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Multi-Focus Image Fusion for Visual Sensor Networks in Wavelet Domain

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Abstract

The aim of multi-focus image fusion is to combine multiple images with different focuses for enhancing the perception of a scene. The result of image fusion is a new image which is more suitable for human and machine perception or further image-processing tasks such as segmentation, feature extraction and object recognition. Existing methods are suffering from some undesirable side effects like blurring or blocking artifacts which reduce the quality of the output image. Furthermore, some of these methods are rather complex. This paper, an efficient approach for fusion of multi-focus images based on variance calculated in wavelet domain is presented. The experimental results and comparisons show that the efficiency improvement proposed fusion model both in output quality and complexity reduction in comparison with several recent proposed techniques.

Keywords: Multi-Focus Images, Image Fusion, Segmentation, Feature Extraction, Object Recognition, Wavelet.

1. Introduction

In sensor networks, every camera can observe scene and to be recorded either still images or video sequences. Therefore, the processing of output information is related to image processing and machine vision subjects [1]. The need for image fusion is increasing mainly due to the increased number and variety of image acquisition techniques [2].

A prominent feature of visual sensors or cameras is the great amount of generated data, thus requires more local processing resources to deliver only the useful information represented in a conceptualized level [1]. Image fusion defined is the process of combining information from several sensors or cameras using mathematical techniques in order to create smaller set of images, usually a single one, that will be more comprehensive and thus, more useful for a human operator or other computer vision tasks [2].

The cameras that are used in visual sensor networks or computer vision systems have a limited depth of field, only the objects at a particular depth or certain distance in the scene are in focus whiles objects at other distances will be blurred thus for extending the depth of focus used multiple cameras. Therefore, the multi-focus image fusion technique is desirable to fuse a set of images.

Recently, multi-resolution analysis has become a widely adopted technique to perform image fusion [3–7]. The algorithms based on multi-scale decompositions are more popular. The key step is to perform a multi-scale transform on each source image, and then performed coefficient combination, the process of merge the coefficient in an appropriate way in order to obtain the best quality in the fused image. These methods for obtaining the best quality, combining the source images by monitoring a quantity that is called the activity level measure. The activity level determines the quality of each source image [8]. The combination can be performed by choosing the coefficients with larger activity level. Examples of this approach include: Laplacian, gradient, morphological pyramids, and the superior ones discrete wavelet transform (DWT) [9] and shift invariant discrete wavelet transform (SIDWT) [10].

In [11], proposed image fusion technique in wavelet domain, that fusion performed by applying wavelet decomposition on source image, then for detailed and approximation subbands, by proposed method in [11] combined the coefficient. Finally apply an inverse wavelet transform to obtain a fused image. The other approach that proposed in [12], to retain the visual quality and performance of the fused image with reduced computations, a discrete cosine harmonic wavelet (DCHWT)-based image fusion is proposed.

The other method is recently introduced in gradient domain [13] which obtains fused image with detecting definite focus region and identifying gradient weight near focused boundaries.

Variance value is usually assumed as a contrast measure in image processing applications. In [8], image fusion technique in DCT domain is proposed. The variance of 8×8 DCT coefficients in a block is considered as a contrast criterion to be used for activity level measure. It was shown that the calculation of the variance value in DCT domain is very easy. Then, with using a consistency verification (CV) stage increases the quality of the output image.

Tang [14] by considering the issue of complexity reduction proposed two image fusion techniques DCT+average and other, based on a contrast measure defined in the DCT domain is presented (DCT+contrast). Tang has implemented his proposed methods on 8×8 DCT blocks defined.

DCT+Average obtains the fused image by averaging of the DCT coefficients of the input images. This method leads to some inappropriate side effects including blurring. In other methods, DCT + contrast, activity level is based on a contrast measure. The DCT block of the output image is made up with highest contrast for AC coefficient and DC coefficient by averaging of DC coefficient produce.

This algorithm also has complexity in calculating the contrast measure for each coefficient and suffering from some side effects including blocking artifacts.

