# Piecewise-consistent Color Mappings of Images Acquired Under Various Conditions

Sefy Kagarlitsky[1], Yael Moses[2], and Yacov Hel-Or[3]
Efi Arazi School of Computer Science,
The Interdisciplinary Center, Herzliya 46150, Israel
[1]sefy@kagarlitsky.com [2]yael@idc.ac.il [3]toky@idc.ac.il

## Abstract

*Many applications in computer vision require comparisons between two images of the same scene. Comparison applications usually assume that corresponding regions in the two images have similar colors. However, this assumption is not always true. One way to deal with this problem is to apply a color mapping to one of the images. In this paper we address the challenge of computing color mappings between pairs of images acquired under different acquisition conditions, and possibly by different cameras. For images taken from different viewpoints, our proposed method overcomes the lack of pixel correspondence. For images taken under different illumination, we show that no single color mapping exists, and we address and solve a new problem of computing a minimal set of piecewise color mappings. When both viewpoint and illumination vary, our method can only handle planar regions of the scene. In this case, the scene planar regions are simultaneously co-segmented in the two images, and piecewise color mappings for these regions are calculated. We demonstrate applications of the proposed method for each of these cases.*

## 1. Introduction

Variations in camera parameters, different illumination conditions, or changes in viewpoint often cause changes in the color values of corresponding regions in two images of a scene. One way to overcome this problem is to compute a mapping between the colors of the two images. However, when the image pair is acquired under different illumination and viewpoint, extracting the color mapping becomes challenging. In this paper we study the problem of computing *consistent color mappings* between a pair of images of a static scene, taken under different acquisition conditions. We define a *consistent color mapping* (CCM) as a monotonically increasing mapping that transforms the color of each pixel in the first image to the color of its corresponding pixel in the second image. All pairs of images considered in this paper may be acquired using different photometric parameters of the camera (e.g., exposure time, white balancing, gamma correction, sensor sensitivity (ISO)) or different cameras.

A classic method for extracting a color mapping between images is *histogram matching*, which calculates a mapping that optimally aligns the histogram of the first image with that of the second one [4]. This method obtains a CCM that accounts for the entire image, assuming that such a CCM exists, and the two images view almost entirely the same scene regions. Clearly, these assumptions hold when the images are taken from the same viewpoint and under the same illumination. In other cases the obtained mapping might be erroneous and inconsistent. In this work we consider cases where these assumptions do not hold, and no global CCM can be found for the two images. Nevertheless, histogram matching is used successfully as a basic building block in our method.

When the viewpoint varies between the two images and the illumination is fixed, the color values of corresponding pixels vary only due to changes in the photometric parameters of the cameras (assuming a Lambertian scene), and a global CCM exists for this case. However, since such images also include non-corresponding regions, applying histogram matching to the entire image will produce an incorrect result. This is demonstrated in Fig. 1 for the degenerate case where the two images are taken with the same camera and same photometric parameters but their histograms differ. Therefore, although the identity mapping is the correct one for this case, histogram matching will produce an incorrect result. We suggest a new algorithm that computes the global mapping function using only a set of corresponding image regions, detected using an illumination invariant feature detector (e.g. SIFT [9]).

When the two images are taken under different illumination conditions, it can be shown that there is no global CCM for the two images even if taken from the same viewpoint. In particular, a set of pixels with the same intensity

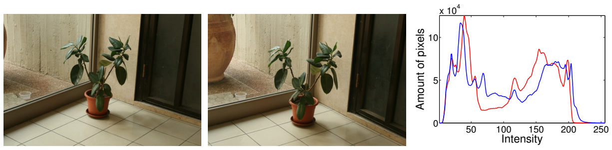



Figure 1. A degenerate case of two images taken from different viewpoints under the same illumination with the same camera and same photometric parameters. Note that the identity color mapping is correct although the histograms of the two images are different (right plot).

value in the first image corresponds to a set of pixels with more than one intensity value in the second one. This is illustrated in Fig. 2 (f)-(g) by the joint histogram (defined in Sec. 3) of two such images. When the regions have a CCM, a monotonically increasing thin line in the joint histogram is expected (as in Fig. 2 (d)). For the case where the regions are not consistent, we propose a new algorithm that computes a minimal set of *piecewise-consistent color mappings* and their associated regions, which are *a priori* unknown.

Finally, the most challenging case is when both illumination and viewpoint vary, for which our method can only handle planar regions of the scene. In this case the proposed method simultaneously co-segments such regions and computes their *piecewise-consistent* color mappings.

Color mapping is often used for applying perceptual consistency of images (e.g., [14]). In contrast, our method is precise and therefore can be used for inspecting differences between images (e.g., *change detection*), taken from the same viewpoint but under extreme variations in lighting (Fig. 8). Our color mapping can be used by algorithms that compare pixels in images taken from different viewpoints at the same time, e.g., surveillance applications using cameras with overlapping fields of view [3]. Finally, co-segmentation of planes in images taken with different cameras under different illumination conditions can be used for verifying identical image regions despite large variations in color (Fig. 9 and 10).

