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Abstract

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INTER-CAMERA COLOR CALIBRATION BY CORRELATION MODEL FUNCTION

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ABSTRACT

We present a novel solution to the inter-camera color calibration problem, which is very important for multi-camera systems. We propose a distance metric and a model function to evaluate the inter-camera radiometric properties. Instead of depending on the shape assumptions of brightness transfer function to find separate radiometric responses, we derive a non-parametric function to model color distortion for pair-wise camera combinations. Our method is based on correlation matrix analysis and dynamic programming. The correlation matrix is computed from three 1-D color histograms, and the model function is obtained from a minimum cost path traced within the matrix. The model function enables accurate compensation of color mismatches, which cannot be done with conventional distance metrics. Furthermore, we show that our metric can be reduced to other commonly used metrics with suitable simplification. Our simulations prove the effectiveness of the proposed method even for severe color distortions.

1. INTRODUCTION

A major problem of multi-camera systems is the color calibration of cameras. Such a system may contain identical cameras that are operating under various lighting conditions, (e.g. indoor cameras under fluorescent/neodmyium lamps or outdoor cameras in bright/overcast daylight), or different cameras that have dissimilar radiometric characteristics. Even identical cameras, which have the same optical properties and are working under the same lighting conditions, may not match in their color responses. Images of the same object acquired under these variants show color dissimilarities. As a result, the correspondence, recognition, and other related computer vision tasks become more challenging. Remote sensing, image retrieval, face identification are among the applications that depend upon accurate color compensation.

In the past few years, many algorithms were developed to compensate for radiometric mismatches. One approach takes images of a uniformly illuminated color chart of a known reflectance as a reference, and estimates the parameters of the brightness transfer function. However, uniform illumination conditions may not be possible outside of a controlled environment, and temperature changes can significantly effect the surface reflectance. Instead of charts, some methods use registered images of a scene taken under different exposure settings [1], [2], [3]. But these methods assume a smooth and polynomial response function.

For a typical multi-camera system, in which the lighting conditions may change frequently, the color calibration becomes a critical concern. It is desirable to have an automatic calibration system that does not require laborious burden of carrying color charts between the cameras and adjustment of environment variables. Mostly, such a control may not be possible.

To solve the above problems, we designed a system that self-calibrates color mismatches using available object detection and tracking information. Here we assume that the images of the same object is available for different cameras in the system. This can be obtained manually or provided by object detection and tracking (Fig.1). We developed a correlation matrix and dynamic programming based method that uses color histograms. Our method computes a correlation matrix from a pair of histograms. This matrix is a superset of all the bin-by-bin distance norms. Then, a minimum cost path within the correlation matrix is found using dynamic programming. This path is projected onto diagonal axis to obtain a model function that can transfer one histogram to other. A distance between histograms [5] can also be computed. In the following section, we explain the proposed calibration setup.

2. COLOR CALIBRATION SETUP

We determine the relation between the radiometric responses of the cameras using color histograms. Histograms are widely accepted as simple and useful probabilistic models. The use of color histograms has been experimented in illumination compensation for satellite imagery, similarity and region searches [4], object searches, as well as image and video retrieval. A histogram, h, is a vector $[h[0], ..., h[M]]$ in which each bin $h[m]$ contains the number of pixels corresponding to the color range of m in the image I where M is the total number of the bins. The partitioning of the color mapping space can be regular with identical bins, as well as it can be irregular if the target distribution properties are known. Without loss of generality, we assume that histogram bin sizes are identical.

The calibration setup computes pair-wise inter-camera model functions that transfer the color histogram response of one camera to the other as illustrated in Fig. 1. First, videos of the same scene or objects are recorded for each camera into the corresponding databases. Let two cameras be C^a and C^b. We create image databases $V^a : \{I_1^a, .., I_K^a\}$ and $V^b : I_1^b, .., I_K^b\}$ where $1 \leq k \leq$. These databases contains images I_k^a and I_k^b that correspond to the same scenes or objects. For each image pair I_k^a,I_k^b we compute three 1-D histograms $h_{k,ch}^a$, $h_{k,ch}^b$, $ch : red, green, blue$ for color channels. We will drop the last index for simplicity. Using histograms h_k^a, h_k^b of each image pair in the databases, we compute correlation matrices $\mathcal{C}_k^{a,b}$ that will be explained in the following section. An aggregated correlation matrix $\mathcal{C}$ is calculated by averaging the individual matrices as $\mathcal{C} = 1/K \sum_{k=1}^{K} \mathcal{C}_k^{a,b}$. The scaling factor is included to normalize the matrix.

