

AN INTERACTIVE WEB BASED TOOLKIT FOR MULTI FOCUS IMAGE FUSION

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Received February 24, 2014

Revised September 17, 2014

This paper presents a web-based multi-focus image fusion toolkit developed by using ASP.NET and MATLAB. The toolkit enables users to explore different image fusion techniques such as basic averaging, Laplacian pyramid, wavelet, Discrete Cosine Transform (DCT), pixel based method using spatial frequency & morphological operators (PBSFMO) and block-based spatial domain fusion (SDMIF) methods. The toolkit also includes a new optimal fusion method based on evolutionary algorithms such as Evolution strategies (ES), Genetic algorithm (GA), Differential evolution (DE), and Adaptive differential evolution (JADE) algorithm. Users will be able to evaluate several image fusion techniques easily and efficiently by employing the toolkit.

Key words: Web based MATLAB applications, multi-focus image fusion, evolutionary algorithms

Communicated by: M. Gaedke & T. Tokuda

1 Introduction

Since imaging systems have been used in many fields, image processing has become an important subject in numerous disciplines [1]. In recent years, image fusion has emerged as a significant sub-area of computer vision and image processing [2, 3]. Image fusion can be defined as a method that constructs a single synthetic image contains more complementary information than each of the images of a scene or object. The images are taken with either more than one sensor or a single sensor with different optical parameters [4]. Optical imaging cameras are seriously affected by the finite depth of field drawback which means objects located at different places cannot be focused in a single shot. As a result, some objects appear in focus (sharp) and the others defocused (blurred). A well-known solution to accomplish this challenge is to use image fusion techniques. Multi-focus image fusion is referred as combining the individual images with diverse focuses of the same scene or object to gather a composite image that is focused entirely [5]. Through this way, sharper images obtained are more useful than defocused images in several areas such as industrial imaging, military and medical applications [6, 7]. Therefore, an image fusion toolkit may be essential for users studying in the area of electronics, biomedical, mechatronics and computer engineering.

One of the main problems of image processing applications is that it has to be convenient for human visual sense in order to obtain effective outputs. Image processing concepts can be conceived better by visualizing the data and process. Consequently, image processing applications should be implemented with interactive, visual and easy accessible software tools and interfaces [8]. Moreover,

users tend to learn the techniques, methods and algorithms, the background theory and their properties by evaluating them with various inputs. This can be achieved traditionally with laboratory courses which have the problems of time, equipment, physical place and lecturer limitations. In recent years, interactive applications and technologies are used to overcome these problems [9]. These technologies include commercial software packages such as MATLAB, free toolkits [10-12], and online HTML based materials containing multimedia objects [13] for image fusion applications. However, the non-commercial toolkits have to be downloaded before using, and they require preliminary other commercial/non-commercial software packages to be installed. Moreover, some of them are often expensive and require a commercial or academic license [14]. Image fusion related web sites have the advantage of easy accessibility but, they are static and do not contain interactive interfaces for better learning [13].

This paper has two goals: first, to introduce a new image fusion method that employs:

- evolution strategies (ES), which is a remarkably simple and easy understandable evolutionary optimization algorithm [15],
- genetic algorithm (GA), which is a frequently used well-known algorithm [16],
- differential evolution (DE), which is an robust, effective and fast algorithm [17],
- adaptive differential evolution (JADE) algorithm [18], which is an improved version of standard DE.

Second, to present a web based interactive simulation toolkit for multi-focus image fusion that includes well-known image fusion methods and our new proposed method. The main advantages of the proposed toolkit include easy accessibility, visualization of the image fusion methods that allow users to understand the concepts, comparing the methods by means of performance and robustness, testing the methods with different inputs and varying parameter values. Furthermore, users can reach the web based toolkit either in the laboratory or home without installing any preliminary other software packages.

The rest of the paper organized as follows: well-known image fusion methods and quality metrics are briefly introduced in next section. Section 3 presents the proposed spatial domain block based image fusion technique with ES, GA, DE and JADE algorithms. And, the web based interactive toolkit is described and illustrated in section 4. Finally, results and some concluding remarks are given in sections 5 and 6, respectively.

2 Image Fusion Methods and Quality Metrics

Well-known image fusion methods can be given as follows: pixel-by-pixel basic averaging, Laplacian pyramid (LP) [19], wavelet [20, 21], Discrete Cosine Transform (DCT) [22] and pixel based method using spatial frequency and morphological operators (PBSFMO) [23]. LP and wavelet methods have the disadvantage of being shift variance and sensitive to noise [2], Li's block based spatial domain method (SDMIF) [24] overcomes these problems. On the other hand, a convenient block size that affects the quality of SDMIF method has to be determined. To fulfil this requirement, genetic algorithm (GA) [25], multi-objective GA [26] and DE algorithm [4] have been proposed in the literature. Image fusion methods can be classified into spatial and transform domain methods:

2.1 Spatial Domain Image Fusion Methods

Spatial domain image fusion methods obtain the fused images by utilizing spatial features such as intensity, gradient and spatial domain frequency. These methods do not require a transform. Consequently, they are much simpler than the transform based methods. The basic spatial domain image fusion method includes taking the pixel-by-pixel average of the source images. This method often results detrimental side effects, such as reduced contrast [7].

To overcome the problems of the traditional fusion methods, SDMIF method is proposed [24]. In SDMIF method, firstly, the input images are divided into equal-sized blocks without spaces or overlaps between the adjacent blocks. Afterwards, for each corresponding block pair, sharpness values are calculated with the help of a sharpness criterion. The fused image is constructed by copying the higher sharpness valued blocks and k th block of the fused image is formed as:

$$F_k = \begin{cases} A_k, & S_k^A > S_k^B \\ B_k, & S_k^A < S_k^B \\ \frac{A_k + B_k}{2}, & otherwise \end{cases} \quad (1)$$

where k is the block index, A_k and B_k are the k th block of multi-focus source images A and B , respectively, S_k^A and S_k^B are the sharpness values of A_k and B_k , respectively. Several sharpness criteria and detailed information can be found in Ref. [2].

Another approach for determining the sharpness is assessing each corresponding pixel by using its neighbours instead of evaluating the whole region in SDMIF method. PBSFMO method is very similar to SDMIF with minor modifications in which it is a pixel based method (SDMIF is region based) and it uses morphological operators for post-processing the fusion results to obtain better consistency. The pixels are evaluated with their neighbouring pixels within a 5×5 window using:

$$FM(i, j) = \begin{cases} 1, & SF^A(i, j) > SF^B(i, j) \\ 0, & otherwise \end{cases} \quad (2)$$

where (i, j) is the pixel index, SF is a criterion metric called spatial frequency and FM is the fusion map consisting 0 and 1's that represents pixels' source origin (A or B). However determining by SF alone leads miscalculation of the sharpness. Thus, morphological opening and closing is applied to the fusion map. Morphological post-processing removes thin connections, joins narrow breaks and fills long thin gulfs [23].

