Differential Evolution Algorithm Based Spatial Multi-sensor Image Fusion

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Abstract: In this paper, a new optimised region based multi-sensor image fusion method is presented. The proposed method works on spatial domain. Differential evolution algorithm is used to optimize the contribution of the input images to fused images based on regions. The method was compared visually and quantitatively with Laplacian Pyramid (LP) and Shift-invariance Discrete Wavelet Transform (SiDWT) methods. Experimental results show that the developed method outperforms other traditional methods and can effectively improve the quality of the fused image.

1 INTRODUCTION

Because of a wide variety of imaging sensor type, image fusion has become an important topic in information fusion area (Aslantas and Kurban, 2009, Zhong and Blum, 1999, Aslantas et al., 2013). For a particular scene, images taken from different type of sensors contain different information. While thermal images present emitted thermal radiation of scene, visible images contain information that is more desirable for human visual perception. All sensors have their own advantages and in many cases complete representation of a scene cannot be obtained with a single sensor. More meaningful representation of a scene can be obtained by transforming complementary information of different sensors to a single image. This can be achieved by image fusion. It is a subtopic of information fusion and produces an image that contains complementary information come from images acquired by different sensors or the same sensor with different parameters. Thus, improvement of human visual perception is intended.

Image fusion is needed and used frequently for different kind of areas such as medical imaging (Qu et al., 2001), enhanced night vision (Toet et al., 1997), concealed weapon detection (Xue et al., 2002), extending depth of field (Aslantas and Kurban, 2010). Accordingly, many image fusion techniques have been developed in recent years. They can be classified as spatial domain and transform domain methods (Li et al., 2011). In the former, local derivation or gradient information is used. On the other hand, the latter are employed on transform coefficients. Determination of valuable information contained each image has a critical role on the image fusion. Human visual perception is sensitive to intensity changing like lines, edges or texture. Multiscale transforms can efficiently emphasize this kind of information therefore various multiscale transforms are frequently used in image fusion (Hu and Li, Miao et al., 2011, Lewis et al., 2007). However, time consuming translation operations increase computational load of these methods. Moreover, affection of operations over the fused image cannot be clearly predictable since the coefficients are chanced in the transform domain and the original pixel values of input images are not preserved in the resulting fused image (Huang and Jing, 2007). Contrary to transform based methods, operations are conducted directly on the pixel values without any transformation in the spatial domain methods. Therefore original pixel values are transferred to the fused image.

In most of the image fusion methods, maximum or average of transform coefficients is utilized. These are not sufficient in many situations, because these types of fusion procedures are not adaptive to information changing in the scene. Hence the contribution of each input image to the fused image should be varied with respect to the information composed in them. Determining the best fused image is an optimization problem.

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In literature, there are some image fusion methods that employed optimization algorithms (Mumtaz and Majid, 2008, Niu and Shen, 2006, Raghavendra et al., 2011). In those studies, DWT is used. However, adaptive rules have been defined for the approximation band of DWT and choosing maximum coefficient rule was used for the other bands. The optimization process carried out in approximation band for determining the optimum contribution of each coefficient of this band, makes the problem more complex for an optimization algorithm. In this study, witout using any transform method, adaptive fusion rules are determined in spatial domain based on groups of pixels i.e., regions. Thus, all information on an image are taken into account.

Rest of the paper is organized as follows. In Section 2.1, the optimization algorithm employed and its implementation over image fusion is described. In Section 2.2 and Section 2.3, the proposed method and the quality metrics are described respectively. in Section 3, the experimental results are presented quantitatively and visually. Finally Section 4 concludes the paper.

2 OPTIMIZATION BASED IMAGE FUSION

2.1 The Differential Evolution Algorithm (DE)

The proposed method makes use of the DE algorithm to construct a fused image in which the regions of source images are emphasised optimally. The DE is a well-known population based, heuristic and evolutionary optimisation algorithm that was proposed by Price and Storn in 1995 (Price and Storn, March 1995). The main steps of DE are:

1. Set the initial control parameters of the DE,
2. Create initial population,
3. Mutation and crossover,
4. Selection,
5. Repeat step 3-4 until stopping conditions are satisfied.

