A Novel Night Vision Image Color Fusion Method Based on Scene Recognition

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***Abstract*—Infrared and low light level image color fusion can make target detection and recognition more precise. Different from the existing color transfer fusion method using fixed reference image, this paper presents a color fusion method based on a combination of scene classification, fusion quality measure and color transfer. We introduce the scene classification method into the color fusion algorithm, which is based on the Gist descriptor and SVM classifier. Afterwards we use the proposed color fusion quality measure structure to find out the best matched reference image for each classified input image. Meanwhile, we get the high quality color fusion image using color transfer method. This method is verified in both linear and non-linear color space. Results show that this method can effectively improve the color fusion effect. More importantly, it can be used in the condition with few prior information.**

Keywords— color fusion; infrared image; low light level image; scene recognition; quality measure

I. INTRODUCTION

Infrared and LLL (low light level) cameras are two kinds of night vision image sensor. LLL image is rich in details but can be easily disturbed by external environmental factors like weather. Infrared images show better thermal contrast as it converts the thermal energy into a visible image, which can hardly be affected by weather and lighting. These two kinds of images can be fused in several ways to get all the benefits they have, which is widely used in night vision. In the early research of image fusion, many scholars put forward different gray fusion algorithms, however, the gray information only cannot accurately and effectively support the scene identification and target detection. As is known, the human eye can only distinguish about 100 shades of gray at any instant, it can discriminate several thousands of colors. Based on this characteristic of human eye, researchers began to develop color fusion technology. The Netherlands Human Factors Research Institute Tote et al proposed false color fusion method using visible and thermal images[1]. this algorithm enhanced image details and retains the unique information of different sensors. Besides, Massachusetts Institute of Technology Lincoln Laboratory Waxman proposed a fusion method based on biological visual model, which is consistent with human visual sense of color[3].

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Most of the false color fusion images are not quite fit with human sense of color, in which case observers recognize different objects by image segmentation based on color contrast of fused image[2]. This may be worse than using single band image. Afterwards scholars studied several different fusion methods to get natural feeling images, among which Toet et al proposed a fusion algorithm based on color transfer. This algorithm uses the statistical parameters of the reference image, which brings a revolutionary progress in the field of color fusion. However, most color mappings do not achieve color constancy or produce color images with an unnatural appearance, thereby seriously degrading observer performance. In 2012, Toet introduced a simple color remapping technique that can give multispectral nighttime imagery an intuitive and stable color appearance, which is called the color look up table method[1]. This method is computationally efficient and can easily be deployed in real time. However this look up table requires the daylight color reference image of the same scenarios, which means it needs much more prior information and limits its usage in night vision.

This paper aims at finding a self-adaptive Infrared and LLL color fusion method with as few prior information needed as possible. By introducing the scene classification method into our algorithm, we set a label for each input gray-level image corresponding to different categories of our image dataset. Afterwards we set the color fusion quality measure structure, using which we find the best matched reference image for each classified input image. This method can effectively improve the fusion result, and once the label is set up, it will shorten the searching time. Compared with the look up table method, this method needs few prior information which is quite fit with the night vision condition.

II. COLOR MAPPING BASED FUSION METHOD

A. Color Space

All of the color image processing is implemented in a certain color space, such as RBG space, $l\alpha\beta$ space and YUV space. RGB color space is the most widely used color space, which is based on the principle of tricolor. R, G, B representing red, green and blue color channels. In the field of infrared and LLL image color fusion, RGB color model is generally used in false color fusion, and the fusion result is

not natural. As the R, G, B channel are not completely independent, once fusion image needs further processing, it needs to be converted to other space, such as $l\alpha\beta$ space, which is more complicated but fit with human visual sense. Another color space is YUV space, which is linearly transformed from RGB space. And Y channel represents luminance. U channel represents chromatic aberration between blue and luminance. V channel represents chromatic aberration between red and luminance. In this paper, we mainly used $l\alpha\beta$ space and YUV space as comparison.

