

# A Novel Image Fusion Algorithm for Visible and PMMW Images based on Clustering and NSCT

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**Abstract.** Aiming at the fusion of visible and Passive Millimeter Wave (PMMW) images, a novel algorithm based on clustering and NSCT (Nonsubsampled Contourlet Transform) is proposed. It takes advantages of the particular ability of PMMW image in presenting metal target and uses the clustering algorithm for PMMW image to extract the potential target regions. In the process of fusion, NSCT is applied to both input images, and then the decomposition coefficients on different scale are combined using different rules. At last, the fusion image is obtained by taking the inverse NSCT of the fusion coefficients. Some methodologies are used to evaluate the fusion results. Experiments demonstrate the superiority of the proposed algorithm for metal target detection compared to wavelet transform and Laplace transform.

## 1 Introduction

A passive millimeter wave (PMMW) imaging system achieves images by detecting the difference of millimeter band energy that objects radiated, which has great performance in penetrating and excellence ability of recognizing a metal target from its surrounding environment [1]. Passive millimeter wave imaging system has large potential in the field of hidden objects detection because it is not harmful to humans [2]. However, the main difficulty in the PMMW imaging systems is low image quality due to wavelength, which cannot meet the demand of practical application. Considering the fact that even PMMW images with low pixel resolution still provide valuable information, it is deserved to combine it with a visible image to enhance the characteristic.

Image fusion is a process of generating a single fused image using a set of input images which are assumed to be registered. The image for fusion may be either the same scene at the same time different sensors acquired, the same sensor at different time period [3]. The resulting image will be more informative than any of the input

images.

The classical image fusion methods have weighted average, Wavelet fusion, Laplace fusion and NSCT fusion. NSCT has the characteristic of shift-invariant; therefore, this paper presents the application of it for image fusion. Before the image fusion, an image pre-processing which specifics to PMMW image is adopted. In this process, an image segmentation based on clustering is adopted. Figure 1 illustrates the diagram of image fusion scheme.

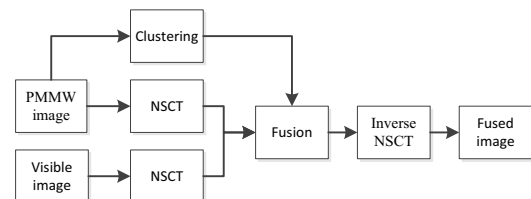


Figure 1. The diagram of fusion scheme.

## 2 Image segmentation based on clustering

Image segmentation is the process of partitioning a digital image into multiple segments. Several general-purpose algorithms and techniques have been developed for image segmentation, such as the method based on threshold segmentation [4].

Image segmentation based on clustering is relatively new image segmentation algorithm, which segmentation accuracy is higher than usual threshold method. Several clustering methods such as k-means clustering, fuzzy c-means (FCM) clustering and GMM (Gaussian Mixture Model) can be used to image segmentation [5, 6].

GMM is one of the most widely used model for statistical segmentation of PMMW images. In the GMM, the probability function is view as the combination of two or more normal Gaussian distribution [7]. GMM is a probabilistic model that assumes all the data points are generated from a mixture of a finite number of Gaussian distributions with unknown parameters; its expression can be defined as:

$$p(x) = \sum_{k=1}^K \pi_k N(x | \mu_k, \Sigma_k) \quad (1)$$

Where  $m$  is the number of models we used,  $\mu$  is  $D$ -dimensional mean vector,  $|\Sigma|$  means the determinant of the covariance matrix, and  $\pi_k$  is the mixing coefficients.

If sample category is not given, the concept of implicit variables is introduced to simplify the solution of model parameters. Suppose there are  $N$  data points, subject to certain distribution  $P_r(x; \theta)$ , trying to search a set of parameters  $\theta$  to make the probability of generating these data points maximum, the expression of this probability is called Likelihood Function, can be defined as:

$$P = \prod_{i=1}^N P_r(x_i; \theta) \quad (2)$$

$$\log p(X; \pi, \mu, \Sigma) = \sum_{i=1}^N \log \left\{ \sum_{k=1}^K \pi_k N(x_i; \mu_k, \Sigma_k) \right\} \quad (3)$$

In the formula (3),  $X = \{x_1, x_2, \dots, x_N\}$  represents the vector of observation, category  $z_k$  each sample  $x_i$  belongs to is unknown. Next, a method called EM (Expectation Maximization) algorithm is applied to search the best model parameters, which used to maximum the expectation showed in formula (3).