Before the optimization processes, some control parameters of DE have to be determined initially like generation size (G), population size (P), scaling factor (F) and crossover constant (CR).

The DE starts with a population of randomly produced P solution vectors (x) that contain weighting factors for the segmented regions.

Mutation and crossover operators are used for creating a new population. The former is employed to expand the search space. At generation g (g = 1,2,…, G), the i^{th} mutant vector ($v_{i,g}$) is generated for each target vector by the combination of vectors randomly chosen from the current population as follow:

$$v_{i,g} = x_{r3,g} + F(x_{r1,g} - x_{r2,g}) \tag{1}$$

where $r1$, $r2$, and $r3$ are different random integer indices selected from {1, 2, ..., P}. In order to increase the diversity of the population, the DE utilizes crossover operation that integrates successful solutions from the previous generation. The elements of the mutated vector and the elements of the target vector are used to produce a trial vector as follow:

$$u_{j,i,g} = \begin{cases} v_{j,i,g} & if\, rand_{j,i} \le CR\; or\; j = I_{rand} \\ x_{j,i,g} & if\, rand_{j,i} > CR\; or\; j \ne I_{rand} \end{cases} \tag{2}$$

where j = 1,2, ..., D; $rand_{j,i}$ ϵ [0; 1] is the random number; CR ϵ [0; 1] is predefined crossover constant and I_{rand} ϵ [1, 2, ..., D] is a randomly chosen index. I_{rand} ensures that $v_{i,g+1} \neq x_{i,g}$ Then the 'greedy' selection scheme is employed to decide whether or not to include the trial vector in the population of the next generation g + 1. If the value returned by the objective function for the trial vector is better than or equal to the value obtained for the target vector the latter is replaced by the former otherwise it is retained in the population of the next generation

$$x_{i,g+1} = \begin{cases} u_{i,g} & f(u_{i,g}) \le f(x_{i,g}) \\ x_{i,g} & otherwise \end{cases} \quad i = 1, \cdots, P \tag{3}$$

2. 2 Proposed Image Fusion Method

In this paper, a new optimization based, multi-sensor image fusion method is proposed for mainly thermal and optical images. These types of sensors have been especially used in image fusion applications like enhanced night vision and concealed weapon detection.

Proposed method works on spatial domain and does not include any transformation. As a consequence, computational load of the method is reduced according to transform based methods.

The general structure of proposed method is given in Figure 1. The method utilises regions rather than pixels to fuse information. Therefore, in the first stage, region map (X_E) computes. X_E contains region labels that indicate related pixels belong to a