We begin with reviewing previous work in Section 2. In Section 3 we define the consistency of a color mapping, which is fundamental for our study. Then, the algorithms for different acquisition conditions are presented in Section 4. Finally, the results of our algorithms are presented in Section 5 and conclusions in Section 6.

## 2. Previous work

Methods for computing color mapping are based on either pixel-to-pixel correspondence, e.g., [2], or based on the statistical distributions of color values [12, 13, 14]. In the statistical approaches, exact correspondence is not required although correctness is not assured (see Sec. 3). All these methods assume that there is a global CCM for the two images, and therefore fail in cases where this assumption is violated. In addition, methods that use pixel-to-pixel correspondence are prone to correspondence inaccuracy. In our method we use the histogram matching approach [4] as a building block, but other statistical methods ([12, 13, 14]) can be used as well.

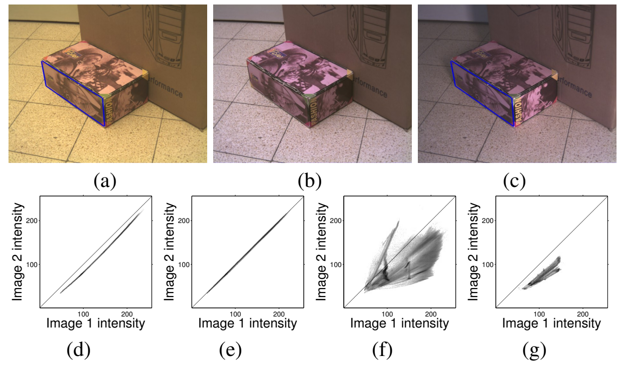



Figure 2. (a) is a reference image. (b) differs from (a) only in the photometric parameters of the camera, and (c) differs also in the illumination conditions. (d) is a joint histogram of (a) and (b), and (e) is a joint histogram of (a) and (b) after applying the histogram matching algorithm to (a). (f) is a joint histogram of images (a) and (c), and (g) is a joint histogram calculated for the planes outlined in (a) and (c). Note that set of pixels with the same intensity in the first image may correspond to a set of pixels with more than one intensity level in the second image. Surprisingly, this is true even for a single plane.

Several approaches find multiple color mappings for a pair of images using corresponding regions [7, 14, 17]. In [14], corresponding regions, *swatches*, are manually detected and matched. In [7, 17], automatic segmentation is performed separately in each image using colors or texture, and the segments in the two images are matched using the mean and variance of the segments' color [17], or using the probability of the existence of a color mapping between the regions [7]. In these methods, the consistency of the color mapping is not guaranteed, and the number of color mappings may be larger than necessary.

When both viewpoint and illumination vary, between the images, our method finds the mapping only between planar regions of the scene. This can be regraded as plane co-segmentation from a pair of images. Co-segmentation of planes was addressed by several studies, where all of them, including ours, compute the homography as a first step using corresponding features. In previous studies the plane's segments are detected by assuming identical colors [16], Delaunay triangulation [1], or by setting the boundaries using the intersection line between planes as determined by their homographies [18]. The first approach makes a strong assumption about scene illumination (identical colors) while the other approaches make a strong assumption about scene structure (e.g., hole-free planes or intersecting planes). In our method none of these assumptions is needed, and segmentation and color mapping are solved simultaneously.

# 3. Consistent Mappings

Here we define the consistency of a color mapping and the consistency of a pair of regions, which play a fundamental role in our method. We then suggest a novel measure for testing consistency.

**Consistency Definitions:** A *color mapping* $M$ is a monotonically increasing scalar function that maps the intensity values between two images. A color mapping is said to be a *consistent color mapping (CCM)* if it maps the color of every pixel in one image to the color of its corresponding pixel in the second one. Here, two pixels correspond if they are projections of the same 3D point in the scene. Formally, let $I_1$ and $I_2$ be two images and let $\alpha$ be a function that associates each pixel $p \in I_1$ with its corresponding pixel $\alpha(p) \in I_2$. Denote by $I_i(p)$ the intensity of a pixel $p$ in image $I_i$. Then, a consistent color mapping $M$ between $I_1$ and $I_2$ must satisfy:

$$\forall p \in I_1, \;\; M(I_1(p)) = I_2(\alpha(p)). \tag{1}$$

When color images are considered, the mapping is defined for RGB channels independently. The integration of the different channels is discussed below.

