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Bispectral image fusion using multi-resolution transform for enhanced target detection in low ambient light conditions

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Performing target detection/identification task using only visible spectrum information becomes extremely difficult during low ambient light conditions. Visible spectrum information consists of information available in the range of 400-700 nm wavelength. However, infrared spectrum carries information beyond 800 nm. To overcome the difficulty of target detection by human operator during the task of surveillance, fusion of visible and infrared spectral image information has been proposed. The image fusion has been performed using multi resolution transform based curvelet technique. The use of curvelet transform has been done because of its high directional sensitivity and reconstruction quality. Curvelet transform has been used to decompose source images to obtain coefficients at coarse, intermediate and fine scale. These coefficients have been fused as per respective decomposition level, followed by reconstruction of fused image using inverse curvelet transform. Bispectral fused image inherits scene information as well as target information both from visible and infrared spectrum images respectively. The proposed image fusion output images are visually and statistically compared with other fusion method outputs. The fused image obtained using proposed fusion method in comparison to other fusion results show clear background details, high target distinctiveness, better reconstruction and lesser clutter.

Keywords: Curvelet transform, Image fusion, Infrared image, Situation awareness, Visible image

1 Introduction

The task of surveillance presents several types of challenges like keeping an alert vigil continuously for instant threat recognition. This requires a high degree of situation awareness (SA) on the part of operator. SA involves perception, comprehension and decision making[1]. Thus, for having good SA the very first thing required is having good perception of the surroundings. In case of surveillance tasks, one of the major concerns is to detect the threat using vision during low ambient lighting conditions. The optimal solution for this situation could be achieved by fusion of infrared and visible images as both these imaging sensors cover information from different bands of electromagnetic spectrum.

It is known that human eye can only visualize objects in visible range of electromagnetic spectrum while infrared image provides information that captures the temperature gradient related information from any scene. The multispectral image fusion result is rich with more information content and conveys information in the dark about hot targets, which go unseen by naked eyes.

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Different multispectral image fusion techniques proposed earlier in literature include: ratio-of-low pass pyramid approach[2], biological opponentcolor fusion approach[3], color space transform approach[4,5], wavelet based fusion approach[6,7], biorthogonal wavelet[8], contourlet transform[9] and others. A review of the techniques proposed in literature for multispectral image was reported by the authors earlier[10]. The review study suggested that use of multi-resolution transform (MRT) based techniques for image fusion is more advantageous than other fusion approaches. Advantages of using MRT with respect to conventional fusion methods are many like: better signal-to-noise ratio, increased directional information, stable inverse transform and improved perception and comprehension. MRT based techniques includes various pyramid-based approaches, wavelet transform based approaches, multi-resolution geometric analysis, etc. The pyramid based approaches and wavelet transform suffer from discrepancies like spatial distortion, spectral distortion, blurring and directional insensitivity. Ma *et al.*[11] presented an extensive review of various image fusion techniques been proposed for fusion of infrared and visible images. Authors have presented that there is a need to have flexible basis selection as per decomposition level during the process of image fusion using MRT. Authors also highlight that the fusion algorithm should be developed keeping in mind the end application. They emphasize that the fusion evaluation metrics being used to judge the quality of image fusion result must be chosen keeping in mind the human visual processing.

In this work, a multi-level fusion algorithm based on curvelet transform for fusion of registered visible and infrared images of the same scene is proposed. The multi-level fusion basis is selected to preserve the details from source images judiciously. The fused images then obtained by using proposed curvelet transform based multilevel fusion (CTMF) algorithm are analyzed qualitatively and quantitatively. The image-fusion evaluation metrics are selected in accordance to the end use application, i.e., surveillance. Thus, the analysis of fused results is done to check whether the fusion will lead to enhancement of observer's SA or not.

2 Materials and Methods

Curvelet transform (CT) is a type of MRT, which involves multi-layer decomposition, and reconstruction, a pattern like human visual system's working. CT is an extension of the wavelet transform, exhibiting better directionality and reconstruction as compared to wavelet transform. CT analyzes an image with different block sizes while using a single transform. In the first generation curvelet, an image is first decomposed into a set of wavelet bands and then each band is analyzed using a ridgelet transform. The block size is adjustable at each scale level.

