Multi-sensor Image Fusion for Effective Night Vision through Contourlet Transform and KPCA and Mutual Information

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Abstract
This paper presents a new image fusion algorithm by combining contourlet transform with Kernel Principle Component Analysis to enhance perception in case of night vision applications. Contourlet Transform improves visual perception preserving the edge and texture information as compared to wavelet transform, while Kernel Principle Component Analysis helps to develop effective fusion decision rule for selecting appropriate coefficients for fusion. Additionally, mutual information is used to adjust the contribution of each image in final fused image. Fusion Quality Index is used for image fusion quality evaluation. Experimental results show that the proposed algorithm performs considerably well as compared to previous wavelet and pyramid based fusion approaches.

Keywords: *Multi-sensor Image Fusion, Contourlet Transform, Kernel Principle Component Analysis (KPCA), Mutual Information, Directional Filter Bank (DFB).*

1. Introduction
Night vision systems are playing an important part in modern warfare for effective battlefield monitoring and better situation assessment. Such systems utilize multiple sensors for getting complementary kind of visual information about the scene. Fused representation of such multiple sensor signals through proper image fusion mechanism may provide more complete representation of the perceived scene to enable surveillance and search operations to be conducted around the clock. Incomplete transfer of information by fusion process may prove costly during wartimes, which requires more sophisticated fusion algorithms.

The operational requirement to fuse night vision imagery is due to the limitations of individual sensors to capture all available visual information about the field of view. Night vision cameras generally provide infrared images in case of forward looking infrared cameras and low light images in case of CCD camera The infrared images are maps of infra-red radiations which are emitted by every object above absolute zero temperature. This amount of radiation emission is partly governed by the temperature of the object. Therefore, such sensors prove good for perceiving hot targets in a busy background, seeing through fog, and seeing paths through a cluttered forest. However, they are not as effective during thermal crossover periods at night or after long periods of rain, and can't image cultural lighting, laser or LED lighting, and text on street signs. On the other hand, infrared cameras are not good at capturing scenery such as trees, leaves and grass in natural scene which low light visible cameras are able to capture. Thus there is a need for visual information integration and multi-sensor image fusion gives a promising solution [1].This paper presents a new image fusion algorithm incorporating recently developed Contourlet transform and widely known Kernel Principle Component Analysis.

A great number of different approaches to multi-sensor image fusion have been used in the past which vary in their complexity, robustness and quality. The most popular approach for image fusion is wavelet based image fusion [2]. It selects maximum absolute wavelet coefficients at each transform scale. Different variants of wavelet based image fusion can be found in literature [1]. Most recently, Contourlet Transform [3], a new extension of wavelet Transform in directionality, has been proposed. Authors in [4] have proposed the use of Contourlet transform for image fusion process rather than Wavelet Transform because of its additional benefits of directionality and anisotropy.

In natural images, discontinuity points are usually located along smooth curves; contours, owing to smooth boundaries of physical objects. Wavelets in 2-D are good at isolating the discontinuities at edge points but are not good to see the smoothness along the contours. They can capture only limited directional information, an important and unique feature of multi-directional information, which requires more powerful representations in higher dimensions. Contourlet Transform tries to overcome these limitations. It inherits the rich wavelet theory and algorithms and better preserves the edge and texture information in images than wavelet. Although Contourlet transform proves good for fusion process but main fusion process depends upon fusion decision rules. A very simple method for decision making is used in [4] by choosing the larger coefficients from both images. In this paper, we propose more sophisticated decision rule for selecting contourlet coefficients from approximation sub band, which is based on KPCA weighted averaging. Usually, averaging is used for fusing approximation coefficients and Max rule is used only for detail information. Max rule gives relatively good fusion decision in case of edges but for rest of the information in images it does not performs so well. Therefore, we have used Principle components based approach. Image contents vary considerably and Principle components retain most of the variability in the data. In case of Kernel Principle Component Analysis; they consider nonlinear features as well. But again ideal composite image in case of night vision is unknown. It may depend upon the situation that what type of contribution is most desirable? It can be made flexible by introducing few parameters. By changing these parameters, we can adjust fusion result according to the desired requirements. For this purpose, we have proposed mutual information which can be used for adjusting the weights of finally fused image. A bit similar approach is used with wavelet based fusion with good fusion results [5].