B. Color Mapping Based Fusion Algorithm

To apply the color mapping method to the field of image fusion was first proposed by toet, afterwards it's applied to the night vision field. The main process of the method is as follows:

(1). mapping infrared and LLL image to R and G channel of an RGB display, B channel can be set to 0. Thus get the false color fusion image as input image;

(2). Transfer input image to another color space(in this paper we use $l\alpha\beta$ space), using transforms defined in (1) and (2);

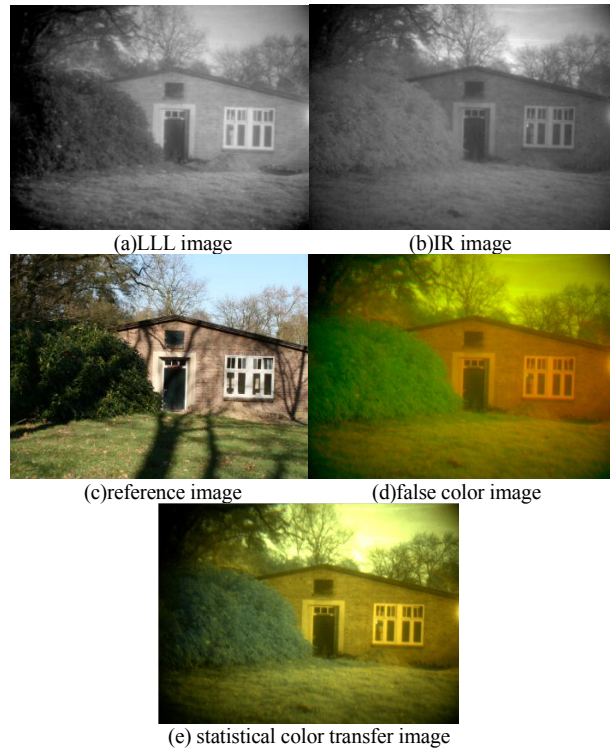
(3). Get color statistics of input and reference images (mean value and standard deviations), then transfer the first order color statistics from reference image (full color daylight image) to the false color multiband image, using transform defined in (3);

(4). Transfer the modified input image to RGB space and display;

$$\begin{bmatrix} L \\ M \\ S \end{bmatrix} = \begin{bmatrix} 0.3811 & 0.5783 & -0.0402 \\ 0.1967 & 0.7244 & 0.0782 \\ 0.0241 & 0.1288 & 0.8444 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{1}$$

$$\begin{bmatrix} l \\ \alpha \\ \beta \end{bmatrix} = \begin{bmatrix} \frac{\sqrt{3}}{3} & 0 & 0 \\ 0 & \frac{\sqrt{6}}{6} & 0 \\ 0 & 0 & \frac{\sqrt{2}}{2} \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & -2 \\ 1 & -1 & 0 \end{bmatrix} \begin{bmatrix} L \\ M \\ S \end{bmatrix} \tag{2}$$

$$\begin{cases} l_s^{'} = \frac{\sigma_t^l}{\sigma_s^l}(l_s - \mu_s^l) + \mu_t^l \\ \alpha_s^{'} = \frac{\sigma_t^\alpha}{\sigma_s^\alpha}(\alpha_s - \mu_s^\alpha) + \mu_t^\alpha \\ \beta_s^{'} = \frac{\sigma_t^\beta}{\sigma_s^\beta}(\beta_s - \mu_s^\beta) + \mu_t^\beta \end{cases} \tag{3}$$



(a)LLL image (b)IR image

(c)reference image (d)false color image

(e) statistical color transfer image

Fig. 1. Color mapping based color fusion result

Color fusion result using color mapping method is shown in Fig.1. We can tell from result that fusion image compensates the details lost in the shade and makes it easier to distinguish objects in the picture. And the color mapping method makes it more natural than false color image. However, this method is computationally expensive and therefore not suitable for real-time implementation. Moreover, although it can give multiband imagery a realistic daylight color appearance, it cannot achieve color constancy for dynamic imagery as the actual mapping depends on the relative amounts of different materials in the scene[10-15]. To solve this problem, Toet proposed the look-up-table–based statistical color transfer method, with 2-tuples input table representing all possible sensor output values and output table representing all possible color values that can occur in the colorized fused image. The input and output table pair defines the statistical color mapping and can therefore be deployed in a color look-up-table transform procedure. But as we have mentioned above, the color look-up-table method's accuracy is highly dependent on the reference image. Which means the methods above cannot solve the basic problem that is how to choose the perfect matched reference image with as little prior information as possible.