Curvelet transform was first proposed to analyze local lines or curves[12]. This transform is often referred to as the first generation curvelet transform and it was quite difficult to implement. Later it was further improvised to come up with second-generation curvelet transform[13-15] which has great applications in image processing. Curvelet transform can be implemented using two different approaches: wrapping based curvelet decomposition and USFFT based curvelet decomposition. The USFFT approach yields most faithful discretization of the continuous definition[15]. The curvelet transform used in this work is based on the USFFT approach. It provides a faithful discretization of the continuous approach. For any input Cartesian arrays of the form $f[t_1, t_2]$, ($0 \le t_1, t_2 <$ n), curvelet coefficients can be calculated as:

$$c^D(j,l,k) := \sum_{0 \le t_1 t_2 < n} f[t_1, t_2]\overline{\varphi^D_{j,l,k}}[t_1, t_2] \quad \ldots (1)$$

Where, each $\varphi^D_{j,l,k}$ is a digital curvelet transform (DCT) [15]. DCT obeys the rule of parabolic scaling. The complete steps of algorithm are shown in Fig. 1.

The coefficients thus obtained after decomposition of the image consist of both approximation and detail information of the image. The approximation coefficients carry mostly the information about the background details of an image whereas, the detail coefficients are abundant in the detail or edge related information of any image.

In the proposed fusion algorithm, USFFT based discrete CT is used to decompose both infrared and visible image to extract approximation and detail coefficients of both the images.

The fusion scheme designed involves separation of the discrete coefficients obtained from DCT into three classes; coarsest scale coefficients, intermediate scale coefficients and finest scale coefficients.

Before discussing the fusion rules let us revisit the goal. The aim here is to improve SA of observer during low ambient lighting operation times. During such conditions, the main hurdle as could be seen from the output of visible cameras (Fig. 2b), the background details are captured well, however, the hot target could nowhere be seen. The same scene captured with infrared image (Fig. 2a) is able to convey the location of the hot target without much background details. So, it could be inferred that the maximum background information is thus being carried by the visible images, however, the details are being stored with the infrared images. The fusion rules have been developed keeping this in mind.

The coarsest scale coefficients contain the most global information related to any scene. The fusion rule defined for the first level of decomposition is:

$$C_L^F = mean\,(C_L^{IR}, C_L^V) \quad \ldots (2)$$

where, C_L^{IR} and C_L^V are the coarsest coefficients of original infrared and visible image, respectively,

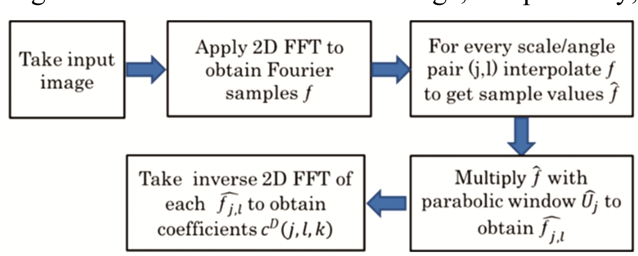

Fig. 1 — Flowcharts for applying discrete curvelet transform to obtain coefficients of input images.

obtained after curvelet decomposition. Some researchers even proposed algorithms based on weighted average method for fusion, however, on analysis it was reported that weighted averaging had not much effect on the final fused image quality. It was seen that weight of value as 0.5, i.e., mean operation was found to be a suitable operation to fuse low frequency coefficients[16].

As we move up the level of decomposition further, the information conveys more and more detailed information about the scene. The fusion rule for the intermediate levels of decomposition coefficients, which lie between the coarsest and finest scale, is described below:

$$C_I^F = max(C_I^{IR}, C_I^V) \quad \ldots (3)$$

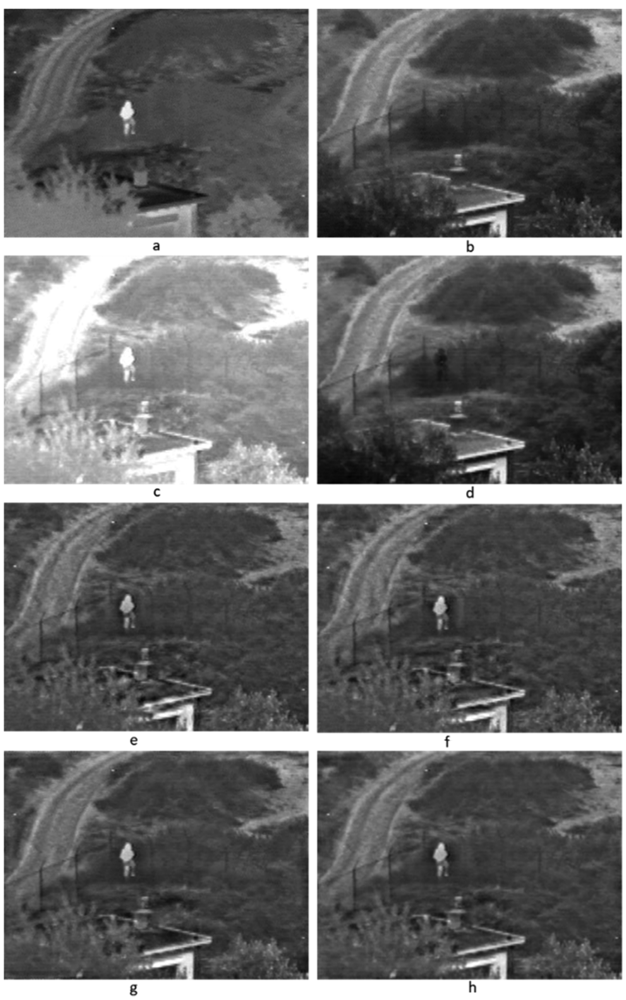

Fig. 2 — (a) Infrared image, (b) visible image, (c) fused image using pixel-by-pixel addition, (d) fused image by Principal component analysis (PCA), (e) fused image by DB5 wavelet, (f) fused image by Biorthogonal wavelet, (g) fused image by Wrapping based curvelet transform and (h) fused image by the proposed method.

Where, C_I^{IR} and C_I^V are the coefficients at intermediate level of decomposition for original infrared and visible image respectively obtained after curvelet decomposition. The aim is to capture the maximum local and global information present in the intermediate scales of decomposition.

In the finest level of decomposition, as per our goal we want the details to be captured the most. Thus, at the finest scale of decomposition we preserve the finest scale coefficients of the infrared image. The fusion rule is defined as:

$$C_H^F = C_H^{IR} \quad \ldots (4)$$

The fused coefficients thus obtained are concatenated according to their level of decomposition to obtain a complete set of fused coefficients. This is then subjected to the inverse CT to obtain fused image.

3 Results and Discussion

The developed algorithm is tested on the infrared and visible image data set provided by Alexander Toer, TNO, Soesterberg, The Netherlands[17]. The images provided in the image fusion dataset consist of registered infrared and visible image of the same scene taken at same point of time. These images were used as the source input images that were fused using the proposed fusion algorithm. Also, the images were fused with other methods proposed in literature to compare the result of the proposed CTMF method. The fusion algorithm is applied on four separate set of images and the fusion results obtained using different fusion schemes are shown in Fig. 2 to Fig. 5. These four image sets have different background conditions and elements on the scene. Different image sets were used for fusion and analysis to check the robustness of proposed fusion approach for varying conditions.

The infrared image and visible image conveys information about the target present on the scene and background information of the scene respectively. The fusion methods proposed in literature have been of mainly three types: pixel based fusion, region based fusion and decision based fusion. The pixel based fusion is preferred because of information integrity and high-quality reconstruction. The method proposed in this paper also follows a pixel based fusion scheme. The other methods which are being used for comparing the proposed CTMF method outputs are: fusion using pixel-by-pixel addition method, fusion based on principal component analysis, fusion by using Daubechies-5 (DB5) wavelet approach, fusion using biorthogonal wavelet approach and curvelet transform based method which follows the wrapping based decomposition approach[16].

For comparing the images, both qualitative as well as quantitative approaches are used in this work. The qualitative approach involves visual analysis of each fused image obtained through different fusion methods and the proposed CTMF method. For quantitative analysis, few fused image quality metrics have been calculated and compared for all fused images obtained with different fusion methods and the proposed method.

