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RESEARCH PAPER

Contrast Enhanced Low-light Visible and Infrared Image Fusion

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ABSTRACT

Multi-modal image fusion objective is to combine complementary information obtained from multiple modalities into a single representation with increased reliability and interpretation. The images obtained from low-light visible cameras containing fine details of the scene and infrared cameras with high contrast details are the two modalities considered for fusion. In this paper, the low-light images with low target contrast are enhanced by using the phenomenon of stochastic resonance prior to fusion. Entropy is used as a measure to tune iteratively the coefficients using bistable system parameters. The combined advantage of multi scale decomposition approach and principal component analysis is utilized for the fusion of enhanced low-light visible and infrared images. Experimental results were carried out on different image datasets and analysis of the proposed methods were discussed.

Keywords: Contrast enhancement, stochastic resonance, multi-modal image fusion

1. INTRODUCTION

Images acquired from multi-modalities such as visual cameras, low-light night vision cameras, infrared cameras (IR) contain complementary information. Infrared image contain few detail with high contrast about the captured scene compared to the visual image. On the other hand, visual image contain plenty of high frequency information but has a bad target contrast especially under bad luminance condition[1]. Therefore, the low-light visible and infrared image fusion is one of the techniques mostly used in the applications of pedestrian recognition, vehicle navigation, night vision surveillance, and monitoring applications.

The quality of imagery obtained from low-light sensors suffers from poor contrast, limited dynamic range and many other reported problems[2]. Stochastic resonance (SR) is a phenomenon introduced in image processing applications for the enhancement of poor contrast images. SR is used for the enhancement of low-contrast sonar images which showed that noise is used to enhance the low-contrast images rather than degrading the performance[3]. Several algorithms were developed for dark image enhancement[4,5], enhancement of diagnostic ultrasound and MRI images[6] in various domains in the recent past. These methods proved that the low quality image is enhanced and the dynamic range is increased. The motivation of this study on SR helped us to make use of this SR phenomenon for the enhancement of low-light visible images in our work prior to the fusion.

Several fusion methods for low-light visible and infrared image fusion have been proposed by researchers[7-9]. Generally, pixel-based fusion methods are employed for fusion as they are simple to implement as compared with the computational complexity in implementing region-based and feature-based fusion techniques. The objective of pixel-level image fusion is to represent the visual information present in two or more number of input images into a single fused image without degradation, distortion and loss of information[10]. Pixel-based image fusion is done either in spatial domain or in transform domain where the pixel intensities are modified in the image itself. However, the spatial domain techniques suffer from the limitation that the images are smoothened resulting in blurred images. The transform domain techniques involving multi scale decomposition (MSD) proved to be one of the best methods for image fusion. The commonly used transforms include the contrast pyramid[11]; gradient pyramid[12], and wavelet transform[13]. The general DWT fusion method involves decomposition of the two source images into low and high frequency details and a fusion rule is used for combining the sub-band images. Finally, inverse discrete wavelet transform (IDWT) is applied to get the fused image. Other transforms such as complex wavelet transform[14], spectral graph wavelet transform[8] and non-sub sampled contourlet[1] (NSCT) have been implemented earlier on multi focus, multi modal and night vision applications. The advantage of HIS and PCA[15] technique is implemented in the fusion of MRI and PET images for medical applications.

Principal component analysis (PCA) is a statistical procedure that transforms a number of possibly correlated variables into a smaller number of variables called principal components with the first principal component having

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largest variance than the successive components. PCA[16] is implemented in image fusion as it has the ability to represent the redundant data in a compact form. In this paper, the basic idea is to fuse the contrast enhanced low-light visible and infrared images considering the advantages of both DWT and PCA. Enhancement of low-light images is the primary step performed using a SR-based adaptive algorithm in discrete-wavelet transform domain.