The remainder of the paper is organized as follows: Section (2) presents theory of Contourlet Transform, Kernel Principle Component Analysis and Mutual Information. Section (3) describes steps of our proposed fusion algorithm. Section (4) describes subjective and objective results. Conclusion, acknowledgements and references follow.

2. Theory

In this section, we present the background theory about the proposed fusion approach which includes Discrete Contourlet transform, Kernel Principle Component Analysis (KPCA) and Mutual Information.

Discrete Contourlet Transform: The contourlet transform is a multi-resolution and directional decomposition of a signal using a combination of Laplacian Pyramid (LP)] and a Directional Filter Bank (DFB). Wavelets are well adaptive to abrupt changes but they are not the dead end. They too have limitations. They fail to capture geometrical regularity in images. Wavelet scheme see edges but not smooth contours. Contours are edges with localized and regular direction. Contourlets are constructed via filter banks and can be viewed as an extension of wavelets with directionality. It has been introduced to allow for different number of directions at each scale/resolution to achieve a critical sampling [3]. It consists of two phases. The first phase is multi-resolution decomposition known as Laplacian Transform [6]. It is quite helpful as the features that might go undetected at one resolution may be easy to spot at another. We have used same implementation of Contourlet Transform as proposed by authors [3] rather than DT-CWT based approach as in [4]. It is rather simple and efficient in a real time scenario. As in case of night vision, brightness and contrast are every different between two input images, Laplacian proves better in such applications as discussed in [7].The idea is to decompose an image into a set of band-pass filtered component images, each of which represents a different band of spatial frequency. It generates at each level a downsampled lowpass version of the original and the difference between the original and the prediction, resulting in a bandpass image. The first step is to lowpass filter the original image g_0 to obtain image g_1, a reduced version of g_0.In similar way, g_2 is formed as a reduced version of g_1 and so on. The level to level averaging process is performed for levels 0<1<N and nodes I,j,0≤i<C_i,0≤j<R_i following the equation:

$$g_l(i,j)=\sum_{m=-2}^{2}\sum_{n=-2}^{2}w(m,n)g_l(2i+m,2j+n),(1)$$

Where N refers to number of levels in the pyramid and C_i and R_i are the dimensions of the *l*th level. The averaging process can be represented by the function *Reduce.*

$$g_l=Reduce(g_{l-1}).(2)$$

Averaging is performed by a convolution with one of a family of local, symmetric weighting functions, as w in equation (1).The reverse operation is called Expand function.

$$g_{l,n}=Expand(g_{l,n-l}).(3)$$

This function expands an (M+1)x(M+1) array into (2M+1)x(2N+1) array by interpolating new node values between the given values.

$$g_{l,n}(i,j)=4\sum_{m=-2}^{2}\sum_{n=-2}^{2}w(m,n)g_{l,n-l}(\frac{i-m}{2},\frac{j-n}{2}).(4)$$

For levels 0<1<N,0≤n and nodes I,j,0≤i<C_{l-i},0≤j<$R_{l-i.}$ The Laplacian Pyramid is just a sequence of error images,L_0,L_1,L_2,…..L_n. Each is the difference between two levels of the Gaussian Pyramid. So, for 0<l<N.

$$L_l=Expand(g_{l+1})=g_l-g_{l+1,1}.(5)$$

The original image can be recovered easily without any loss by expanding, then assuming all the levels of Laplacian Pyramid:

$$g=\sum_{i=0}^{N}L_{l,1}.(6)$$

Other details about Laplacian Pyramid can be found in [6]. In second step, iterative directional filter banks are used. The original construction of the DFB involves two building blocks. The first building block is two channel quincunx filter bank with fan filters that divides a 2-D spectrum into horizontal and vertical direction. The second building block is a shearing operator which accounts to reordering of input samples. By adding a pair of shearing operators before and after a two channel filter bank, we obtain a different directional frequency partition while maintaining perfect reconstruction. This fact provides an opportunity to combine multi-resolution transform to DFB, where low frequencies of the input image are removed before applying the DFB.