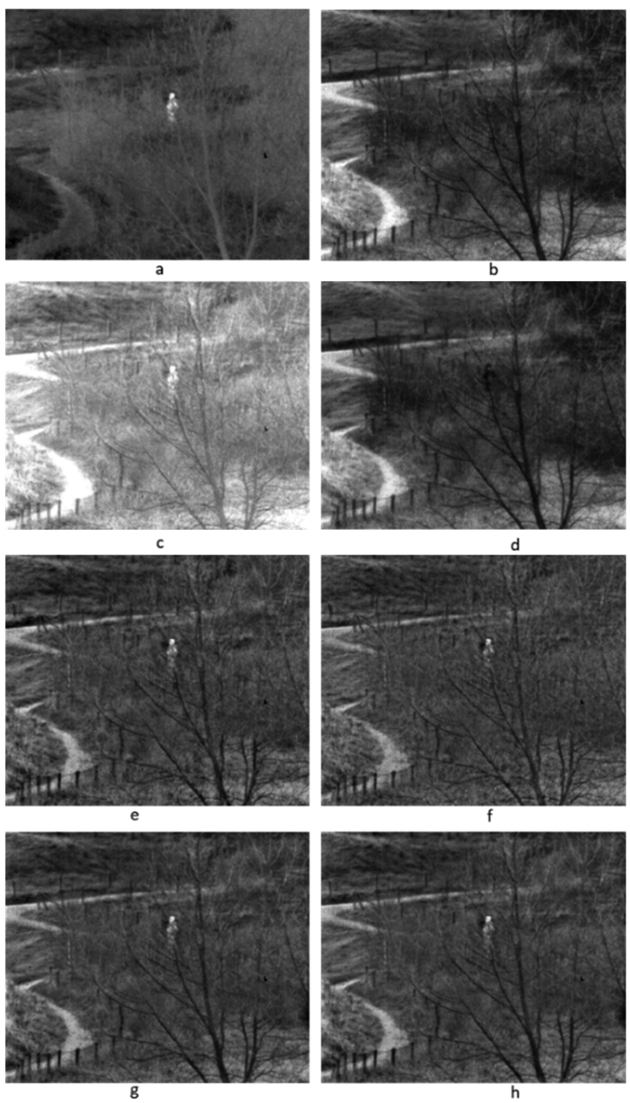

Fig. 3 — (a) Infrared image, (b) visible image, (c) fused image using pixel-by-pixel addition, (d) fused image by Principal component analysis (PCA), (e) fused image by DB5 wavelet, (f) fused image by Biorthogonal wavelet, (g) fused image by Wrapping based curvelet transform and (h) fused image by the proposed method.

3.1 Visual analysis

The visual analysis of the fused result gives first level decision on the suitability of the fusion algorithm. The fused output requires being informative as well as strain-free experience to user eyes. If the fused output conveys information at the cost of producing more stress on user, it will hamper SA of the user leading to fatigue. The images (a) and (b) in Fig. 2 are the infrared and visible images of the same scene, respectively. In Fig. 2(a), while the hot target is clearly identifiable, the fencing and other background boundary details are blurred. In Fig. 2(b), the fence and other background details are clearly visible but detection of hot target presence is not possible. On fusion by different methods, we observe that in case of pixel-by-pixel addition (Fig. 2(c)), the

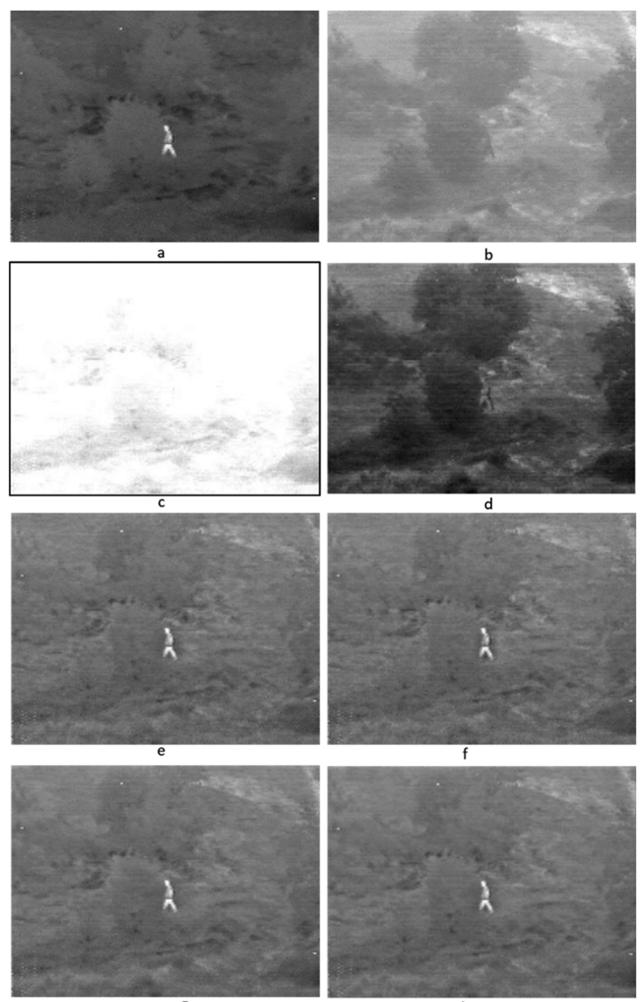

Fig. 4 — (a) Infrared image, (b) visible image, (c) fused image using pixel-by-pixel addition, (d) fused image by Principal component analysis (PCA), (e) fused image by DB5 wavelet, (f) fused image by Biorthogonal wavelet, (g) fused image by Wrapping based curvelet transform and (h) fused image by the proposed method.

overall fused image obtained seems oversaturated and the image has high blooming effect that is undesirable.

