INTER-CAMERA COLOR CALIBRATION USING CROSS-CORRELATION MODEL FUNCTION

Fatih Porikli

Mitsubishi Electric Research Labs
Murray Hill, NJ 07974, USA

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 modeling function to evaluate the inter-camera radiometric properties using color histograms. Instead of depending on the shape assumptions of brightness transfer function to find separate radiometric responses, we derive a relative non-parametric non-linear color distortion model function of each camera combination. Our method is based on cross-correlation matrix analysis and dynamic programming. The model function enables effective compensation for lighting changes and radiometric distortions, 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 for compensation of even severe inter-camera color distortion.

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, etc., and different brand cameras that have dissimilar radiometric responses. Even between identical cameras working that have same geometrical properties and working under the same lighting, it is possible to have color deviations due to deficiencies of electronics and optical materials. Images of object acquired under these variants usually show dissimilar color characteristics, and this makes the correspondence, recognition, and other related computer vision tasks more challenging. Remote sensing, image retrieval, face identification are among the other applications depend upon the accurate and efficient color correction methods.

In the past few years, many algorithms were developed to compensate radiometric distortions. One way to recover the radiometric response by taking an image of a uniformly illuminated color chart of known reflectance. Unfortunately, a uniform illumination 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 with different exposures [1], [2], [3]. However these approaches require additional assumptions (e.g. smoothness, gamma curve, polynomials, etc.) on the shape of the radiometric response function. To overcome these shortcomings, we use 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, video indexing and summarization. In the following section, we explain the proposed setup in detail.

2. CALIBRATION SETUP

The calibration setup computes pair-wise inter-camera color compensation 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. Without loss of generality, let assume we have two cameras $\mathcal{C}^a$ and $\mathcal{C}^b$. We obtain image databases $\mathcal{V}^a : \{\mathcal{I}_1^a, .., \mathcal{I}_K^a\}$ and $\mathcal{V}^b : \{\mathcal{I}_1^b, .., \mathcal{I}_K^b\}$ such that $\mathcal{I}_k^a$ and $\mathcal{I}_k^b$ where $1 \leq k \leq K$ correspond to the same scene or objects. Then, for each image pair, e.g. $\mathcal{I}_k^a$,$\mathcal{I}_k^b$, we extract the separate channels color histograms $h_{k,ch}^a$, $h_{k,ch}^b$ where $ch : red, green, blue$. We will drop the last index in the remaining of this paper for simplicity. Using the histograms h_k^a, h_k^b of each image pair in the databases, we compute cross-correlation matrices $C_k^{a,b}$. An aggregated cross-correlation matrix $C$is calculated by averaging these matrices $C = 1/K \sum_{k=1}^{K} C_k^{a,b}$. Although the scaling factor can be neglected in extraction of a minimum cost path as explained in the following section, it is included to enable the use of minimum cost as a distance metric. Using matrix C, a minimum cost path is found by dynamic programming. This path models the compensation function between two histograms. Thus, for a pair of color cameras, three model functions establish the radiometric relation. Some examples of the different scenarios of light-camera combinations are given in Fig. 1-c. Since model functions are transitive, by using model functions from $\mathcal{C}^a$ to $\mathcal{C}^b$ and from $\mathcal{C}^b$ to $\mathcal{C}^c$, we can find the radiometric relation between $\mathcal{C}^a$ and $\mathcal{C}^c$.

A histogram, h, is a vector $[h[0], \ldots, h[M]]$ in which each bin $h[m]$ contains the number of pixels corresponding to the color range of m in the image $\mathcal{I}$ where M is the total number of the bins. In other words, it is a mapping from the set of color vectors to the set of positive real numbers $\mathcal{R}^+$. 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. In this paper, we assume that $h[m]$ are identical and the histogram is normalized such that $\sum_{m=0}^{M} h[m] = 1$.

