighted sum of arithmetic operators is applied to the input images. The proposed technique uses an automated approach for the membership function formulation. We propose to use a Gaussian-Galton distribution mixture to model the probability density function of the TWR images. The number of mixture components 'K' is calculated using the Bayesian information criterion.
Generally, in a typical TWR image, the lowest intensity values are mostly due to the clutter or background noise and the high intensity levels belong to the target regions. Hence, obviously, there will be a low concentration of very high pixel values and high concentration of low pixel values. Here, the noise and clutter region with the low pixel values and the target regions with high pixel values are modelled using the Galton or lognormal distribution

$$P_{ln}(x) = \frac{1}{\sqrt{2\pi\sigma^2 x^2}} \exp\left(-\frac{(\ln(x)-v)^2}{2\sigma^2}\right), \ x > 0$$

and the remaining regions are modelled as Gaussian distribution

$$P_g(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-v)^2}{2\sigma^2}\right), \ x \geq 0$$

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The Gaussian-Galton mixture uses the Expectation-Maximization algorithm to estimate the mixture parameters like weights, mean and variance. The probability density function can be expressed as a weighted sum of the K class conditional pdfs given as

$$P(x) = \sum_{k=1}^{K} \omega_k P_k(x/\theta_k)$$

Where ω_k corresponds to the component weight and
θ_k represents the parameters, $\theta_k = (v_k, \sigma_k{}^2)$.

Before going into the process, we need to concatenate the two input images to find out a composite image X. Let x_i denote the ith pixel in the array X. The pixel values in the array X are ordered into a Q×1 vector lexicographically. Initially, the mixture components are estimated randomly from the intensity distribution of the composite input image X. Using the EM algorithm, the conditional pdf of the Kth mixture component $P_k(x,\widehat{\theta_k})$ is computed based on the current parameter estimate $\hat{\theta}_k$.

$$P_k(x,\hat{\theta}_k) = \begin{cases} \frac{1}{\sqrt{2\pi\widehat{\sigma_k}^2 x^2}} \exp\left(-\frac{(\ln(x)-\widehat{v_k})^2}{2\widehat{\sigma_k}^2}\right) u(x), & if\ k = 1 \\ \frac{1}{\sqrt{2\pi\widehat{\sigma_k}^2}} \exp\left(-\frac{(x-\widehat{v_k})^2}{2\widehat{\sigma_k}^2}\right), & if\ 1 < k < K \\ \frac{1}{\sqrt{2\pi\widehat{\sigma_k}^2 (255-x)^2}} \exp\left(-\frac{(\ln(255-x)-\widehat{v_k})^2}{2\widehat{\sigma_k}^2}\right) u(255-x), & \text{if k = K} \end{cases}$$

After computing the conditional pdfs, the posterior probability of class k, given pixel x_i is calculated as

$$\hat{P}_{k,i} = \frac{\widehat{\omega}_k P_k(x_i/\hat{\theta}_k)}{\sum_{k=1}^{K} \widehat{\omega}_k P_k(x_i/\hat{\theta}_k)}, \quad k = 1,2,\ldots K.$$

Then, the component weights $\widehat{\omega}_k$ and the parameter vector are then updated as

$$\widehat{\omega}_k = \frac{1}{Q}\sum_{i=1}^{Q} \hat{P}_{k,i},$$

$$\hat{v}_k = \begin{cases} 0, & if\ k = 1\ or\ K \\ \frac{1}{Q}\sum_{i=1}^{Q} \frac{\hat{P}_{k,i}\, x_i}{\widehat{\omega}_k}, & if\ 1 < k < K \end{cases}$$

$$\hat{\sigma}_k{}^2 = \begin{cases} \frac{1}{Q}\sum_{i=1}^{Q} \frac{\hat{P}_{k,i}\, x_i{}^2}{\widehat{\omega}_k}, & if\ k = 1\ or\ K \\ \frac{1}{Q}\sum_{i=1}^{Q} \frac{\hat{P}_{k,i}(x_i - \hat{v}_k)^2}{\widehat{\omega}_k}, & if\ 1 < k < K \end{cases}$$

These steps of computing the conditional pdfs, determining the posterior probability and updating the component weights and parameter vector are repeated until the relative change in the mixture parameter estimates is smaller than a tolerance $\varepsilon = 10^{-5}$.

Then the next step after obtaining the mixture parameter estimates $\widehat{\omega}_k$ and $\hat{\theta}_k$ is to combine the K components in the eq.10 to M regions to formulate the fuzzy membership functions of the input fuzzy sets. We assume that the kth component as the strong target region and (K-1)th component as the weak target region and (K-2)th component as the clutter\sidelobe region and the remaining (K-3) components are combined to form the background noise region.