In order to reduce the complication and enhance the quality of the output image, an image fusion technique in wavelet domain is proposed in this paper. The variance of 8×8 wavelet coefficients in a block is considered as a contrast criterion to be used for activity level measure. Then, the quality of the output image increases by using a consistency verification (CV) stage. Simulation results and comparisons show the considerable improvement in the quality of the output image and reduction in computation complexity.

This paper is organized as follows: In Section 2, presents our proposed method of image fusion. In Section 3 the simulation results are demonstrated and analyzed, and finally, the main conclusion is drawn in Section 4.

2. Proposed Method

As it was explained, area of focus in multi focus images has more useful information. This information is related to the area with more variance. Variance usually considers as contrast in the functions of image processing, and areas with bigger variance cause more contrast and cleaner and also sharper edges. This is also true for wavelet coefficients. figure 1a is an extracted 64×64 block out of "Lena" image. figure 1b-e is the blurred versions of figure 1a with disks with the radius of 3, 5, 7, 9, respectively. The multi-resolution decomposition gives four bands at each level, where contain detailed information in horizontal, vertical, diagonal directions and the approximation that illustrate with H, V, D and A, respectively. For 5 levels of decomposition, H1, …, H5 represent horizontal subbands, V1, …, V5 represent vertical subbands, D1, …, D5 represent diagonal subbands, and A5 represents approximate subband. Sum of subbands' variance in each level of wavelet transform is shown in Table 1.

As it is shown in Table 1, when blurring rate increases, variance decreases. Now the wavelet coefficient related to each of these images which are shown in figure 1 is calculated.

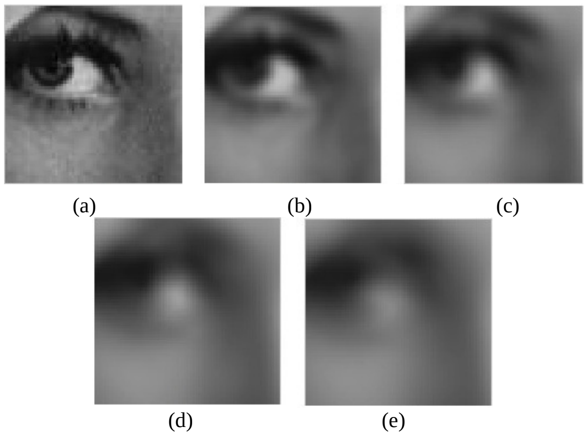

Figure 1. Original and blurred version of an image block extracted from the "Lena" image. (a) original image. (b) radius=3. (c) radius=5. (d) radius=7. (e) radius=9

These results produce the same results for second image which is an acquired image of "Cameraman" (Figure 2 and Table 2). As it is shown, variance can be used as a criterion of clarity image.

Table 1. Sum of subbands' variance of the image blocks in figure 1

Subband \ image	Fig. 1(a)	Fig. 1(b)	Fig. 1(c)	Fig. 1(d)	Fig. 1(e)
A5	13.5685	12.6137	11.5548	10.0610	8.4054
H1+V1+D1	0.0011	0.000123	0.000062	0.000038	0.000027
H2+V2+D2	0.0138	0.0039	0.0017	0.00087	0.00059
H3+V3+D3	0.1285	0.0723	0.0344	0.0165	0.0107
H4+V4+D4	0.5189	0.4194	0.3248	0.2562	0.2078
H5+V5+D5	9.0560	7.8360	6.5107	5.2364	4.1257

After dividing the source images into blocks of 8×8 pixels and calculating the wavelet coefficients in 5 levels of decomposition for each block, the fusion algorithm is performed with calculating variance of these subbands coefficients in four dimensions and five scales. Here, considered the variance values of the blocks from source images as activity level measures that computed using Eq. (1).

$$AC_I(P) = \left[\frac{1}{NM}\sum \left(X_I(P) - \overline{X}_I(P)\right)^2\right] \quad (1)$$

To simplify the processing of just two source images, if more than two source images are observed, they are combined one by one by iteratively applying the method, so we consider two source images F and G, and the fused image Z. Generally, an image I has its MSD representation denoted as X_I and the activity level as AC_I. Thus, we have X_F, X_G, X_Z as MSD representation of source and fused images and AC_F, AC_G as activity level of source images.