The process of EM algorithm can be viewed as two steps: E-step and M-step. As to E-step, it is under the assumption that the model parameters are given, and seeking expectation with implicit variable  $z$ .

$$\gamma(i, k) = P_r(z_k | x_i; \pi, \mu, \Sigma) \quad (4)$$

$$\gamma(i, k) = \frac{\pi_k N(x_i | \mu_k, \Sigma_k)}{\sum_{j=1}^K \pi_j N(x_i | \mu_j, \Sigma_j)} \quad (5)$$

For M-step, the maximum likelihood function derivative separately to mean, covariance, mixing coefficients, and put the result to zero, new expression of three parameters can be obtained:

$$N_k = \sum_{i=1}^N \gamma(i, k) \quad (6)$$

$$\mu_k = \frac{1}{N_k} \sum_{i=1}^N \gamma(i, k) x_i \quad (7)$$

$$\mu_k = \frac{1}{N_k} \sum_{i=1}^N \gamma(i, k) (x_i - \mu_k)(x_i - \mu_k)^T \quad (8)$$

$$\pi_k = \frac{N_k}{N} \quad (9)$$

To verify the clustering algorithm based on GMM can be used in millimeter wave image segmentation, a series of scene detection experiments is carried out; some PMMW image samples are obtained for the verification and analysis to the algorithm.



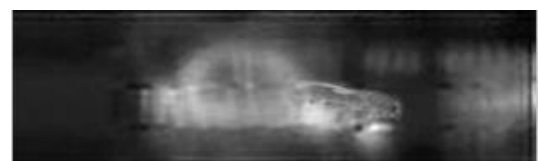
(a) PMMW image (b) Segmentation result

**Figure 2.** Person with two concealed targets



(a) PMMW image (b) Segmentation result

**Figure 3.** Person with one concealed target



(a) PMMW image with concealed car



(b) Segmentation result

Figure 4. The concealed car

As shown in Figure 2-Figure 4, image segmentation through GMM has a well segmentation result.

### 3 Image fusion based on NSCT

NSCT is a method of multi-scale decomposition which has the characteristic of shift-invariance. NSCT contains NSP (NonSubsampled Pyramid Decomposition) and DFB (Nonsubsampled Directional Filter Banks). In the multi-scale transform of pyramid transform, the high frequency image is acquired through upsampling or downsampling the filtered image and then subtract the higher level image, however, in that case, image will lost the characteristic of shift-invariant. Unlike pyramid transform, NSCT will not sample the image, but sample the filter. The filter of each level is obtained through sampling higher level filter. Each level's low-frequency sub-band image and high-frequency sub-band image are acquired by filtering the image with the resulting filter [8]. In the process of reconstruction, filters must satisfy to Bezout equation:

$$H_0(z)G_0(z)+H_1(z)G_1(z)=1 \quad (10)$$

$\{H_0(z),H_1(z)\}$  is the analysis filter,  $\{G_0(z),G_1(z)\}$  is the synthesis filter [9]. The NSP is shown in Figure 5.

DFB is a two-channel filter, it is the improvement of fan filter bank proposed by Bamberger and Smith, its analysis filters and synthesis filters also need to meet Bezout equation.

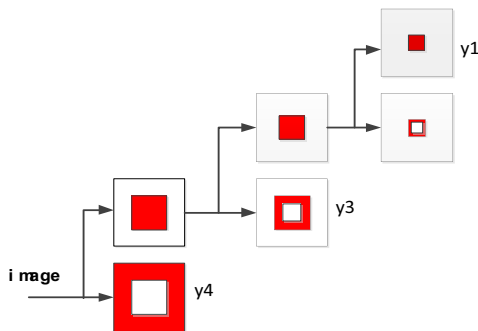


Figure 5. NSP with three stages

The NSCT is constructed by combining the NSP and

DFB as shown as Figure 6.