III. PROPOSED LLL AND INFRARED IMAGE COLOR FUSION METHOD

Our method of LLL and infrared image color fusion is shown in Fig.2. We introduce the scene recognition and quality measure method into our algorithm, which is highlighted in yellow. Our intention is to find the best

matched reference image with as few prior information as possible, so that it can be used in different application scenarios.

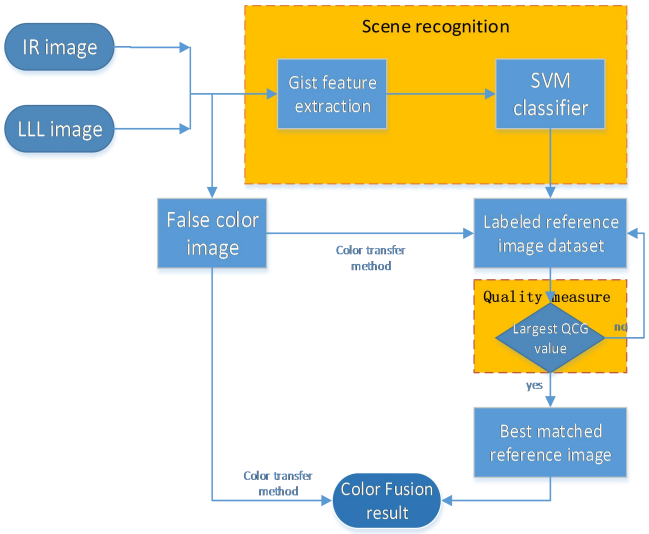


Fig. 2. Proposed LLL and IR image color fusion method

A. Scene recognition

Scene classification is an important branch of visual classification. The conceptions of scene description and scene understanding are specified in the 2006 MIT Workshop on Scene Understanding, and they are regarded having a bright prospect. Three respects are included in the scene classification thinking: scene classification based on object, scene classification based on region, and scene classification based on context[18-23].

Many experts and scholars have tried to give the definition of scenario within which Oliva and Torralba[8] used the distance between the observer and the target to describe the scene, they point out that if the distance between the observer and fixed area is within 1 to 2 meters, the fixed region of the image will be considered object; And when the distance between the observer and fixed area is larger than 5 meters, that image is scene. Scene recognition is very common in our daily life. Movies use fast switches between scenes: after a quick look at each picture, you can feel the meaning of each shot and actors' emotions in the scene, even though you don't remember the details of each shot.

In this paper, we introduce the fast scene classification method based on scene Gist, which extracts degree of the naturalness, openness, roughness and expansion. See [8]. The Gist model is based on visual cortex feature channel, which is shown in Fig.3. Since our input images are gray level images, we put on more weight on the orientation channel and intensity channel than the color channel.

