Asian Journal of Electrical Sciences (AJES)
Vol.3.No.1 2015 pp 23-28
available at: www.goniv.com
Paper Received :08-03-2015
Paper Accepted:20-03-2015
Paper Reviewed by: 1. R. Venkatakrishnan 2. R. Marimuthu
Editor : Prof. P.Muthukumar

IMAGE PIXEL CLASSIFICATION THROUGH AWB AND AE CORRECTION METHODS

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ABSTRACT

This paper describes a method for color stabilization of shots of the same scene, taken under the same illumination, where one image is chosen as reference and one or several other images are modified so that their colors match those of the reference. We make use of two crucial but often overlooked observations: first, that the core of the color correction chain in a digital camera is simply a multiplication by a 3 × 3 matrix; second, that to color-match a source image to a reference image we do not need to compute their two color correction matrices, it is enough to compute the operation that transforms one matrix into the other. This operation is a 3 × 3 matrix as well, which we call H. Once we have H, we just multiply by it each pixel value of the source and obtain an image which matches in color the reference. To compute H we only require a set of pixel correspondences, we do not need any information about the cameras used neither models nor specifications or parameter values. We propose an implementation of our framework which is very simple and fast, and show how it can be successfully employed in a number of situations, comparing favorably with the state of the art. There is a wide range of applications of our technique, both for amateur and professional photography and video: color matching for multi camera TV broadcasts, color matching for 3D cinema, color stabilization for amateur video, etc.

Index Terms—Color stabilisation , color transfer, color image analysis, color matching.

INTRODUCTION

Two pictures of the same scene, taken under the same illumination, to be consistent in terms of color. But if we have used different cameras to take the pictures, or just a single camera with automatic white balance (AWB) and/or automatic exposure (AE) correction, then the most common situation is that there are objects in the scene for which the color appearance is different in the two shots. This is problematic in many contexts. With a single camera, the only way to ensure that all pictures of the same scene are color consistent would be to save images in the RAW format, or to use the same set of manually fixed parameters for all the shots. These are not common choices for amateur users, but even professional users face the same challenges: the most popular DSLR cameras for shooting HD video don't have the option of recording in RAW; and while in cinema the exposure and color balance values are always kept constant for the duration of a take (i.e. AE and AWB are never used), the shooting conditions may require to change these values from shot to shot. For instance, TV broadcasts employ devices called camera control units, operated by a technician called Video Controller or Technical Director (TD): while each camera operator controls most of his/her camera functions such as framing or focus, the TD controls the color balance and shutter speed of a set of cameras so as to ensure color consistency across them. We can see then that an automatic color stabilization procedure would be both a very useful tool for amateur users and a key asset for the industry. Our contribution is to propose a framework for color stabilization of shots of the same scene, taken under the same illumination, where one image is taken as reference and one or several other images are modified so that their colors match those of the reference. This framework is very simple and does not require calibrated cameras nor any information about the cameras used, neither specifications nor camera parameters. We make use of two crucial but often overlooked observations: firstly, that the core of the color correction chain in a digital camera is simply a multiplication by a 3 × 3 matrix; secondly, that to color-match a source image to a reference image we don't need to compute their two color correction matrices, it's enough to compute the operation that transforms one matrix into the other, and this only requires a set of pixel correspondences. Although we rely on the estimation of a 3 × 3 matrix, what we propose is not a color constancy method: we do not try to recover reflectance neither illuminants, but to remove color fluctuations, making all images look the same in terms of color (even if those colors correspond to an incorrect white balance procedure).

COLOR TRANSFER

One of the most common tasks in image processing is to alter an image's color. Often this means removing a dominant and undesirable color cast, such as the yellow in photos taken under incandescent illumination. This article describes a method for a more general form of color correction that borrows one image's color characteristics from another. Example of this process, where we applied the colors of a sunset photograph to a daytime computer graphics rendering. We can imagine many methods for applying the colors of one image to another. Our goal is to do so with a simple algorithm, and our core strategy is to choose a suitable color space and then to apply simple operations there. When a typical three channel image is represented in any of the most well-known color spaces, there will be correlations between the different channels' values. For example, in RGB space, most pixels will have large values for the red and green channel if the blue channel is large. This implies that if we want to change the appearance of a pixel's color in a coherent way, we must modify all color channels in tandem. This complicates any color modification process. What we want is an orthogonal color space without correlations between the axes. Recently, Ruder man et al. developed a color space, called lαβ, which minimizes correlation between channels for many natural scenes. 2 This space is based on data-driven human perception research that assumes the human visual system is ideally suited for processing natural scenes. The authors discovered lαβcolor space in the context of understanding the human visual sys-tem, and to our knowledge, l αβspace has never been applied otherwise or compared to other color spaces. There's little correlation between the axes in lαβ space, which lets us apply different operations in different color channels with some confidence that undesirable cross-channel artifacts won't occur. Additionally, this color space is logarithmic, which means to a first approximation that uniform changes in channel intensity tend to be equally detectable.

OBJECT-BASED IMAGE ANALYSIS

Object-Based Image Analysis (OBIA) – also Geographic Object-Based Image Analysis (GEOBIA) – "is a sub-discipline of geoinformation science devoted to (...) partitioning remote sensing (RS) imagery into meaningful image-objects, and assessing their characteristics through spatial, spectral and temporal scale". The two main processes in OBIA are (1) segmentation and (2) classification. Traditional image segmentation is on a per-pixel basis. However, OBIA groups pixels into homogeneous objects. These objects can have different shapes and scale. Objects also have statistics associated with them which can be used to classify objects. Statistics can include geometry, context and texture of image objects. The analyst defines statistics in the classification process to generate land cover Each of these application areas has spawned separate subfields of digital image analysis, with a large collection of specialized algorithms and concepts—and with their own journals, conferences, technical societies, and so on.