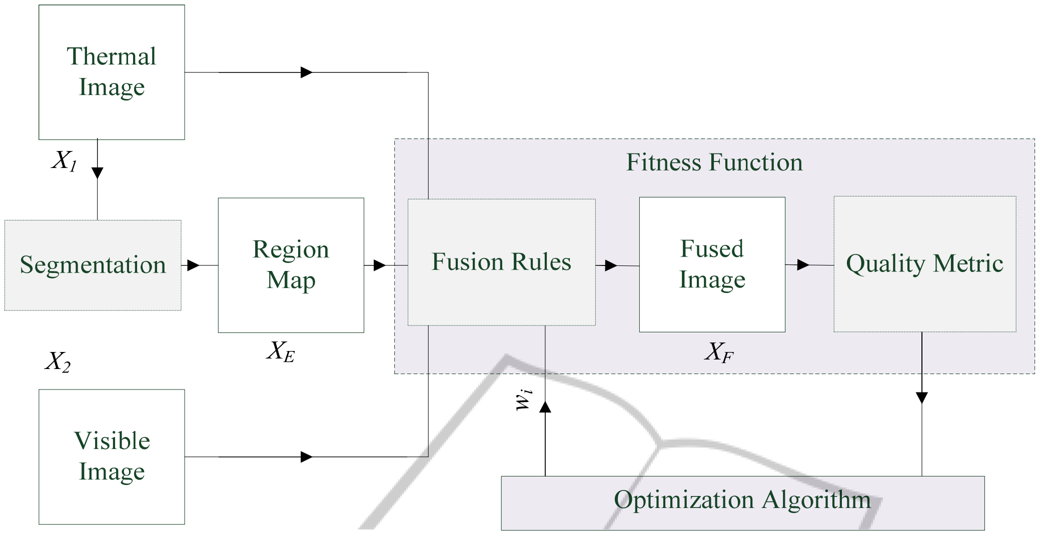

Figure 1: The general structure of the proposed method.

region. Region map can be produced by employing one of the input images (thermal or visible). Optical cameras provide a similar vision with human eye. However, thermal cameras provide a vision related with the temperature which the human eye cannot see. The main purpose of fusing thermal and visible images is to support the visible information with the complementary thermal information (Kun et al., 2009). Similar objects in an environment almost emit similar thermal radiations. The regions corresponding to these objects are nearly viewed homogeneously with respect to their intensity values. To emphasize complementary information, it is a good idea to segment the thermal image. Accordingly, the thermal image is utilized for producing X_E. K-Means has been used as segmentation algorithm in this study.

An adaptive fusion rule can be defined as in (1). As can be seen in Figure 1, the fusion rule uses input images (X_1 and X_2) and region map (X_E). For all regions, a fusion rule is suggested by determining w coefficients. For i^{th} region w_i coefficient has a value between [0-1] and determines the rate of the information transferred from the input image to fused one. Optimization algorithm has been used to obtain the best contribution of input images to the fused image in the proposed method.

$$X_B(i) = w_i \cdot X_1(i) + (1 - w_i) \cdot X_2(i) \tag{4}$$

The fused image must be evaluated by a quality metric to attain a fitness value.

2.3 The Quality Metrics

2.3.1 Sum of the Correlation of Differences (SCD)

Amount of information that transferred from source images is an important measure for image fusion. The difference between the fused image (X_F) and one of the source input image (X_2) almost reveals the information contained one in the other source image (X_1) and vice versa (Aslantas et al., 2013). These can be formulated as:

$$\begin{aligned} X_{F1} &= X_F - X_2 \\ X_{F2} &= X_F - X_1 \end{aligned} \tag{5}$$

The value obtained by correlating X_{F1} with X_1 (or X_{F2} with X_2) is a similarity measure between these images. Sum of these values indicate the amount of information shifted to the fused image from the source images. The larger the SCD value, the better the quality of the fused image. SCD metric expressed as:

$$SCD = corr(X_{F1}, X_1) + corr(X_{F2}, X_2) \tag{6}$$

2.3.2 Quality of Edge (QE)

QE is one of the image quality metric that takes input images and fusion image. Edge information is very important to human perception. QE is a measure of quality based on edge information transferred from input images to fused image (Xydeas and Petrovid, 2000). QE is calculated as:

$$QE = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} k^a(i,j)w^a(i,j) + k^b(i,j)w^b(i,j)}{\sum_{i=1}^{n}\sum_{j=1}^{m} w^a(i,j) + w^b(i,j)} \quad (7)$$

where w^a and w^b are weighting coefficients based on sobel edge strength of the input images, k^a ve k^b edge preservation coefficients.

2.3.3 Standard Deviation (SS)

Human perception is sensitive to intensity changes and in an image, higher intensity changes cause bigger standard deviation. SD metric is based on this idea and calculated by using gray level values as:

$$SD = \sqrt{\frac{1}{mn}\sum_{i=1}^{n}\sum_{j=1}^{m}(f(i,j) - \bar{f})^2} \quad (8)$$

$$\bar{f} = \frac{1}{mn}\sum_{i=1}^{n}\sum_{j=1}^{m} f(i,j) \quad (9)$$

2.3.4 Fusion Factor (FF)

Mutual information (MI) calculates shared information by two images. MI calculated as:

$$MI_{RF} = \sum_{i,j} P_{RF}(i,j)\log\frac{P_{RF}(i,j)}{P_R(i)P_F(j)} \quad (10)$$

where P_{RF} is the normalized joint gray level histogram of images R and F, P_R and P_F are the normalized marginal histograms of the two images.