2. PRELIMINARIES

2.1 Stochastic Resonance

Stochastic resonance (SR) is a non-linear phenomenon where a weak input signal can be amplified and optimised by the additive noise. Generally, noise is considered to degrade the performance of the system. But in SR, it is observed that adding noise to a weak input signal would improve the signal strength. This phenomenon occurs in bistable systems or in systems with threshold-like behaviour[17]. When a weak input signal added with additive white noise with a threshold is applied to a non-linear system, then the system exhibits resonance like behavior as a function of noise level.

Stochastic resonance in a non-linear dynamic system is described by Langevin[18] Equation as:

$$\frac{dx(t)}{dt} = ax(t) - bx^3(t) + s(t) + \eta(t) \tag{1}$$

where $s(t)$ is the input signal, $\eta(t) = \sqrt{D}\xi(t)$ is additive noise with D representing the noise intensity and a, b are real parameters of a double-well system exhibiting SR with bistable potential $u(x)$ given by

$$u(x) = -\frac{ax^2}{2} + \frac{bx^4}{4} \tag{2}$$

Substituting Eqn. (2) in Eqn. (1) results in Eqn. (3) as:

$$\frac{dx(t)}{dt} = -\frac{du(x)}{dx} + s(t) + \sqrt{D}\xi(t) \tag{3}$$

In the absence of signal and noise, the height of the bistable potential is obtained as $\Delta u = \frac{a^2}{4b}$ at $x = \pm\sqrt{\frac{a}{b}}$. If the noise term is present with $s(t) = 0$ then it is observed that the particle fluctuates and makes transitions. The rate of transition from one to other is given by Kramer's rate[19] in Eqn. (4) as:

$$r = \frac{a}{\sqrt{2}\pi}\exp\left(-2\frac{\Delta u}{D}\right) \tag{4}$$

The increase in noise intensity increases the switching rate and the transition between the states occurs more likely when the barrier height is minimum.

If the signal is added then the Eqn. (3) becomes

$$\frac{dx(t)}{dt} = -\frac{du(x)}{dx} + Bsin\omega t + \sqrt{D}\xi(t) \tag{5}$$

Solving the above differential equation using Euler-Maruyama's[20] iterative discretised method, the SR equation is represented in Eqn. (5) as:

$$x(n+1) = x(n) + \Delta t\left[ax(n) - bx^3(n) + input(n)\right] \tag{6}$$

where *input* (n) denotes the input sequence with noise and with initial condition $x(0)=0$.

Selection of parameters a and b can be done based on the knowledge of noise intensity, frequency band and plots of output to input signal-to-noise ratio (SNR). The SNR for SR is given by

$$SNR = \left[\frac{4a}{\sqrt{2}\sigma_0^2\sigma_1^2}\right]\exp\left[\frac{-a}{2\sigma_0^2}\right] \tag{7}$$

where σ_0^2 is the variance of original bistable system and σ_1^2 is the variance of added noise in the SR based system.

In the proposed technique the SNR plot for one of the image dataset wrt parameter a is depicted in Fig.1.

It is observed from Fig. 1 that the SNR decreases for higher values of a and is maximum around 0.02. Hence in our experiment a value is selected to be 0.02.

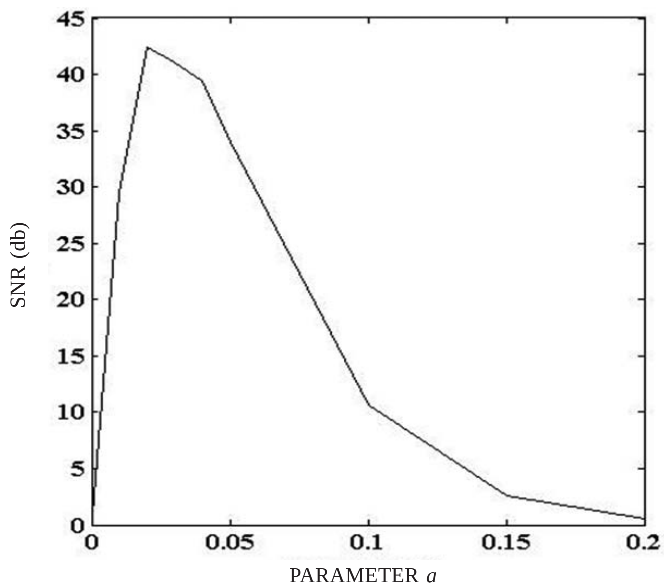


Figure 1. SNR *vs* parameter *a*.