2.2 Transform Domain Image Fusion Methods

Transform-based image fusion methods use multi-scale transforms to analyse the information content of source images. These methods basically consist of following three stages: applying a multi-scale transform on input images to obtain multi-scale coefficients, combining coefficients according to the predefined fusion rules for generating a composite multi-scale representation, and using an inverse transform to reconstruct fused image from the composite multi-scale representation.

Laplacian pyramid (LP) is a well-known multi-scale transform method. LP can be defined as a collection of bandpass copies of source images in which each level is produced by filtering and sub-sampling of its predecessor [19]. To obtain LP, each bandpass copy is produced from its previous level by performing low-pass filtering, sub-sampling, interpolation and subtraction of two images pixel by pixel. The lowest levels of the pyramids are the original images A and B . Let G_k^A and G_k^B be the k th levels of Gaussian pyramids ($k = \{1, \dots, n\}$):

$$G_k^A = [\omega \times G_{k-1}^A]_{\downarrow 2}, \quad G_k^B = [\omega \times G_{k-1}^B]_{\downarrow 2} \quad (3)$$

where ω is the blurring convolution mask, $G_0^A = A$, $G_0^B = B$ and $[\]_{\downarrow 2}$ is the down-sampling process. The weighted difference between sequential levels of Gaussian pyramids is described as the k th level of the LP:

$$L_k^A = G_k^A - 4\omega \times [G_{k+1}^A]_{\uparrow 2}, \quad L_k^B = G_k^B - 4\omega \times [G_{k+1}^B]_{\uparrow 2} \quad (4)$$

where $[\]_{\uparrow 2}$ is the up sampling process.

The basic idea of LP image fusion is to construct a pyramid by performing LP decomposition then implement fusion for each level of pyramid by using a decision mechanism, based on selecting the maximum absolute coefficient value, which applies a feature selection:

$$L_k^F(i, j) = \begin{cases} L_k^A(i, j), & |L_k^A(i, j)| > |L_k^B(i, j)| \\ L_k^B(i, j), & \text{otherwise} \end{cases} \quad (5)$$

The fused image is reconstructed by performing an inverse pyramid transform:

$$G_k^F = L_k^F + 4\omega \times [G_{k+1}^F]_{\uparrow 2} \quad (6)$$

where G_k^F is the recovered Gaussian pyramid, and the fused image F is G_0^F [8].

Another well-known transform domain image fusion method is discrete wavelet transform. At the first step of this fusion process, wavelet transform is applied for each source images and decompositions of source images are obtained. Wavelet coefficient matrices A'_L, B'_L and A'_H, B'_H , are obtained by filtering and down-sampling by using lowpass filter L and highpass filter H to each row of source images A and B . Then, each column of the two resulting images is convolved with lowpass filter L and highpass filter H followed by down-sampling to produce for subbands: low-low A'_{LL}, B'_{LL} , (an image at coarser resolution level), low-high A'_{LH}, B'_{LH} (containing horizontal edge information), high-low A'_{HL}, B'_{HL} (containing vertical edge information) and high-high A'_{HH}, B'_{HH} , (containing diagonal edge information). This process can be repeated recursively until reaching a predefined level. Having multi-scale coefficients computed, a composite representation is obtained by selection of salient wavelet coefficients. The following selection process is applied on all subbands:

$$F'(i, j) = \begin{cases} A'(i, j), & A'(i, j) > B'(i, j) \\ B'(i, j), & \text{otherwise} \end{cases} \quad (7)$$

where A' and B' are wavelet coefficients of the corresponding subbands of multi-focus source images. Finally, fused image is achieved by applying inverse wavelet transform on the composite wavelet representation [21].

DCT is a widely used method in image and video compression and can be also used in image fusion area. DCT based image fusion method is a region based method in which the source images are divided in to $N \times N$ by blocks. DCT of each block is computed by:

$$d(k, l) = \frac{2\alpha(k)\alpha(l)}{N} \times \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} x(m, n) \times \cos\left[\frac{(2m+1)\pi k}{2N}\right] \times \cos\left[\frac{(2n+1)\pi l}{2N}\right] \quad (8)$$

where $k, l = 0, 1, \dots, N-1$ and

$$\alpha(k) = \begin{cases} \frac{1}{\sqrt{2}}, & \text{if } k = 0 \\ 1, & \text{otherwise} \end{cases} \quad (9)$$

DCT variances of corresponding blocks are evaluated to determine the sharper block. The block with the highest variance is chosen as the appropriate one for the fused image. Therefore, DCT representation of the fused image consisting of the blocks with highest activity levels is constructed. Consistency verification can be used optionally to improve the quality of the result. At the final stage, an inverse DCT is applied to obtain the visual result in spatial domain [22].

2.3 Quality Metrics

Measuring the quality of the results produced by an image fusion method is a challenging problem. Therefore, extensive research has been carried on developing metrics that precisely measures the quality of the fused image in terms of what degree the useful pattern information is gathered from the source images without distortion. The quality metrics used in this paper can be divided into two groups: 1) metrics that require the ‘‘ground truth’’ reference image in order to calculate the error or similarity between this image and the fused image: mean square error (MSE), peak signal-to-noise ratio (PSNR), mutual information (MI) and structural similarity (SSIM) [27], 2) metrics that do not require a reference image: variance (VAR), fusion factor (FF) [28] and the objective edge based quality measure (QE) [29].

3 The Proposed Image Fusion Method

In this section, the evolutionary algorithms based fusion method is described. In SDMIF, firstly, input images are divided into regular block based regions like a chessboard. Second, a final fused image is produced by selecting sharper blocks. Problem of selecting a suitable block size needs to be addressed. To overcome this problem, evolutionary algorithms such as ES, GA, DE, and JADE algorithms are utilized in this paper.

3.1 Evolutionary Algorithms

ES was first introduced in 1960’s as a global optimization algorithm based on adaptation and evolution. $(\mu+\lambda)$ -ES is the most frequently used type of ES in which μ parents can contribute to the reproduction of λ offspring. Mutation is realized by adding a Gaussian random noise with a variance of σ^2 . Afterwards, the obtained $\mu+\lambda$ individuals will be reduced to μ individuals of the next generation by greedy selection [30].