Fusion Factor (FF) is metric uses mutual information. FF takes input images and fusion image to calculate MI between input images and fusion image. Therefore, FF can be defined as a metric that calculate how much information transferred to fused image from all input images. FF can be defined as:

$$FF = MI_{AF} + MI_{BF} \quad (11)$$

3 EXPERIMENTAL RESULTS

The proposed fusion method is a region based method. Therefore, number of region (NR) has to be determined beforehand. In addition to this, the parameters of the optimization algorithm described in section 2.1, have to be set. In this paper, DE parameters are selected as CR=0.3, F=0.3 and P=40. SCD metric was employed during the optimization process.

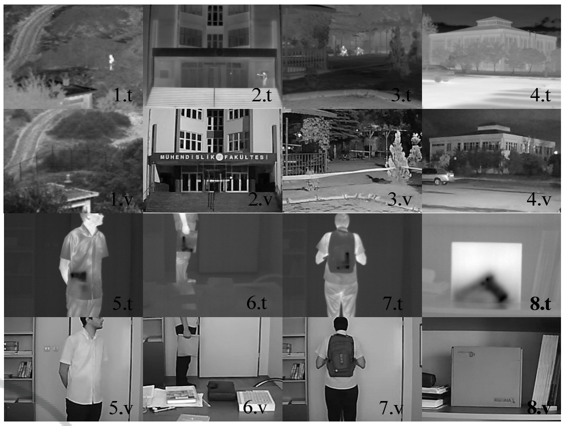

Figure 2: Images used in experiments.

In total, eight test image groups used in the experiments are given in Figure 2 (Group, 2012, Lewis et al., 2005). An image set consists of an visible (v) and a thermal (t) image of the same scene. According to application area, the image sets can be categorized into two groups: enhanced night vision images or concealed weapon detection. Numbers are used for naming the source images. Numbers in the range of [1 - 4] and [5 - 8] are signed for the night vision images and for the concealed weapon images, respectively. 1st

Experimental results are shown in two groups according to application area of input images. In Table 1 and Table 2 quantitative results are illustrated as mean value and standard deviation of 30 parallel optimization runs in terms of all used quality metrics and NR. In the tables, images are represented in the first column (I). For an image, NR values are given in column wise and metric values given along the rows. The higher metric values are indicated in tables. Results for enhanced night vision image sets can be seen in Table 1. The best results for SCD were obtained with NR=16. On the other hand, for the other metrics, the best results were mostly obtained when NR is set as 4 or 8. In addition, the same situation is occurred for concealed weapon detection images as can be seen from Table 2.

The proposed method is compared with LP (Burt and Adelson, 1983) and SiDWT (Rockinger, 1997) methods that are well known fusion methods in the literature.

Visual results are given in Figure 3 and Figure 4. Enhanced night vision images can be seen in Figure 3. Especially, for image 1 and 2, the proposed method demonstrated superior performance in visual aspect. From analysis of the visual results of enhanced night vision, it can be easily noticed that the complementary information of the source images successfully transferred to the fused image.

The men in the images that cannot be seen in visible images are emphasized in fused images. In the result of proposed method for image 2, the sign board and the man can be more clearly perceived than LP and SiDWT. Furthermore, the details of the building are less affected in proposed method. For image 1 and 3, details like leaf of trees were noticeably transferred to fused images in the proposed method.

Similarly, for the concealed weapon detection images, proposed method produces remarkable better visual results. Details of scene in visible image are less affected; meanwhile, the gun can be expressed in fused image. Result of the SiDWT methods are more darkened from the others.