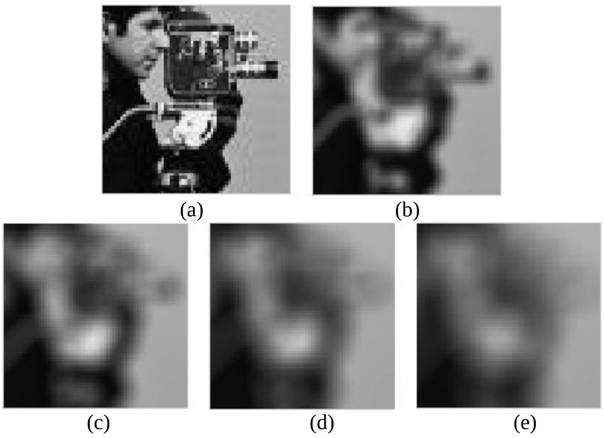

Figure 2. Original and blurred version of an image block extracted from the "Cameraman" image.(a) original image. (b) radius=3. (c) radius=5. (d) radius=7. (e) radius=9.

Let $P = (k; l)$ indicates the index corresponding to MSD coefficients, where *k* indicates the decomposition level, and *l* the frequency band of the MSD representation.

The subband of blocks which have high value of AC_I is considered clearer, consequently fused wavelet coefficients is obtained by choosing maximum AC_I for each frequency bands (horizontal, vertical, diagonal and approximation) of source coefficients. Therefore, a good integration rule just picks the coefficient with larger activity level and discards the other. If *Z* is the fused image, this can be described as $X_Z(P) = X_i(P)$, where $i = F$ or G depends on which source image establish Eq. (2).

$$AC_i(P) = \max\left(AC_F(P), AC_G(P)\right) \tag{2}$$

Simultaneously, a binary decision map is created to record the selection results based on a maximum selection rule in Eq. (2). This binary map is subject to a consistency verification that follows in section 2.1.

Table 2. Variance of the image blocks in figure 2

Image / Subband	Fig. 1(a)	Fig. 1(b)	Fig. 1(c)	Fig. 1(d)	Fig. 1(e)
A5	73.7344	71.7995	70.2338	68.8835	68.2379
H1+V1+D1	0.0319	0.000559	0.000149	0.000063	0.000032
H2+V2+D2	0.1217	0.0160	0.0048	0.0021	0.0009
H3+V3+D3	0.4324	0.2131	0.0893	0.0366	0.0179
H4+V4+D4	1.9969	1.4714	0.9334	0.5321	0.2984
H5+V5+D5	3.2494	2.9424	2.7866	2.6337	2.3760

2.1. Consistency Verification (CV)

Assume a region in a scene including several blocks which is completely in the depth of focus of image F, so all the blocks in this region must be chosen from image F, but due to noise or inappropriate effects during the selection process that can lead to erroneous selection of some blocks from image G. This defect can be solved with a consistency verification procedure [8]. The algorithm plan is demonstrated in figure. 3. Li [9] applied consistency verification using a majority filter.

If the center block comes from source image *G* while the majority of the surrounding blocks come from source image *F*, the center sample is then changed to image *F*. The fused image is finally obtained based on this modified decision map. The steps of the proposed method are elucidated as follows.

3. Experimental Results and Analysis

In this section, experiments are conducted to compare performance of the proposed approach with other prominent techniques.

Two of them are DCT based image fusion techniques named DCT+Variance+CV in [8], DCT+Average in [14], also the other algorithm which is recently suggested named MWGF in [13], and the other four techniques are multi-focus and multi-spectral image fusion based on pixel significance using discrete cosine harmonic wavelet transform (DCHWT) [12], adaptive multi-focus image fusion using a wavelet-based statistical sharpness measure [11] that represent with SP, standard wavelet based fusion (DWT) [9] and the shift invariant wavelet based technique (SIDWT) [10] that have been briefly described in Section 1,are mentioned to compare with proposed method.