GA is an optimization method and frequently used in many research areas to find solutions to the problems [16]. The main operators (mutation, selection and crossover) of GA are motivated by biology and genetics. The algorithm starts from a random initial population and the genetic operators are implemented to produce a population of higher quality. GA finalizes the evolution when a set of predefined termination criteria have been achieved [31].

DE is a population-based stochastic search optimization method developed for finding the optimal solutions for nonlinear and multimodal functions by minimizing the real valued parameters[17]. Steps of DE are initial population generation, population evaluation, mutation, crossover and selection [32]. In each generation, DE operators are conducted until the termination criteria are met. DE differs from other algorithms with its underlying mutation operator which depends on the difference between randomly chosen solution vectors. Hence, DE not only improves the performance but also allows different search regions and makes the method more robust [16].

JADE is an improved version of standard DE with a new mutation strategy (i.e., DE/current-to-pbest) with optional external archive. It updates the control parameters with an adaptive strategy. Archive operation use past data of previous iterations to provide information about the direction of the progress. These operations differentiate the population and increase the performance. Adaptive parameter updating is a helpful tool for avoiding the user's prior expertise about the relation between the parameter selection and problem characteristics [18].

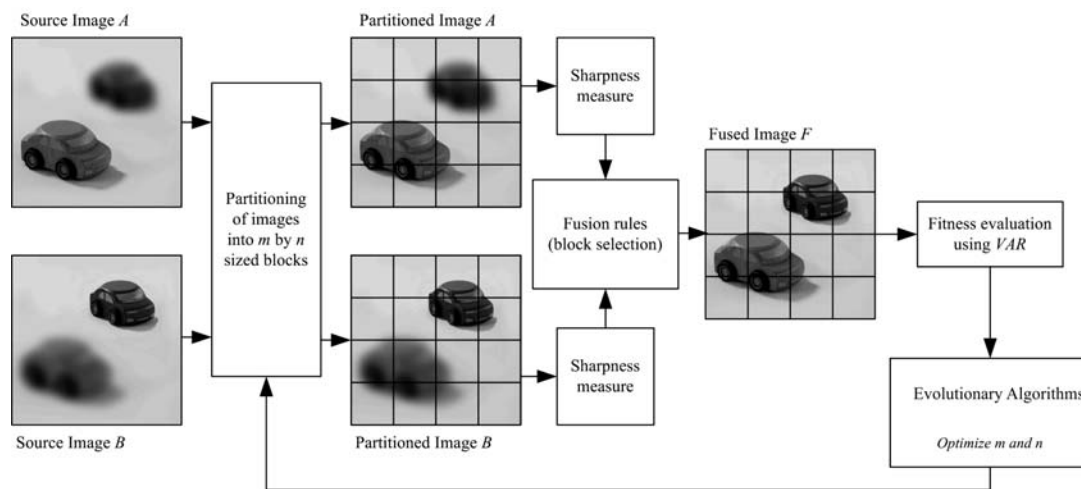


Figure 1. Schematic diagram of image fusion using proposed evolutionary algorithms based SDMIF method.

3.2 Fusion of Multi-focus Images using Evolutionary Algorithms

Several studies show that, in SDMIF method, block size depends heavily on the content and focused regions of the source images [2, 33, 34]. A constant block size may not be suitable for every input image. If a block contains both sharp and blurry parts of objects, it results in a significant error in the fused image. Many combinations of block size are possible and determining suitable block size is a challenging problem. Therefore, the optimization of the block size will improve the performance of

traditional SDMIF method. The proposed method in this paper, illustrated in Figure 1, utilizes ES, GA, DE, and JADE algorithms for tuning the block size parameter that is used in the SDMIF method.

Let A and B , in Figure 1, be the images of an object or scene captured from a fixed point with different focus parameters. Thus, A and B composed of sharp and blur regions. The sharply focused regions of A and B has to be detected appropriately to construct a single everywhere-in-focus image. Proposed method consists of following steps: first, both input images are divided as blocks. Afterwards, the sharpness values of block pairs are calculated for comparison. After all, sharper blocks are transferred to construct fused image. Since block size affects the performance of the method, block height and width are adjusted by employing ES, DE, GA, and JADE. The proposed image fusion scheme is formed by following steps:

1. Control parameters of evolutionary algorithms and stopping conditions are defined.
2. Initial population P is produced. The individuals of the population include block width and height and represented as $x = \{m, n\}$.

Steps 3 and 4 are repeated until the stopping conditions are met.

3. Fitness values of the individuals of population P are determined:
 - a. Input images are decomposed to $m \times n$ sized blocks. k th image blocks of A and B are referred by A_k and B_k , respectively.
 - b. Sharpness values of A_k and B_k are calculated by spatial frequency (SF) and denoted by SF_k^A , and SF_k^B , respectively. SF is an image quality metric and used as a sharpness criteria [35]:

$$SF = \sqrt{C^2 + R^2} \quad (10)$$

where C and R denote gradients of rows and columns, respectively:

$$C = \left[\frac{1}{m \times n} \sum_i \sum_j [f(i, j) - f(i-1, j)]^2 \right]^{1/2} \quad (11)$$

$$R = \left[\frac{1}{m \times n} \sum_i \sum_j [f(i, j) - f(i, j-1)]^2 \right]^{1/2}$$

- c. Sharpness values of corresponding blocks are compared for determining the sharper block, and k th block of the fused image F_k computed as:

$$F_k = \begin{cases} A_k, & SF_k^A > SF_k^B \\ B_k, & SF_k^A < SF_k^B \\ \frac{A_k + B_k}{2}, & otherwise \end{cases} \quad (12)$$

- d. Final fused image's fitness measure is calculated using VAR metric [2]. Larger variance values indicate better solutions. Fitness function can be given as:

$$fitness(m,n) = VAR(F) \quad (13)$$

4. The operators of Evolutionary algorithms' are applied to the population to produce new solutions.

4 Web Based Interactive Toolkit for Image Fusion

In this section, the proposed web based toolkit which is accessible from the URL <http://ce.erciyes.edu.tr/v1>, is introduced. Two major underlying technologies are used to develop the toolkit: Microsoft ASP.NET for web interface and MATLAB for realizing image fusion tasks. The main reason for using ASP.NET and MATLAB together is the fact that ASP.NET gives the easy web interface development skills, and MATLAB presents huge libraries for image processing, wavelet, optimization, and so on.

