IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Vol.-6, Issue-11, Nov 2018 E-ISSN: 2347-2693

Energy Efficient Compressive Sensing based Multi-focus Image Fusion Scheme for WVSN

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Available online at: www.ijcseonline.org

Accepted: 15/Nov/2018, Published: 30/Nov/2018

Abstract - Wireless Visual Sensor Networks (WVSN) is the enhanced version of WSN that captures and processes visual data from the environment. Owing to the numerous advantages, the WVSN is widely applicable in several real-time applications. The main considerations of WVSN are energy efficiency and quality. This work intends to propose an energy efficient compressive sensing based multi-focus image fusion scheme for WVSN. The image fusion is carried out by contourlet and curvelet, as these have multi-scale and multi-directional properties. The image fusion rule is framed by considering the energy of the pixels. Finally, the image reconstruction is carried out by CoSaMP (Compressive Sampling Matching Pursuit) algorithm. The performance of the proposed approach is tested in terms of image quality, energy and time consumption and the results are compared with the existing approaches. The proposed image fusion scheme outperforms the existing approaches, while proving better quality.

***Keywords*—**WVSN, multi-focus image fusion, energy efficiency.

I. INTRODUCTION

The Wireless Visual Sensor Networks (WVSN), which is an improvised version of WSN has grabbed the attention of several researchers, owing to its multimedia data processing ability. Now-a-days, most of the real time applications such as surveillance systems, environment monitoring systems, traffic monitoring systems, target detection and tracking systems and many other applications exploit visual data for achieving the goal. The visual data processing by wireless sensors faces two crucial challenges, which are energy consumption and quality of visual data.

Basically, the wireless sensors are energy constrained and processing visual data consumes even more energy, which could drain the energy faster. Energy deterioration decreases the lifetime of the sensor, which makes sense that the objective of the network cannot be fulfilled. Hence, the energy consumption pattern of sensor nodes must be controlled by some means. Out of all the operations being performed by the sensors such as visual data sensing, local processing and transmission, visual data transmission consumed more energy. One of the effective ways to achieve better energy conservation, while transferring visual data is compressive sensing.

The central theme of compressive sensing is to limit the data being transmitted to the destination by performing some manipulations. This idea saves energy and time as well. However, as the compressive sensing theory compresses the original data for energy conservation, the quality of the data may be affected. In order to ensure better quality, the proposed work intends to fuse the digital images by combining the information from different images, in order to provide detailed and high quality image by means of compressive sensing. Though there are numerous techniques to fuse images in the existing literature, the image fusion based on compressive sensing is very limited and uncommon.

Considering the potential of compressive sensing, this article presents an image fusion scheme based on compressive sensing that combines the merits of both curvelet [1] and contourlet [2]. The reason for employing curvelet and contourlet is its multi-scale and multi-directional operational ability. In addition to this, both these transforms preserve the edge information of an image [3, 4]. Some of the highlighting points of this work are listed as follows.

- Compressive sensing based image fusion preserves energy and ensures better quality.
- The utilization of curvelet and contourlet performs multi-scale and multi-directional operations over the image to ensure better image quality.
- The performance of this work is proven with respect to energy conservation and quality of data by means

of Peak to Signal Noise Ratio (PSNR) and energy efficiency.

The remaining part of this article is organized as follows. Section 2 discusses the review of literature with respect to compressive sensing based image fusion. The proposed image fusion technique based on compressive sensing is described in section 3. The performance of the proposed approach is evaluated in section 4 and the concluding points of this article are summarized in section 5.

II. RELATED WORK

This section reviews the related literature with respect to compressive sensing based image fusion.

In [5], a technique to fuse images by compressive sensing is proposed. This work creates a dictionary that coordinates the high-resolutional images to the low resolution images. The low resolution images are used to fuse the images. Principal Component Analysis (PCA) is utilized to detect the orthogonal mode of the co-occurring low and high resolutional patches of images. However, this work involves computational and time complexity.

An image fusion system for satellite images by ripplet transform and compressed sensing (CS) is proposed in [6]. This work aims to minimize the spectral distortion by employing CS theory. However, this work is meant for satellite images and consumes more time to accomplish the goal. In [7], a spatio-temporal fusion of remote sensing by means of CS theory. This work focuses on explicit down-sampling process for reconstructing the images. The similarity of sparse coefficients is managed by coupled dictionary. This work suffers from computational complexity.