Then, a minimum cost path that connects two ends of the correlation matrix is obtained by dynamic programming. This path represents a mapping from one histogram to another. The shape of the path indicates the amount of warping between the histograms.

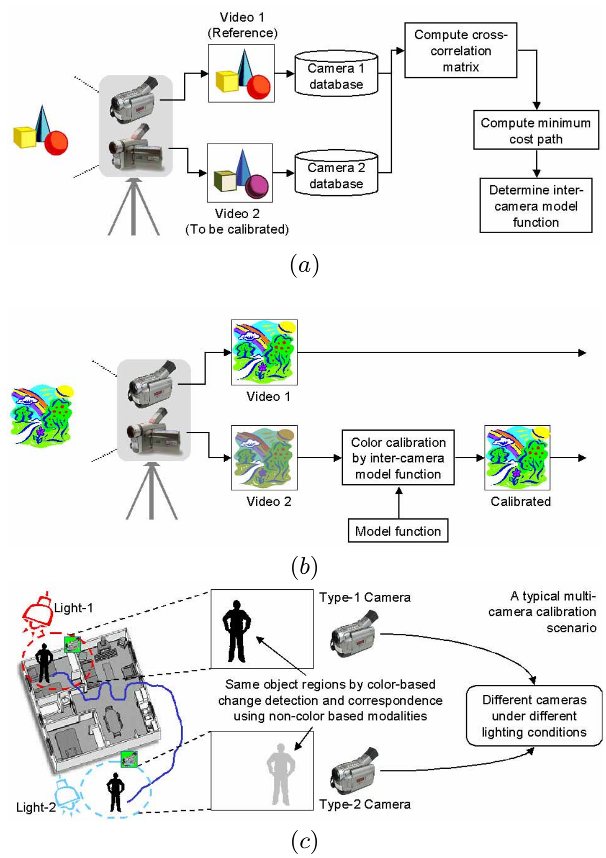

Fig. 1. (a) A multi-camera setup, which can contain one reference and several uncalibrated cameras, generates camera-wise video databases. After obtaining frame-wise histograms and computing a correlation matrix, a minimum cost path is found by dynamic programming. This path is converted to the inter-camera model function. (b) Using the model function obtained in the previous stage, the output of the second camera is compensated to match its color distribution with the reference camera. (c) If the initial lighting conditions change, the object tracking information is utilized to calibrate again.

Since certain linkage rules (as explained in section 4) are integrated in the tracing process, the histogram bin ordering after the mapping is maintained and any bin cross-over is prevented. A model function between the histograms are formulated from this path. We use three model functions to establish the radiometric relation between two color cameras by assuming that the radiometric relation is separable and channel-wise independent. Our motivation is to reduce the computational load of the calibration. Since the model functions have transitive property, by using model functions from C^a to C^b and from C^b to C^c, we can compute the function between C^a and C^c.

3. CORRELATION MATRIX AND MODEL FUNCTION

We define a correlation matrix $\mathcal{C}$ between two histograms as the set of positive real numbers that represent the bin-wise mutual distances. Let $h_1[m]$ and $h_2[m]$ be two histograms with $m = 1, \ldots, M$ and $m = 1, \ldots, N$. The correlation matrix is

$$\mathcal{C}_{M\times N} = h_1 \otimes h_2 = \begin{bmatrix} c_{11} & c_{12} & \ldots & c_{1N} \\ c_{21} & \cdot & & \cdot \\ \cdot & & \cdot & \cdot \\ c_{M1} & & \ldots & c_{MN} \end{bmatrix} \quad (1)$$

where each element c_{mn} is a the distance between the corresponding histogram bins. Note that, the sum of the diagonal elements of $\mathcal{C}$ represents the bin-by-bin distance with given norm $d(\cdot)$ if the histograms have equal number of bins, i.e. $M = N$. For example, by choosing the distance norm as L_1, the sum of the diagonals becomes the magnitude distance between the histograms

$$\sum_m^M c_{mm} = \sum_m^M |h_1[m] - h_2[m]| = d_{L1}(h_1, h_2). \quad (2)$$

Let $p : \{(m_0, n_0), ..., (m_i, n_i), ..., (m_I, n_I)\}$ represents a minimum cost path from the c_{11} to c_{MN} in the matrix $\mathcal{C}$. The sum of the matrix elements on the path p gives the minimum score among all possible routes. The total length of the path I is limited as