Region $P \subseteq I_1$ is defined to be *consistent* with region $Q \subseteq I_2$, if there exists a CCM between all corresponding pixels of the regions. For simplicity, we say that $P$ and $Q$ are *consistent regions*. Formally, let $\alpha$ be the correspondence function between the regions' pixels. Then $P$ and $Q$ are consistent if and only if the following conditions hold:

- Color consistency: For any two pixels in the set $P$ with the same color, their corresponding pixels in $Q$ must have the same color as well. That is, if $p_1, p_2 \in P$ such that $I_1(p_1) = I_1(p_2)$, it follows that $I_2(\alpha(p_1)) = I_2(\alpha(p_2))$.
- Monotonicity: The color order is maintained for corresponding pixels. That is, if $p_1, p_2 \in P$ such that $I_1(p_1) < I_1(p_2)$, it follows that $I_2(\alpha(p_1)) \leq I_2(\alpha(p_2))$.

**Computing the mapping:** Pixel correspondence can be used directly to compute the color mapping between a pair of images. However, it is not necessarily available or reliable, even when images are taken from the same viewpoint. (The correspondence may be inaccurate due to small camera movements or imprecise image alignment, as in Sec. 4.4.) Histogram matching [4] is based on color distributions of two images, hence it avoids the necessity of using reliable pixel correspondence. Roughly speaking, it defines the mapping, $M_{P,Q}$, that best converts the histogram of a region $P$ to that of another region $Q$. Note that $M_{P,Q}$ is not necessarily a CCM, in particular when a CCM does not exist or when the image histograms include non-corresponding

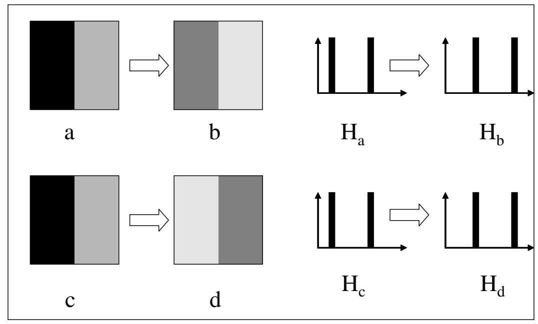



Figure 3. Regions $a$ and $b$ are consistent regions but regions $c$ and $d$ are inconsistent, since the monotonicity requirement is not satisfied. Nevertheless, in both cases the corresponding histograms are similar.

regions. Histogram matching is used as a building block by our method for computing color mapping between a pair of images. Other methods that are based on color distributions, e.g., [12, 14], could be used as well.

**Testing consistency:** A test for the consistency of a pair of regions and the consistency of a color mapping with respect to a pair of regions is essential for our method. Given a pair of regions and their pixel-to-pixel correspondence, the consistency conditions defined above can be directly used. This can be illustrated by the joint histogram of two consistent images. The intensity of point $(v_1, v_2)$ in the joint histogram indicates the number of pixels in the first image with intensity $v_1$ that correspond to pixels in the second image with intensity $v_2$. When the regions are consistent, a monotonically increasing thin line in the joint histogram is expected (see Fig. 2(d)). However, as discussed before, we do not assume exact correspondence, since it is not necessarily available or reliable. Rather, we use a distance measure on the statistical distribution of pixel colors. This allows mapping evaluation without exact pixel-to-pixel correspondence.

Denote by $d(M, P, Q)$, a measure which indicates the consistency of mapping $M$ with respect to the regions $P$ and $Q$. In our implementation, $d$ measures the discrepancy between the histogram of $P$ after applying the color mapping $M$, $P' = M(P)$, and that of $Q$. We use the sum of absolute difference (SAD) between two cumulative histograms as a distance measure. Formally, let $C_{P'}$ and $C_Q$ denote the cumulative histograms of regions $P'$ and $Q$. Then, we define:

$$d(M, P, Q) = \sum_s |C_{P'}(s) - C_Q(s)|, \tag{2}$$

where the summation is over the color values of a given color channel. This distance is also shown to be the Earth Mover's Distance (EMD) for 1D histograms [15] and is computed for each color channel separately. Since the mapping should be consistent for all three color channels, the maximal distance between the three channels is taken.

**Hierarchical consistency measure:** Since only histograms are considered in $d$, low distance value is a necessary but not a sufficient condition for $P$ and $Q$ to be consistent. A toy example demonstrating this point is presented in Fig. 3. In this example, regions $a$ and $b$ are consistent regions but regions $c$ and $d$ are inconsistent, since the monotonicity requirement is not satisfied. Nevertheless, in both cases the corresponding histograms are similar. Furthermore, as $M$ is computed using histogram matching, the histograms of $P'$ and $Q$ are usually similar. Therefore, histogram based measures cannot distinguish between these cases unless subregions are tested as well.

We use this observation to define our new measure of consistency between regions. Let a set of subregions of $P$ be given by $\{P_i\}_{i=1}^k$ and let $\{Q_i\}_{i=1}^k$ be their corresponding regions in $Q$. The *region consistency measure* between $P$ and $Q$ is defined as follows:

$$C_k(P,Q) = \max_{1\le i\le k} d(M_{P,Q}, P_i, Q_i). \tag{3}$$

Small measure values indicate that the mapping, $M_{P,Q}$, can be applied to each subregion $P_i$, mapping its histogram close to that of its corresponding region $Q_i$.

