Transfer color to night vision images

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Natural color appearance is the key problem of color night vision field. In this paper, the color mood of daytime color image is transferred to the monochromic night vision image. This method gives the night image a natural color appearance. For each pixel in the night vision image, the best matching pixel in the color image is found based on texture similarity measure. Entropy, energy, contrast, homogeneity, and correlation features based on co-occurrence matrix are combined as texture similarity measure to find the corresponding pixels between the two images. We use a genetic algorithm (GA) to find the optimistic weighting factors assigned to the five different features. GA is also employed in searching the matching pixels to make the color transfer algorithm faster. When the best matching pixel in the color image is found, the chromaticity values are transferred to the corresponding pixel of the night vision image. The experiment results demonstrate the efficiency of this natural color transfer technique.

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Night vision technology enables human beings to operate at night. Low light level imaging and infrared imaging are two key technologies in night vision field. However, the images obtained through the night vision imaging systems are monochromatic, this hinders observers from interpreting the scene well. In order to improve target detection and identification abilities, color night vision technology is being pursued as an effective method for solving the problem. The main methods of realizing color night vision are false color fusion method, The Netherlands Organization (TNO) method, and Massachusetts Institute of Technology (MIT) method[1−4]. All of these methods are based on fusion of two night vision images — the low light level image and infrared image. Although a color night vision image can be gotten through these methods, sometimes it could not be helpful due to the false color. If we can give the color night vision image a natural daytime color appearance, things will be changed.

Recently true color transfer technology has been developed. Reinhard *et al.* developed this method firstly[5]. They introduced a method to transfer one image's color characteristics to another color image, which can give synthetic color images a natural appearance. For the color night vision application, Toet developed a natural color mapping for multi-band night vision imagery based on the Reinhard's method[6]. Toet first got a false color R(red)G(green)B(blue) image that was produced by mapping three individual bands of a multi-band night vision system to the respective channels of a RGB image. Then characteristics of a natural color image were transferred to the false color night vision image. Inspired by Reinhard's work, Welsh *et al.* developed a method for transferring color to grayscale images[7]. Rather than choosing RGB colors from a palette to color individual components, they transferred the entire color "mood" of the source color image to the target grayscale image by matching luminance and pixel neighborhood statistics between the two images.

In this paper, unlike Toet's method of transferring the characteristics of natural daylight color images to the false color fused night vision images, the natural color image's characteristics were transferred to the grayscale night vision image directly. Out concept of this method is inspired by the work of Welsh *et al.* and Reinhard *et al.*. We combine entropy, energy, contrast, homogeneity, and correlation features based on co-occurrence matrix as texture similarity measure to find the corresponding pixels between the two images. A genetic algorithm (GA) is used to find the optimistic weighting factors assigned to the five different features. GA is also employed in searching the matching pixels to make the color transfer algorithm faster. When the best matching pixel in the color image is found, the chromaticity values are transferred to the corresponding pixel of the night vision image. The results show that the method is effective and the color night vision images have a natural appearance.

In order to transfer the color characteristics of the daytime color image to the grayscale night vision image, we must find the corresponding pixel in the color image for each pixel in the grayscale night image. Entropy, energy, contrast, homogeneity and correlation features based on co-occurrence matrix are combined as texture similarity measure to find the corresponding pixels between the two images. The definitions of these features are

$$S = -\sum_i \sum_j P[i,j] \log P[i,j], \tag{1}$$

$$J = -\sum_i \sum_j P^2[i,j], \tag{2}$$

$$\mathrm{Con} = -\sum_i \sum_j (i-j)^2 P[i,j], \tag{3}$$

$$H = -\sum_i \sum_j \frac{P[i,j]}{1+|i-j|}, \tag{4}$$

$$\mathrm{Cor} = \frac{1}{\sigma_i \sigma_j}[\sum_i \sum_j ijP[i,j] - \mu_i \mu_j], \tag{5}$$

where S is the entropy, J is the energy, Con is the contrast, H is the homogeneity, and Cor is the correlation. $P[i,j]$ is the value of element in the co-occurrence matrix and $[i,j]$ is the coordinate; μ_i and μ_j are the mean of p_i and p_j, respectively; σ_i and σ_j are the standard deviation of p_i and p_j, respectively, where $p_i = \sum_j P[i,j]$ is the sum of all elements in every row and $p_j = \sum_i P[i,j]$ is the sum of all elements in every column.

In order to ensure equal emphasis of each feature element, we use Gaussian normalization[8] to map the feature element values within the range of $[-1,1]$. After the normalization, the pixels matching measure between two images is defined as

$$M = w_1 S + w_2 J + w_3 \text{Con} + w_4 H + w_5 \text{Cor}, \tag{6}$$

where w_1, w_2, w_3, w_4 and w_5 are the weights assigned to the entropy, energy, contrast, homogeneity, and correlation, respectively.