$$\sqrt{M^2 + N^2} \leq I \leq M + N \quad (3)$$

We define a mapping $f(n_i) = m_i$ using the bin indices of histograms using the minimum cost path p. The model function is a mapping from the histogram h_2 to h_1. Depending on the shape of the path, this mapping may not be one-to-one. An inverse mapping $f^{-1}(m_i) = n_i$ is also defined. Figure 2 illustrates the definitions. Using the derivatives of the functions f, f^{-1} with respect to the both indices m_i, n_i, we can determine the amount of warping between the bins of the two histograms;

$$\begin{aligned} \partial f(n_i) = \partial f^{-1}(m_i) &\quad : \quad \text{no warping} \\ \partial f(n_i) < \partial f^{-1}(m_i) &\quad : \quad \text{h}_1 \text{ squeezed} \\ \partial f(n_i) > \partial f^{-1}(m_i) &\quad : \quad \text{h}_2 \text{ squeezed.} \end{aligned}$$

Let $f_{12}(j)$ be the model function from the histogram h_1 to h_2, and f_{23} be the model function from h_2 to h_3. Then, the model function from the h_1 to h_3 is $f_{13} = f_{23}(f_{12})$.

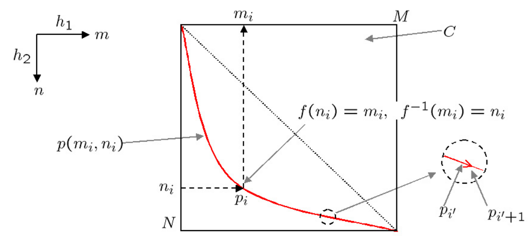

Fig. 2. Relation of minimum cost path to model function.

4. DETERMINATION OF MINIMUM COST PATH

Given two histograms, the question is what is the best alignment of their shapes and how can the alignment be determined? We reduce the comparison of two histograms to finding the minimum cost path in a directed weighted graph. Let v be a vertex and e

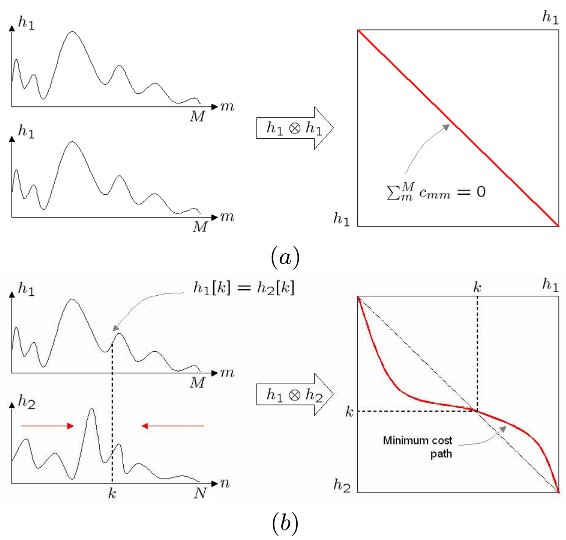

Fig. 3. (a) Minimum cost path for the same histograms, (b) and warped histograms. With respect to warping direction, the model function $f(j)$ becomes negative or positive.

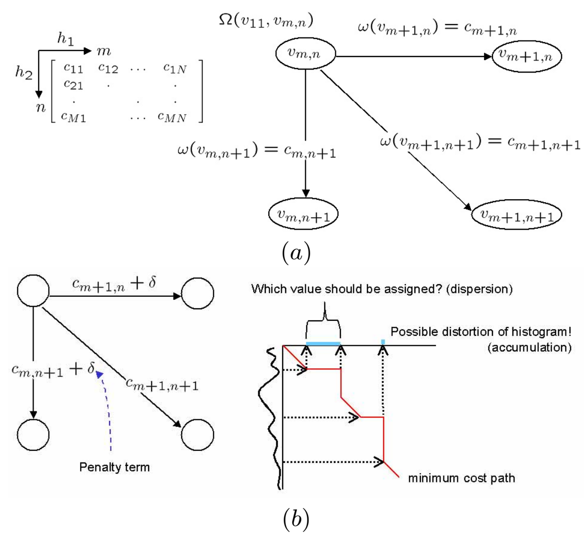

Fig. 4. (a) Each vertex represents a matrix index combination and each edge is the corresponding matrix element for that index. (b) vertical and horizontal links have a penalty term to reduce accumulation and dispersion.