The aim of the developed toolkit is to provide a simple web page that can easily be accessible by users to image fusion sources and simulations from any place. Users can evaluate either their own multi-focus source images or can use source images provided by our image database for different image fusion methods. Users can also change several parameters of the fusion techniques to observe the effects of parameters on the fusion results.

The developed toolkit is composed of web interface, fusion engine and database. The web interface has a user-friendly design which allows users to submit the images to be fused and get numeric and visual fusion results within minutes. To make the design user-friendly and increase the interactivity of the website ASP.NET technology (with AJAX extensions) is preferred. The fusion and evaluation stages are carried out in a compiled MATLAB .NET component which called as fusion engine. That component has implementation of various methods and quality metrics that mentioned in this paper. Fusion engine is developed in MATLAB environment and then embedded into web site. At last, toolkit has a MySQL based database to save the fusion results of all users and multi-focus image sets. Basic architecture of the toolkit is illustrated in Figure 2.

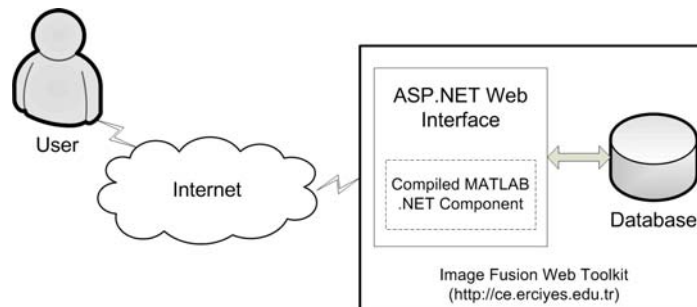


Figure 2. Proposed web based image fusion toolkit architecture.

The toolkit consists of four web pages: 1) *main page* that obtains source images and the parameter values of the methods from the user, presents visual and quantitative fusion results, 2) *help page* presents brief information about image fusion schemes, 3) *previous results page* allows a user to view the results obtained by previous users and 4) *image database page* that contains several real and artificially produced multi-focus test images.

Main page of the web interface is illustrated as screenshots in Figures 3 and 4. In Figure 3, introductory information about toolkit and user data forms can be seen. Firstly, users can provide personal information optionally and choose source images from their computer as Windows Bitmap format (.BMP). Users can also reach *image database* for previously presented multi-focus test images. Another important feature of the web toolkit is the parameter selection section for image fusion techniques. The toolkit includes the following image fusion methods: basic averaging, LP, wavelet, DCT, PBSFMO, SDMIF and SDMIF-ES, SDMIF-GA, SDMIF-DE and SDMIF-JADE.

The parameter sets consist of decomposition level selection for LP method, decomposition level and filter family choice for wavelet method, block size for SDMIF method and maximum generation number, population size and mutation rate choice for evolutionary SDMIF methods.

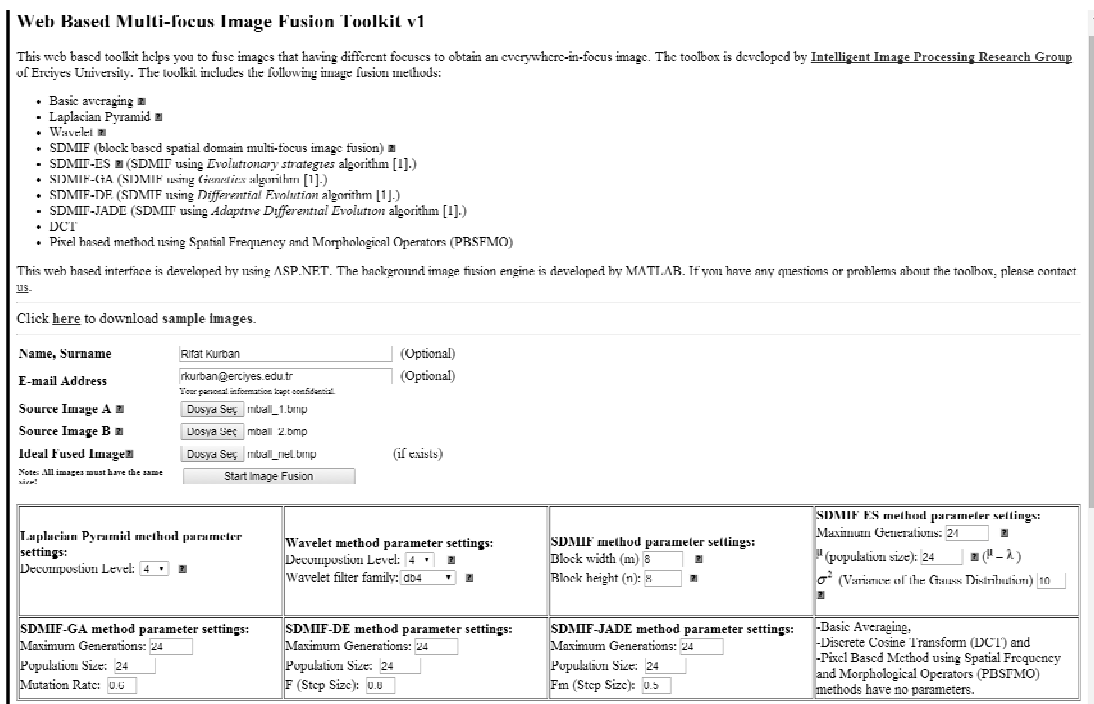


Figure 3. Main page of web based toolkit.

After clicking the *Start Image Fusion* button, source images and parameter values sent to the compiled MATLAB .NET component which is called *fusion engine*. This component has a MATLAB function with the input parameters that receives source images, reference image (if exists) and the method parameters. Outputs of the fusion function are the numerical and visual fusion results of the image fusion techniques mentioned above. The fusion function is converted to a .NET component by using MATLAB .NET compiler tool which is also called MATLAB Builder NE. In this manner, the *fusion engine* function is converted to .NET component and embedded to the ASP.NET web application. The results of the fusion process, illustrated in Figure 4, can be seen after clicking the *Start Image Fusion* button. ASP.NET application generates a unique request identity (ID) code for all sessions. This ID is used for storing the fusion results in application database.