In Fig. 5, the proposed method, LP and SiDWT are compared in terms of four quality metrics. In this figure, there are four graphs for all metrics. In the figure, the metric values are shown in vertical axis and the images are illustrated in horizontal axis. For SCD, FF and SD metrics, the proposed method has superior performance as can be seen from the figure. QE metric is a measure for transferred edge amount from the source images. Consequently, any edge information do not transferred causes worse QE results. The proposed method optimise amount the complementary information not directly edge information. Thus, some redundant edges are eliminated. Therefore in some images, the method gives smaller QE metric values.

Table 1: Quantitative metric values of proposed method on enhanced night vision images.

		SCD		QE		FF		SD	
I	***NR***	***Mean***	***Sd***	***Mean***	***Sd***	***Mean***	***Sd***	***Mean***	***Sd***
1	***4***	1,6811	2,5E-05	0,4276	0,0002	4,6293	0,015	**13,1426**	0,0249
	8	1,7089	5,6E-05	0,4420	0,0002	**4,8687**	0,02	13,0549	0,0311
	16	**1,7121**	1,3E-04	**0,4427**	0,0019	4,3046	0,0924	12,6203	0,0598
2	***4***	1,8623	4,7E-06	**0,7405**	0,0002	5,8901	0,0088	32,6549	0,0265
	8	1,8779	4,9E-05	0,7265	0,0009	**6,0274**	0,0493	**33,2886**	0,0557
	16	**1,8918**	3,7E-05	0,7230	0,0012	5,9466	0,0262	32,8598	0,0664
3	***4***	1,6814	1,9E-04	0,6617	0,0056	5,0728	0,0403	24,7487	0,0683
	8	1,7110	3,8E-04	**0,6715**	0,0066	**5,1144**	0,0494	**24,8753**	0,1143
	16	**1,7168**	4,3E-04	0,6611	0,0068	5,0156	0,0547	24,7280	0,1393
4	***4***	1,3426	1,4E-04	**0,5440**	0,0001	**5,9977**	0,016	13,4117	0,0109
	8	1,3960	4,1E-04	0,5137	0,0013	6,1987	0,0456	**13,5703**	0,0608
	16	**1,4516**	2,6E-04	0,4951	0,0015	6,4637	0,032	13,3122	0,0731

Table 2: Quantitative metric values of proposed method on concealed weapon detection images.

		SCD		QE		FF		SD	
I	***NR***	***Mean***	***Sd***	***Mean***	***Sd***	***Mean***	***Sd***	***Mean***	***Sd***
5	***4***	1,8190	1,3E-04	0,7642	0,0004	7,2460	0,0038	21,8141	0,0041
	8	1,8386	6,7E-05	**0,7727**	0,0007	**7,2954**	0,0089	**21,8684**	0,0086
	16	**1,8419**	5,5E-04	0,7672	0,0024	7,1230	0,0236	21,5918	0,0353
6	***4***	1,7482	6,8E-05	0,6321	0,0029	5,6574	0,0334	15,5627	0,0991
	8	1,7681	8,8E-05	0,6385	0,002	5,6954	0,019	**16,3073**	0,0727
	16	**1,7731**	2,9E-04	**0,6430**	0,0037	**5,7890**	0,0407	16,2750	0,1086
7	***4***	1,5953	1,6E-04	**0,4789**	0,0024	**6,0943**	0,022	**13,8252**	0,0178
	8	1,5959	3,2E-04	0,4597	0,0117	5,8943	0,051	13,5828	0,0876
	16	**1,5974**	4,7E-04	0,4450	0,0219	5,8543	0,0987	13,3263	0,1569
8	***4***	1,9284	6,6E-07	**0,6763**	0,0001	**7,8687**	0,0058	**18,4296**	0,0088
	8	1,9497	3,7E-06	0,6548	0,0001	7,6373	0,0025	18,0308	0,0044
	16	**1,9535**	1,7E-05	0,6600	0,0004	7,5924	0,0061	17,8978	0,0093