In [8], a multi-focus image fusion and reconstruction framework is presented on the basis of CS theory. This work utilizes wavelets for achieving image fusion. Initially, this work represents the images with the sparse coefficients using Discrete Wavelet Transform (DWT). This step is followed by obtaining measurements with the help of random Gaussian matrix and fusion is carried out by adaptive local energy metrics. The sparse coefficients are reconstructed by means of Fast Continuous Linearized Augmented Lagrangian Method (FCLALM). However, this work misses out the edge based information being present in the images.

A multi-resolution image fusion technique based on CS and graph cuts is proposed in [9]. This work attempts to fuse multiresolutional images, so as to obtain high spectral and spatial resolution image. However, this work is meant for satellite images and consumes more time. In [10], a muti-spectral image fusion algorithm is proposed by employing CS theory. This work combines the intensity components of multi-spectral and panchromatic images. Wavelet transform is utilized for decomposition and the high frequency components are extracted. Orthogonal Matching Pursuit (OMP) algorithm is utilized for restoring high frequency components. Though this work is simple, the quality of the reconstructed image is not convincing.

A multi-focus image fusion technique is presented for visual sensor networks based on CS theory in [11]. This work claims that it has reduced energy consumption of visual sensors by employing CS theory. However, the quality of fused images is not evaluated by proper means. In [12], three different sampling algorithms are investigated for their performance on CS reconstruction. A new sampling model is then proposed for performing image fusion. However, the quality of the image after fusion is not satisfactory.

In [13], a technique to fuse satellite images by means of Compressive Sampling Matching Pursuit (CoSaMP) method is proposed. This work generates sparse coefficients by correlating the low resolution multispectral image with the low resolution pan dictionary. However, the quality of the reconstructed image is not satisfactory. An image fusion scheme for remote sensing images is presented by CS in the contourlet domain in [14]. Initially, the contourlet transform is applied and the compressive samplings are fused by linear weighting. Finally, the image reconstruction is carried out by Iterative Threshold Projection (ITP). However, this work is meant for remote sensing images.

In [15], the remote sensing images are fused together by CS using wavelet sparse basis. This work extracts the Red, Green and Blue components of both panchromatic and multispectral images. The wavelet transform is applied and the CS data is obtained by Gaussian random matrix for sparse data sampling. The fused image is reconstructed by OMP algorithm. However, the quality of the reconstructed image could even be improved. An image fusion scheme based on adaptive deviation feature is proposed in [16]. In this work, the infrared and visible light images are decomposed by means of Non Subsampled Contourlet Transform (NSCT) and the CS theory is applied and fusion is carried out by fusion rule based on standard deviation. The image is reconstructed by means of inverse NSCT. However, this work suffers from time complexity.

Motivated by the existing works, this article proposes an energy efficient image fusion scheme based on compressive sensing that relies on curvelet and contourlet transforms. The following section describes the proposed approach in detail.

III. PROPOSED ENERGY EFFICIENT COMPRESSIVE SENSING BASED IMAGE FUSION

This section describes the working principle of the proposed approach in addition to the overall flow of the work.

A. Overall Flow of the Work

The aim of this work is to attain energy efficiency while improving the quality of an image by fusing the multi-focus images. The visual sensors are widely distributed and the visual images are captured. However, all the information cannot be captured at a single snap but the image can be made even more detailed, when the multi-focus images are fused together. Several image fusion approaches employ wavelets [17-19], yet they cannot handle restricted directional information and are ineffective to deal with contours and edges. This issue can be better addressed by multi-scale analysis. Hence, this work employs curvelet and contourlet, which have multi-scale and multi-directional features for handling images.

The underlying reasons for the choice of curvelet are the ability to deal with the whole spectral domain, ability to deal with multi-scales and orientations. Contourlet is a multi-scale, multidirectional and multi-resolution transform, which presents an iterative filter bank, which makes it superior to other transforms. Hence, this work utilizes both these 'lets' and the entire work is organized in three phases. The initial phase is meant for representing and fusing the image, followed by the computation of compressive measurement and image reconstruction. All these phases are explained in the forthcoming section.