be an edge between the vertices of a directed weighted graph. We associate a cost to each edge $\omega(e)$. We want to find the minimum cost path by moving from an origin vertex v_0 to a destination vertex v_S. The cost of a path $p(v_0, v_S) = \{v_0, .., v_S\}$ is the sum of its constituent edges

$$\Omega(p(v_0, v_S)) = \sum_{s}^{S} \omega(v_s) \tag{4}$$

Suppose we already know the costs $\Omega(v_0, v_*)$ from v_0 to every other vertex. Let's say v_* is the last vertex the path goes through before v_S. Then, the overall path must be formed by concatenating a path from v_0 to v_*, i.e. $p(v_0, v_*)$, with the edge $e(v_*, v_S)$. Further, the path $p(v_0, v_*)$ must itself be a minimum cost path since otherwise concatenating the minimum cost path with edge $e(v_*, v_S)$ would decrease the cost of the overall path. Another observation is that $\Omega(v_0, v_*)$ must be equal or less than $\Omega(v_0, v_S)$, since $\Omega(v_0, v_S) = \Omega(v_0, v_*) + \omega(v_*, v_S)$ and we are assuming all edges have non-negative costs, i.e. $\omega(v_*, v_S) \geq 0$. Therefore if we only know the correct value of $\Omega(v_0, v_*)$ we can find a minimum cost path.

We modified Dijkstra's algorithm for this purpose. Let Q be the set of active vertices whose minimum cost paths from v_0 have already been determined, and $\vec{p}(v)$ is a back pointer vector that shows the neighboring minimum cost vertex of v. Then the iterative procedure is given as

1. Set $u_0 = v_0$ $Q = \{u_0\}$, $\Omega(u_0) = 0$, $\vec{p}(v_0) = v_0$, and $\omega(v) = \infty$ for $v \neq u_0$.
2. Find u_i that has the minimum cost $\omega(u_i)$.
3. For each $u_i \in Q$: if v is a connected to u_i, assign $\omega(v) \leftarrow \min\{\omega(u_i), \Omega(u_i) + \omega(v)\}$. If $\omega(v)$ is changed, assign $\vec{p}(v) = u_i$ and update $Q \leftarrow Q \cup v$.
4. Remove u_i from Q. If $Q \neq \emptyset$ go to step 2.

Then the minimum cost path $p(v_0, v_s) = \{v_0, ..., v_S\}$ is obtained by tracing back pointers by starting from the destination vertex v_S as $v_{s-1} = \vec{p}(v_s)$. The algorithm takes time $O(S^2)$. As shown in Fig. 4, the graph that is converted from the cross-correlation matrix is directed such that a vertex v_{mn} has directional edges to vertices $v_{m+1,n}, v_{m,n+1}, v_{m+1,n+1}$ only. Therefore, we do not allow overlaps of the bin indices, and eliminate cyclic paths.

However, since we are working on a finite grid, accumulation and dispersion of the values will occur if the path does not traverse diagonally. To minimize such routes, we added a penalty term δ to each horizontal $e(v_{m,n}, v_{m+1,n})$ and vertical $e(v_{m,n}, v_{m,n+1})$ edges. The value of the penalty term is set to $\delta = 0.001c_{max}$ where c_max is the maximum value in the correlation matrix.

5. EXPERIMENTS AND CONCLUSION

We designed an experiment to evaluate the distortion compensation capability of the model function. We conducted this experiment with several image-pairs. Each pair consists of a reference image and a distorted version of its illumination histogram as in Fig.5-a,b. The histogram distortions were non-linear. After we computed the correlation matrix and the model function (Fig.5-c), we transformed the histogram of the distorted image (Fig.5-b) accordingly to obtained the illumination corrected image (Fig.5-d). As visible in the histogram graphics the model function was able to successfully compensate for the distortions. The results of the other pairs confirmed this statement. The improvement is significant even though the histogram operations are invariant to spatial transformations, and thus have limited impact. In a second experiment, we used the Oulu dataset. The cameras acquired images under different lighting conditions, i.e. Planckian 2856K and 2300K. Fig. 6-a,b shows sample pairs. Since each picture is taken at a different time, there are appearance mismatches in addition to the lighting and the camera difference. We computed