Note that $d(M_{P,Q}, P_i, Q_i)$ is not symmetric because $M_{P,Q}$ may be a many-to-one mapping. However, symmetry is required to avoid degenerate mapping, e.g., mapping a structured area into a constant value. Therefore, we define a *symmetric* region consistency measure indicating whether $P$ and $Q$ are non-trivially consistent:

$$\hat{C}_k(P,Q) = \max(C_k(P,Q), C_k(Q,P)). \tag{4}$$

To measure the consistency of two regions, $\hat{C}_k$ is applied to their subregions. Note, that this score indicates whether subregions $\{P_i\}_{i=1}^k$ can be merged into a bigger region that is still consistent with its counterpart. For $k=1$, $C_1(P,Q)$ is simply given by $d(M_{P,Q}, P, Q)$. These measures are used in various parts of our algorithm as described below.

# 4. Method: The four cases

For each of the four acquisition conditions, we suggest a method for computing the piecewise-consistent color mapping. In all cases we assume that the photometric parameters of the cameras may vary.

## 4.1. Basic case: Same viewpoint, same illumination

Here we consider a pair of images taken from the same viewpoint for which only the photometric parameters of the cameras vary (see Fig. 2(a,b)). We describe this case only for the sake of completeness. The two images are consistent, as demonstrated by the joint histogram in Fig. 2(d), and the CCM can therefore be solved using histogram matching. After the computed CCM is applied, the joint histogram consists of a thin line along the diagonal, representing the identity as desired (Fig. 2(e)).

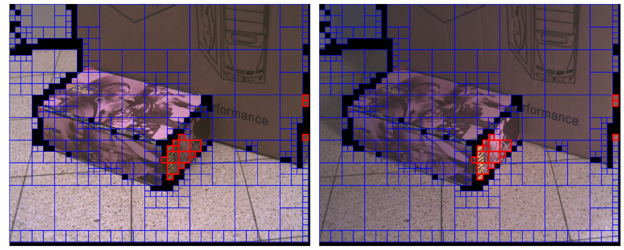


Figure 4. Two images taken under different illumination divided into consistent regions. Regions which are small but inconsistent are discarded (black colored). One of the clusters, found in the clustering phase, is shown in red.

## 4.2. Same viewpoint, different illumination

Here, we consider two images of the same scene whose illumination varies. The images are taken from the same viewpoint under possibly different photometric parameters. In this case, the correspondence is trivial; however, there is no global CCM between the two images since the differences between the intensities of corresponding pixels depend also on the pixels' normals. The joint histogram of the two images in Fig. 2(f) demonstrates that indeed no CCM exists. The joint histogram of a single plane of the box in Fig. 2(g) shows that even for a single plane, for which, theoretically, a CCM is expected to exist, this is not the case. This may be explained by image noise, non-Lambertian reflectance, illumination not at infinity, shadows, inter-reflections, and so forth.

We suggest a new approach for computing a minimal set of piecewise color mappings and their *induced* consistent regions (regions for which the mapping is consistent). Note that without the minimal set requirement, any single pixel can be chosen as an independent region. To the best of our knowledge, this problem has not been addressed before.

**Piecewise consistent mappings:** To compute the minimal set of consistent color mappings, we decompose the image using a quad-tree. That is, each region is recursively divided into four quarters up to a predefined leaf size. Note that choosing too small a leaf size results in many spatially incoherent mappings (a 1-pixel leaf is always consistent). In a top-down manner, each node in this tree is tested for its consistency with respect to its corresponding region in the other image. The consistency of a node is determined using the symmetric region consistency measure, $\hat{C}_k$ (Eq. 4), where the subregions considered are the $k$ leaves of its subtree. A lower level of the subtree is tested for consistency only if its parent is determined to be inconsistent. When a leaf tested by $\hat{C}_1$ is determined to be inconsistent, it is discarded. Such leaves usually indicate changes between the images. At the end of this process, we end up with a set of consistent regions and their consistent color mappings.

In the next phase, we cluster the obtained color mappings to reduce their number. The distance between each pair of consistent regions from the previous phase is defined by $\hat{C}_2$. A minimal number of regions are computed by grouping together close regions using a complete linkage clustering algorithm [5]. That is, a hierarchical clustering where two clusters are grouped together according to their furthest neighbors. For each cluster a *new* color mapping is computed using the regions associated with it. The result of this process is a set of consistent mappings and their associated consistent regions in the two images.

**Consistent region detection:** The consistent regions computed in the previous phase are inaccurate and blocky due to the quad-tree structure. We next suggest a method for refining the induced regions for each of the computed CCMs. Our goal is to compute piecewise continuous consistent regions, and to avoid detection of pixels and regions that are accidentally consistent with the mapping.