The sparse coefficients of the multi-focus images are fused together, such that the important information in the images are clubbed together and the measurement matrix is formed, which is capable of attaining reduced reconstruction error. The image fusion is carried out by clubbing high-pass and low-pass sub-bands separately. The high-pass sub-bands are processed with respect to the directional coefficients and is performed by contourlet and the low-pass sub-bands are processed by curvelet. This idea overthrows blocking artefact and minimal fidelity. The high-pass and low-pass sub-bands are fused separately, as both provide different kind of information. The high-pass sub-bands provide intricate details of an image that includes edges, lines and contours. The low-pass sub-bands are processed by curvelet. The following section elaborates the proposed approach.

B. Proposed Image Fusion Technique

The proposed approach involves three key phases as stated earlier. The initial phase is meant for image representation and fusion. The compressive measurements are computed in the second phase and finally, the image is reconstructed. The idea of segregating high-pass and low-pass sub-bands results in obtaining better information about the image, such that the quality degradation in reconstruction phase is overthrown. Contourlet is employed to handle high-pass sub-bands and on the other hand, curvelet handles low-pass sub-bands.

- Contourlet

Certain basic image representational properties are multiresolution, localization, directionality and anisotropy [20]. Multiresolution is the ability to represent digital images in all resolutions ranging from coarse to fine. Localization makes sure that the image components are localized in terms of both spatial and frequency domains. A standard image representation technique should sustain different directional orientations and this feature satisfies the directionality. Finally, the image representation technique must be capable of extracting the contours being present in the image, by considering different shapes with aspect ratio. The wavelets hold only two of these properties, which are multiresolution and localization.

Curvelets meet these image representational requirements, yet the discrete images cannot be handled and this issue is solved by contourlets which operates over the discrete domain. Though numerous transforms support multi-direction and multi-resolution abilities, most of the transforms do not allow multiple directions at a single scale. The contourlets utilizes iterated filter banks, which makes it effective than the analogous transforms.

Contourlet clubs Laplacian Pyramid (LP) and Directional Filter Bank (DFB) together. The DFB captures the high frequency components and the low frequency components are discarded. Let $x_0[n]$ be the input image which is treated by LP. The result of this step is the K bandpass images as indicated by the following equation.

$$y_k[n]; k = (1,2, \dots K) and\ x_K[n] \tag{1}$$

In eqn.1, $y_k[n]; k = (1,2, \dots K)$ denotes the image in fine to coarse order and $x_K[n]$ is the lowpass image. Hence, the k^{th} level of LP decomposes the input image $x_{k-1}[n]$ into a coarse and a fine image, as indicated by $x_k[n]$ and $y_k[n]$ respectively. Each bandpass image $y_k[n]$ is decomposed to a extent of d_k to 2^{d_k} bandpass directional images as given by

$$a_{k,l}^{(d_k)}[n]; \quad k = (0,1, \dots, 2^{d_k} - 1) \tag{2}$$

By this way, the contourlet processes the image and the summary of curvelet is presented as follows.

- Curvelet

Curvelet is an improvised version of ridgelet transform that considers lines. The ridgelet transform is indicated by

$$RT_f(a,b,\theta) = \int\int \psi_{a,b,\theta}(x,y) I(x,y) dxdy \tag{3}$$

In eqn.(3), $I(x,y)$ is the image and ψ is the ridgelet function as denoted in the following equation.

$$\psi_{a,b,\theta}(x,y) = a^{-1/2}\psi\left(\frac{xcos\theta + ysin\theta - b}{a}\right) \tag{4}$$

The curvelet sub-bands of an image are built by modifying the ridgelet in multiple scales and orientations followed by which, the curvelet subbands are analysed for energy by

$$E(a,\theta) = \sum_x \sum_y |Sb_{a,\theta}(x,y)| \tag{5}$$

Curvelets can operate over entire spectral domain, because of its wedge shape. Hence, curvelet is employed for fusing low-pass sub-bands. Initially, the images are decomposed by contourlet transform and are then treated by curvelet transform to obtain another HH, HL, LH and LL bands. After the process of obtaining all the sub-bands, the corresponding high pass and low pass sub-bands are passed to the compressive sensing part.