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The membership functions for M regions are formed as

$$f_m(\mathrm{x}) = \begin{cases} \sum_{k=1}^{K-3} \frac{\hat{\omega}_k \ P_k(\mathrm{x},\hat{\theta}_k)}{P(x)}, & if\ m = 1 \\ \frac{\hat{\omega}_q \ P_q(\mathrm{x},\hat{\theta}_q)}{P(x)}, \ q = k - 4 + m, & if\ m = 2,3,4 \end{cases}$$

Then the formulated MFs are then evaluated with the input pixel values. The output of each of the above membership function is a degree of membership $\mu_m(x_i)$ associated with the pixel value x_i. The above membership functions are evaluated to produce the set { $\mu_1(x_i), \mu_2(x_i), \mu_3(x_i), \mu_4(x_i)$ }.
In the final step after calculating the M degrees of membership of each pixel, we propose to use a combination of arithmetic operators like multiplication, maximum and square root for fusion purpose to calculate the pixel value of the output image. Here, multiplicative operator is used to suppress the background noise, clutter and sidelobe pixels. We use maximum operator to maintain the pixel values in the weak target region and squareroot operator to enhance the pixel values in the strong target region.
Let us consider N input images$\mathrm{X}_1, \mathrm{X}_2, \ldots \ldots \ldots \mathrm{X}_\mathrm{N}$ and $x_{i,j}$denotes the ith pixel in the jth image. Here j* denotes the index of the largest pixel $x_{i,j}$ at the ith position for j = 1,2,…..N. The output pixel value is finally calculated as a weighted sum of the fused input regions given by

$$\mathrm{y_i} = \sum_{\mathrm{m}=1}^{\mathrm{M}} \mu_\mathrm{m}(\mathrm{x}_{\mathrm{i,j*}}) \ \mathrm{F_m}(\mathrm{x_{i,j}})$$

$$\text{Where } F_m(x_{i,j}) = \begin{cases} \prod_{j=1}^{N} x_{i,j}, & if\ m \leq 2 \\ x_{i,j*}, & if\ m = 3 \\ \sqrt{x_{i,j}}, & if\ m = 4 \end{cases}$$

In this way, the fusion process is repeated for each and every pixel in the input images.

IV.EVALUATION SCHEMES

In order to evaluate the performance of the fusion methods, we are using two performance metrics which are discussed below.
i.Improvement Factor in the Target-to-Clutter Ratio (IF)
The IF measures the overall enhancement of the output image

$$\mathrm{IF} = 10\log\left[\frac{\mathcal{P}_{\mathrm{target,output}} \ \mathrm{X} \ \mathcal{P}_{\mathrm{clutter,input}}}{\mathcal{P}_{\mathrm{target,input}} \ \mathrm{X} \ \mathcal{P}_{\mathrm{clutter,output}}}\right]$$

Let $\mathcal{P}_{\mathrm{r,q}}$ denote the average power of region ‘r’ in the image X_q , where ‘r’ is the target or clutter region and ‘q’ is the input or output image. Generally, average power $\mathcal{P}_{\mathrm{r,q}}$ can be expressed as

$$\mathcal{P}_{\mathrm{r,q}} = \frac{1}{Q_r} \sum_{(k,l)\in r} {X_q}^2(k,l).$$

ii.*Target Improvement Factor*
TIF concentrates specifically on the enhancement of the target regions and can be defined as

$$\mathrm{TIF} = 10\log\left[\frac{\mathcal{P}_{\mathrm{target,output}}}{\mathcal{P}_{\mathrm{target,input}}}\right]$$

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Where Q_r is the no. of pixels in the region 'r'. Here, X_q consists of either the original images to be fused or the fused image. Based on the performance metrics, we could compare and analyse different fusion techniques.

V. EXPERIMENTAL RESULTS AND DISCUSSION

For evaluation purpose, let us consider two differently polarized TWR input images. Proposed fusion process is performed on those two images to get the desired output. The output of the proposed approach is compared with the other techniques like additive, multiplicative, DWT, PCA and the existing fusion methods.

Fig.3 shows the input and output images produced by the fusion techniques like additive, multiplicative, DWT, PCA and the fuzzy fusion methods along with the proposed probabilistic approach. By observing the output images, we can observe that the additive fusion simply adds the two input images and retains most of the noise from the input images. The multiplicative fusion suppresses the noise and also it reduces the intensity of the target images. In the same way, DWT and PCA based fusion techniques also retains most of the noise.