Figure 2(d) is the image fusion output obtained by using principal component analysis (PCA) based fusion. This method tends to maintain consistent gray scale mean and variance in the fused image. The fused image output conveys the background details with fidelity; however, the hot target region leans towards darker shade of grey. The recognition of hot target would demand more attention from user for the identification task and hence will not help in improving the SA of user.

Figure 2(e) and Fig. 2(f) are fused image outputs obtained by two different variation of wavelet transform; DB5 and biorthogonal wavelet, respectively. Both these methods decompose images at different scales and obtain approximation as well as detail coefficients at every scale. Biorthogonal wavelets are different in respect of operation that it uses different function for decomposition and reconstruction process. Both these images represent background details with high fidelity, however, the images suffer from blurring at edges, the sharpness of images as compared to the image outputs in Fig. 2(g) and Fig. 2(h) is significantly lower.

Figure 2(g) shows fused image output obtained by using wrapping based CT approach. The output image has better quality in terms of sharpness with respect to other image fusion methods reported in Fig. 2(c-f). However, when compared with the proposed CTMF fusion approach Fig. 2(h), it is observed that the target edges with CTMF fusion approach are more crisp and sharp in the fused image as seen in Fig. 2(h). In this fused image, the hot target information is clearly visible from the infrared source along with the background details that include roof top, fences, boundaries, road, grass, etc. are also clear and sharp.

Similarly, on analysis of image sets shown in Fig. 3, Fig. 4 and Fig. 5, it is seen that in case of pixel-by-pixel fusion, the blooming effect is dominant in case of Fig. 3(c) and Fig. 4(c), while Fig. 5(c) has been totally oversaturated and nothing is visible. When comparing the fused image outputs obtained using PCA based fusion, as seen in case of Fig. 3(d), Fig. 4(d) and Fig. 5(d), the background details are clear and distinct but the hot target visibility has been reduced or completely lost (as seen in Fig. 5(d)).

While analysis of fused output of wavelet based methods and wrapping based CT in Fig. 3(e), Fig. 3(f) and Fig. 3(g), the presence of hot target is noticeable but with significant blurring of edges. The image output of proposed fusion method (Fig. 3(h)) shows distinct hot target presence with sharp edges and clear background information details.

In case of the third and fourth image sets, fusion results of wavelet based fusion approach and curvet based fusion approach are seen in Fig. 4(e), 4(f), 5(e) and 5(f) and Fig. 4(g), 4(h), 5(g) and 5(h), respectively. In case of wavelet based fused images as shown in Fig. 4(e) and 4(f) as well as in Fig. 5(e) and 5(f), hot target presence is distinct but the edges are found to be blurred. Whereas, in case of curvelet based fused images, Fig. 4(g) and 4(h) and Fig. 5(g) and 5(h) convey distinct hot target presence with similar background fidelity and sharpness. This,