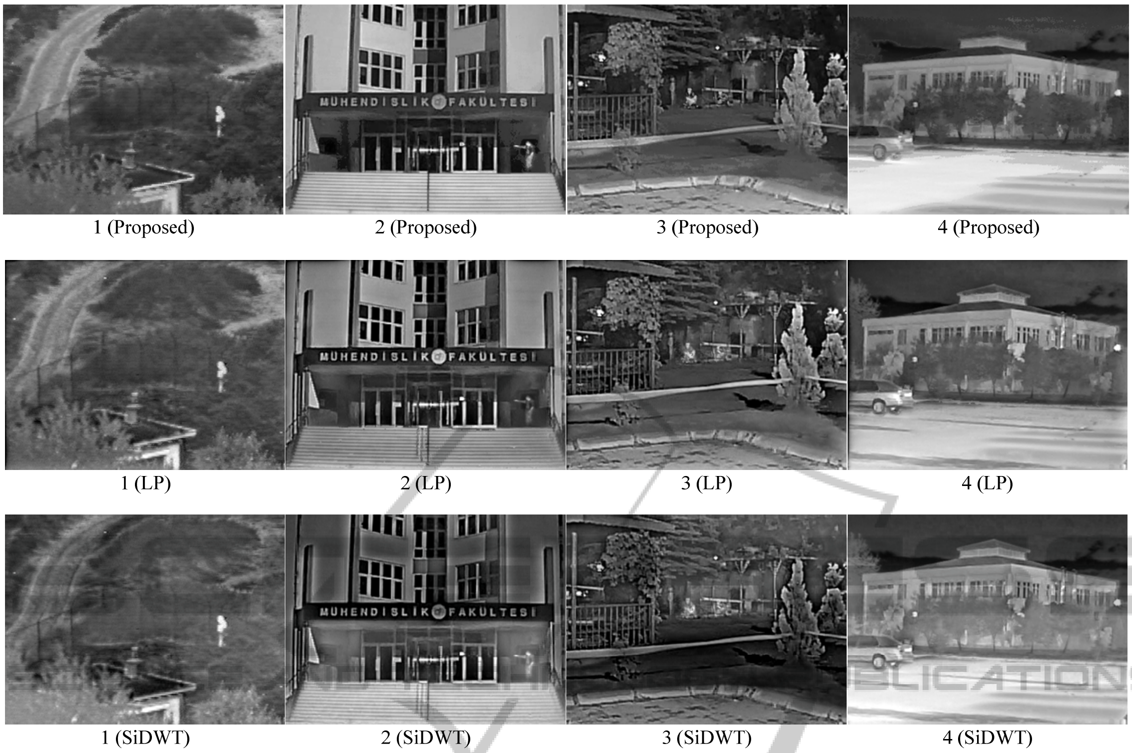

Figure 3: Visual results of methods on enhanced night vision images.