For simulation of DWT and SIDWT, the "Image Fusion Toolbox", kindly provided by Rockinger [15] and for proposed method in [11], the code in [16], was used. The presented algorithm in [13] is available in [17].

The proposed approach exploits a five-level wavelet decomposition using a coiflet wavelet.

3.1 Performance Measure

The known factor of SSIM [18] is used for the evaluation of images which are artificially created out of ideal image. The acquired results of this measure are shown in Table 3.

On the other hand, three image quality evaluation criterions are used to provide objective performance comparisons in our work.

In fact, mutual information [19] as a mean of information theory states the amount information which the fusion image of Z have from the source images of F and G which is measurable like following:

$$I_{ZF}(z,f) = \sum_{z,f} P_{ZF}(z,f)\log_2 \frac{P_{ZF}(z,f)}{P_Z(z)P_F(f)} \tag{3}$$

$$I_{ZG}(z,g) = \sum_{z,g} P_{ZG}(z,g)\log_2 \frac{P_{ZG}(z,g)}{P_Z(z)P_G(g)} \tag{4}$$

Equations 3 and 4 state Mutual information between the source image of F and the fusion image of Z and also the mutual information between source image and the fusion image of Z.

Finally, performance evaluation criterion of the fusion method defines as the following:

ALGORITHM

Step 1: Divide source images into 8×8 blocks.
Step 2: Compute the multilevel 2D wavelet decomposition of 8×8 blocks.
Step 3: Calculate variance of wavelet coefficients for all subbands as activity level (AC_i).
Step 4: *if* $\mathrm{AC_F} > \mathrm{AC_G}$
Then $\mathrm{X_F(P)}$ is selected for $\mathrm{X_Z(P)}$.
Other wise $X_Z(P) = X_G(P)$.
Step 5: Repeat step 4 for all subband.
Step 6: The fused sub image is obtained by applying the inverse wavelet transform on the fused wavelet coefficient.
Step 7: Repeat above steps until all the sub images in the entire images are processed.
Step 8: Applying consistency verification using a majority filter to modify the incorrect decision map.

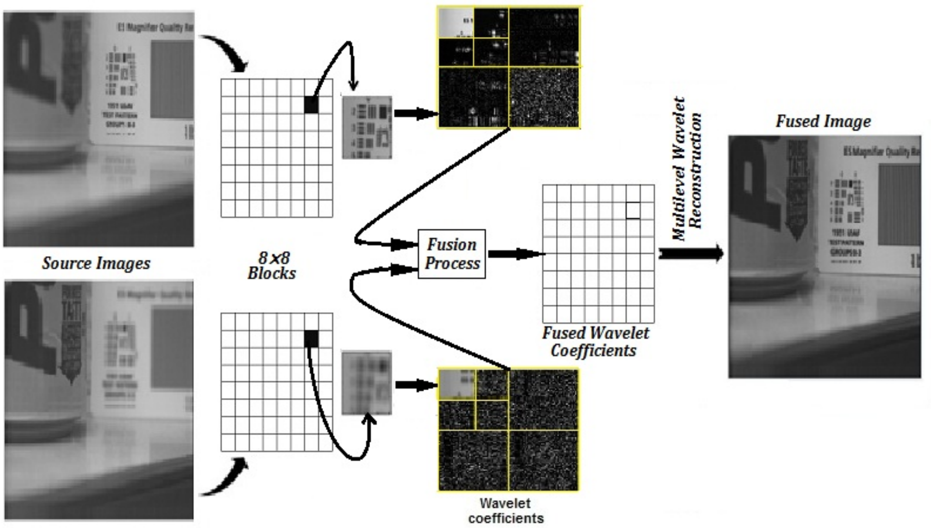

Figure 3. Proposed image fusion method.

$$\mathrm{MI_Z^{FG} = I_{ZF}(z, f) + I_{ZG}(z, g)} \quad (5)$$

The other criterion is introduced in [20] is known as Petrovic metric (Qabf). This criterion measures the information related to edges of F and G source images which is transferred to fusion image of Z.

