Experiments on image enhancement for night-vision and surveillance

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***Abstract*—We present an overview of recent progress in techniques of color image enhancement for night vision in surveillance applications. Inspired by previously developed color constancy schemes, we firstly test simple algorithms in order to enhance dark images. These methods have been successfully deployed in different research areas, however, this enhancing approach occasionally does not produce realistic colors. We continue our discussion, now applying color mapping from daylight images, transferring first order statistics from a target image to the dark one. Particularly, we have explored the use of color transfer algorithms in the RLAB color space, procedure that yields outstanding results, with realistic and vivid colors. Finally, another method commented here, consists of applying the statistical mapping approach in a color look-up table framework, where both color constancy and computational simplicity are achieved. Some experimental results are shown and discussed in order to glimpse the importance of these approaches in surveillance tasks.**

***Index Terms*—night vision, color constancy, color transfer, video surveillance, image enhancement.**

I. Introduction

Night vision is a crucial area for a wide-range of military and law enforcement applications related to surveillance [1], [2], scene recognition [3], [4], [5], and security [6]. Night vision, refers to the action of watching under the night or under very low light conditions. Traditionally, two common approaches of night-time imaging systems have been followed. The low-light level (image-intensified) cameras, and the thermal infrared (IR) cameras. The first increases the few visible light to the near-infrared band (VNIR). The second type of systems convert thermal energy from the mid-wave $(3-5\mu m)$ or the long-wave $(8-12\mu m)$ as part of the infrared spectrum into a visible image.

The human eye cannot distinguish all gray tones at any instant and the night vision imagery is usually difficult to distinguish. In spite of that, a gray scale (or green scale) representation has been a standard over decades in the night vision field. By contrast, people can discriminate several thousands of colors defined by varying hue, saturation, and brightness. Thereby, color images have numerous benefits over monochromatic images for surveillance and security applications, and a color representation may facilitate the recognition of night vision imagery and its interpretation.

A third approach to night-vision includes methodologies focused to reproduction of color in night or low light conditions imagery. One simple way of generating a better color representation is stretching the dynamic range in a dark image. Mainly, three approaches for enhancing the dynamic range of an image have been conducted in the last years: color constancy, color transfer and sample-based color mapping. Color constancy and color transfer have attracted attention because both can be performed in images captured using a standard camera. By contrast, image fusion has grown due to the increasing availability of multispectral images and sensor systems.

Color constancy, has been defined as the ability of a system to recognize the actual colors of surfaces, independently of the illuminant present in a scene [7]. According to the computational point of view, color constancy is considered as the transformation of an input image captured under an unknown lighting, to another picture apparently obtained under daylight [8]. Provenzi et al. [9] explored the use of two color constancy algorithms, the White-Patch (WP) [10], [11] and the Gray-World (GW) [12], for color image enhancement purposes. Although color constancy algorithms have been originally developed just for the color estimation of a light source, they improve the chromatic content substantially when are applied on dark images [13]. Thus, color constancy algorithms are an option for the enhancement of dark images. Thereby, emulating in a machine vision system, and to certain degree, the innate capability of the human vision system to correct the effects of the light source on the perceived color [14]. However, this scheme can produce false color images having an unnatural color appearance.

Currently, color transfer techniques, also known as color mapping in the literature is another methodology under consideration for the enhancement of images under low light conditions. Color transfer methods aim to recolor a given image or video by deriving a transference between that image and another image serving as a reference. There are three strategies usually handled for color transfer between images; using a geometric-based methods, statistical approaches and solutions assisted by the user. Some studies have demonstrated that if a color transfer to night-time imagery is designed appropriately, it improves the observer interpretation and reaction time [15]. Such studies have been specifically oriented in tasks like scene segmentation and classification [15], [16]. However, incorrect color assignation (false colors) could impede a mindfulness to specific tasks [17], [18]. Hence, color transfer can be a viable option in order to correct these false colors.

Finally, we can say that image fusion is another technique used in night vision tasks. This technique allows the increasing of visual information in an image, for example, combining bands in the RGB space to increase the dynamic range of a sensor system [19]. In image fusion, generally two monochromatic images in different spectral range are used. One near-infrared or visible image is considered as the R component, and a thermal image is designed to be the G component [20], [3]. This fusion helps to the creation of a look-up table for transferring colors to other images.