In the pixels matching measure, how to determine the weights is important. A suitable weight should be assigned to different feature element rather than with an ad hoc procedure. In this paper we find the suitable weights using GA. Let M_1 and M_2 be the two measure values of two images. The Euclidean distance between M_1 and M_2 is defined as

$$D_M = \sqrt{(M_1 - M_2)^2}. \tag{7}$$

The fitness function in the GA is defined as

$$\text{FIT} = \frac{1}{1 + D_M}. \tag{8}$$

A chromosome representation in our GA is defined as

$$c = (w_1, w_2, w_3, w_4, w_5). \tag{9}$$

A population P is defined as

$$P = \{c_1, c_2, \cdots, c_i, \cdots, c_n\}, \tag{10}$$

where n is the number of individuals in the population and c_i is a chromosome.

We apply the GA in several pairs of similar images to find the suitable weights which make the distance between M_1 and M_2 the furthest. The values of the weights are bound by 0 and 1. The experiment result is

$$\begin{aligned} &w_1 = 0.16, \quad w_2 = 0.11, \quad w_3 = 0.34, \\ &w_4 = 0.05, \quad w_5 = 0.34. \end{aligned} \tag{11}$$

In order to make the color transfer algorithm faster, when we search the matching pixels between the daytime color image and the night vision image, we use the search strategy based on GA. Suppose the size of color image is $M \times M$, and the size of night vision image is $N \times N$. We choose a neighborhood size of $n \times n$ for each pixel. Then the times of global search for each pixel is $(M-n) \times (M-n)$. The position coordinate of the matching pixel in the color image (x,y) is the chromosome representation in GA, defined as $c = (x,y)$. The color image is segmented into small windows averagely. The initial population is generated by choosing a pixel randomly in every small window. The number of small windows is the number of individuals in the population. The fitness function in GA is the same as Eq. (8).

Because the grayscale images are represented by one dimensional luminance distribution, while color images are usually displayed in RGB space, in order to get the values of the color characteristics of the color images and retain the luminance value of the night vision images, we convert both color and grayscale images to a decorrelated color space $l\alpha\beta$, which was derived from a principal component transform by Ruderman *et al.*[9]. First the RGB signal values are converted to LMS cone space values by

$$\begin{bmatrix} L \\ M \\ S \end{bmatrix} = \begin{bmatrix} 0.3811 & 0.5783 & 0.0402 \\ 0.1967 & 0.7244 & 0.0782 \\ 0.0241 & 0.1288 & 0.8444 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}. \tag{12}$$

The data in this LMS color space shows a great deal of skew, which can be largely eliminated by converting the data to logarithmic space

$$\mathbf{L} = \log L, \quad \mathbf{M} = \log M, \quad \mathbf{S} = \log S. \tag{13}$$

Ruderman *et al.* suggest the following transform to decorrelate the axes in the LMS space:

$$\begin{bmatrix} l \\ \alpha \\ \beta \end{bmatrix} = \begin{bmatrix} \frac{1}{\sqrt{3}} & 0 & 0 \\ 0 & \frac{1}{\sqrt{6}} & 0 \\ 0 & 0 & \frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & -2 \\ 1 & -1 & 0 \end{bmatrix} \begin{bmatrix} \mathbf{L} \\ \mathbf{M} \\ \mathbf{S} \end{bmatrix}. \tag{14}$$

In the $l\alpha\beta$ space, the l axis represents an achromatic channel, while the α and β channels are chromatic yellow-blue and red-green opponent channels. Our color transferring method operates in this $l\alpha\beta$ space because it provides a decorrelated achromatic channel for color images. This makes us retain the luminance channel of the grayscale image and selectively transfer the chromatic α and β channels from the color image to the grayscale image conveniently.

After color transfer processing in $l\alpha\beta$ space, we must transfer the result back to RGB space to display it. The inverse transformation from $l\alpha\beta$ space to RGB space can be realized using

$$\begin{bmatrix} \mathbf{L} \\ \mathbf{M} \\ \mathbf{S} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & -1 \\ 1 & -2 & 0 \end{bmatrix} \begin{bmatrix} \frac{\sqrt{3}}{3} & 0 & 0 \\ 0 & \frac{\sqrt{6}}{6} & 0 \\ 0 & 0 & \frac{\sqrt{2}}{2} \end{bmatrix} \begin{bmatrix} l \\ \alpha \\ \beta \end{bmatrix}, \tag{15}$$

$$L = 10^{\mathbf{L}}, \quad M = 10^{\mathbf{M}}, \quad S = 10^{\mathbf{S}}, \tag{16}$$

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 4.4679 & -3.5873 & 0.1193 \\ -1.2186 & 2.3809 & -0.1624 \\ 0.0497 & -0.2439 & 1.2045 \end{bmatrix} \begin{bmatrix} L \\ M \\ S \end{bmatrix}. \tag{17}$$