- Fusion rule formation

The fusion rules are formed by taking the frequency components into account. LL band is called the approximation band of the image, which is responsible for deciding the contrast and brightness of the fused image. This work utilizes the fusing rule with respect to local spatial frequency and is represented by the following equation.

$$RLSp_f(p,q) = \sqrt{\sum_{a\in W, b\in W} \frac{\left(f(p+a,q+b)-f(p+a,q-1+b)\right)^2}{(w\times w)}} \quad (6)$$

$$CLSp_f(p,q) = \sqrt{\sum_{a\in W, b\in W} \frac{\left(f(p+a,q+b)-f(p-1+a,q+b)\right)^2}{(w\times w)}} \quad (7)$$

$$LSp_f(p,q) = \sqrt{RLSp_f(p,q)^2 + CLSP_f(p,q)^2} \quad (8)$$

In the above equations, $RLSp_f(a,b)$ and $CLSp_f(p,q)$ indicate the row-wise and column-wise local spatial frequencies of the pixel (p,q) respectively. $w\times w$ indicates the size of the window and the local spatial frequency of the pixel (p,q) is represented by $LSp_f(p,q)$. The fusion rule is formed by considering the energy as presented below.

$$E(p,q) = \sum_{a\in W, b\in W}\left(f(p+a,q+b)\right)^2 \quad (9)$$

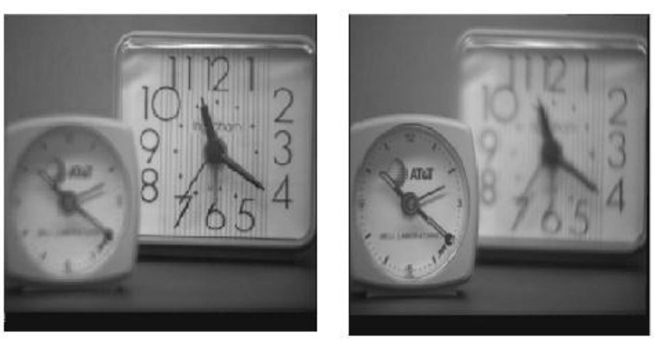
The reason for the choice of energy is that the region with greater energy can be easily ruled out in the fused image. The edge of the image is observed in the LH and HL sub-bands and hence, these sub-bands are given more importance with respect to greater energy, as denoted by

$$F(p,q) = \begin{cases} S1(p,q) if\ E_1(p,q) > E_2(p,q) \\ S_2(p,q) if\ E_1(p,q) < E_2(p,q) \end{cases} \quad (10)$$

This idea retains all the details of the images during the process of image fusion. This image is reconstructed by CoSaMP algorithm as presented in [21]. The performance of the proposed approach is evaluated in the following section.

IV. Results and Discussion

The proposed approach is simulated in Matlab environment of version 2013a on a stand alone computer with 8 GB RAM. The proposed approach is analysed by different multi-focus images downloaded from [22]. The performance of the proposed approach is compared against multifocus image fusion [8], CS based image fusion [11] and the proposed approach without compressive sensing. Some of the sample visual results that could prove the efficacy of the proposed approach are presented below.



(a) (b)

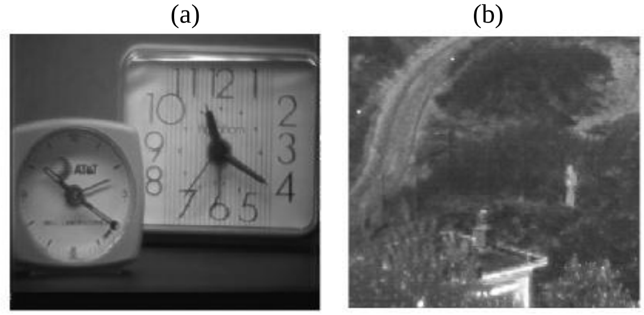
(c) (d)

(e) (f)

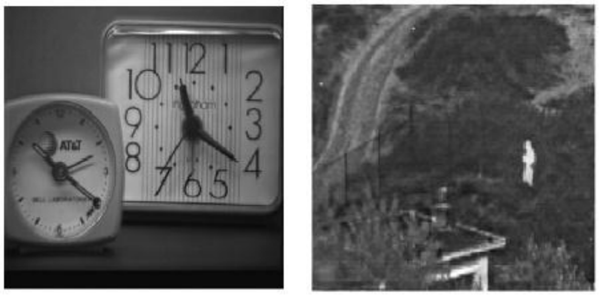
Figure 1. (a-f) Sample multi-focus images

From figure 1, it could be noted that figure 1a and 1b are same but the focus is different. Figure 1a and 1b focus on big clock and small clock respectively. Similarly, figure 1c and d shows a scenery image in different focuses. The objective here is to prove better quality images upon fusion.