In this study, we describe the aforementioned algorithms and their applications in the enhancement of dark images. We include experiments of color constancy-based enhancement, the mapping of a daylight image to night imagery and, also, the image fusion using look-up tables, in a sample-based color mapping. Particular issues and certain advantages are discussed, emphasizing their possible application in night surveillance tasks.

The rest of this article is organized as follows. In Section 2 some approaches commonly used for night vision and surveillance tasks are described. Section 3 presents and discusses the experimental results, followed by the concluding remarks in Section 4.

II. Approaches for night-image enhancement

The discussed approaches in this study are focussed to the transformation of a dark image to another with a natural appearance. In this section, we include the basics of these approaches for achieving such transformation. Firstly, an introduction to a couple of color constancy algorithms is given. Secondly, a statistical color transfer technique is presented. Finally, we describe the use of a look-up table for attaining the lightening of the image.

A. Color constancy

Two popular color constancy algorithms, the White-Patch (WP) and the Gray-World (GW), assume that the illumination is uniform across the scene. The relationship of the color intensity under a light source in an image is given by

$$f_i(x, y) = G(x, y)R_i(x, y)I_i, \tag{1}$$

where, $f_i(x, y)$ is the pixel intensity at the position (x, y), $G(x, y)$ is a geometry factor, $R_i(x, y)$ is the reflectance of the object, I_i is the illuminant, and i corresponds to the color channel.

Once a color constancy algorithm is applied over an image $f_i(x, y)$, the outcome, $o_i(x, y)$, just depends on $G(x, y)$ and $R_i(x, y)$. Color constancy algorithms assume that the output images, $o_i(x, y) = G(x, y)R_i(x, y)I'_i$, are influenced by a white light source, where $\mathbf{I}' = \{1, 1, 1\}$ is the illuminant in the output. Then, the relation between the output and the input is

$$o_i(x, y) = G(x, y)R_i(x, y) = f_i(x, y)/I_i. \tag{2}$$

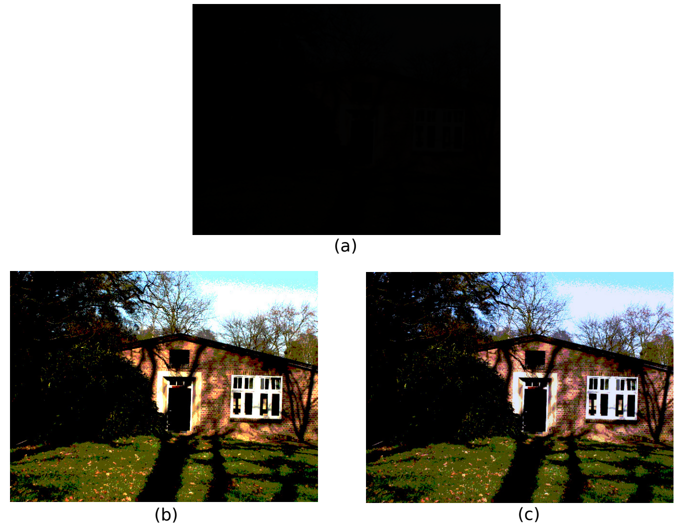

Fig. 1. (a) Image darkened syntetically. (b) Outcome using White-Patch algorithm (c) Outcome using Gray-World algorithm.

1) White-Patch: The Retinex algorithm was proposed by Land [10]. This algorithm, in its simplest form, is called White-Patch Retinex (WP) [11], which takes into account the highest value in each color channel as the white representation for the image. Computationally, such values are found from the maximum intensity in each channel $I_i = \max\{f_i(x, y)\}$.

Later, all pixel intensities are scaled according to the illumination computed using Eq. (2). The outcome image for this algorithm is given by

$$\mathrm{WP}_i(x, y) = f_i(x, y)/\max\{f_i(x, y)\}. \tag{3}$$

Finlayson et al.[21] improved this algorithm using a 99% in the histogram for each color channel for the estimation of the illuminant. This improvement is the WP algorithm considered in our study.