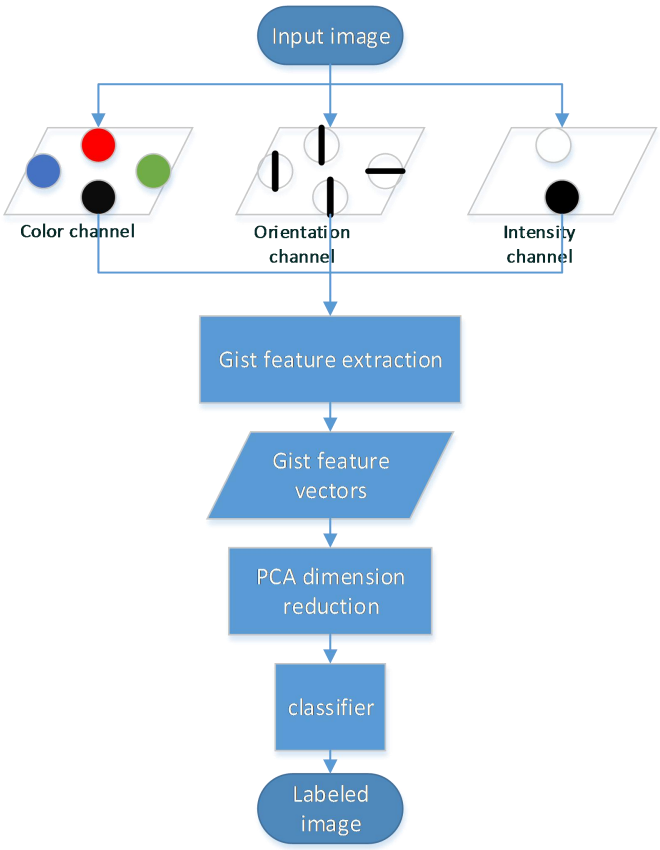


Fig. 3. Gist model based on visual feature channel

We choose the image dataset of Oliva and Torralba[8]. It contains eight different categories images, including coast(360), forest(328), highway(260), city(308), mountain(374), open-country(410), street(292) and building(356). We classify these images into two main categories : natural image and man-made image. Based on the gist model, the data structure of an image is in table.1.

TABLE I. THE DATA STRUCTURE OF AN IMAGE

Data structure	Description
Naturalness **s**	integration of energy spectrum and naturalness
Eigenvector **g**	The gist vector extracted from visual feature channel, dimension reduction if needed
Image category label **L**	From 1 to 8, each number represents a category
Image category predict label **LP**	From 1 to 8, predict label by SVM classifier

We use half the dataset as training set and the rest as testing set. Result is shown in table.2. There is still one question needs to be solved that is how to choose the extracted features since input image includes infrared and LLL image of the same scene at each time. We do several experiments and get the conclusion that features from the LLL images are more reliable under Gist Model, which is quite fit with the imaging principle of these two cameras.

TABLE II. RECOGNITION RATE BASED ON GIST MODEL

Condition		Accuracy
Natural scene	Coast	87.22%
	Forest	95.12%
	Mountain	89.84%
	Open country	84.63%
Man-made scene	Highway	83.46%
	City	88.63%
	Street	95.55%
	Building	95.50%

B. Color fusion quality measure

As we mentioned above, it seems that to choose the perfect reference images is the key to color mapping based color fusion. So it's essential to find appropriate quality measure to evaluate multi-sensor color image fusion[24-29]. Our quality measure is based on Color Fusion Objective Index (CFOI) proposed by Anwaar-uI-Haq[5,16]. Which combined colorfulness, gradient similarity and mutual information. Mutual information is defined in (4). Where $h_{F,A}$ is the normalized joint gray level histogram of images F and A, h_F and h_A are the normalized marginal histogram of two images and L is the number of gray levels.

$$M(F,A)=\sum_{i_1=1}^{L}\sum_{i_2=1}^{L}h_{F,A}(i_1,i_2)\log_2\frac{h_{F,A}(i_1,i_2)}{h_F(i_1)h_A(i_2)} \tag{4}$$

The quality of fused image then is (5), A and B are infrared and LLL image. F is the color fusion image. λ is spatial frequencies.

$$Q(A,B,F)=\lambda M(A,F)+(1-\lambda)M(B,F) \tag{5}$$

For colorfulness similarity evaluation, Hasler and susstrunk proposed the colorfulness metric[6] defined as:

$$C=\sqrt{\sigma_{rg}{}^2+\sigma_{yb}{}^2}+0.3\sqrt{\mu_{rg}{}^2+\mu_{yb}{}^2} \tag{6}$$