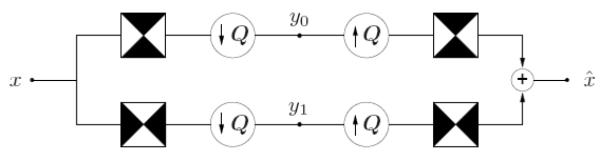

Figure 1.Quincunx Filter Bank with Fan Filters

Figure .1 is taken from [3]. Bandpass images from the LP are fed into DFB to capture directional information. The combined result is a double iterated filter bank structure, named contourlet filter bank which decomposes images into directional subbands at multiple scales.

Specifically, (LP+ DFB=CONTOURLET).

Kernel Principle Component Analysis: Target information in the images can be extracted using Principle Component Analysis. This method; however can only guarantee that linear features are extracted while the nonlinear features may be lost. According to feature classification, nonlinear features are those features which are not linearly separable and are not easy to extract by simple methods. KPCA uses a kernel function and performs PCA in some high dimensional feature space which is non-linearly related to input space. The essensial operations underlining the Kernel representation are non-linear mappings of the input data X on to a high dimensional feature space F through the mapping function $\Phi : x^{(i)} \to \Phi^{(i)}$. More details for theory and algorithm can be found in [8].

Mutual Information: The mutual information of X and Y, written I(X, Y) is the amount of information gained about X when Y is learned, and vice versa [9]. I(X, Y) = 0 if and only if X and Y are independent. In case of images F and A, we can write it as:

$$MI = \sum_{i_1=1}^{L} \sum_{i_1=1}^{L} h_{F,A}(i_1,i_2) \log_2 \frac{h_{F,A}(i_1,i_2)}{h_F(i_1)h_A(i_2)}, (7)$$

where $h_{F,A}$ is the normalized joint gray level histogram of images F and A, h_F and h_A are the normalized marginal histogram of two images and L is the number of gray levels.

3. Our Proposed Fusion Scheme

In this section, we present our image fusion algorithm as well as objective image fusion performance evaluation technique known as Image Quality Index (IQI).

Algorithm: The steps of the proposed algorithm are as followed;

1. Apply KPCA on source images A and B and select eigenvector values corresponding to the largest eigenvalues, α_1, α_2.
2. Decompose the two source images by Discrete Contourlet Transform utilizing Laplacian Transform and Directional Filter Bank. Let $A_0[n]$ and $B_0[n]$ be the input images. The output after the LP stage is *J* bandpass images, $Abj[n]$, *j=1,2,…,J* and a lowpass image, $Aaj[n]$ for image $A_0[n]$ and J bandpass images $Bbj[n]$, *j=1,2-…..,J*, and a lowpass image $Baj[n]$ for image $B_0[n]$. This mean that *J*th level of LP decomposes the image $A_{j-1}[n]$ into a coarser image $Aaj[n]$ and detail image $Abj[n]$. Each bandpass image is further decomposed by an l_j level DFB into $2^{l}j$ bandpass directional images. $c_{j,k}(lj)$, *k=0,1,…..,*2^{lj}*-1*[3].
3. For lowpass image, apply fusion rule based on KPCA using following equation

$$Faj[n] = \frac{(\alpha_1 * Aaj[n]) + (\alpha_2 * Baj[n])}{\alpha_1 + \alpha_2}, (8)$$

where α_1, α_2 are elements of principle eigenvector, and $Aaj[n]$ and $Baj[n]$ are lowpass coefficients of image A and B.