3. CROSS-CORRELATION MATRIX AND MODEL FUNCTION

We define a cross-correlation matrix C between two histograms as the set of positive real numbers that represent the bin-wise mu-

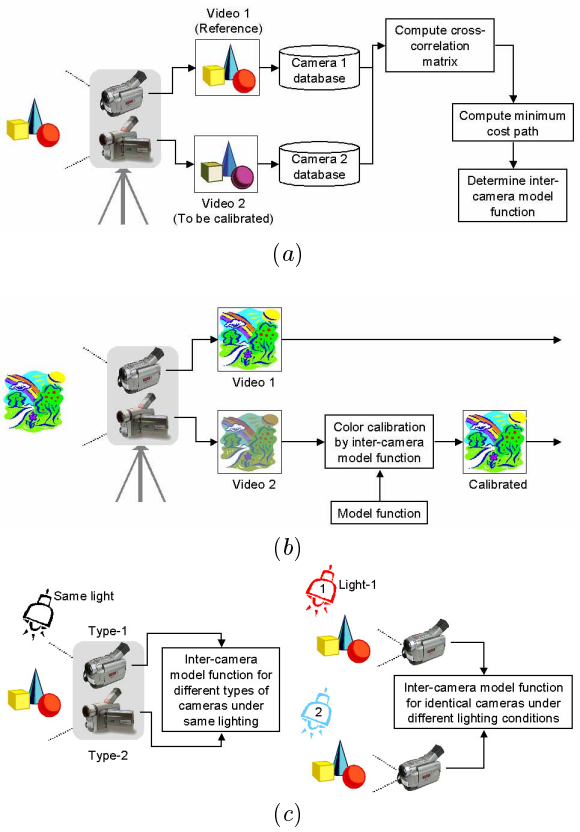

Fig. 1. (a) A multi-camera setup, which can contain one reference and several uncalibrated cameras, generates camera-wise databases of videos. After obtaining frame-wise histograms and computing the total cross-correlation matrix, a minimum cost path is found by dynamic programming. This path is converted to an 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) Some possible scenarios: single-light different type camera setup, and different-light identical camera setup.

tual distances. Let $h_1[m]$ and $h_2[m]$ be two histograms with $m = 1, \ldots, M$ and $m = 1, \ldots, N$ i.e. the number of bins are not necessarily same. The cross-correlation matrix is

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

where each element c_{mn} is a positive real number such that $c_{mn} = d(h_1[m], h_2[n])$ where $d(\cdot) \geq 0$ is a distance norm which satisfies the triangle-inequality.

Theorem 1 *The sum of the diagonal elements of C represents the bin-by-bin distance with given norm $d(\cdot)$ for the histograms have equal number of bins $M = N$.*

For example, by choosing the distance norm as L_1, i.e. the magnitude norm, the sum of the diagonals becomes the magnitude distance between a pair of histograms

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

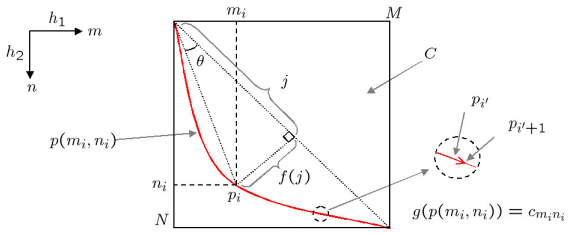

Fig. 2. The relation of minimum cost path to model function $f(j)$.

Let $p : \{(m_0, n_0), ..., (m_i, n_i), ..., (m_I, n_I)\}$ represents a minimum cost path (defined in the next section) from the c_{11} to c_{MN} in the matrix C, i.e. the sum of the matrix elements on the connected path p gives the minimum score among all possible routes. The total length of the path cannot be more than the sum of the lengths of the histograms

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

We define a cost function for the path as $g(p_i) = c_{m_i,n_i}$ where p_i denotes a path element (m_i, n_i). We define a mapping $i \rightarrow j$ from the path indices to the projection onto the diagonal of the matrix C, and a model function $f(j)$ that gives the distance from the diagonal with respect to the projection j. The model function is a mapping from the matrix indices to real numbers

$$(m_i, n_i) \quad \xrightarrow{t} \quad f(j) \quad (4)$$

where $j = 1, \ldots, J$. Depending on the shape of the path, these mappings may not be one-to-one. From Fig.2, the angle between the diagonal and the current path index is

$$\theta = \tan^{-1}\left(\frac{M}{N}\right) - \tan^{-1}\left(\frac{m_i}{n_i}\right) \quad (5)$$