2) Gray-World assumption: The Gray-World assumption (GW) is the most popular algorithm for color constancy. Proposed by Buchsbaum [12], it is based on the assumption that, on average, the colors found in real world images tend to a gray tone, and hence the illuminant is estimated using the average color of all pixels.

Basically, this algorithm consists in computing the illuminant based on $a_i = \mathrm{mean}\{f_i(x, y)\}$. Some assumptions are proposed in [22] for simplifying the method, and the illuminant is adopted as $I_i \approx 2a_i$. Then, the outcome image for this algorithm is given by

$$\mathrm{GW}_i(x, y) = f_i(x, y)/\left(2 \cdot \mathrm{mean}\{f_i(x, y)\}\right). \tag{4}$$

The GW assumption is useful for the enhancement of night imagery, clearly illuminating dark areas but avoiding the possible saturation arising when the WP is applied.

B. Statistical color transfer

Color transfer methods aim to recolor a given image or video by deriving a mapping between that image and another image serving as a reference [23]. In this study, the proposal of Reinhard et al. [24] is used, where only global statistics in the image are calculated. The goal of this method is making a new image with a look similar to a reference image, named target.

The method was proposed using the $l\alpha\beta$ color space, although the use of the CIELAB model has also been under consideration [25]. In this study, we present results of color transfer in the RLAB color space. Firstly, it is necessary to transform the image to the RLAB color space, then the color transfer is applied in the luminance channel and in the two chromatic components. The RLAB space, is an improvement to the CIELAB space, correcting problems presented by CIELAB under extreme lightings (very low or high) [26]. Later, Fairchild [27] performed a refinement in this space, in order to further improve the model. Only the average and standard deviation are used along each three color channels or components; L^*, a^* and b^*. Therefore, these measures in both images, source and target, are obtained. It is important to note that the averages and standard deviations are computed for each i channel separately as follows

$$\mu_i^S = \frac{1}{M_S N_S} \sum_{x=1}^{M_S} \sum_{y=1}^{N_S} S_i(x,y), \tag{5}$$

$$\mu_i^T = \frac{1}{M_T N_T} \sum_{x=1}^{M_T} \sum_{y=1}^{N_T} T_i(x,y), \tag{6}$$

$$\sigma_i^S = \sqrt{\frac{1}{M_S N_S} \sum_{x=1}^{M_S} \sum_{y=1}^{N_S} \left(S_i(x,y) - \mu_i^S\right)^2}, \tag{7}$$

$$\sigma_i^T = \sqrt{\frac{1}{M_T N_T} \sum_{x=1}^{M_T} \sum_{y=1}^{N_T} \left(T_i(x,y) - \mu_i^T\right)^2}, \tag{8}$$

where the μ_i and σ_i are the respective mean and standard deviation, and i corresponds to the index channel. Here, the signals T and S correspond to the target and source images, respectively.

The distribution transfer between the source and the target for the corresponding channel is performed by the next general equation

$$\mathrm{O}_i(x,y) = \frac{\sigma_i^T}{\sigma_i^S}(\mathrm{S}_i(x,y) - \mu_i^S) + \mu_i^T. \tag{9}$$

where O represents to the output image in the transfer. Finally, we take the image back to RGB for visualization purposes. Figure 2 shows two examples of color transfer. In the first case, the application on a false color image and, in the second one the result after the application on a dark scene.

C. Sample-based color mapping

An alternative look-up table-based method has been proposed [3] for applying realistic colors to multiband (commonly visual, near-infrared and thermal) images. The color transformation is derived from a corresponding set of samples for which both the multiband sensor values and the corresponding realistic color (RGB-value) are known. We can appreciate that this method results in rendered multiband images with colors that match the day-time colors more closely than the result of the statistical approach. Nonetheless, in contrast to the statistical method, the derivation of the color mapping requires a registered image pair consisting of a multiband image and a daytime reference image of the same scene, since corresponding sets of pixels are used to define color transform pairs in this approach. Once the color mapping has been derived, it can be applied to different multiband night-time images. Again, the color transformation is implemented using a color look-up-table transform, thus enabling real-time implementation.