In the absence of noise and with signal $s(t) = B\sin\omega t$ in Eqn. (3) , if $B>0$; then each potential minimum is alternatively lowered and raised with respect to barrier height and bistability is lost at $B \geq \sqrt{\frac{4a^3}{27b}}$. To get maximum signal strength B is selected to be 1 and hence the value of b is selected such that $b \leq \frac{4a^3}{27}$. In the proposed method b is selected as $b = \frac{4a^3}{27}$. Δt is the sampling time which is considered to be very small to get maximum SNR. Experimentally, Δt is selected as 0.015 in our proposed technique.

2.2 Discrete Wavelet Transform

The limitation of short term fourier transform (STFT) not applicable to stationary signals is avoided in DWT. In applications of DWT in image processing, DWT provides information of an image's spatial and frequency characteristics[21]. The 2-D DWT transforms the image into four sub-bands comprising of approximate (LL), vertical (LH), horizontal (HL) and diagonal (HH) components. The high frequency information content such as edges are described by the detailed coefficients with vertical orientation while the basic information content is described in the low frequency coefficients. The inverse discrete wavelet transform (IDWT) allows reconstructing the image at increasingly higher resolutions. In this paper DWT is used in both the enhancement step and fusion process.

2.3 Principal Component Analysis

Principal component analysis (PCA) is a technique which transforms a number of possibly correlated variables into a smaller number of variables called principal components. It is used to analyse large datasets. It mainly finds applications in image processing for compression and de-noising. PCA uses a vector space transform to reduce the dimensionality of large datasets[22]. The principal components are derived based on the direction of maximum variance.

3. PROPOSED METHOD

The proposed method involves the steps for enhancing poor contrast and low dynamic range low-light visible image followed by the steps for the fusion of enhanced low-light visible and infrared image.

3.1 Enhancement of Low-light Visible Image

The low-light visible images suffer from poor illumination and it is necessary to improve the quality of such images as a pre-processing step in image processing applications. In this paper, the following are the algorithmic steps used for enhancing the low-light visible image obtained from low-light intensifiers. SR phenomenon in DWT domain is the technique utilised for improving the contrast of image.

Step 1: Compute 1-level DWT decomposition of the low-light visible image.

Step 2: Compute the tuned coefficients using the iterative Eqn. (6) given as:

$$x(n+1) = x(n) + \Delta t\left[ax(n) - bx^3(n) + DWT\ \ coefficient\right]$$

Initialising $x(0)=0$ and using the parameter values discussed above.

Step 3: Repeat *Step 2* for LH, HL and HH coefficients.

Step 4: Apply IDWT to the tuned coefficients and compute entropy of the reconstructed image after every $(n+1)^{th}$ iteration.

Step 5: *Steps 2 - 4* is applied iteratively until the entropy of the reconstructed image no longer increases and starts decreasing.

3.2 Fusion of Enhanced Low-light Visible and Infrared Images

After the preliminary step of enhancing the visible image quality, the next process is to integrate the information in both the visible and infrared images in more compact form. To perform fusion the following are the steps implemented in this proposed technique:

Step 1: Compute 1-level DWT decomposition of the enhanced low-light visible image and infrared image.

Step 2: Compute principal components using PCA for the coefficients obtained in step1.

Step 3: The low and high frequency coefficients are then fused based on the principal components derived in Step 2.

Step 4: IDWT is then applied to obtain the final fused image.

The algorithmic steps is illustrated as shown in Fig. 2.