According to the information concept in image based on its features which is well known for feature image, measuring the information related to the features transferred from the source images to fusion image can be a suitable criterion for evaluating the approaches image fusion. This criterion named Feature Mutual Information (FMI) which is introduced in [21] solves the problem. The objective performance comparisons are presented in Tables 4-6.

3.2. Fusion Results Evaluation

First, algorithm is done for 20 pair of images blurred artificially which only some of the images can be seen because of low space in figure 4. These images are made with blur in left and right half. The average of SSIM acquired from performing different algorithms includes the proposed method are given in Table 3 for these 20 images. The first column is the average of SSIM related to proposed approach done by Tang [14]. The columns of second, third and fourth are methods based on wavelet which are provided in [9], [10], [12], respectively. DCT+Variance+CV and MWGF in fifth and sixth columns are the proposed approach in [8], [13], respectively. The average of SSIM related to proposed method is shown in the last column.

It is clear that the proposed method has a phenomenon improvement in the quality of image with noticing to the average SSIM numbers in Table 3.

The subjective test of the resultant images approves the objective measures. By careful observing to the fusion results in figure 5, it is concluded that the method DCT+Average results in the side effect of reduction in contrast or blurring the fused image (figure 5c). In addition, there are some artifacts for the wavelet based methods DWT, SIDWT, SP, DCHWT, DCT+Variance+CV and MWGF given in figure 5d-i, respectively.

As it can be seen in the magnified images referred to DWT, SIDWT, SP, DCHWT, DCT+Variance+CV and MWGF respectively, in figure 5l-q, the wavelet based algorithms suffer from a kind of ringing artifact. This ringing artifact is a common problem in wavelet based algorithms and some wavelet based methods (e.g. SIDWT) has somewhat blurring problem.

Figure 5i is the results of our proposed method. One can see that the fused images obtained using the proposed method yield better image quality than that of conventional approaches. In order to have some real viable experiments, other experiments were conducted on other well-known images.

Eventually, the corresponding objective results are given in Tables 5-6. These quantitative evaluations prove the superiority of our proposed method.

Figure 4.Some images are blurred artificially for simulating

Table 3. Average SSIM values of algorithms for 20 image

DCT+average	DWT	SIDWT	DCHWT	DCT +Variance+cv	MWGF	Proposed method
0.9102	0.9854	0.9880	0.9903	0.9979	0.9973	**0.9986**

Table 4. Objective evaluation of the image fusion algorithms for ‘‘Pepsi’’ database in Figure 5

Method	Metric Qabf	MI	FMI
DCT + average	0.6420	6.8393	0.9122
DWT	0.7266	6.4371	0.9190
SIDWT	0.7506	6.7590	0.9193
SP	0.7425	7.3136	0.9238
DCHWT	0.7568	6.8542	0.9182
DCT+Variance+cv	0.7920	8.6712	0.9246
MWGF	0.7862	8.5013	0.9245
Proposed method	**0.7929**	**8.8150**	**0.9247**

Table 5. Objective evaluation of the image fusion algorithms for ‘‘Clock’’ database in Figure 6

Method	Metric Qabf	MI	FMI
DCT + average	0.5323	6.7311	0.9049
DWT	0.5873	6.2185	0.9097
SIDWT	0.6283	6.5239	0.9126
SP	0.6288	7.0382	0.9143
DCHWT	0.6026	6.6047	0.9132
DCT+Variance+cv	0.6460	7.1799	0.9157
MWGF	0.6431	6.9414	0.9155
Proposed method	**0.6485**	**7.1802**	**0.9166**

Table 6. Objective evaluation of the image fusion algorithms for ‘‘Disk’’ database in Figure 7