This last step is performed by applying each of the mappings to the first image and comparing the mapped image to the second one. A simple comparison of the two images may result in incorrect detection of consistent regions due to inaccurate pixel correspondence (resulting in false negative detection) and accidental color correspondence (resulting in false positive detection). To overcome the accidental color correspondence of pixels, we search for continuous regions that are associated with the same color mapping. That is, a pixel is detected as associated with a color mapping only if its neighboring area is associated with this mapping as well. For overcoming small location errors due to correspondence inaccuracy, we compare the colors, while allowing small jittering of the neighboring area of the pixel. Finally, smooth color regions can also be accidentally detected, just like a single pixel. Such regions are expected to result in association to the same color mapping, regardless of the size and direction of the considered jitter. If this is the case, these regions are discarded. For implementing this process, without setting the size of the region a priori, we use a modification of the patch correlation suggested in [10].

The image pixels which correspond to a particular color mapping are marked as a binary image, which we call *color mapping mask*. Conflicts between masks are arbitrarily resolved, as conflicting pixels can be affiliated with both color mappings. To preserve the spatial coherence of the comparison result, the mask is smoothed using a Gaussian Filter and the result is binarized using a threshold. The result of the algorithm is a set of piecewise consistent color mappings along with their masks (the induced regions).

### 4.3. Different viewpoint, same illumination

In this scenario two images are taken from different viewpoints, but with a fixed illumination. As in the other cases, we assume that the photometric parameters of the cameras may vary. Assuming a Lambertian scene, the two images are consistent with a global color mapping, but contain non-corresponding regions. Thus, naively applying the histogram matching will produce a non-consistent mapping. This is demonstrated in Fig. 6(e). Regions that are viewed in both images can be used for computing the CCM, as long as they cover the entire color range of the images. Because the color mapping is monotonic, the histogram matching algorithm can handle gaps in the matched histograms even if the entire range of colors is not covered.

The challenge is, therefore, to detect corresponding regions in the two images despite the variations in their colors. Several image features suggested in the literature are designed to be insensitive to illumination changes. We use the SIFT features [9] for this purpose. SIFT correspondence is determined using the distance between SIFT descriptors. RANSAC is used for removing incorrect correspondences using the epipolar constraints. Each corresponding SIFT feature determines a corresponding region. We use a square region centered at the SIFT position whose size is proportional to the SIFT scale. Note that SIFT features are usually located in textured areas, and hence their regions are likely to cover a large range of colors.

A global color mapping is calculated from the union of all matched SIFT regions. This is expected to provide sufficient statistics over the color domain for the histogram mapping method. Fig. 6 shows the matched SIFT regions found for the two images, along with the induced color mapped image.

### 4.4. Different viewpoint, different illumination

The most challenging case is when the two images are taken from different viewpoints and under different illumination conditions. Such images are not consistent, in contrast to Sec. 4.3, and the correspondence is not trivial, in contrast to Sec. 4.2. Here we present an extension of the method suggested in Sec. 4.2, for finding a set of piecewise consistent mappings and their induced regions. The method is limited to planar regions, since variations in the intensity of corresponding pixels depends on their surface normals as well. Therefore, pixels with different normals will usually have different mappings.

We simultaneously co-segment planar regions in the two images and compute their piecewise color mapping. We use RANSAC on corresponding SIFT features in the two images in order to compute the homography transformations that align image scene planes (as [16]). The set of SIFT features computed for each planes is often too small to provide sufficient statistics over the color domain of the plane. In addition, a single plane may have more than a single CCM. Hence, applying the method described in Sec. 4.3 is insufficient. For co-segmenting the plane defined by a given homography transformation, we apply the method described in Sec. 4.2 to the entire image, after aligning the images using the homography transformation. Note that the regions that lie off the considered plane are incorrectly aligned. Most of these regions are discarded during the division phase due to their inconsistency, or in the consistent region detection phase due to the lack of support from their surrounding regions. This method is sequentially applied to each of the detected homography transformations (one for each plane) on the original images. Finally, association conflicts between different color mappings or different planes are arbitrarily resolved. Such conflicts, however, are rare.

## 5. Results and Applications

In this section we demonstrate the results of applying our algorithms on indoor and outdoor scenes. More results are presented in [6]. All pairs of images were taken under different photometric parameters. The algorithms were implemented in MATLAB, using in part code from [8], [9] and [10].

Results of applying the algorithm to images taken under identical illumination but from different viewpoints (see Sec. 4.3) are presented in Fig. 6. For accuracy assessment, we present (c), an image taken from the same viewpoint as the target image (b), but with photometric parameters of the source image (a). This image is referred as the ground truth. The images resulting from our algorithm (d) bear a strong visual resemblance to the ground truth. For comparison, the results of applying the naive histogram matching to the entire images are presented in (e). The inefficiency of the naive approach is clear (e.g., the color of the left wall of the building, and the left part of the teddy bear's head). For qualitative evaluation, we present in Fig. 5(a-b) the joint histograms of the resulting images with respect to their ground truth. As can be seen, the joint histograms of the proposed method resemble the identity histogram indicating the accuracy of the results. We also measured the Root Mean Squared Error (RMSE) between the resulting images and the ground truth. The RMSE were 16 and 19 gray-values for the upper and lower images in Fig. 6, and 26 and 33 gray-values for the naive approach.