The method works as follows. Given a set of samples (pixels) for which both the multiband sensor output and the corresponding day-time colors are known. The problem of deriving the optimal color transformation is finding a transformation that optimally maps the N-dimensional (in our examples, N = 2) multiband sensor output vectors (one for each sample) to the 3-D vectors corresponding to the daytime colors (RGB).

First, the multiband sensor image is transformed to a false-color image by taking the visual image as input in R channel and NIR image to the G channel (Figs. 3a and 3b, respectively), referred to as the RG image (Fig. 3c). Mapping the two bands to a false color RGB image allows us to use standard image conversion techniques such as indexing. In the next step, the resulting false color (RG image, Fig. 3c), is converted to an indexed image. Each pixel in such an image contains a single index. The index refers to an RGB value in a color look-up table.

For each index representing a given R-G combination, the corresponding realistic color equivalent is obtained by locating the pixels in the target image with this index and finding the corresponding pixels in the (realistic color) reference image (Fig. 3f). In that case, all pixels are located in the (indexed) false color multiband target image with color i index. Then, all corresponding pixels are collected (i.e., pixels with the same image coordinates) in the reference daytime color image, and their average is computed. Finally, this average in RGB value is assigned to i index of the new color look-up table. These steps are successively carried out for all color indexes. This process yields a newcolor look-up table containing the realistic colors associated with the various multiband combinations in the false color (RG) color look-up table. Replacing the RG color look-up table (Fig. 3d) with the realistic color look-up table (Fig. 3e) yields an image with a realistic color appearance, in which the colors are optimized for this particular sample set.

III. Experimental results

According to our knowledge, there are no databases of dark images for research purposes like this. Consequently, we have created a collection of 100 dark images taken with a standard camera. 60 images were taken under dark light conditions or

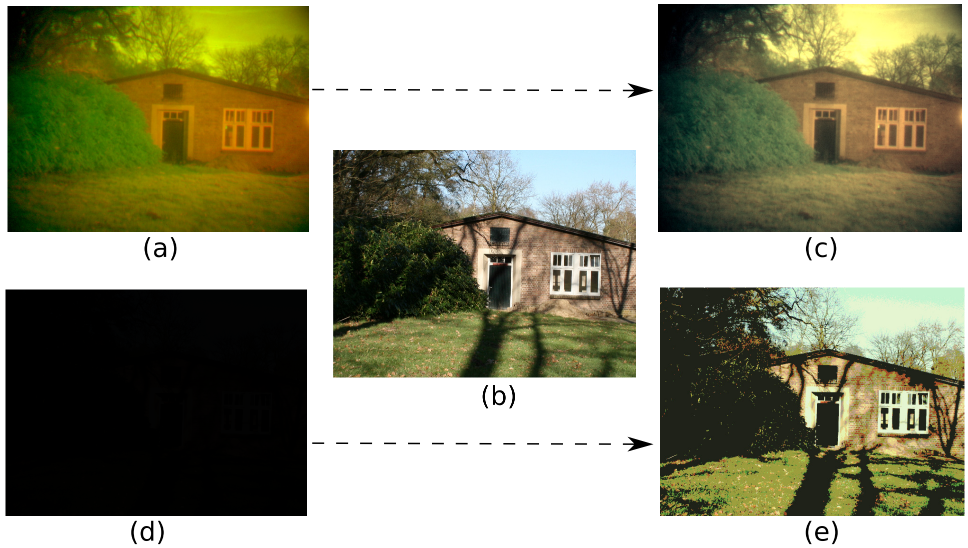

Fig. 2. Two examples of color transfer. (a) A false color image, (b) a realistic daylight color reference image [3] and, (c) the outcome obtained after the color transfer from the reference image (b) to the (a) image. (d) An image darkened synthetically, and (e) its corresponding outcome using (b) as the reference.