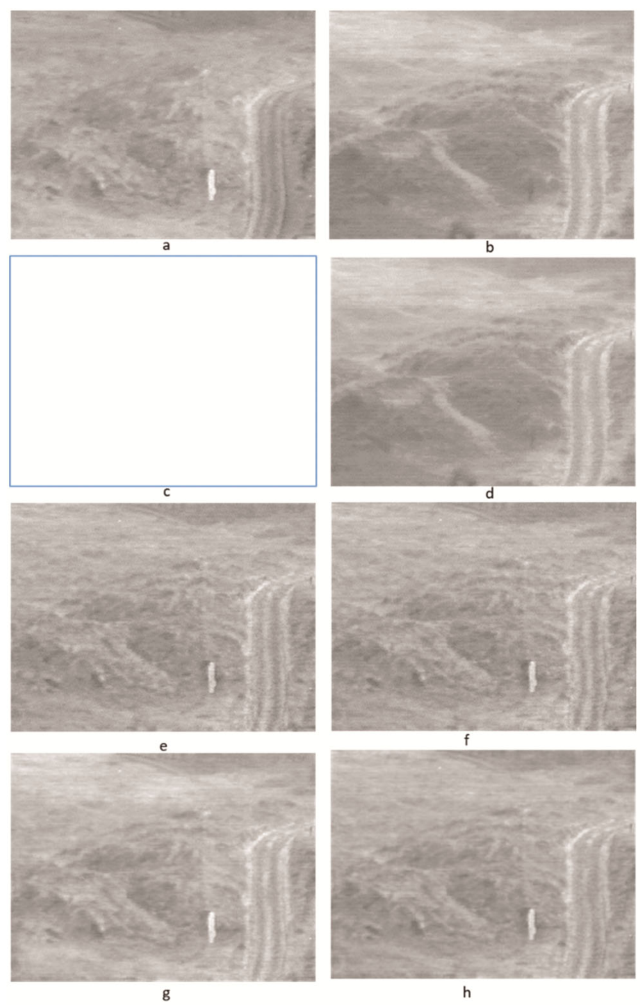

Fig. 5 — (a) Infrared image, (b) visible image, (c) fused image using pixel-by-pixel addition, (d) fused image by principal component analysis (pca), (e) fused image by DB5 wavelet, (f) fused image by biorthogonal wavelet, (g) fused image by wrapping based curvelet transform and (h) fused image by the proposed method.

however, is in agreement with the postulation that curvelet transform is able to resolve edges better than the wavelet transform.

The visual analysis of four set of images provides merit of the proposed CTMF method. The fusion results demonstrate that the proposed CTMF provides better fusion results as compared to other fusion methods. In the third and fourth image fusion set (Fig. 5 and Fig. 6), fused output of CTMF is better than pixel-by-pixel addition and PCA approach, while, output of wavelet and wrapping based CT methods are almost comparable with proposed CTMF result. However, the edge sharpness of hot target is always found to be better with proposed CTMF fusion method. To assess the image output quantitatively, statistical parameters are used to calculate the fused image quality obtained through multi-resolution transform approach based fusion methods.

3.2 Statistical analysis

The main goal of this work is to enhance situation awareness of user by providing him an enhanced content image having crisp information about hot target and background details. The visual analysis of the four images sets lead to the inference that the multiresolution transform approach based methods exhibited better fused image quality in subjective terms as compared to other reported methods. Now, the statistical image features are used to correlate the qualitative analysis of the fused image through calculated image features[18]. This approach compares statistical image quality features to check the efficiency of different fusion algorithms.

In this study, the image features are calculated to determine quality of fused image in terms of; (a) similarity with the original source image and (b) enhanced visibility of target with lesser amount of noise & clutter added to the image. Various parameters and their respective values for the four fusion methods are shown in Fig. 7 to Fig. 11. The results show image quality parameter outputs for fusion by using DB5 wavelet approach, fusion using biorthogonal wavelet approach, fusion by wrapping based CT approach and the proposed CTMF method. The statistical parameters used for measuring image quality analysis are: structural similarity index (SSIM), correlation (CORR), target-versus-background entropy (ETB), peak signal-to-noise ratio (PSNR) and signal-to-clutter (SCR) ratio.

Structural similarity index (SSIM) assesses the quality of fused image output (target image) with respect to reference image in terms of three parameters namely luminance, contrast and structure. It is given by:

$$SSIM\ (x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \qquad \ldots (5)$$

Where, μ_x and μ_y are mean of target and reference images, σ_x^2 and σ_y^2 are variance of target and reference image, respectively; C_1 and C_2 are the regularization constants[19]. SSIM helps in measuring how close the

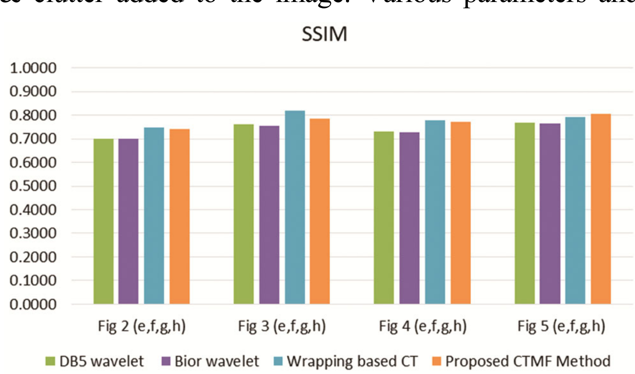

Fig. 6 — Trend of parameter SSIM for all four fused image sets obtained through methods A, B, C and the proposed CTMF method.