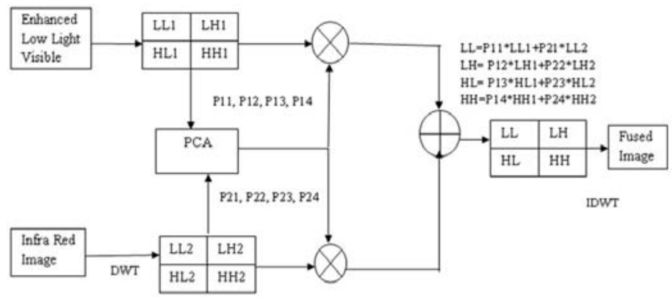


Figure 2. Flow chart for algorithmic steps.

4. PERFORMANCE EVALUATION

4.1 Subjective and Objective Evaluation

The subjective evaluation is based on psycho-visual examination of the fused images by human observers. Five performance metrics such as mean, standard deviation, entropy, spatial frequency and Q_0 are calculated for objective evaluation of the proposed framework described as:

Mean and standard deviation: The statistical parameters mean (μ), a measure of average intensity and variance (σ^2), a measure of average contrast are computed using Eqn. (8) and Eqn. (9) as

$$\mu = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} x_{ij} \tag{8}$$

$$\sigma^2 = \frac{1}{(M-1)(N-1)}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(x_{ij}-\mu\right)^2 \tag{9}$$

where MN is the total number of pixels in the image and x_{ij} is the pixel intensity at that location.

Entropy: Entropy is a measure of randomness. It measures the amount of information content in an image. Higher the value of entropy better is the information quality of the fused image. Mathematically, entropy is defined in Eqn. (10) as

$$E = -\sum_{i=1}^{M}\sum_{j=1}^{N} p(x_{ij}) \ln p(x_{ij}) \tag{10}$$

where $p(x_{ij})$is the probability of occurrence of x_{ij}.

Spatial frequency: Spatial frequency (SF) is a measure of overall activity level in an image. Higher the value of SF better is the fusion quality. The mathematical expression for computing SF is given in Eqn. (11) as

$$SF = \sqrt{RF^2 + CF^2} \tag{11}$$

where RF and CF are row and column frequencies determined in Eqns. (12)-(13) as

$$RF = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=2}^{N}(x_{i,j}-x_{i,j-1})^2} \tag{12}$$

$$CF = \sqrt{\frac{1}{MN}\sum_{j=1}^{N}\sum_{i=2}^{M}(x_{i,j} - x_{i-1,j})^2} \tag{13}$$

Similarity Measure (Q_0): Q_0 is a measure of similarity between the two source images. It is used to quantify the structural distortion between the two images.

Mathematically, Q_0[23] is defined in Eqn. (14) as

$$Q_0 = \frac{4\sigma_{xy}\overline{x}\,\overline{y}}{\left(\overline{x}^2 + \overline{y}^2\right)\left(\sigma_x^{\,2} + \sigma_y^{\,2}\right)} \tag{14}$$

where σ_{xy} is the co-variance of the two images x and y, $\sigma_x^{\,2}$, $\sigma_y^{\,2}$ represent the variance of x and y and $\overline{x}, \overline{y}$ represent mean of x and y, respectively.

4.2 Simulation Results and Discussions

Simulations were carried out on four experimental image datasets of visible and infrared images downloaded from http://home.ustc.edu.cn/liuvu1/[24]. These image datasets are shown in Fig. 3. The low-light images with low contrast are improved using SR phenomenon iteratively and the results of enhanced images are shown in Fig. 4 for the image datasets 1-4. Figure 4 shows that the low-light images are enhanced at different iterations based on the entropy as an enhancement factor. Since entropy is a measure of contrast, it is observed that the entropy value increases with the number of iterations and once the entropy value starts decreasing, the iteration stops and the enhanced image is obtained. The iterations required to improve were mentioned in Fig. 4 for the datasets considered. Visual quality of the images in Fig. 4 shows that the contrast of these images is improved at different iterations for different images.