Where μ and σ are mean and standard deviations of the pixel cloud along two axes in a simple opponent space rg=R-B and yb=0.5(R+G)-B, respectively. Normalize C and the fused and reference image colorfulness similarity is defined as:

$$C(F,T)=\frac{C_F}{0.5(C_T+1)} \tag{7}$$

The gradient similarity G is relatively complicated as is defined as a combination of luminance, contrast and structural comparison[7]:

$$G(a,b)=[l(a,b)]^{\alpha}.[cg(a,b)]^{\beta}.[sg(a,b)]^{\gamma} \tag{8}$$

$$l(a,b)=\frac{2\mu_a\mu_b}{\mu_a{}^2+\mu_b{}^2} \tag{9}$$

$$cg(a,b)=\frac{2\sigma_a\sigma_b}{\sigma_a{}^2+\sigma_b{}^2} \tag{10}$$

$$sg(a,b)=\frac{\sigma_{ab}}{\sigma_a\sigma_b} \tag{11}$$

Now the CFOI value is calculated as:

$$CFOI=\frac{\alpha.Q+\beta.C+\gamma.G}{3} \tag{12}$$

Where α, β and γ can be changed according to actual conditions. We make slight changes according to the fusion Algorithm we take. Since we use false color image as input, mutual information between A, B and F is therefore less important than mutual information between reference image T and fused color image F. So Q is modified as (13). As for gradient similarity, we also make some adjustment. We retain the l and cg parts, and use Sobel operators to calculate the gradient vectors a and b. As we are measuring color fusion result, so we increase the proportion of C. Final QCG value is (14).

$$Q(A,B,T,F)=\frac{\lambda M(A,F)+(1-\lambda)M(B,F)+2M(T,F)}{4} \tag{13}$$

$$QCG=\frac{Q+2C+G}{4} \tag{14}$$

C. color transfer

The color transfer method is shown in (3). We transfer all the reference images to $l\alpha\beta$ space and calculate image's mean and standard deviation value in each channel. The coast dataset statistic distribution in l, α, β channels are shown in Fig. 4. We can tell from Fig.3 that these distributions accord with normal distribution. We calculate the statistics of image dataset in advance to reduce the computational work. Once we get the classified input LLL and infrared image, we can find the best matched reference image in the corresponding dataset according to largest QCG value, thus we can use the color transfer method to get high quality color fusion result.

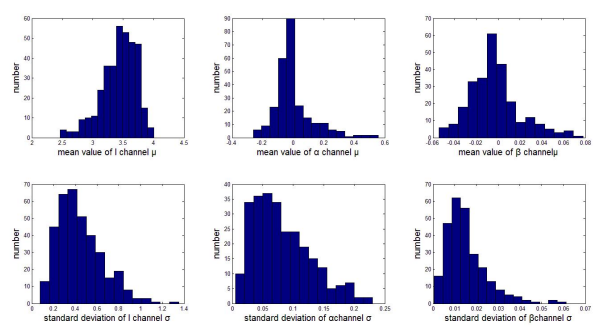


Fig. 4. Statistic distribution of mean and standard deviation in l, α, β channels

IV. EXPERIMENT AND ANALYSIS

A. Color fusion experiment

We use Toet's dataset of infrared and LLL images to conduct our experiments. We choose 15 different scenes, which is shown in Fig.5. Steps are as follows:

(1). Input IR/LLL image to get the gist features and start scene recognition, after that each image has a label;

(2). Find the labeled image dataset(according to (1)), in this paper we have 8 labels;

(3). calculate the fusion quality measure QCG value using images in (2) as reference images, the best matched reference image has the highest QCG value;

(4). calculate the fusion quality measure QCG value using the rest images to verify if our method works

Fig. 5. Input images of different scenes

We present image#2 and image #14's color fusion result in this paper. Color transfer is conducted in $l\alpha\beta$ space. Image #14's label we get is CITY. So we turn to the CITY image dataset and using these images to do the color transfer and get the QCG value of each image. Thus we find the image with the highest QCG value which we believe is the best matched reference image. Results are shown in fig.6, which contains result in both linear (YUV, image e, f) and non-linear ($l\alpha\beta$, image c, d) space[17]. Afterwards we use the rest dataset which has not been chosen according to the Gist model. We calculate the mean QCG values which is shown in table 3 and Fig.7. Results show that the dataset chosen by the Gist model has the highest mean QCG value, which means the scene recognition progress and the fusion quality measure progress has made the same decision. This is really what we want, and we can make the conclusion that the color fusion result based on scene recognition and fusion quality measure really works.