Method	Metric Qabf	MI	FMI
DCT+average	0.5213	5.9791	0.9013
DWT	0.6325	5.5305	0.9041
SIDWT	0.6741	5.9688	0.9054
DCHWT	0.6542	6.0930	0.9075
DCT+Variance +cv	0.7320	8.3383	**0.9115**
MWGF	0.7286	7.7665	0.9110
Proposed method	**0.7332**	**8.3550**	0.9113

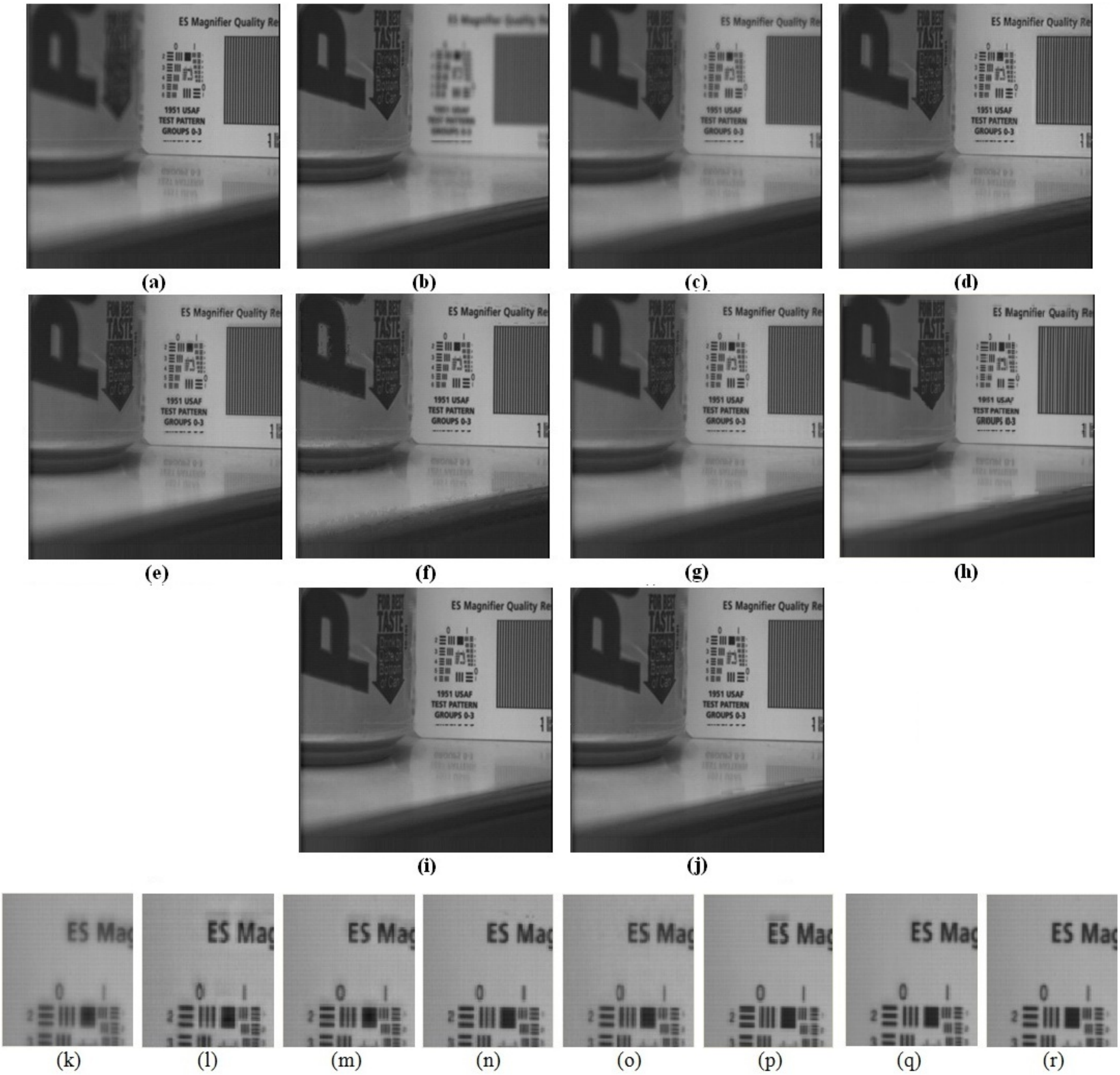

Figure 5. Source images ''Pepsi'' and the fusion results. (a) The first source image with focus on the right. (b) The second source image with focus on the left. (c) DCT+Average result. (d) DWT result. (e) SIDWT result. (f) SP result. (g) DCHWT result. (h) DCT+Variance+CV result. (i) MWGF result. (j) Proposed method. (k), (l), (m), (n), (o), (p), (q), (r) are the local magnified version of (c), (d), (e), (f), (g), (h), (i) and (j) respectively