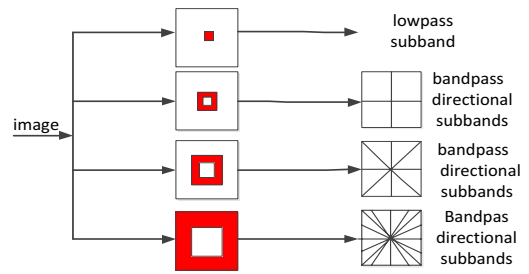


Figure 6. Segmentation map in frequency domain

This paper will take three times NSCT decomposition both to visible image and PMMW image, then separately fusion the sub-image with different fusion rule. The rule of absolute value is adopted for third layer's high frequency sub-images. Regional average gradient is used to fusion both first and second layer's high frequency sub-images. As for the low frequency images of third layer, a fusion criterion called regional variance is adopted in Article [10], the definition of regional variance is:

$$V^s(i, j) = \frac{1}{(M-1)(N-1)} \sum_{m=-(M-1)/2}^{(M-1)/2} \sum_{n=-(N-1)/2}^{(N-1)/2} \left| C^s(i+m, j+n) - \bar{C} \right|^2 \quad (11)$$

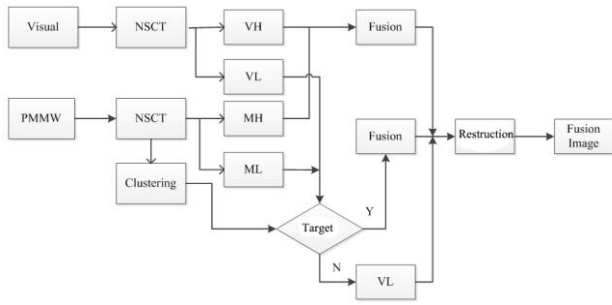
Where  $m$  and  $n$  represent the length and width of region respectively,  $C(i, j)$  is the coefficient of decomposition, superscript  $s$  is the sign of visible image or PMMW image. As is shown in the regional variance expression, regional variance is treated separately for the two images, and do not link the two images. In this paper, a new fusion criterion which used to distinguish the regional differences between two images is proposed.

$$Diff(i, j) = \frac{1}{(M-1)(N-1)} \sum_{m=-(M-1)/2}^{(M-1)/2} \sum_{n=-(N-1)/2}^{(N-1)/2} f(i, j, m, n) \quad (12)$$

$$f(i, j, m, n) = (V(i+m, j+n) - M(i+m, j+n))^2 / (V(i, j)^2 + M(i, j)^2)$$

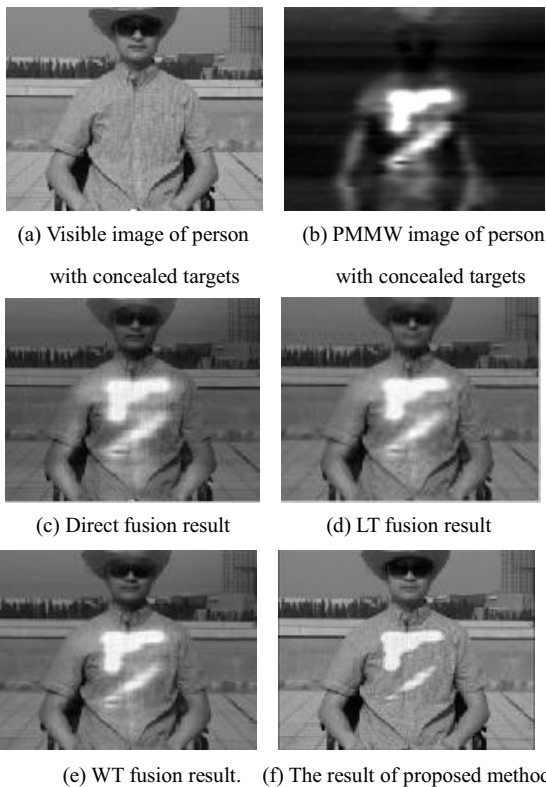
Where  $V(i, j)$  stands for visible image,  $M(i, j)$  represents PMMW image. Fused image by compared  $Diff(i, j)$  with a threshold  $\partial$

$$F(i, j) = \begin{cases} \max(V(i, j), M(i, j)) & Diff(i, j) > \partial \\ k1 * V(i, j) + k2 * M(i, j) & Diff(i, j) \leq \partial \end{cases} \quad (13)$$



**Figure 7.** The diagram of fusion scheme.

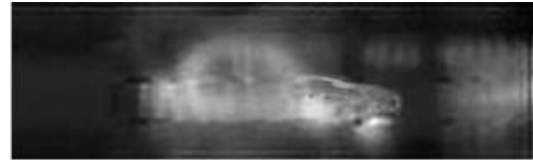
In the process of image fusion, a novel image fusion algorithm is proposed. In classical fusion methods, visible image fusion with PMMW image or the segmentation result of PMMW directly, however, the former will cause the problem of blur non-target area, and the latter tends to lead the matter of poor visual effect. In this paper, we not fusion the visible image with PMMW or the segmentation result, but using the segmentation result as a label to mark one point of image whether belongs to target, if so, fusing images with above fusion rules, otherwise, treating visible image as the fusion result directly. In this way, the fusion image not only has the complex optical background, but also with nice visual effect. The diagram of fusion scheme is show as Figure 7, where VH/VL and MH/ML represent to decomposed high-frequency/low-frequency image of visible image and PMMW image respectively.