Comparative analysis to the proposed method is performed by implementing the fusion techniques on the same source images using simple PCA and basic DWT methods. The simulation fusion results of the experimental datasets used in this paper are shown in Figs. 5-8. The subjective analysis indicates that the proposed method performs better with more information regarding the scene with improved contrast in the fused image compared to the other two methods for all the cases considered in Figs. 5-8. The PCA[14] and DWT[8] techniques can be considered as reference for evaluating the subjective quality of our method.

The objective evaluation on test images is performed by computing the performance indices described and are tabulated in Table 1 for all the image datasets. The tabulated results shows that all the metrics calculated for the proposed method are maximum indicating fusion quality to be better for the

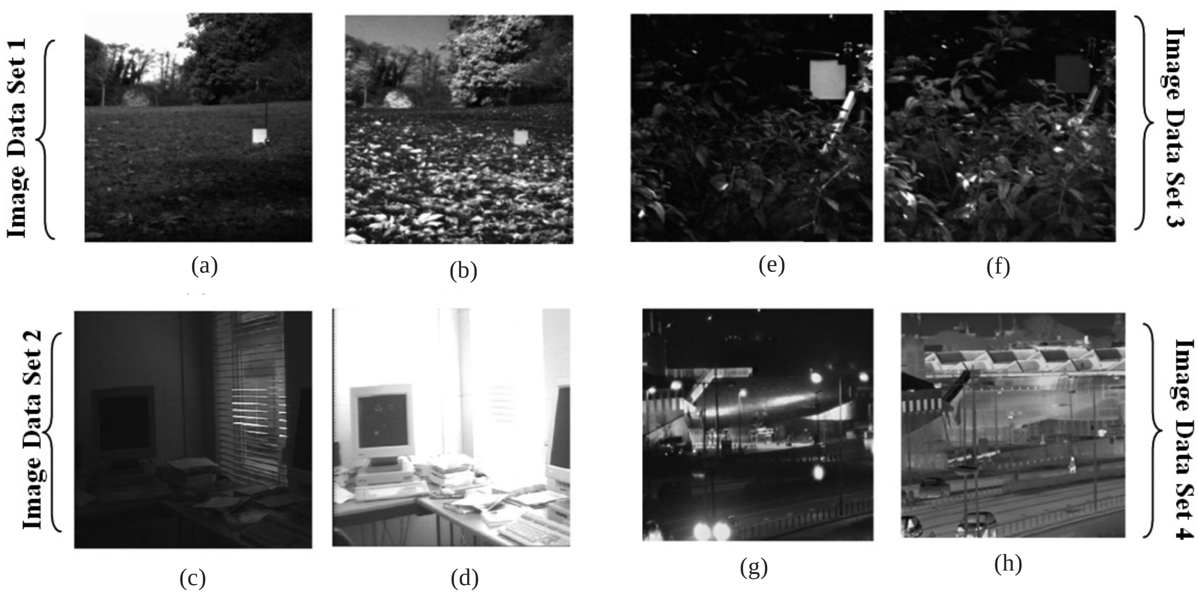


Figure 3. Low-light visible (a), (c), (e), (g) and infrared (b), (d), (f), (h) image datasets.