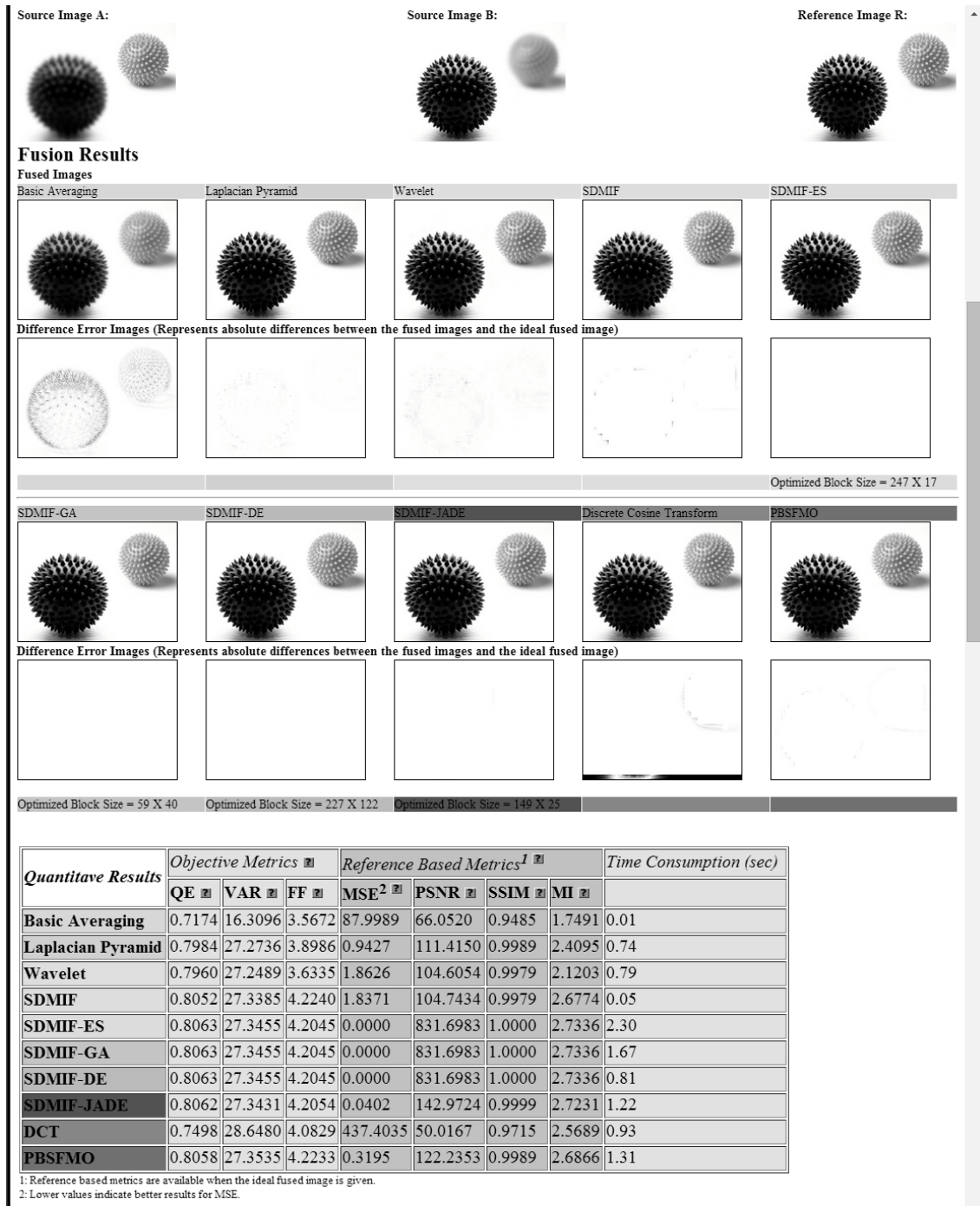


Figure 4. Main page: visual and quantitative fusion results.

User submitted images are shown and visual fusion results of different fusion methods are shown in the web page given in Figure 4. To improve the visual evaluation, the absolute error images that computed by subtracting the fused image from the reference image are also shown under the fusion results. Since, there is no reference image in real multi-focus images; the difference error images generated by subtracting source images from fused image are also shown.

Help page can be reached from the help buttons (yellow question marks) located several places on main page. When a user click a help button, a new page is opened with related information associated with the help button.

Previous results page shows the previous results of all users who has used the toolkit before. Firstly, user has to select a date interval from the date/time picker. Then, the fusion tasks which have been realized on that particular dates are listed. User can select any task to see the details of that previous image fusion task. The details include, personal information of the previous user (if available), source images, reference image (if available), previously selected parameters of the image fusion methods, visual fusion results of the methods, difference error images and finally the numerical results.

Image database page allows users to reach several test images. The collection consists of both real and artificial multi-focus test images. Some of the well-known real images are obtained from the literature, some of them are captured with an optical digital camera and the rest are produced artificially from sharp images.

5 Result and Discussions

In this section, firstly, the proposed evolutionary SDMIF methods are compared with well-known image fusion methods included in the toolkit in terms of four image sets: *Toy cars*, *PCB*, *Wrist watch*, *Lab*. Multi-focus *Toy cars* and *PCB* image set is produced synthetically. *Wrist watch* image set is captured with The Imaging Source DMK-31BF03 firewire optical zoom camera equipment with different focal settings. *Lab* is a well-known image for the multi-focus image fusion literature [36] captured with different focal settings. The multi-focus source image pairs can be seen in Figure 5.

For artificial multi-focus image sets such as *Toy cars* and *PCB*, both reference based quality metrics and objective metrics can be used. Hence, in this case we have the “ground truth” reference image (assumed that everywhere-in-focus). For natural multi-focus images such as *Wrist watch* and *Lab* only non-reference based metrics which needs only the fused image and/or source images (not the reference image) to evaluate the result quantitatively.