(a)IR image (b)LLL image

(c)matched reference image (d)fusion result in $l\alpha\beta$ space

(e)matched reference image (f)fusion result in YUV space

Fig. 6. Color fusion result of image#14

TABLE III. MEAN VALUE OF QCG USING DIFFERENT CATEGORIES OF IMAGE

Label	Mean value	Label	Mean value
coast	0.4359	mountain	0.4603
forest	0.4488	open-country	0.4501
highway	0.4538	street	0.4368
city	0.4788	building	0.4581

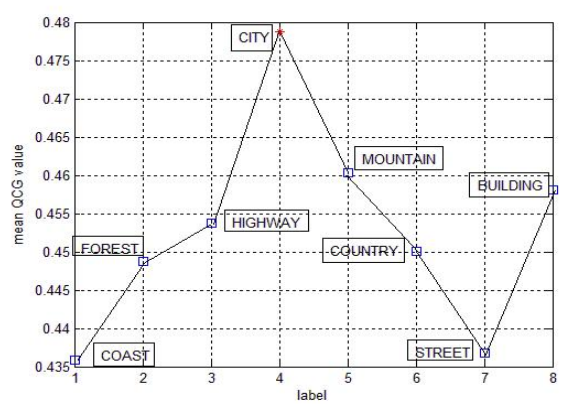
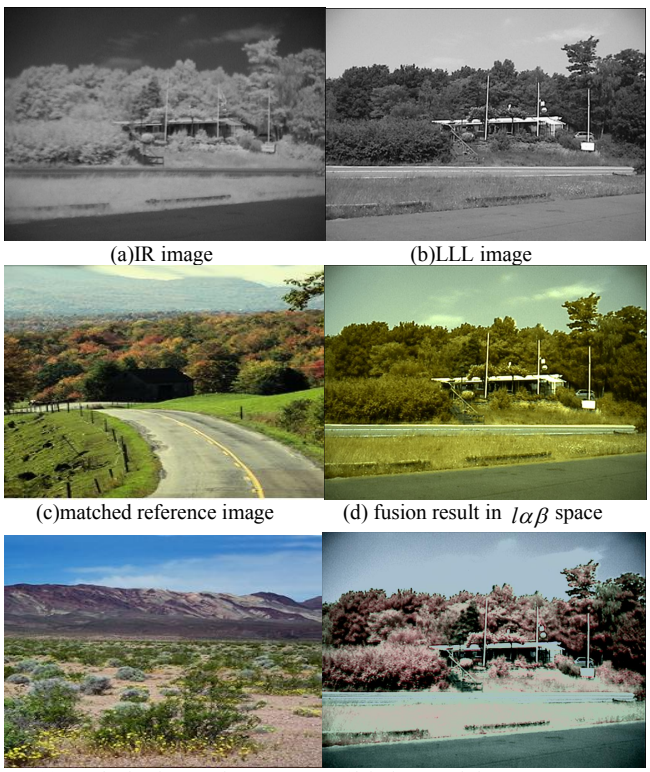


Fig. 7. Mean QCG value of image#14 using different categories reference images

Another fusion result of image#2 is shown in Fig.8. This image's label we get from the Gist model is COUNTRY. The following steps are the same as for image#14. In comparison with dataset COUNTRY, we also use the rest datasets as reference images for color fusion progress. Result is shown in table 5 and figure 9. The dataset COUNTRY has the highest mean QCG value than the rest datasets when they are used as reference images in our color fusion progress, which means the scene recognition and quality measure progress(highlighted in flow chart) of our method has made the same decision.

We can make the conclusion that the recognition progress we have introduced into our method helps selecting the best dataset and the quality measure progress helps matching the perfect reference image in this dataset for the color fusion progress. Although these two progresses are separated mathematically, we still combine them together for the reason that they have made the same right decision for our color fusion method.