In order to get better results, the daytime color image should have the similar scene as the night vision image. Figure 1 shows the results of color transfer between daytime color images and night vision images. Figure 2 shows the results of color transfer between the daytime color image and the fused night vision image. Figure 2(a) is the low light level image; (b) infrared image; (c) fused image. Figures 2(d), (e), and (f) are resulted color images using the RGB color night vision method with

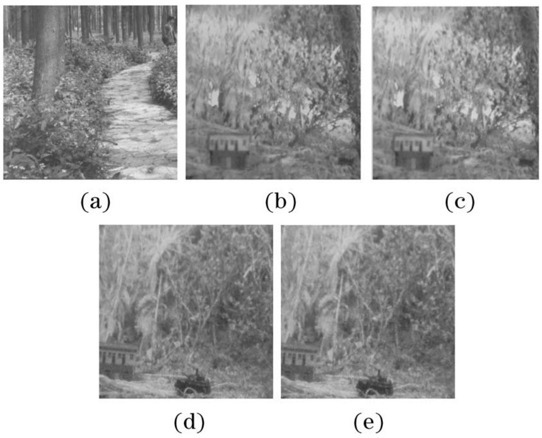

Fig. 1. Results of color transferring algorithm. (a) Daytime color image; (b) near infrared image; (c) result color image of (b); (d) low light level image; (e) result color image of (d).

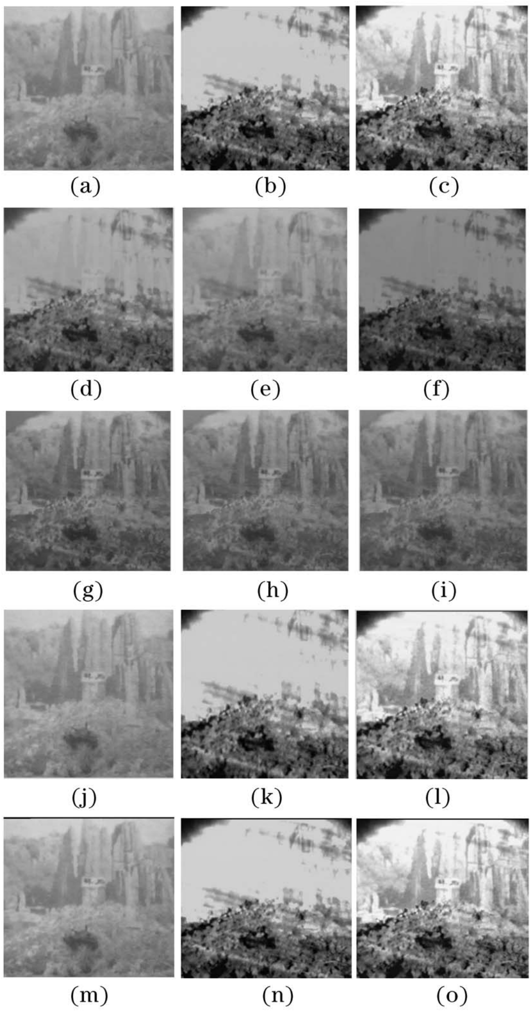

Fig. 2. Results of traditional color night vision algorithms and color transfer algorithm. (a) Low light level image; (b) infrared image; (c) fused image; (d), (e), (f) results of RGB fusion; (g), (h), (i) results of TNO fusion; (j), (k), (l) results of proposed algorithm; (m), (n), (o) results of algorithm in Ref. [7].

low light level image as the R channel input, infrared image G channel input, zero value B channel input (d); infrared image as the R channel input, low light level image G channel input, zero value B channel input (e); zero value as the R channel input, low light level image G channel input, infrared image B channel input (f) respectively. Figures 2(g), (h), and (i) are results of TNO fusion using TNO1, TNO2, and TNO3 methods, respectively. Figures 2(j), (k), and (l) are results of directly transferring the source color image's characteristics (Fig. 1(a)) to the low light level image, near infrared image, and fused image, respectively. Figures 2(m), (n), and (o) are results of algorithm in Ref. [7] of which the source color image and the target grayscale images are the same as Figs. 2(j), (k), and (l). We can compare the appearance of the result images using the algorithm proposed in this paper and in Ref. [7]. The images (j), (k), and (l) in Fig. 2 have a more natural color than the images (m), (n), (o).

In this paper a realization scheme for color night vision is presented. In this scheme, the color mood of a daytime color image is transferred to the monochromic night vision image using natural color transfer technique. This method gives the night image a natural color appearance. It can avoid the drawback of unnatural color appearance in RGB fusion method, and registration is not necessary in this color transfer method. We use a GA to find the optimistic weighting factors assigned to the different texture similarity measure features. GA is also employed in searching the matching pixels to make the color transfer algorithm faster. The experiment results demonstrated the efficiency of this natural color transfer technique.

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