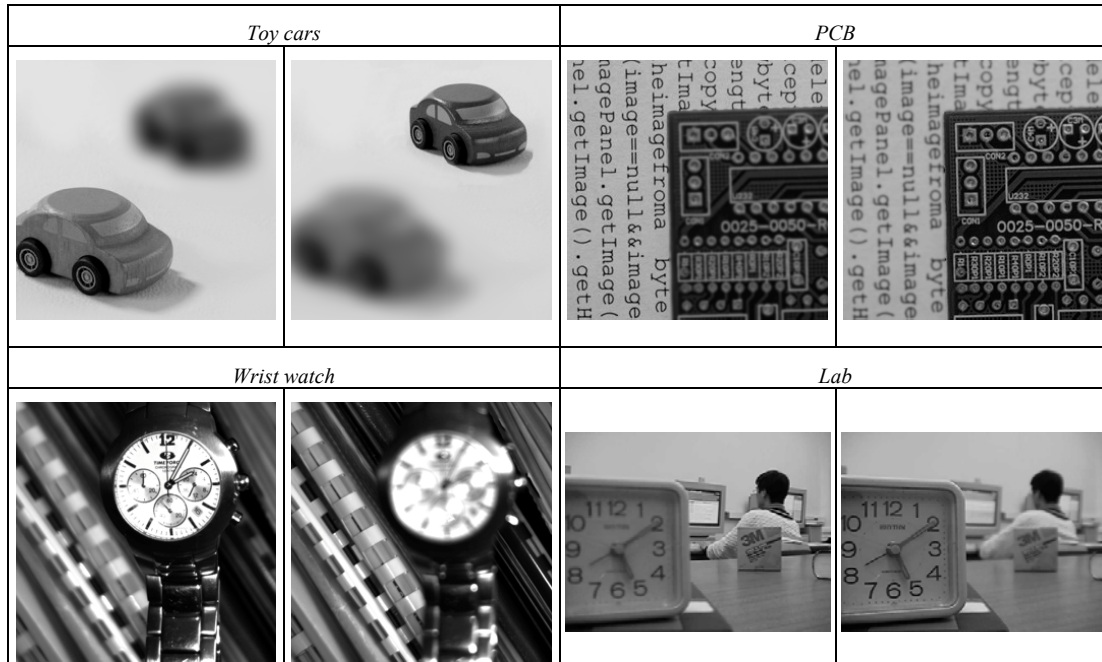


Figure 5. Source images used in the experiments.

Both wavelet and LP methods employ 4-level decomposition. Daubechies ‘db4’ filter is used in wavelet. Consistency verification is used in DCT method. 5×5 window size is used in PBSFMO. For SDMIF method the block size is chosen 8×8 . For evolutionary based SDMIF methods, maximum generation number is 32 and population size is 32.

Table 1. Numerical results for *Toy cars* image of different image fusion methods.

	Objective Metrics			Reference Based Metrics				CPU Time	
	QE	VAR	FF	MSE	PSNR	SSIM	MI	Sec.	
Basic Ave.	0,663	6,608	6,776	77,928	67,268	0,939	3,436	0,000	
Lap. Pyramid	0,756	12,094	6,809	4,087	96,748	0,996	4,487	0,440	
Wavelet	0,723	11,996	6,103	41,644	73,534	0,980	3,593	0,140	
DCT	0,783	12,142	8,642	0,347	121,422	0,998	6,214	0,570	
PBSFMO	0,799	12,763	8,731	38,300	74,371	0,949	5,581	2,590	
SDMIF	0,786	12,443	8,643	28,331	77,386	0,955	5,652	0,050	
SDMIF-ES	0,785 (0,09)	12,139 (0,95)	8,700 (0,79)	0,013 (0,002)	154,067 (7,1)	1,000 (0,07)	6,401 (0,71)	8,720 (0,78)	
SDMIF-GA	0,785 (0,08)	12,139 (0,99)	8,693 (0,77)	0,012 (0,001)	155,265 (6,2)	1,000 (0,08)	6,406 (0,66)	5,420 (0,55)	
SDMIF-DE	0,785 (0,07)	12,139 (0,90)	8,696 (0,78)	0,011 (0,001)	156,104 (5,7)	1,000 (0,06)	6,408 (0,68)	3,850 (0,41)	
SDMIF-JADE	0,785 (0,07)	12,139 (0,88)	8,700 (0,71)	0,013 (0,001)	154,067 (4,5)	1,000 (0,06)	6,408 (0,62)	5,510 (0,57)	

For different image fusion methods, the numerical results of the fused images are given in Table 1, 2 for *Toy cars* and *PCB* images, respectively and results for *Wrist watch* and *Lab* images are given in Table 3.

Table 2. Numerical results for *PCB* image of different image fusion methods.

	Objective Metrics			Reference Based Metrics				CPU Time
	QE	VAR	FF	MSE	PSNR	SSIM	MI	Sec.
Basic Ave.	0,818	26,373	5,992	73,742	67,820	0,959	2,964	0,000
Lap. Pyramid	0,776	37,858	7,135	5,937	93,014	0,996	5,256	0,470
Wavelet	0,768	37,932	6,299	3,944	97,102	0,996	4,410	0,130
DCT	0,788	37,940	8,682	5,326	94,100	0,996	6,816	0,570
PBSFMO	0,790	38,175	8,773	0,927	111,583	1,000	6,975	2,590
SDMIF	0,790	38,120	8,691	1,903	104,393	0,998	6,859	0,050
SDMIF-ES	0,787 (0,08)	38,190 (3,1)	8,813 (0,81)	0,600 (0,06)	117,590 (9,8)	1,000 (0,05)	7,033 (0,61)	17,080 (1,51)
SDMIF-GA	0,788 (0,09)	38,192 (3,2)	8,813 (0,83)	0,625 (0,05)	117,590 (9,9)	1,000(0,04)	7,033 (0,62)	11,270 (1,13)
SDMIF-DE	0,790 (0,07)	38,194 (2,2)	8,813 (0,78)	0,580 (0,06)	117,590 (8,1)	1,000(0,04)	7,033 (0,57)	4,250 (0,54)
SDMIF-JADE	0,791 (0,07)	38,195 (2,7)	8,819 (0,71)	0,508 (0,04)	119,098 (8,8)	1,000(0,03)	7,041 (0,55)	12,090 (1,33)

Due to the random nature of the evolutionary algorithms, experiments for these algorithms are repeated 30 times with the same parameter configurations. Average numerical values and the standard deviations (given in the parenthesis) of the quality metrics are shown in Table 1, 2 and 3.

Table 3. Numerical results for *Wrist watch* and *Lab* image of different image fusion methods.

	<i>Wrist watch image</i>				<i>Lab image</i>			
	Objective Metrics			CPU Time	Objective Metrics			CPU Time
	QE	VAR	FF	Sec.	QE	VAR	FF	Sec.
Basic Ave.	0,721	20,263	6,641	0,000	0,686	12,341	8,195	0,000
Lap. Pyramid	0,750	31,146	6,684	0,430	0,701	19,015	8,063	0,470
Wavelet	0,716	30,825	5,948	0,120	0,669	19,260	7,275	0,130
DCT	0,765	30,844	8,921	0,560	0,745	18,985	9,863	0,650
PBSFMO	0,767	31,744	8,907	2,590	0,746	19,294	9,803	3,010
SDMIF	0,761	31,602	8,918	0,050	0,744	19,210	9,791	0,060
SDMIF-ES	0,766 (0,08)	31,281 (3,1)	8,925 (0,98)	8,310 (0,94)	0,745 (0,09)	19,069 (2,1)	10,177 (0,92)	8,740 (0,94)
SDMIF-GA	0,767 (0,08)	31,388 (3,2)	8,924 (0,87)	6,810 (0,77)	0,746 (0,08)	19,158 (1,8)	10,114 (1,13)	5,270 (0,66)
SDMIF-DE	0,765 (0,07)	31,353 (2,9)	8,906 (0,88)	4,480 (0,51)	0,747 (0,06)	19,113 (1,9)	10,153 (1,07)	3,480 (0,42)
SDMIF-JADE	0,768 (0,06)	31,389 (2,8)	8,964 (0,81)	13,510 (1,41)	0,746 (0,08)	19,093 (2,0)	10,179 (0,99)	5,630 (0,45)