(a) (b)



(c) (d)



(e) (f)

Figure 2. (a,b) Fused image [8], (c,d) Fused image by [11], (e,f) Fused image by proposed approach

From figure 2, the visual quality of the images shown by proposed approach is better than the existing approaches and the details are clearly visible. The performance of the proposed approach is evaluated in terms of PSNR to prove the image quality, energy and time consumption. The sampling rate is set as 0.7, as it proves better performance and the following table presents the PSNR analysis of the proposed approach.

Table 1. PSNR (dB) Analysis of the proposed approach

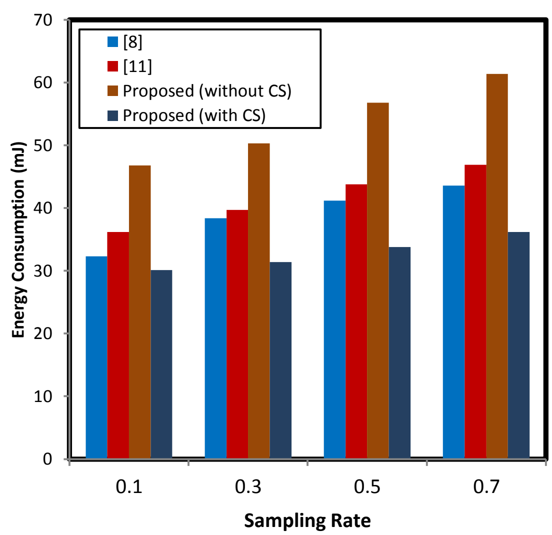
Input	Sampling Rate	[8]	[11]	Proposed
Image 1	0.1	25.6	28.3	**32.4**
	0.3	27.2	31.4	**33.9**
	0.5	28.4	34.6	**38.3**
	0.7	31.2	36.9	**39.6**
Image 2	0.1	26.9	33.6	**33.6**
	0.3	28.7	35.7	**35.3**
	0.5	32.3	38.2	**37.6**
	0.7	35.6	38.4	**39.8**
Image 3	0.1	22.4	27.6	**31.4**
	0.3	26.7	26.4	**32.6**
	0.5	29.8	29.7	**35.9**
	0.7	32.6	30.7	**39.7**
Average PSNR Rates (dB)		28.95	32.62	**35.84**

From the experimental results, it is proven that the PSNR value of the proposed approach is greater than the existing approaches. The main reason for increased quality is the consideration of energy, while forming image fusion rule. The average PSNR value of the proposed approach is 35.84, which is better than the existing approaches. The following table presents the time consumption of the proposed approach.