We may assume $M = N$, i.e. $\tan^{-1}(\frac{M}{N}) = \frac{\pi}{4}$. Then, the magnitude of the projection j is

$$j = |p_i| \cdot \cos\theta = \frac{m_i + n_i}{\sqrt{2}} \quad (6)$$

Thus, the model function $f(j)$ becomes

$$f(j)^2 = \frac{1}{2}\left(m_i^2 + n_i^2\right) + m_i n_i \quad (7)$$

The $f(j)$ is negative if $m_i < n_i$. The mapping t in equation 4 is decomposed into two functions $t_m(m_i) = n_i$ and $t_n(n_i) = m_i$ such that they give the minimum cost path as a function of histogram index. Their derivatives with respect to both indices represent the amount of warping of the bins

$$\partial t_m(m_i) = t_m(m_i) - t_m(m_i - 1) \quad (8)$$
$$\partial t_n(n_i) = t_n(n_i) - t_n(n_i - 1) \quad (9)$$

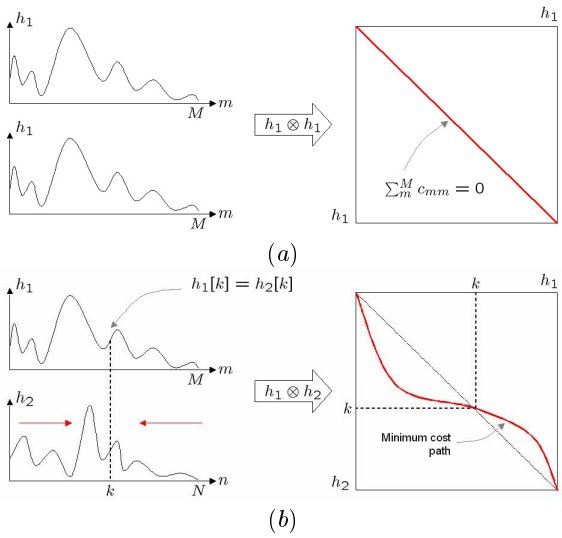

Fig. 3. (a) Minimum cost path for the same histograms, (b) and warped histograms. With respect to warping direction, the model function $f(j)$ becomes negative or positive.

Definition The cross-correlation distance (CCD) is the total cost along the model function (CCF)

$$d_{CC}(h_1, h_2) = \sum_{i=0}^{I} |g(m_i, n_i)| \tag{10}$$

An alternative definition of the above distance metric weights the model function with the current cost

$$d_{CC}(h_1, h_2) = \sum_{j=0}^{J} |f(j)|g((m_i, n_i)) \tag{11}$$

The distance can also be measured as the length of the path

$$d_{CC}(h_1, h_2) = J. \tag{12}$$

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 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

$$\Omega(p(v_0, v_S)) = \sum_{s}^{S} \omega(v_s) \tag{13}$$

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 $e(v_*, v_S)$.

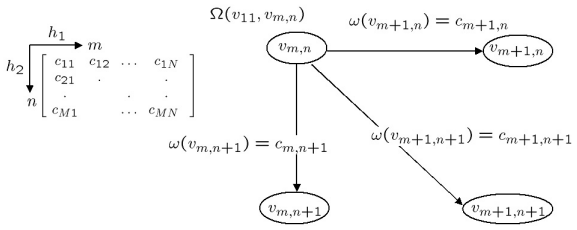

Fig. 4. Each vertex represents a matrix index combination and each edge is the corresponding matrix element for that index.

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. 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 $Q \leftarrow Q \cup v$.
3. 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.

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 random, non-linear, and non-parametric. After we computed the cross-correlation matrix (Fig.5-c) and the model function (Fig.5-d), we transformed the histogram of the distorted image (Fig.5-b) accordingly to obtained the illumination corrected image (Fig.5-e). 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 substantial even though histogram operations are invariant to spatial transformations, and thus have limited impact. Note that, no other distance metric can give histogram distortions compensated distance. In a second experiment, we used the Oulu dataset. The cameras acquired images under different lighting conditions, i.e. Planckian 2856K and