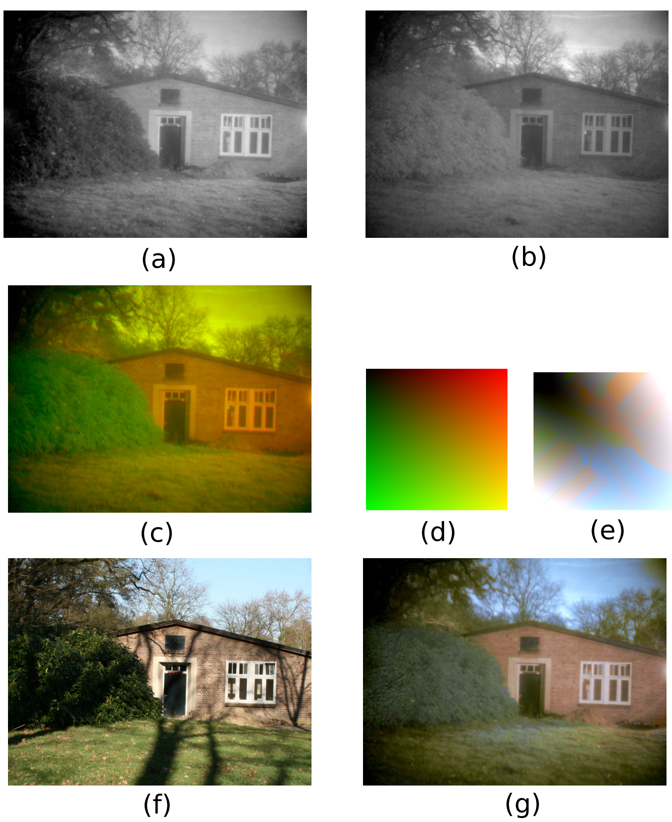

Fig. 3. Sample-based color mapping. (a) Visible and (b) NIR images of the same scene. (c) Combined RG false color representation of (a) and (b), obtained by assigning (a) to the R and (b) to the G channel of an RGB color image (the B channel is set to zero); this color map is shown in (d). (e) The color mapping derived from corresponding pixel pairs in (c) and (f), the realistic daylight color reference image [3]. (g) Resultant of the application of the mapping scheme in (e) to the two-band false color image in (c).

under the moonlight. The remaining 40 images, were daylight images darkened synthetically. Additionally, the image set contains 20 target images taken under daylight conditions. Target images are diverse scenes in nature but captured under daylight conditions.

Some experiments using color constancy and color transfer have been recently performed. For instance, a study showed that color constancy algorithm are an excellent tool for enhancing dark images [13]. Also, our experiments in progress have shown that, for processing dark images using color transfer, the RLAB color space is the best-suited.

A first example is about enhancing an outdoor image. Figure 4 shows this dark image and its corresponding outcomes. Figure 4b is the outcome using the WP algorithm and 4c is the outcome using GW algorithm. Figure 4d is a color reference used for the color transfer, while Figure 4e is the corresponding outcome using sample-based color mapping. The second example, given in Figure 5, includes an indoor image.

IV. Discussion

The present study has been oriented to the transformation of a night-time image to another with a daylight appearance. Three approaches to achieve this enhancement have been explored: color constancy, color transfer, and sample-based color mapping from the image fusion field. The first two approaches use only an input color image taken by a standard camera, instead of the two or more images (in the NIR or IR bands) required for the latter method. Particularly, we have explored the use of color transfer algorithms in the RLAB color space, obtaining outstanding results. Nonetheless, for practical applications a noise removal step can be necessary. Additionally, we have used an own dataset of dark images, captured using a standard camera. The outcomes from the