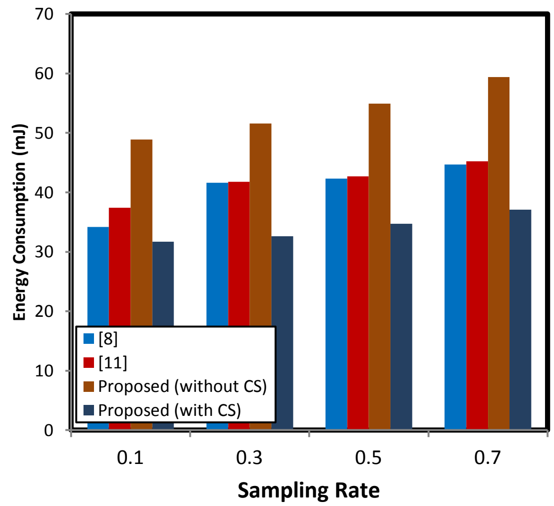
Table 2. Time consumption (ms) analysis

Input	Sampling Rate	[8]	[11]	Proposed (without CS)	Proposed (with CS)
Image 1	0.1	2846	3047	**3326**	**2647**
	0.3	2889	3146	**3597**	**2686**
	0.5	2948	3185	**3739**	**2721**
	0.7	3147	3214	**3886**	**2729**
Image 2	0.1	2978	2996	**4013**	**2568**
	0.3	3019	3016	**4198**	**2642**
	0.5	3341	3128	**4260**	**2731**
	0.7	3418	3286	**4339**	**2895**
Image 3	0.1	3041	2987	**4549**	**2469**
	0.3	3078	3246	**4613**	**2547**
	0.5	3147	3279	**4741**	**2597**
	0.7	3249	3288	**4886**	**2691**
Average Time Consumption (ms)		3091.75	3151.5	**4178**	**2660.25**

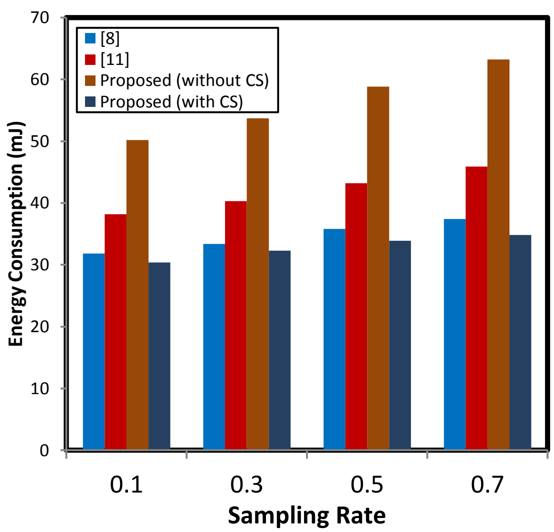
From table 2, it is clearly evident that the proposed approach shows minimal time consumption, when compared to other existing approaches. The proposed approach shows an average of 2660.25 ms and on the other hand, the existing approaches show more than 3000 ms. The proposed approach without compressive sensing shows maximum time consumption with 4178 ms. Hence, the time conservation ability of compressive sensing is proven. The energy consumption analysis of the proposed approach is presented in the following figure.



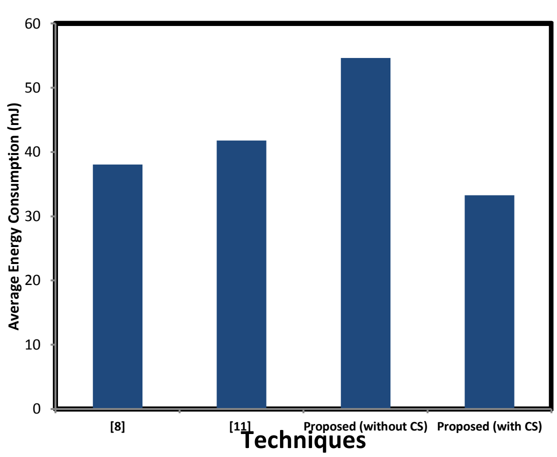
(a)



(b)



(c)



(d)

Figure 3. Energy consumption analysis of (a) image 1 (b) image 2 (c) image 3, (d) average

Based on the results, it is clearly proven that the performance of the proposed approach is better than the existing approaches. The proposed approach without compressive sensing consumes more energy than all other works. The reason for greater energy consumption is that the data is passed without compressive sensing, such that the original data is transferred without any manipulation. This increases the energy consumption and obviously, the lifetime of the network is reduced. In fine, the proposed approach with compressive sensing proves better performance by consuming minima energy and time. Initially, the proposed approach is tested for quality by means of PSNR and the energy, time efficiency are then analysed. The proposed approach consumes reasonable energy and time, when compared to the existing approaches and hence, the purpose of this work is justified. The following section concludes the article.

V. Conclusion and Future Scope

This article presents an energy efficient compressive sensing based image fusion scheme for WVSN. This work attains the research goal by segregating the work into three important phases and they are image representation and fusion, reconstruction. Both contourlet and curvelet are utilized for image fusion and the image fusion rule is framed by considering the energy into account. The performance of the proposed approach is found to be satisfactory in terms of PSNR, energy and time consumption. In future, this work plans to handle 3D images.

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