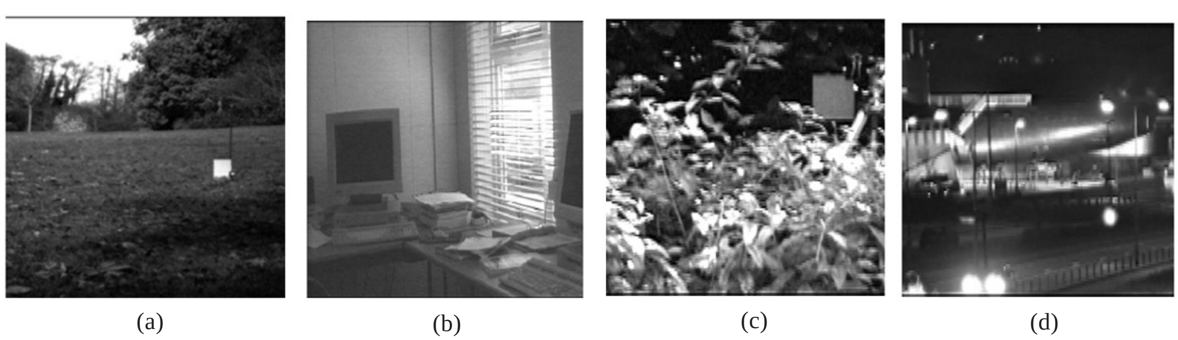


Figure 4. Enhanced low-light images SR with iterations (a) n = 82, (b) n = 152, (c) n = 159, (d) n = 73.

(a) (b) (c)

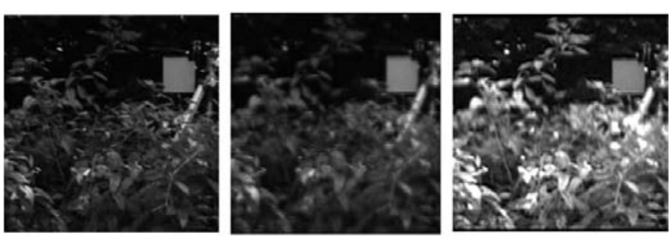
Figure 5. Fusion results of image dataset 1 using (a) PCA (b) DWT, (c) proposed method.

(a) (b) (c)

Figure 6. Fusion results of image dataset 2 using (a) PCA (b) DWT, (c) proposed method.

(a) (b) (c)

Figure 7. Fusion results of image dataset 3 using (a) PCA (b) DWT (c) proposed method.



(a) (b) (c)

Figure 8. Fusion results of image dataset 4 using (a) PCA (b) DWT (c) proposed method.

proposed method than the existing techniques. The method of enhancing the low-light image forms the basis for improving the fusion quality in this proposed technique.

5. CONCLUSIONS AND FUTURE WORK

In this paper, the phenomenon of Stochastic Resonance considered as a non-linear filter is used for enhancing the low-light images generated from low-light intensifiers. The SR method for tuning the coefficients is made iterative with the enhancement factor as entropy and the contrast of low light image is improved. The idea of enhancing the poor contrast low-light image prior to integrate with infrared image proved that the proposed method performs better in terms of visual quality and objective quality. The proposed framework may be implemented in future work to night vision fusion in navigation and surveillance applications to avoid accidents and to detect the targets. The proposed method is applicable for real-time applications in medical image processing wherein the low contrast MRI and CT images can be enhanced and then fused for medical diagnosis.

Table 1. Objective evaluation

Images	Metrics	PCA[14]	DWT[8]	Proposed
Dataset 1	Mean	80.014	82.6341	93.7438
	St.D.	49.6675	43.1141	52.1693
	Entropy	7.0914	7.0352	7.4553
	SF	13.0514	12.0864	21.2881
	Q_0	0.7077	0.2778	0.7892
Dataset 2	Mean	170.606	132.6887	163.2263
	St.D.	49.0745	39.3671	54.6323
	Entropy	6.7512	6.9966	7.4301
	SF	11.0668	8.2381	18.4639
	Q_0	0.5744	0.2164	0.9002
Dataset 3	Mean	35.35	34.8371	84.0116
	St.D.	31.33572	28.4816	63.0186
	Entropy	6.387	6.4086	7.5622
	SF	15.5032	14.6287	26.4187
	Q_0	0.8516	0.738	0.3933
Dataset 4	Mean	74.77	86.655	79.0868
	St.D.	41.4236	33.3391	43.4529
	Entropy	6.8412	6.9712	7.1137
	SF	13.677	15.7712	17.5086
	Q_0	0.7801	0.7427	0.5113

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In current study, she has given suggestions for the improvement of this paper.