Obtained fused images by using basic averaging, LP, wavelet, DCT, PBSFMO, SDMIF and the proposed SDMIF-ES, SDMIF-GA, SDMIF-DE and SDMIF-JADE methods are visualized in Figure 6, 7, 8, and 9 for *Toy cars*, *PCB*, *Wrist watch* and *Lab*, respectively. As can be seen from the visual results, the basic averaging method decreases the contrast and objects are still blurry. The results of wavelet and SDMIF method also have some distortions in all images. However, the results of LP, DCT, PBSFMO and evolutionary SDMIF methods seem satisfactory.

To make a better subjective evaluation, difference error images are computed by subtracting the fused image from the reference “ground truth” in *Toy cars* and *PCB* image sets. *Wrist watch* and *Lab* image sets cannot be evaluated by this technique, because there is no “ground truth” in these kinds of real multi-focus images.

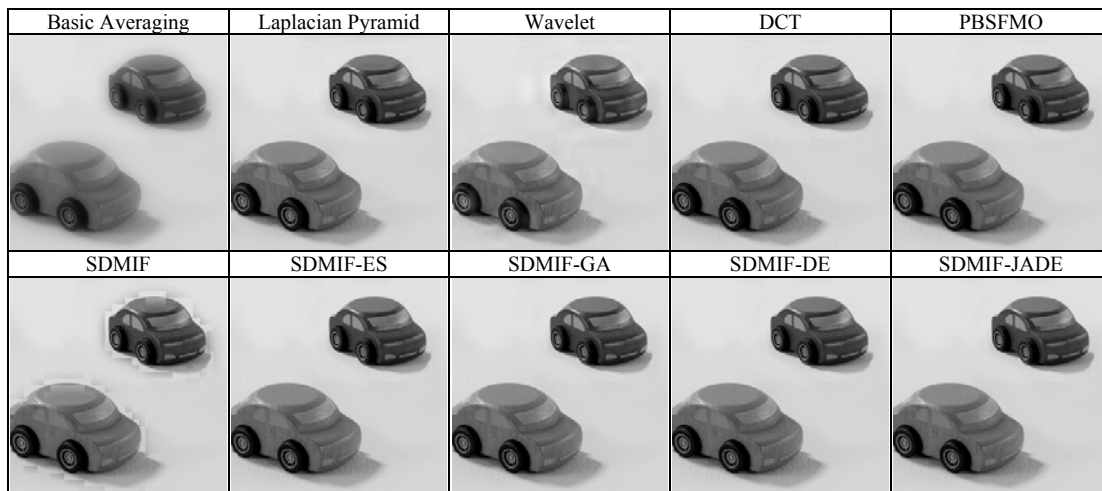


Figure 6. Fusion results of *Toy cars* image.

In a successful fusion process, difference error image has to be constructed with fully white pixels. As can be seen in Figure 10, normalized difference error images show that evolutionary SDMIF methods are better than other methods in terms of difference error images.

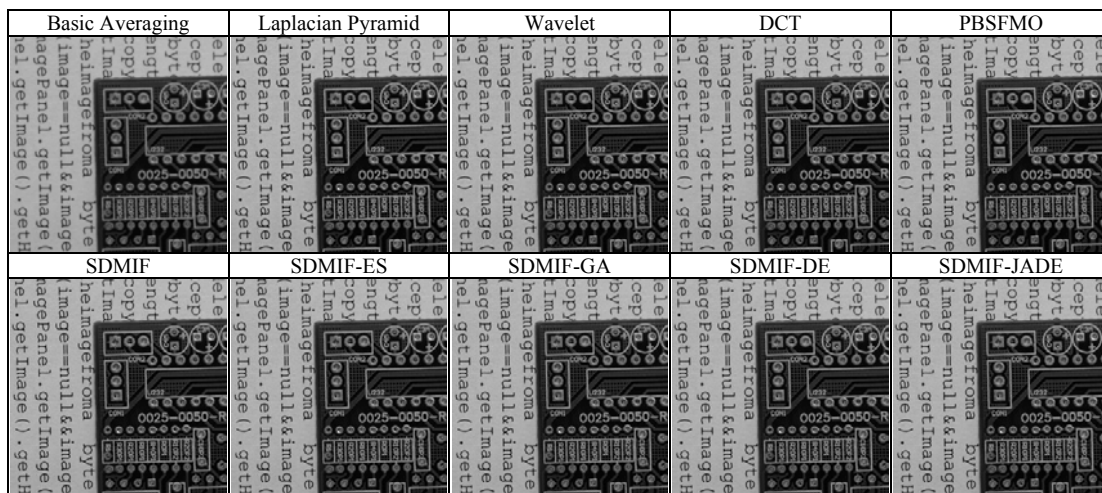


Figure 7. Fusion results of *PCB* image.

As can be seen from the Table 1, 2 and 3, evolutionary SDMIF method outperforms the other methods in terms of all reference based quality metrics. When the objective metric results are considered, in Table 1, PBSFMO method seems better than other methods in terms of all objective metrics and in Table 3, again PBSFMO method seems better than other methods in term of VAR metric. However, due to the erroneous saw-tooth like pseudo edges produced by PBSFMO method, objective metrics fall into error [2]. Considering both reference based and objective metrics,

evolutionary SDMIF methods are better than other methods both in visual and numerical evaluations. Results of LP, DCT and PBSFMO are also acceptable for image fusion applications. Among the evolutionary SDMIF methods, DE and JADE are slightly better than ES and GA.