4. For highpass coefficients, at every scale, choose larger absolute coefficient values and then apply one of the two following methods for further processing.
   a. Consistency verification [2], which uses majority filter as: if center pixel value in binary decision map comes from image X, while majority of surrounding values comes from image Y, the center pixel value is switched to that of image Y.
   b. Morphological filtering [7], which use morphological "fill "and "clean" operators to remove isolated points in the binary decision map.
5. Construct intermediate Fused image IF, using modified contourlet coefficients and inverse contourlet transform.
6. Calculate mutual information between intermediate fused image IF and source images A and B as MI1, MI2, respectively. If values are equal or their difference D is less than a minimum threshold I_Φ, there is no need for adjustment. If otherwise, we need for iterative fusion with that image which has contributed less in the final image. We do so by adjusting weights in equation (2).
7. We update α_1 by α_{1+} (α1-1) and α2 by α_{2+} α_1*α_2 if MI1 is lower and vice versa. These new values come from mathematically after solving equation (2) by changing $Aaj[n]$ and $Baj[n]$ by $Faj[n]$.
8. Construct final fused image F using new weights and inverse contourlet transform.

Image Quality Index: For image fusion quality evaluation, we use, Image Quality Index, which is recently proposed [10] for image fusion quality measurement.

If δ denotes variance, the global image quality index for two vectors A, B is defined as

$$Q_\circ(A,B) = \frac{\delta_{AB}}{\delta_A \delta_B} \frac{2\overline{AB}}{(\overline{A}^2 + \overline{B}^2)} \frac{2\delta_A \delta_B}{(\delta_A{}^2 + \delta_B{}^2)}, (9)$$

Author [10] has introduced a weighting procedure in image quality index calculation. A local weight λ was introduced which tells about the relative importance of one image compared to the other. If SF(A), SF(B) are special frequencies of image A and B then

$$\lambda = {SF(A)} \big/ {[SF(A) + SF(B)]}. (10)$$

Then, the quality of fused image, Q_F can be calculated as;

$$Q_F = \lambda Q_\circ(A,F) + (1-\lambda) Q_\circ(B,F) (11)$$

4. Experimental Results and Discussion

In our experiments, we compare the results of our fusion algorithm with three other well-known fusion techniques i.e. simple PCA based fusion, DWT based fusion, Contourlet with simple fusion rules (Contour(s)) and Contourlet with advanced fusion rules Contour(a).The last one represents our fusion technique. The images are already registered (spatially aligned) and with 256 grey levels. The experiments are performed for more than 90 image pairs but standard images are shown here in this result section to provide an ease for comparison. We apply each fusion method to different imagery groups and calculate their fusion performance with the objective fusion measure IQI, which is mentioned in the previous section. Image processing and Wavelet Toolbox in Matlab 7 were used for implementation.

Figure 2. Night Vision (A) presents a situation where input is coming from two different sensors, visual and IR. From visual image (a) it is difficult to distinguish a person in camouflage from the background which is observable in infra-red image. In contrast, the background like fence is Indiscernible in IR image. The final fused images (c, d, e, f) contain the composite information where (c) is simple PCA, (d) is DWT, (e) is simple Contourlet and (f) is the proposed advanced Contourlet based fusion result.

Figure 3. Night Vision (B) is presenting another situation. Visual image does not provide good information about background and shadow. IR image looks like a map of radiations from which any inference feels difficult. The final fused images (c, d, e, f) contain the composite information where (c) is simple PCA, (d) is DWT, (e) is simple Contourlet and (f) is the proposed advanced Contourlet based fusion result.

Figure 4 and 5. IQI Comparison presents the comparison of these fusion techniques which is based on image fusion quality measure, IQI calculation. It shows clearly that proposed fusion approach performs considerably well as compared to other approaches.