We next consider the results of our algorithm when applied to images taken under different illumination and the same viewpoint. The first two rows of Fig. 7 show this case. Columns (a) and (b) present the source and target images, (c) shows the results of applying our piecewise consistent mapping, and (d) shows the results of applying histogram matching. The ground truth, in this case, is simply the target image. Note that the black areas of our matching (c) are regions where no color mapping was found. These regions indicate mainly scene change. Some smooth regions were not matched either, since our method removes smooth regions. Note, that in the street image our approach managed to "copy" the shadowed areas of the road (c). After applying our method, the joint histogram resembles the identity histogram (Fig. 5 (c)), indicating a precise mapping. When the

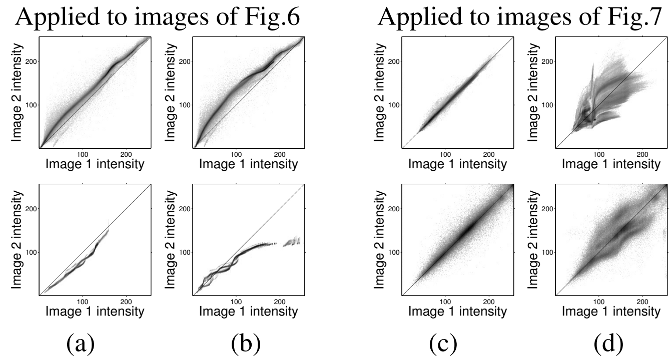


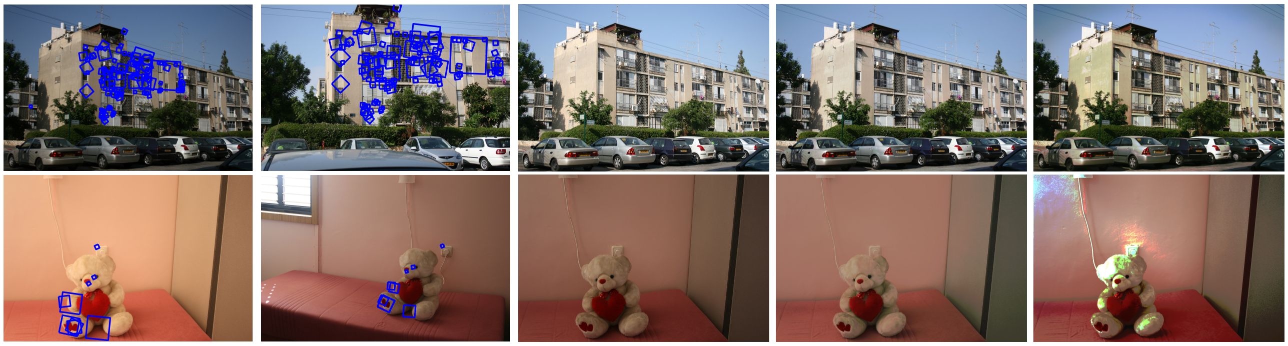

Figure 5. The first and the second rows of (a-b) and (c-d) correspond to the first and the second rows of Fig. 6 and Fig. 7, respectively. (a) and (c) are the joint histograms of the proposed approach and the ground-truth/target image; (b) and (d) are the joint histograms of the naive approach and the ground truth/target image.

naive method is applied, the joint histogram looks like a fan (Fig. 5 (d)), indicating inaccurate mapping. The RMSE between the resulting and target images for our approach were 3 and 15 gray-values as opposed to 24 and 25 gray-value for the naive approach.

Finally, the last two rows of Fig. 7 present the results of our algorithm when applied to images taken from different viewpoints and different illuminations (Sec. 4.4). In this case the black areas are the non-planar regions of the scene (they can also be smooth regions without support from their surroundings). The joint histograms for this case are not presented since ground truth is not available. The results of plane segmentations are shown in Fig. 9.