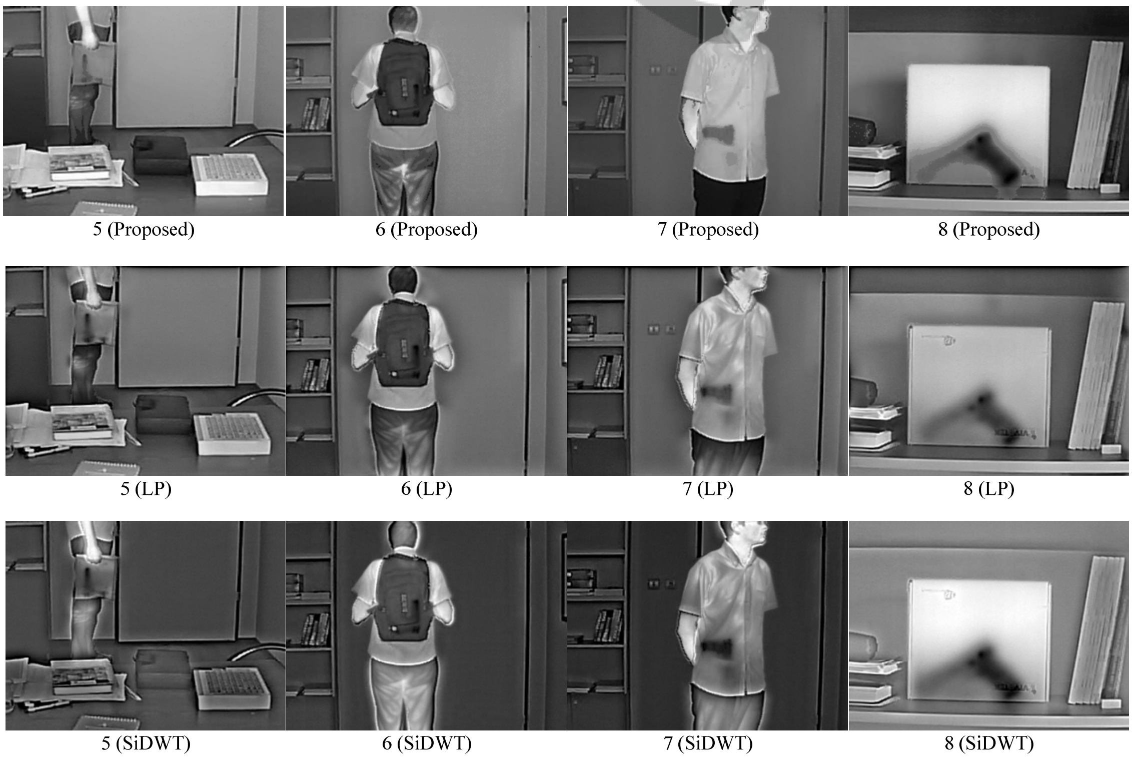

Figure 4: Visual results of methods on concealed weapon detection images.

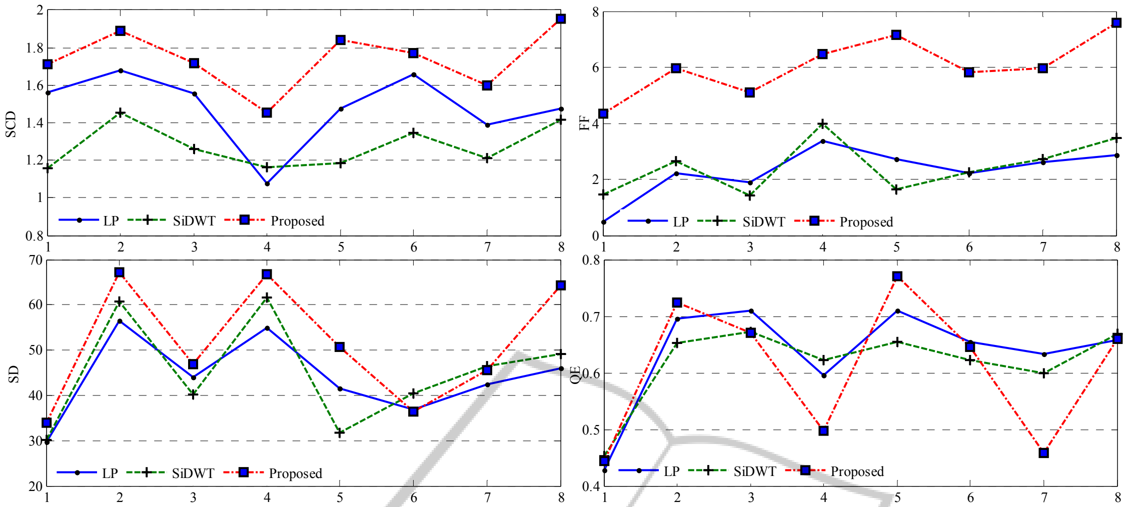

Figure 5: Quantitative comparison of Fusion Methods.

4 CONCLUSIONS

In this paper, a new optimized region based image fusion method is proposed in spatial domain. K-Means is used as segmentation method, and differential evolution algorithm is utilized in optimization stage. Performance of the method is compared with the classical techniques using eight thermal and visible image sets.

The visual and the quantitative results given, the proposed method produced better results than the others. Especially in the night vision images, visual results of the proposed method represent more meaningful visual information than the others for human perception.

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