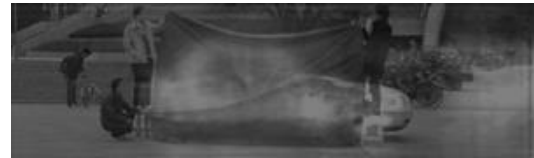
**Figure 8.** Person with two concealed targets



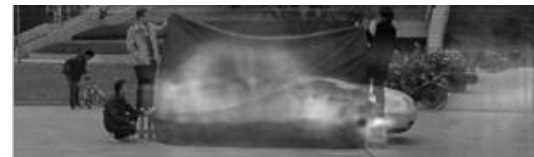
(a) Visible image of concealed car



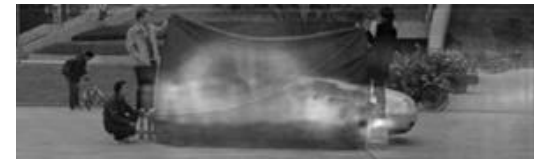
(b) PMMW image of concealed car



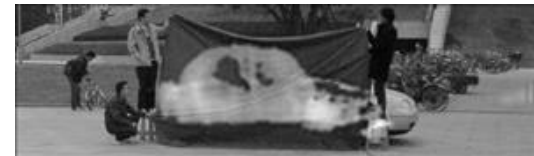
(c) Direct fusion result



(d) LT fusion result



(e) WT fusion result



(f) The result of proposed method

**Figure 9.** The concealed car

As shown in figure 8-figure 9, the images fusion based on weighted average makes entire image becomes blurred, particularly non-target background area, and the optical image comparison shows that the entire image dimmed. Though, the fusion result based on Laplace and Wavelet is better than weighted average, still causing blurred background [11]. However the fusion algorithm based on clustering and NSCT not only well maintained complex optical image background, but also the target's contour information has been well maintained.

To evaluate the effects of fusion in better fashion, three objective evaluation indicators are introduced to evaluate the effect of fusion. Information entropy is a measure of image information richness index, a direct reflection to

information image contained. Average gradient reflects the degree of detail of the image contrast of the image. Spatial frequency reflects the overall level of activity in the spatial domain of an image [12].

**Table 1.** Objective evaluation indicators corresponding to Figure 8

	EN	AG	SF
Figure 8. (a)	6.7779	5.8767	4.2737e+005
Figure 8. (b)	6.6533	2.2263	1.6907e+005
Figure 8. (d)	6.8367	3.9731	2.8977e+005
Figure 8. (e)	6.8273	4.0299	2.9443e+005
Figure 8. (f)	7.0015	6.2941	4.5341e+005

**Table 2.** Objective evaluation indicators corresponding to Figure 9

	EN	AG	SF
Figure 9. (a)	7.0697	6.3155	2.5980e+005
Figure 9. (b)	7.1125	3.0172	1.2640e+005
Figure 9. (d)	6.8197	4.3755	1.7771e+005
Figure 9. (e)	6.7773	4.3446	1.7728e+005
Figure 9. (f)	7.2728	7.4150	3.0520e+005

Where EN denotes entropy, AG represents average gradient, and SF stands for spatial frequency. Seen from the Table 1 and Table 2, the fusion results generated from our algorithm, comparing with weighted average, Wavelet and Laplace, contain more information, and the fusion image are clearer and overall activity are also higher.

## 4 Conclusion

EM (Expectation Maximization) algorithm can be used to estimate the parameters of Gaussian Mixture Model. Though Parametric Learning algorithm takes a relatively long time, its segmentation accuracy is higher than almost threshold method. Image fusion technique can overcome the shortcoming of single image information; a complementary form can be obtained through fusing image acquired from different sensors. According to the characteristics of millimeter wave image, a novel image fusion algorithm for visible and PMMW images based on clustering and NSCT is proposed. The proposed fusion algorithm, comparing to Laplace fusion and Wavelet fusion, not only on the image information contents and the image sharpness, but also the overall level of activity, have great improvement.

## References

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