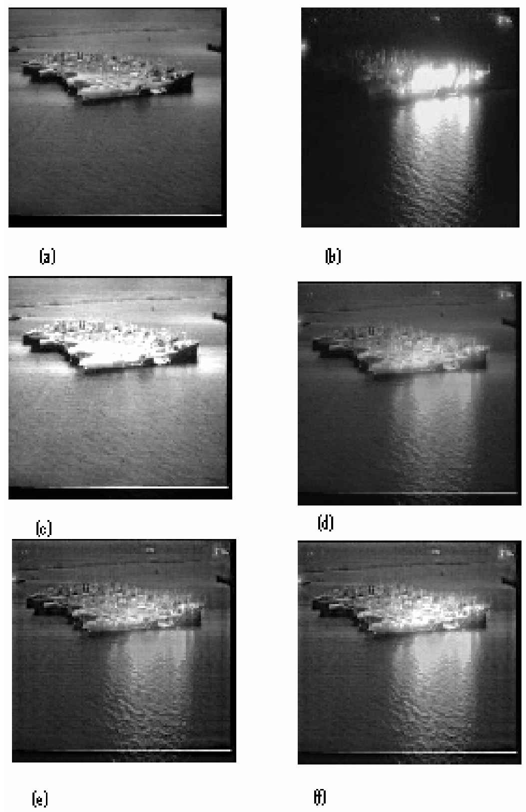

Figure 2. Night Vision (A)

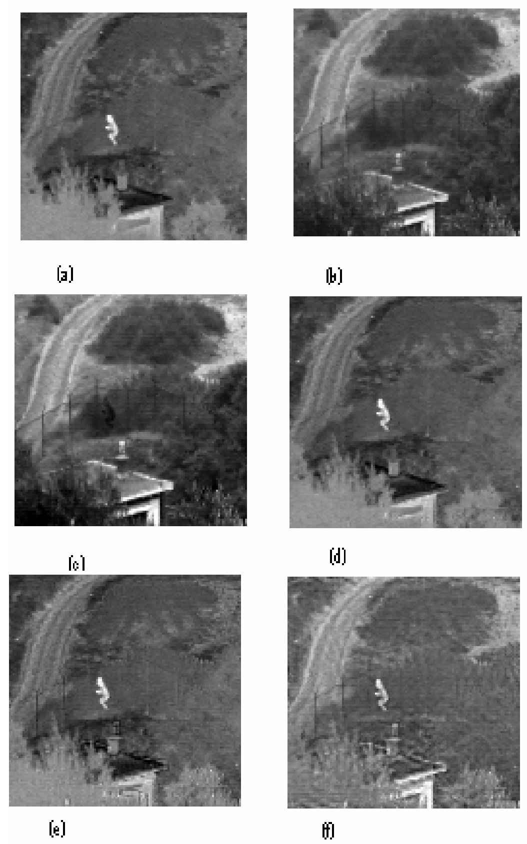

Figure 3. Night Vision (B)

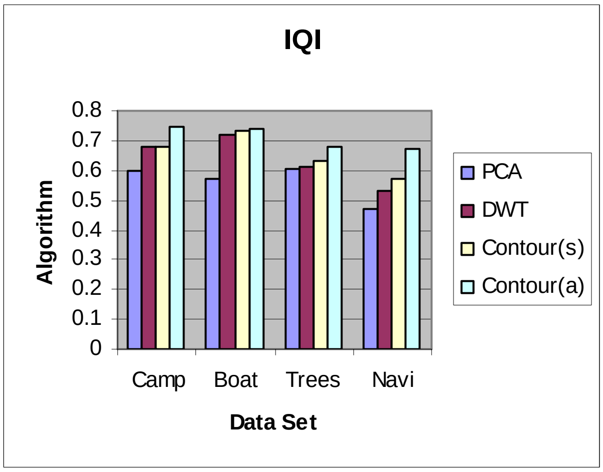

Figure 4. IQI Comparison

	PCA	DWT	Contour(s)	Contour(a)
Camp	0.5953	0.6794	0.6822	0.7439
Boat	0.5701	0.7198	0.7358	0.7418
Trees	0.6061	0.6134	0.6334	0.679
NaviG	0.4712	0.532	0.5694	0.6698

Figure 5. IQI values

5. Conclusion

In this work, we proposed an advanced technique for multi-sensor image fusion using Discrete Contourlet Transform, Kernel Principle Component Analysis and Mutual Information. Contourlet Transform overcomes limitations of wavelet transform by its two key features, namely directionality and anisotropy. Image Fusion through contourlet can be improved using advanced fusion rules. KPCA based fusion rule utilizes its feature extraction capability to perform better as compared to simple fusion rules. Detailed subjective and objective experimental results show that proposed technique performs considerably well in case of night vision applications. In future, we will enhance this technique to be used for other fusion applications as well.

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