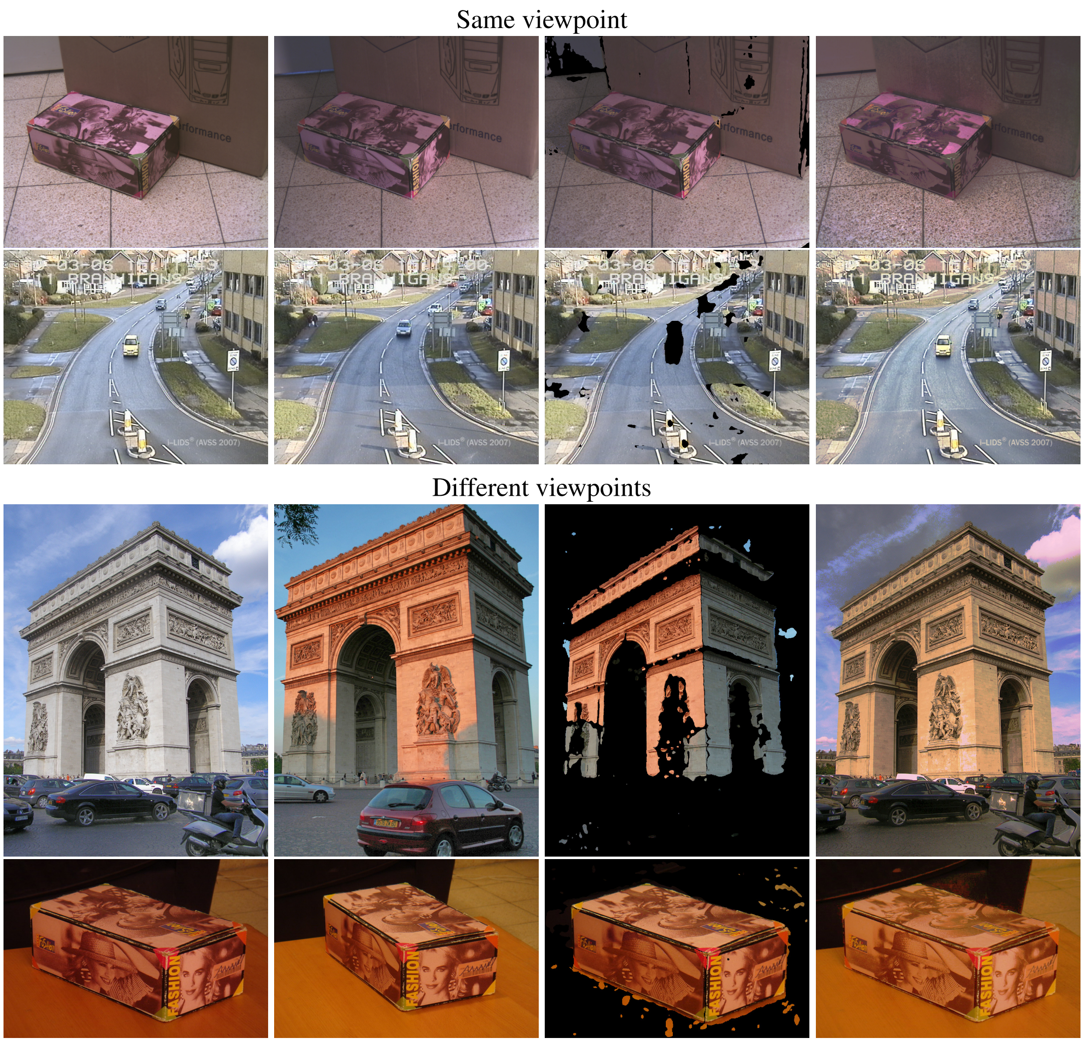
One possible application of the proposed algorithm is to detect changes between images taken from the same viewpoint despite large variations in illuminations. Regions for which no color mapping is found are determined as candidate scene changes. Fig. 8 demonstrates that this is solved by our method, without any further post-processing. The changes found between images (a) and (b) are marked in red in image (c). For comparison, we present in (d) the normalized gray-scale correlations method, which accounts for affine gray-scale variations. In (e) we present change detected by image differences in the color chrominance domain (to account for illumination changes). These images demonstrate the limitations of these methods with respect to the suggested approach.

Our algorithm can be considered as the second phase of a recognition algorithm that is based on homography of SIFT features [11]. It allows verification of the correspondence of regions that were determined by the set of SIFTs and their homography as demonstrated in Fig. 10. Such verification is not trivial due to the severe change of colors between images.



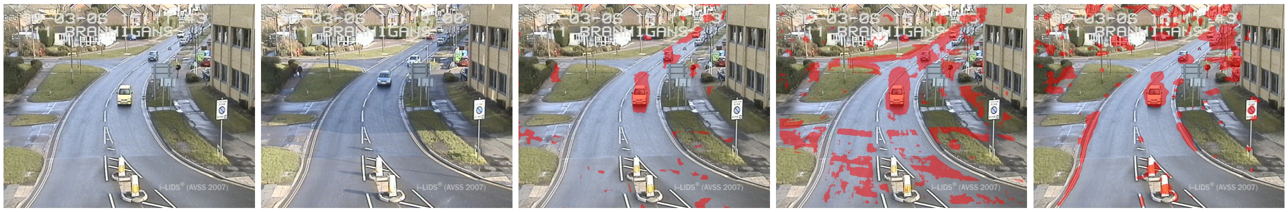
(a) (b) (c) (d) (e)

Figure 6. Results of our method for identical illumination and different viewpoints. Images are ordered in rows (a)-(e): (a),(b), source and target images along with their SIFT features; (c), the ground truth; (d), resulting images using the suggested approach; (e), the results using histogram matching.