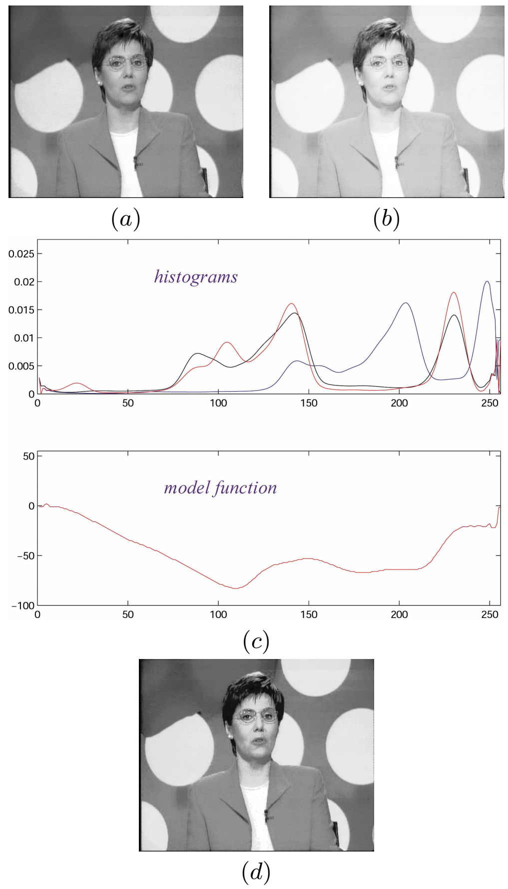

Fig. 5. (a) Reference, and (b) over-exposed image. (c) The intensity histograms of the input image (shown as black), of the over-exposed image (blue), and of the compensated image (red). The model function that maps the over-exposed image to the original (red). (d) The compensated image.

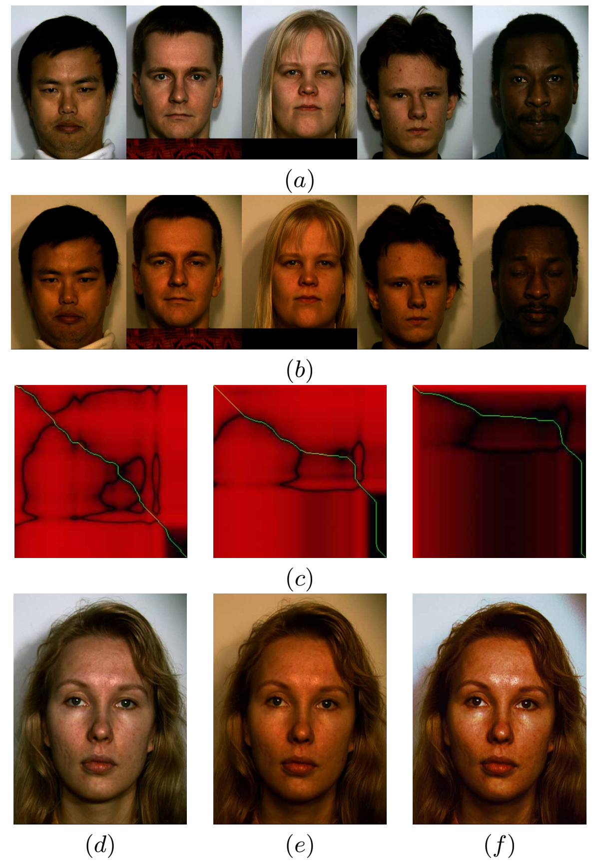

Fig. 6. Samples from the training data: (a) images acquired under Plankian 2856K light using a camera balanced for Plankian 2856K, (b) images acquired under the same light but a camera balanced for Planckian 2300K. (c) Computed correlation matrices and minimum cost paths for the R ,G, B color channels. Last row: The (d) reference, (e) input, and (f) compensated images. Note that, the images are not acquired at the same time instant which makes the calibration more challenging. *Dataset is courtesy of Matti Pietikinen, University of Oulu, Finland.*

the aggregated correlation matrices (Fig.6-c) for each color channel from 25 image pairs. Using the extracted model functions, we calibrated the second camera to compensate for color mismatches. A sample test image pair is given in Fig. 6-d,e. As visible in Fig.6-f, the model function method achieves color compensation successfully although the color distribution of the second image is very different from the reference (attenuated blue and biased red, green channels). Using larger datasets improves the accuracy of the model function.

We presented a novel inter-camera color calibration method that uses a model function to determine how the color histograms of images taken at each camera are correlated. Unlike the existing calibration approaches, our method does not require special, uniformly illuminated color charts, does not compute individual radiometric responses, does not depend on the additional shape assumptions of the brightness transfer functions, and does not involve exposure control. Furthermore, our method can model nonlinear, non-parametric color mismatches and it can handle cameras that have different color dynamic ranges. As a future work, we plan to apply this method to recognize objects in a non-overlapping field of view multi-camera system.

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