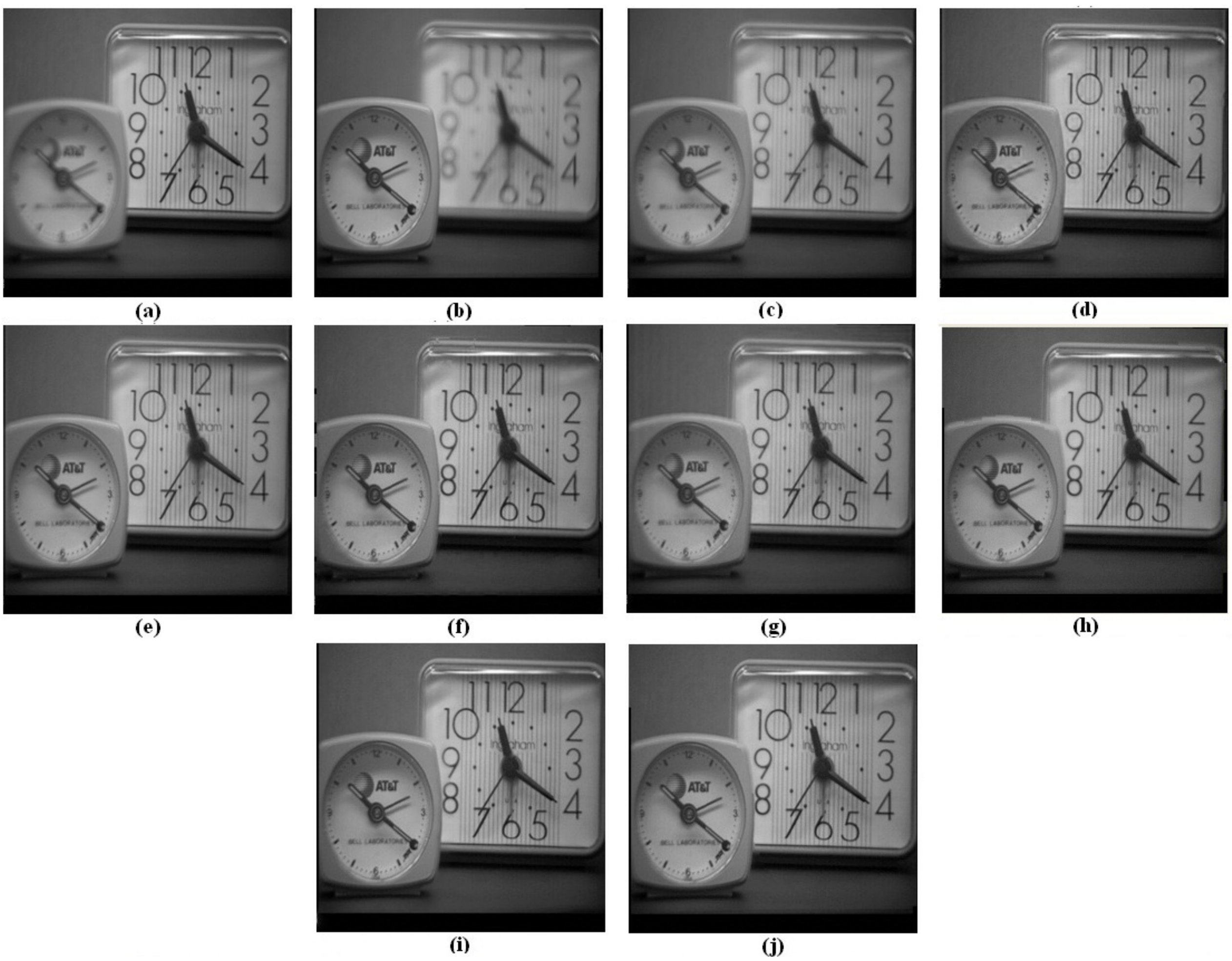

Figure. 6. ‘‘Clock’’ database source images and the fusion results: same order as in figure 5

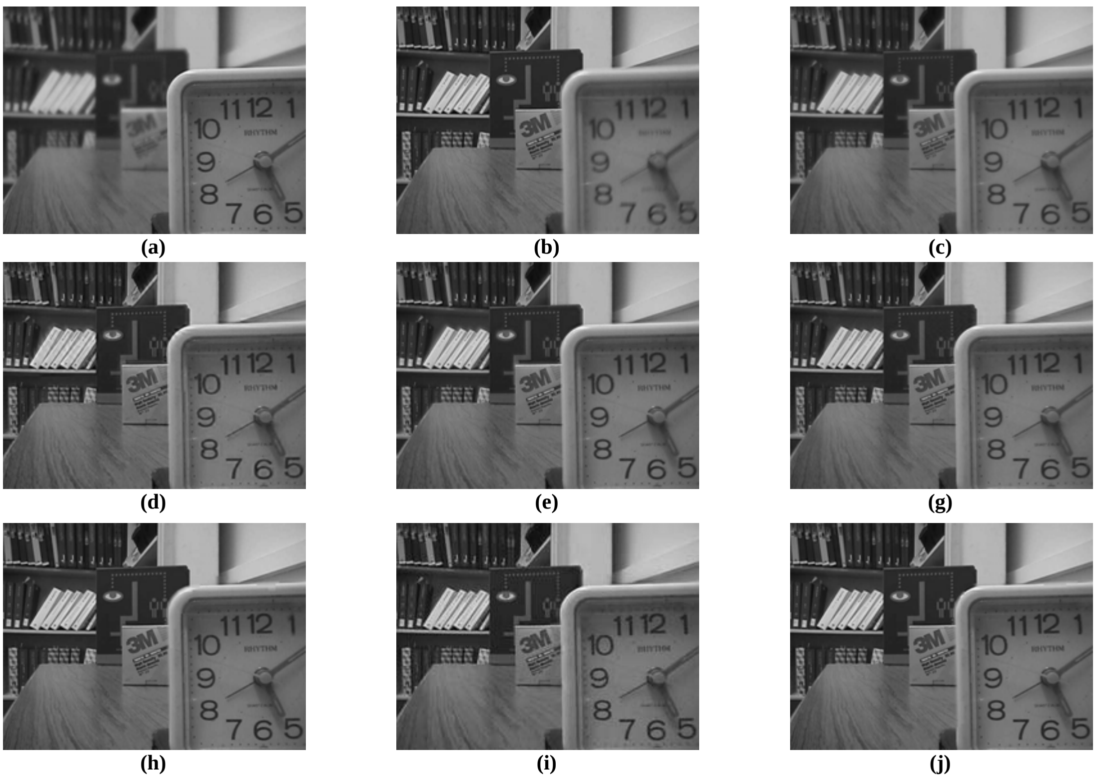

Figure 7. ‘‘Disk’’ database source images and the fusion results: same order as in Figure 5

4. Conclusion

In this paper, a new wavelet based image fusion technique for multi-focus images was proposed. The method is based on the variance in wavelet domain. Utilization of variance in the proposed algorithm, leads to better quality of the fused image. Numerous experiments on evaluating the fusion performance were conducted and the results show that the proposed method outperforms the previous wavelet and DCT based methods both in quality and complexity reduction.

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