(a) (b) (c) (d)

Figure 7. Results of our method for different illumination. In the upper two rows images were taken from the same viewpoints, and in the lower two rows the viewpoints are different. Images are ordered in columns (a)-(d): (a),(b) the source images and the target images; (c), resulting images using the suggested approach; (d), the results using histogram matching.



(a) (b) (c) (d) (e)

Figure 8. (a) and (b) show two images from different frames of a time-lapse video. Areas detected as different are marked in red. (c) shows change detection using our method; (d) shows change detection using normalized gray-scale correlation; and (e) shows change detection using image chrominance comparison. *Images taken from i-Lids vehicle detection challenge.*

## 6. Conclusions

The paper presents a complete solution for color mapping between images when acquisition conditions vary. Although the considered cases are different to a large extent, all proposed solutions basically rely on the *consistency* definitions and the *consistency test*. We believe that one of the contributions of this paper is the observation that in many cases a precise global mapping cannot account for the entire image, and a piecewise mapping is a feasible solution.

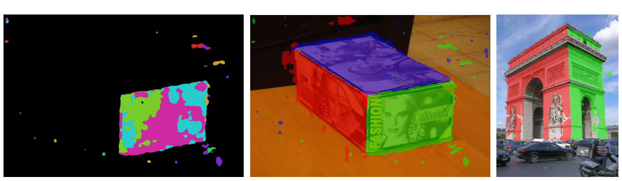
## References


[1] P. Beardsley, P. Torr, and A. Zisserman. 3D model acquisition from extended image sequences. *Lecture Notes in Computer Science*, pages 683–695, 1996.

[2] F. Candocia and D. Mandarino. A semiparametric model for accurate camera response function modeling and exposure estimation from comparametric data. *IEEE Transactions on Image Processing*, 14(8):1138–1150, 2005.

[3] R. Eshel and Y. Moses. Homography Based Multiple Camera Detection and Tracking of People in a Dense Crowd. In *Proc. IEEE Conf. Comp. Vision Patt. Recog.*, pages 1–8, 2008.

[4] R. Gonzalez and R. Woods. *Digital Image Processing*. Prentice Hall, 2007.

(a) (b) (c)

Figure 9. (a), The piecewise consistent color mappings of the green plane of (b) (each color indicates a different color mapping). (b),(c), are the plane segmentations.

Figure 10. Two images from the Oxford database and the dense co-segmentation of a plane after applying homography.


[5] T. Hastie, R. Tibshirani, and J. Friedman. *The Elements of Statistical Learning*. Springer, 2001.

[6] S. Kagarlitsky. Consistent color mappings of images acquired under various conditions. Master's thesis, The Interdisciplinary Center, Herzlia, Israel, 2009.

[7] M. Kolomenkin and I. Shimshoni. Image Matching Using Photometric Information. In *Proc. IEEE Conf. Comp. Vision Patt. Recog.*, pages 2506–2514. IEEE Computer Society Washington, DC, USA, 2006.

[8] P. D. Kovesi. MATLAB functions for computer vision. http://www.csse.uwa.edu.au/∼pk/research/matlabfns/.

[9] D. Lowe. Object recognition from local scale-invariant features. In *Proc. Int. Conf. Comp. Vision*, volume 2, 1999.

[10] A. Ogale and Y. Aloimonos. Shape and the stereo correspondence problem. *IJCV*, 65(3):147–162, 2005.

[11] J. Philbin, O. Chum, M. Isard, J. Sivic, and A. Zisserman. Lost in quantization: Improving particular object retrieval in large scale image databases. In *Proc. IEEE Conf. Comp. Vision Patt. Recog.*, pages 1–8, 2008.

[12] F. Pitie, A. Kokaram, and R. Dahyot. N-dimensional probablility density function transfer and its application to colour transfer. *Proc. Int. Conf. Comp. Vision*, 2:1434–1439, 2005.

[13] F. Porikli. Inter-camera color calibration by correlation model function. In *IEEE ICIP*, 2003.

[14] E. Reinhard, M. Ashikhmin, B. Gooch, and P. Shirley. Color transfer between images. *IEEE Computer Graphics and Applications*, 21(5):34–41, 2001.

[15] Y. Rubner, C. Tomasi, and L. Guibas. The earth mover's distance as a metric for image retrieval. *Int. J. of Comp. Vision*, 40(2):99–121, 2000.

[16] E. Vincent and R. Laganiere. Detecting planar homographies in an image pair. In *Proc. Int. Sym. on Image and Signal Processing and Analysis*, pages 182–187, 2001.

[17] C. Wang and Y. Huang. A Novel Automatic Color Transfer Algorithm between Images. *Journal of the Chinese Institute of Engineers*, 29(6):1051–1060, 2006.

[18] G. Wang, H. Tsui, and Z. Hu. Reconstruction of structured scenes from two uncalibrated images. *Pattern Recognition Letters*, 26(2):207–220, 2005.