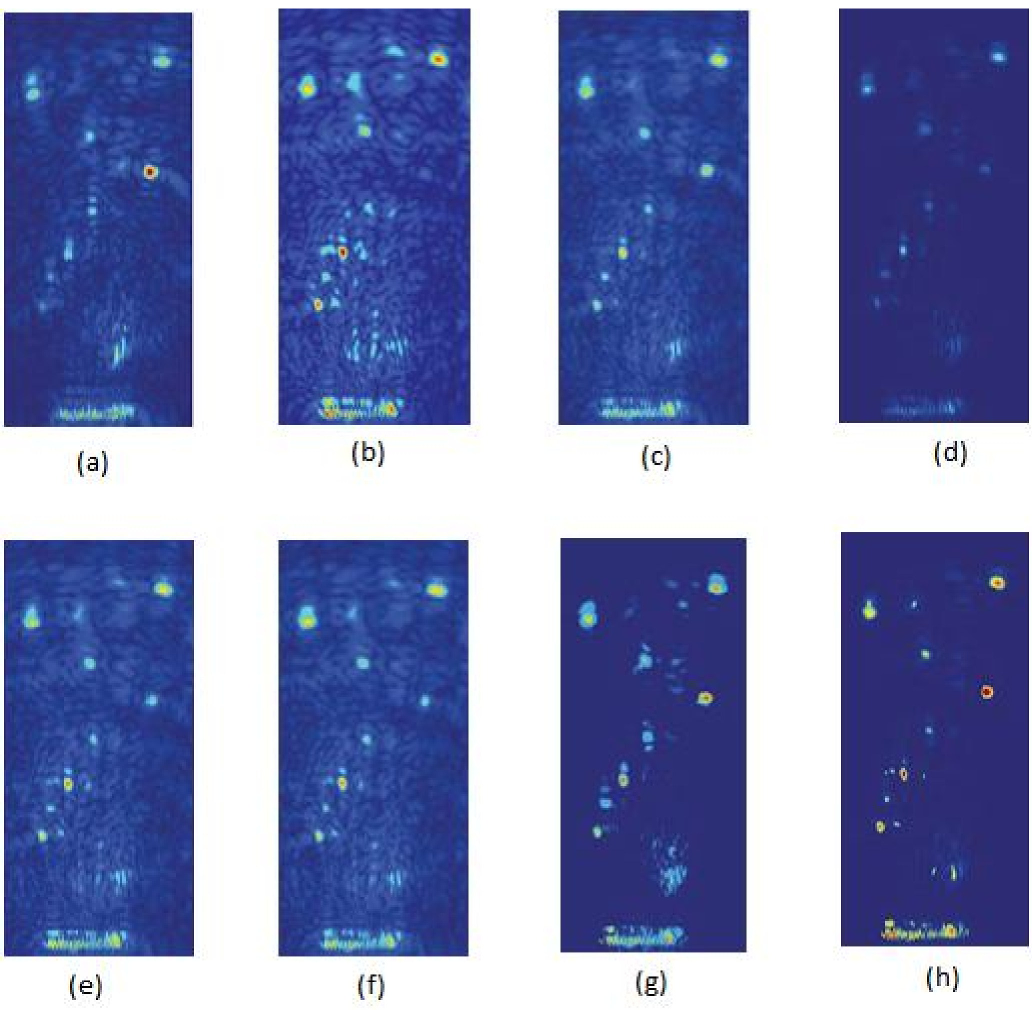

Fig.3. Image fusion results: (a) horizontal and (b) vertical polarization input images, and output images of (c) additive, (d) multiplicative, (e) DWT, (f) PCA, and the (g) existing and (h) proposed probabilistic fuzzy logic based fusion

IMPROVEMENT FACTOR IN THE TARGET-TO-CLUTTER RATIOS (IF) IN dB OF THE DIFFERENT IMAGE FUSION METHODS

Method	Horizontal polarization	Vertical polarization	Additive fusion
Additive fusion	-1.5624	1.1247	0
Multiplicative fusion	6.8542	9.5481	8.2463
DWT fusion	-1.8568	0.8569	-0.3758
PCA fusion	-1.7582	0.8054	-0.3859
Fuzzy fusion	4.8597	8.0625	6.6587
Probabilistic Fuzzy Fusion	10.3598	13.3450	12.1256

TABLE III
TARGET IMPROVEMENT FACTOR (TIF) IN dB OF THE DIFFERENT IMAGE FUSION METHODS

Method	Horizontal polarization	Vertical polarization	Additive fusion
Additive fusion	0.2135	-1.1253	0
Multiplicative fusion	-7.2138	-8.3652	-6.9546
DWT fusion	0.4563	-0.8564	0.1547
PCA fusion	0.5268	-0.9276	0.1589
Fuzzy fusion	0.4025	-0.8457	0.1258
Probabilistic Fuzzy Fusion	1.1458	0.0863	1.1548

Both the fuzzy logic based fusion techniques perform better than the other methods by maintaining the target regions and suppressing the noise regions. Comparatively, the proposed Gaussian-Galton mixture based fuzzy fusion gives better results than the existing fuzzy fusion technique.
If we want to emphasize on the clarity of target regions, TIF gives a better idea. TABLE.III shows the TIF values calculated for the output images of different fusion techniques. It shows that all the fusion techniques outperforms the multiplicative fusion because, it suppresses the target intensities.

VI.CONCLUSION

This paper proposes a probability based hybrid approach for fuzzy image fusion. It makes use of Gaussian-Galton distribution mixture along with EM algorithm to formulate the MFs automatically without human intervention. Experimental results show that the proposed approach is significantly effective for fusion of differently polarized TWR images.

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