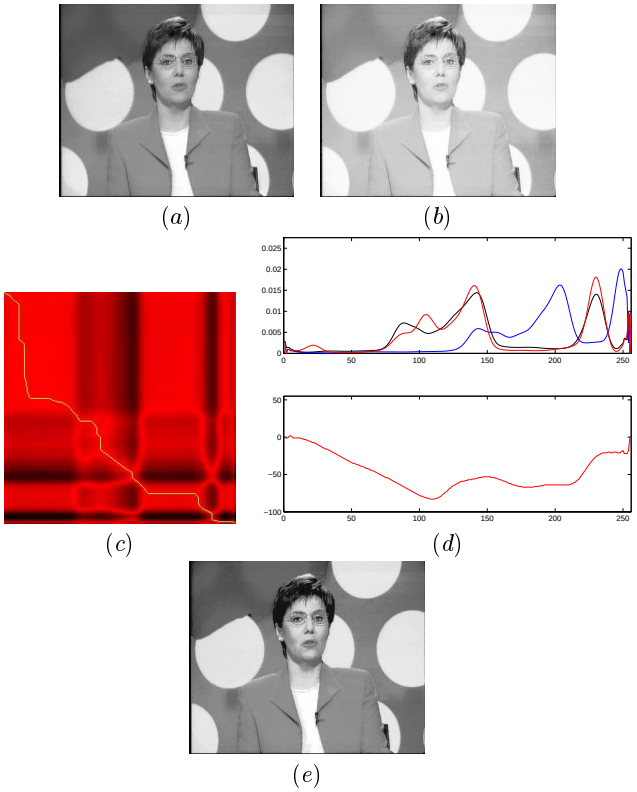

Fig. 5. (a) A reference, and (b) an over-exposed image of the same scene. (c) The cross-correlation matrix and the minimum cost path (shown in yellow). The intensity of the red indicates the magnitude of the bin distance, i.e. higher red strength corresponds smaller distance. (d) (above) The intensity histograms of the input image (black), of the over-exposed image (blue), and of the compensated image (red). (below) Model function that maps the over-exposed image to the original. (e) The compensation result.

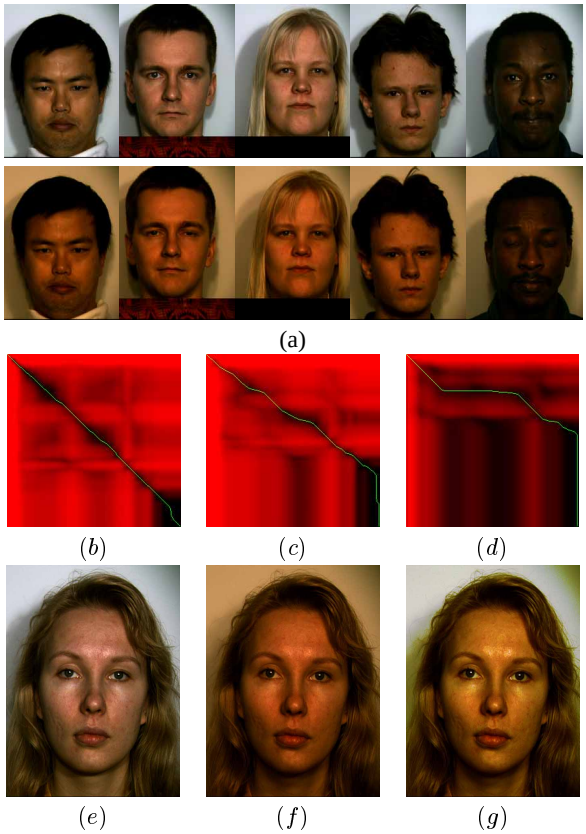

Fig. 6. (a) Training data: (First row) Sample reference-camera database images acquired using Plankian 2856K light, (Second row) corresponding images from a second-camera database which are obtained using Planckian 2300K. *Dataset is courtesy of Matti Pietikinen, University of Oulu, Finland.* Note that, the images are not acquired at the same time instant which makes the calibration more challenging. These databases are used to compute the cross-correlation matrices of the red (b), green (c), and (d) blue channels. (e) Test sample: an image from the reference-camera, and (f) corresponding image from the second camera. (g) The result image that is the image (f) is automatically compensated to match the color distribution of the image (e).

2300K. Fig. 6-a 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 the aggregated cross-correlation matrices (Fig.6-b,c,d) for each color channel from 150 pairs. Using the extracted model functions, we calibrated the second camera to compensate radiometric distortions. A sample test image pair is given in Fig. 6-e,f. As visible in Fig.6-g, the non-parametric model function method successfully achieve color compensation although the color distribution of the second image is very different from the reference (attenuated blue and biased red channels). Using larger datasets also 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 additional shape assumptions of the brightness transfer functions, and does not involve controlled exposure image sets. Furthermore, our method can model non-linear, non-parametric distortions and inter-camera color transfer functions, 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.

6. REFERENCES

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