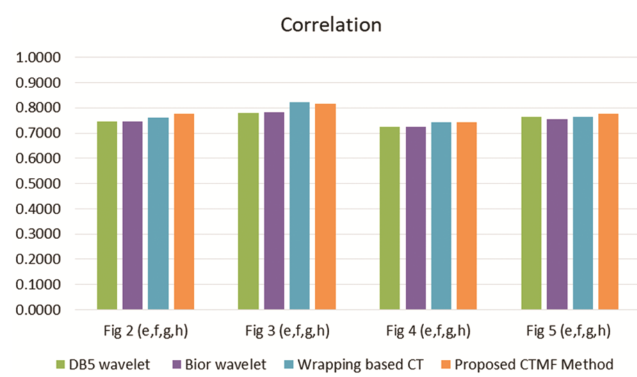

Fig. 7 — Trend of parameter correlation for all four fused image sets obtained through methods A, B, C and the proposed CTMF method.

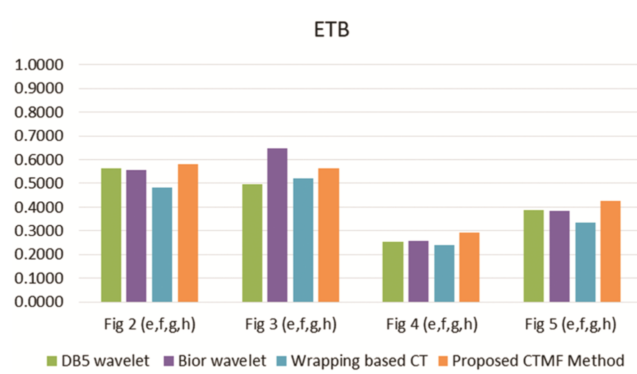

Fig. 8 — Trend of parameter ETB for all four fused image sets obtained through methods A, B, C and the proposed CTMF method.

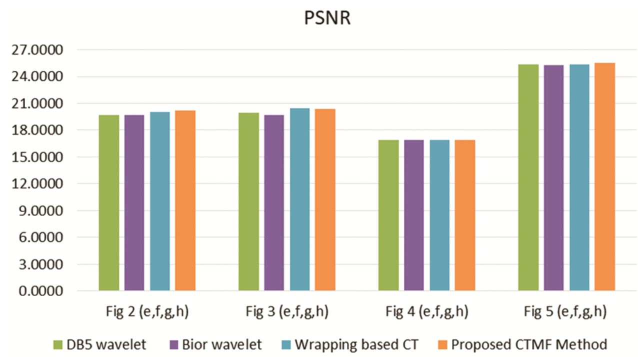

Fig. 9 — Trend of parameter PSNR for all four fused image sets obtained through methods A, B, C and the proposed CTMF method.

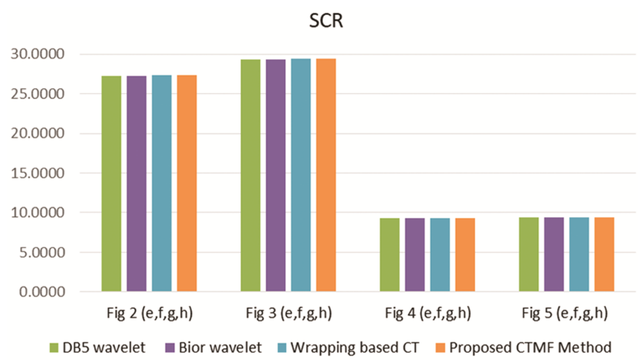

Fig. 10 — Trend of parameter SCR for all four fused image sets obtained through methods A, B, C and the proposed CTMF method.

fused image is from the source image. SSIM results for fused images obtained using Methods A, B, C and the proposed CTMF method are shown in Fig. 6.

As can be seen from the graph, SSIM is highest for all image sets with the proposed CTMF method in comparison to the wavelet based approaches. However, the results of method C and proposed CTMF were found to be almost similar in three out of four cases of fused results. For the second image set, method C achieved higher SSIM as compared to proposed CTMF. However, visual analysis for Fig. 4 suggest that the Method C shows distinct presence of hot target but with more blurring at edges in background details as compared to the proposed CTMF method. It can be concluded that proposed CTMF method is able to retain the maximum similarity to the original scene in respect of luminance, contrast and structure along with conveying hot target details with fidelity.

The second parameter used for measurement of fused image quality is correlation between the fused image and original visible scene. Correlation (CORR) between the two images is calculated by using following formula:

$$CORR = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{(\sum_m \sum_n (A_{mn} - \bar{A})^2)(\sum_m \sum_n (B_{mn} - \bar{B})^2)}} \quad \ldots (6)$$

Where, $\bar{A}$ and $\bar{B}$ are mean of the target and reference visible images respectively. The correlation results obtained for fused images obtained using Methods A, B, C and the proposed CTMF method are shown in Fig. 7.