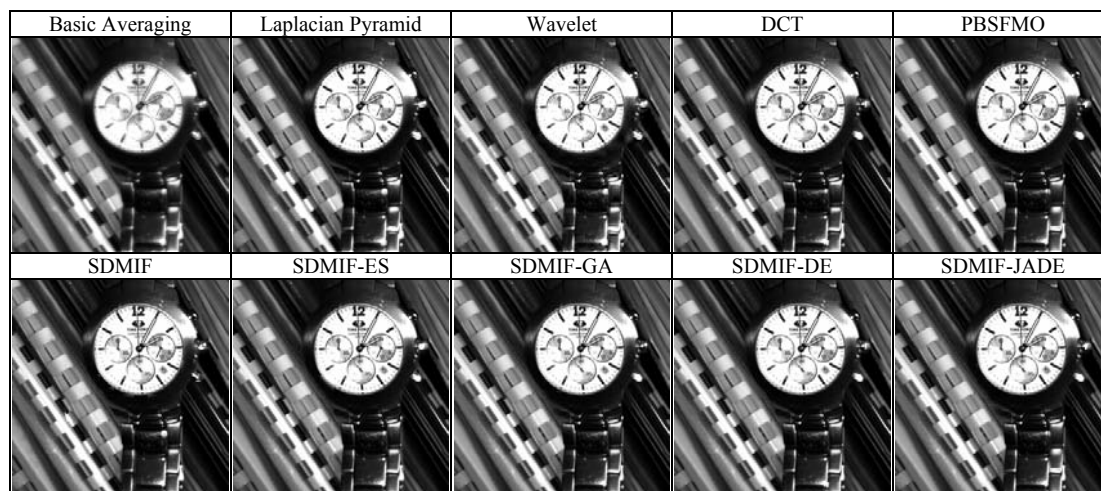


Figure 8. Fusion results of *Wrist watch* image.

Time comparison of the methods is realized by calculating the CPU runtimes of the methods in seconds and given in Table 1, 2 and 3 for test image sets. The time results of the evolutionary methods for 30 runs are averaged and the standard deviations are also given in the tables. In the experiments, a virtual machine equipped with dual-core Intel Xeon E5620 @ 2.4GHz CPU and 3GB of memory is used. Basic averaging method is the fastest fusion method according to Table 1, 2 and 3. However, fusion results of basic averaging are not satisfactory in most cases. Non-evolutionary methods are faster than evolutionary methods in general except for PBSFMO method. Evolutionary algorithms are sorted in the order of DE, GA, JADE and ES in terms of running times from good to bad.

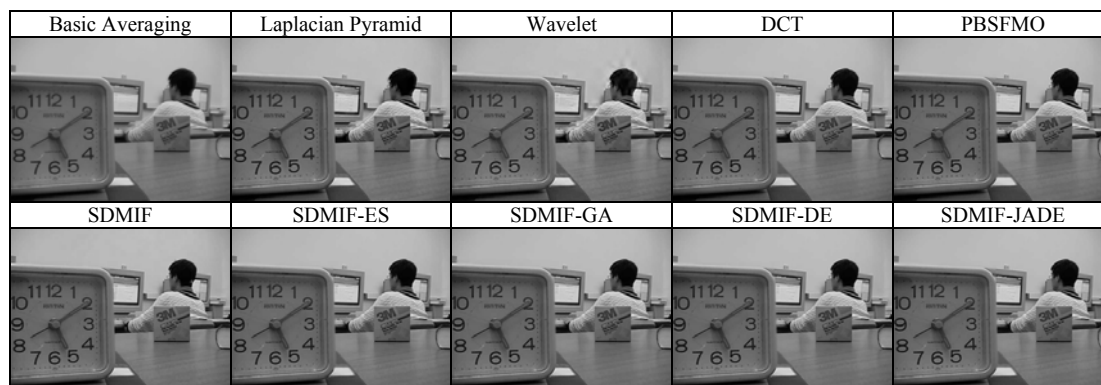


Figure 9. Fusion results of *Lab* image.











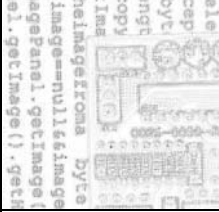


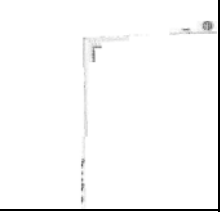






Basic Averaging	Laplacian Pyramid	Wavelet	DCT	PBSFMO
				
SDMIF	SDMIF-ES	SDMIF-GA	SDMIF-DE	SDMIF-JADE
				
Basic Averaging	Laplacian Pyramid	Wavelet	DCT	PBSFMO
				
SDMIF	SDMIF-ES	SDMIF-GA	SDMIF-DE	SDMIF-JADE
				

Figure 10. Difference error images of the fusion results *Toy cars* and *PCB* image.

6 Conclusion

In this paper, a web based interactive toolkit for multi-focus image fusion that includes well-known image fusion methods and also a new image fusion method based on evolutionary algorithms is presented. The web based interface of the toolkit is developed with ASP.NET and the background image fusion engine is implemented with MATLAB. The proposed toolkit visualizes the image fusion methods that allow the users to understand the basic principles of image fusion, compares the methods by means of performance and robustness, and evaluates the methods with different inputs and parameter values. Moreover, the users can use the web based toolkit from anywhere without installing a preliminary other software packages. The proposed toolkit enables users to practice and learn image fusion. In future works, the toolkit can also be improved to include other image fusion methods and image processing topics.

On the other hand, we developed a new multi-focus image fusion method that uses evolutionary techniques. The method, first, divides source images into block based regions then compares each corresponding block by means of a sharpness criterion. And consequently, constructs the fused image with the sharper blocks. Evolutionary algorithms optimize the block size to maximize the overall sharpness of the fused image. Not only the block based spatial domain image fusion method and evolutionary algorithms are very simple, but also the proposed evolutionary SDMIF methods outperform other well-known image fusion.

The main contributions of this study can be summarized as:

- Two goals are realized successfully: a) proposing an image fusion web toolkit for researchers and students, and, b) proposing an improved image fusion method for multi-focus images.
- The proposed web based toolkit is the first and only web implementation for image fusion, to the best of our knowledge.
- The experiments are conducted on 4 images consisting of two artificially produced, one obtained with a firewire zoom camera equipment and the last obtained from the literature.
- 6 deterministic image fusion methods are included in the study such as basic averaging, laplacian pyramid, wavelet, DCT, pixel based method using spatial frequency & morphological operators (PBSFMO) and block-based spatial domain fusion (SDMIF).
- 4 adaptive implementations of classical SDMIF method using evolutionary techniques as Evolution Strategies (ES), Genetic Algorithms (GA), Differential Evolution (DE) algorithm and adaptive differential evolution (JADE) algorithms are also evaluated.
- Extensive experimental results show that evolutionary SDMIF methods are better than other methods in subjective and objective assessments.

Acknowledgments

This work is supported by Turkish Scientific and Research Council (TUBITAK) under the Grant No.110E058.

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