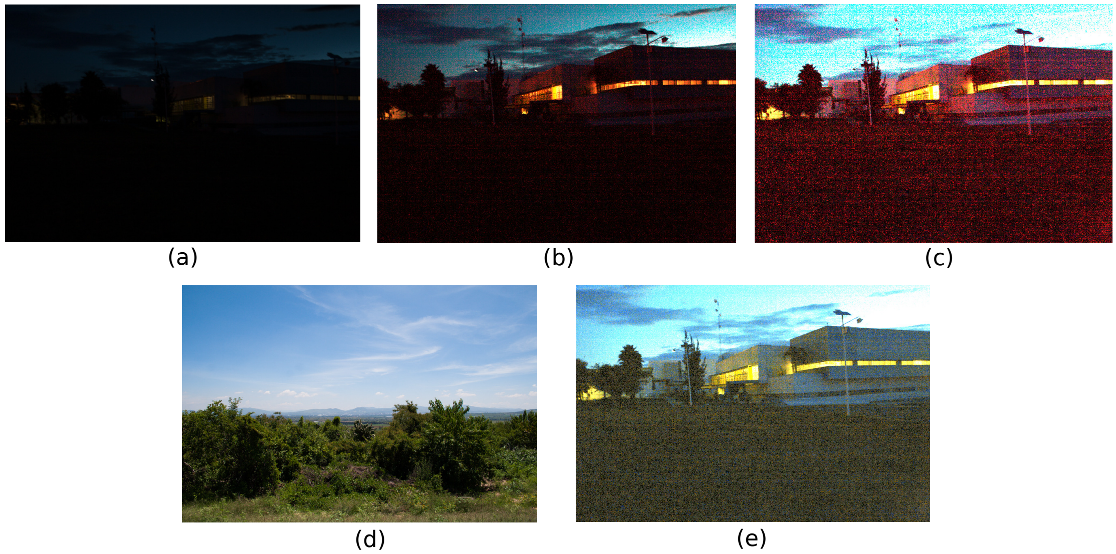

Fig. 4. Outdoor example. (a) Original dark image. (b) Outcome using the White-Patch algorithm. (c) Outcome using the Gray-World algorithm. (d) Color reference image. (e) Outcome using (d) in the statistical color transfer.

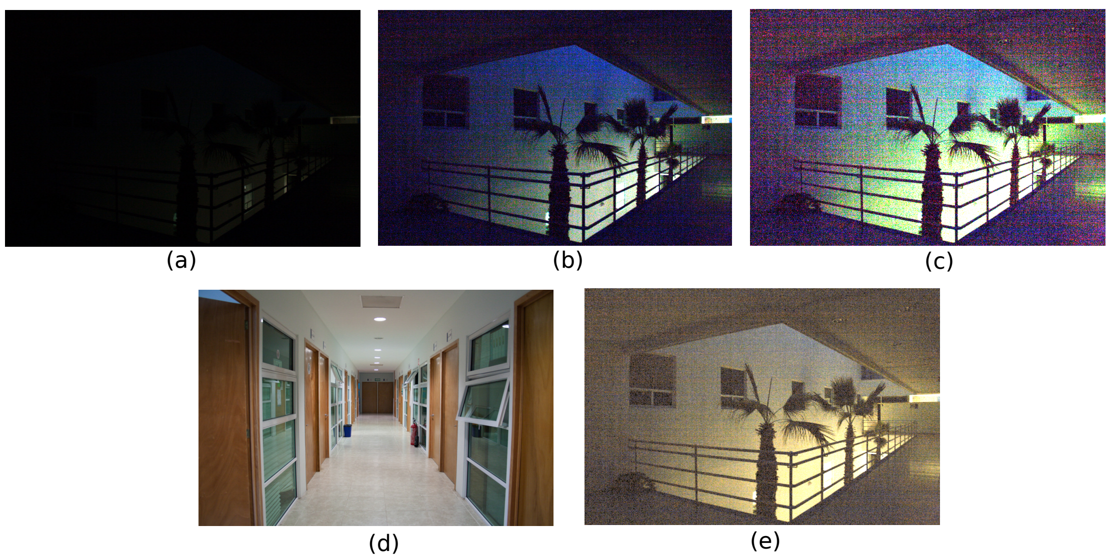

Fig. 5. Indoor example. (a) Original dark image. (b) Outcome using the White-Patch algorithm. (c) Outcome using the Gray-World algorithm. (d) Color reference image. (e) Outcome using (d) in the statistical color transfer.

application of the discussed methods, may facilitate night-time imagery recognition and its interpretation, as well as to obtain numerous benefits for surveillance and security issues. Besides, these methods can be used in mobile devices because of the simple calculations required.

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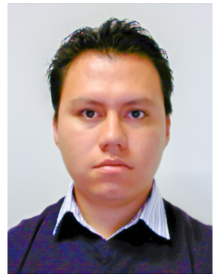

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