(a)IR image (b)LLL image

(c)matched reference image (d) fusion result in $l\alpha\beta$ space

(e)matched reference image (f)fusion result in YUV space

Fig. 8. Color fusion result of image#2

TABLE IV. MEAN VALUE OF QCG USING DIFFERENT CATEGORIES OF IMAGE

Label	Mean value	Label	Mean value
coast	0.3866	mountain	0.4507
forest	0.4037	open-country	0.4852
highway	0.4325	street	0.4217
city	0.4018	building	0.3912

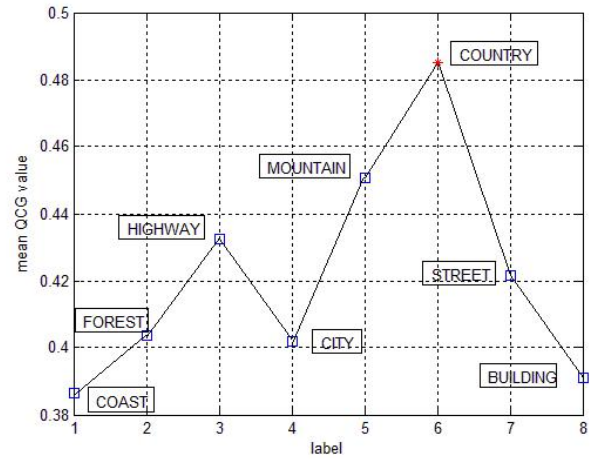


Fig. 9. Mean QCG value of image#2 using different categories reference images

B. Evaluate our method

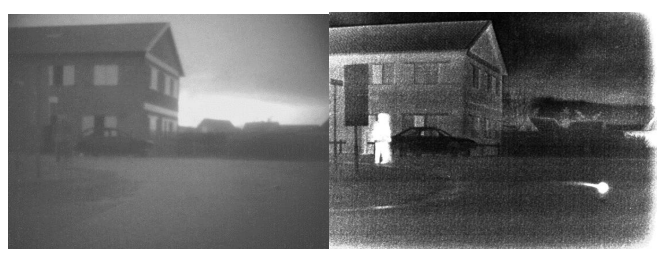
Since we have used the QCG value to find the best matched reference image. There is no need to evaluate the fusion result still using the QCG value. We are going to evaluate the fusion result in two ways:

(a). Separate the region of interest(ROI) and the background area and evaluate separately;

(b). Transform the color fusion image into gray-level image, make comparison with infrared and LLL image

(a)IR image (b)color fusion image of gray level

Fig. 10. Compare the ROI contrast



(a)LLL image (b)color fusion image of gray level

Fig. 11. Compare the gray level statistics

From Fig.10 we can see that the ROI is brighter than the background area both in IR image and color fusion image. We don't compare the ROI of LLL image since we can

hardlly tell the ROI from the background. The comparison result is in table 5.

TABLE V. STATISTIC COMPARISON RESULTS

	Contrast		**Entropy**
IR image	18.8913	LLL image	6. 73
Color fusion image of gray level	32.2961	Color fusion image of gray level	6. 57

Result shows the color fusion image has larger contrast than the IR image and little smaller entropy than LLL image. But as for colorfulness color fusion image obviously is better than gray level image.

Compared with other color fusion methods, like the look-up-table method, the advantage of our method is that we need few prior information and can always get the best matched reference images as long as the dataset is good enough. Once we have labeled the scene, we can set a threshold and skip the scene recognition progress which frees much computational resource.

V. CONCLUSION

In this paper, we present a novel color fusion method of infrared and low light level image. We introduce the scene recognition method into our algorithm which is based on Gist descriptor and SVM classifier. We use the color fusion quality measure structure to select the best matched reference images for input gray level images. Compared with the state-of-art color fusion method like the look-up-table method, our method can get natural looking fusion result with fewer prior information, which means we don't need the daylight colorful image of the same scene to get high quality color fusion result. However, there are still 2 out of 15 input images which don't comply with the conclusion we have made, which means there's still room for improvement of both scene recognition and color fusion quality measure. This is reasonable considering we use natural colorful images as training set and gray level images as input images. So our next step will focus on improving the recognition rate when we input gray level images and use more comprehensive dataset.

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