The correlation between fused images obtained through the proposed CTMF method is also found to be higher in comparison to other wavelet based fusion methods for all image sets and higher from wrapping based CT method for three out of four cases.

For enhancing situation awareness of user, it is important to convey the background information with fidelity but equally important is to detect target information prominently. To measure the detectability of hot target with respect to background, the parameter 'Target versus background entropy (ETB)' is used. The theory behind its operation is that the high entropy target would be easily visible with respect to low entropy background. The results obtained for Methods A, B, C and the proposed CTMF are shown in Fig. 8. It is calculated using following formula:

$$ETB = |E(T) - E(B)| \quad \ldots (7)$$

Where, $E(T)$ and $E(B)$ are the entropy of target and reference images, respectively.

The ETB results support the visual analysis, the target distinctiveness is found to be higher with the proposed CTMF fusion algorithm in three of four image sets clearly, while in the second image set, ETB is slightly lower than method B. Also, it can be seen that proposed CTMF method outperforms wrapping based CT approach in all cases providing better target distinctiveness.

Further, to assess the image quality in terms of reconstruction capability, peak signal-to-noise ratio (PSNR) is calculated for the four image sets obtained through methods A, B, C and the proposed CTMF method. PSNR is a parameter commonly used to estimate the quality of reconstructed image versus original image. PSNR is calculated using the following formula:

$$PSNR = 10 \ log_{10} \left(\frac{peakval^2}{MSE} \right) \quad \ldots (8)$$

Where, peak value^2 is calculated based on image data type and MSE is the mean-square-error between the target image and reference image. It signifies that higher the PSNR value, better is the reconstructed image quality. The PSNR values obtained for the four different fusion methods are shown in the Fig. 9.

In the PSNR results obtained for all four different image sets, PSNR value achieved by the proposed CTMF method is more than the other wavelet based fusion approaches for all image sets and higher from wrapping based CT method for three out of four cases.

The last quality metric used for measurement of fused image quality is signal-to-clutter ratio (SCR). According to theory of SA, lesser the clutter in the image better is SA of user. Clutter mainly refers to the presence of unwanted/excess information in any image, which can affect the target recognition, hampering SA of observer and adding to more confusion. The values of SCR obtained for all four fused image outputs obtained by using methods A, B, C and the proposed CTMF method are shown in Fig. 10.SCR is calculated using the following formula[20,21]:

$$SCR = 10\ log\frac{a^2}{\sigma^2}\text{q} \quad \dots (9)$$

Where, a^2 is intensity of the target and σ^2 the variance of local background.

Results show that the SCR value achieved using proposed CTMF method is higher than the wavelet based approaches and similar for the wrapping based CT approach. Thus, it can be inferred that the proposed CTMF method helps in maintaining the target recognition with minimum amount of clutter in the fused output.

The comparison of all image quality parameters can be summed up as; Curvelet based approach outperforms the wavelet based fusion approaches in terms of better reconstruction, sharpness and background fidelity. The comparison of two curvelet based fusion approaches show that the wrapping based approach produced fusion image quality comparable to proposed CTMF in terms of correlation and background fidelity. However, the target distinctiveness achieved by proposed CTMF is higher from what is obtained using wrapping based curvelet approach. As per the defined goals, the proposed CTMF approach is found to be the most suitable approach for fusion of infrared and visible image for generating an enhanced information content, which will lead to enhancement of situation awareness of observer during low visibility conditions.

4 Conclusions

A MRT based multi-level-fusion algorithm for bispectral image fusion was proposed in this work. The infrared and visible images were fused to combine the complimentary information of these two spectral bands to obtain a single informative image. This would help in enhancing target detection by human operator during low ambient lighting conditions. The proposed fusion algorithm uses digital curvelet transform to decompose infrared and visible images at different scales and orientations. The coefficients obtained after decomposition at coarse, intermediate and finest scale were fused using three different fusion operatives as per their respective decomposition level. The fused images obtained after application of proposed algorithm were then compared with other fusion method outputs. Visual and statistical analysis of fused the images obtained shows that the proposed CTMF method succeeds in maintaining background fidelity with improved target distinguishability. The images obtained using the proposed CTMF method merits on preserving background details, target distinctiveness, better reconstruction and lesser clutter. Thus, it could be inferred that the use of this fusion method will help in enhancing target detection ability of human operator during low ambient lighting conditions.

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