LIMITATIONS AND POSSIBLE IMPROVEMENTS

Instead of SIFT, a method which gives a more populated set of pixel correspondences between I 1 and I 2 (in this example we have applied to the ground truth image a state-of-the-art optical flow computation algorithm), at the expense of increasing the computational cost. For the wide angle shots on the top our result is poor, probably due to the lack of enough SIFT matches caused by the great disparity among the shots; a more sophisticated method than SIFT for finding correspondences, could improve the results. For the stereo shots on the bottom our results are also lacking, and we think that for this example a global approach like ours isn't enough, because the color differences may be due to color aberrations of the beam-splitter and therefore local instead of global, not an uncommon scenario in 3D cinema. Another limitation of our method is related to highly saturated colors, which tend to fall outside the color gamut of the output format and therefore are usually clipped. The result is that for pixels with these colors the in-camera color processing can no longer be modeled as a linear transformation, as stated by Kim et al. Since these colors do not fulfill our basic assumption of a linear model for the color pipeline, as stated in eq. 4, they might be transferred incorrectly.

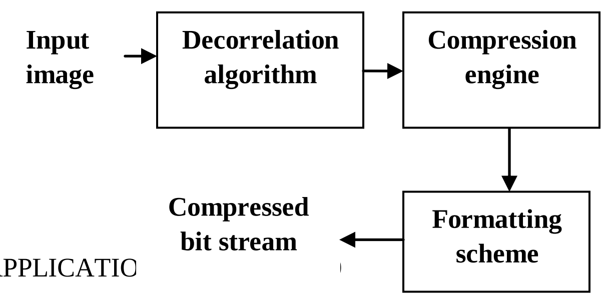
EXISTING SYSTEM

In this paper we study a first-order primal-d UAL algorithm for convex optimization problems with known saddle-point structure. We prove convergence to a saddle point with rate O(1/N)in finite dimensions, which is optimal for the complete class of non-smooth problems we are considering in this paper. We further show accelerations of t he proposed algorithm to yield optimal rates on easier problems. In particular we s how that we can achieve O(1/N2) convergence on problems, where the primal or the dual objective is uniformly convex, and we can show linear convergence i.e. O(1/e N) on problems where both are uniformly convex. The wide applicability of the proposed algorithm is demonstrated on several imaging problems such as image denoising, image deconvolution, image inpainting, motion estimation and image segmentation.

This paper presents a new efficient method for recovering reliable local sets of dense correspondences between two images with some shared content. Our method is designed for pairs of images depicting similar regions acquired by different cameras and lenses, under non-rigid transformations, under different lighting, and over different backgrounds. We utilize a new coarse-to-fine scheme in which nearest-neighbor field computations using Generalized Patch Match [Barnes et al. 2010] are interleaved with fitting a global non-linear parametric color model and aggregating consistent matching regions using locally adaptive constraints. Compared to previous correspondence approaches, our method combines the better of two worlds: It is dense, like optical flow and stereo re-construction methods, and it is also robust to geometric and photo metric variations, like sparse feature matching. We demonstrate the usefulness of our method using three applications for automatic example-based photograph enhancement: adjusting the tonal characteristics of a source image to match a reference, transferring a known mask to a new image, and kernel estimation for image de-blurring.

PROPOSED COMPRESSION METHOD

We then group the wavelet coefficients into 3-D groups and compute the mean energy of each group. We encode each group of coefficients independently using a modified EBCOT with 3-D contexts to create a separate scalable layered bit-stream for each group. The coordinates of the VOI in the spatial domain, in conjunction with the information about the mean energy of the grouped coefficients, are then used in a weight assignment model to compute a weight for each group of coded wavelet coefficients. These weights are used to reorder the output bit stream and create an optimized scalable layered bit-stream with VOI decoding capabilities and gradual increase in peripheral quality around the VOI. At the decoder side, the wavelet coefficients are obtained by applying the EBCOT decoder. Finally, an inverse 3D-IWT is applied to obtain the reconstructed 3-D image.



APPLICATIO

Some markets and applications intended to be served by this standard are listed below:

- Consumer applications such as multimedia devices (e.g., digital cameras, personal digital assistants, 3G mobile phones, color facsimile, printers, scanners, etc.)
- Client/server communication (e.g., the Internet, Image database, Video streaming, video server, Second Life, etc.)
- Military/surveillance (e.g., HD satellite images, Motion detection, network distribution and storage, etc.)
- Medical imagery, esp. the DICOM specifications for medical data interchange.
- Remote sensing
- High-quality frame-based video recording, editing and storage.
- Digital cinema

PRIVATE WATERMARKS

A private (secret) watermark may contain information for identifying the licensee or to prove ownership in disputes. Retrieval of secret watermark information requires at least one secret key, known only to the embedded. A private watermark puts heavy demands on a watermarking algorithm regarding robustness, although the demands for capacity are relaxed. Embedded information usually includes licensee-identifying serial numbers or hash values. In general, a serial number is just a pointer or link to externally stored information, such as a customer record.

PUBLIC WATERMARKS

A public watermark is retrieved by the receiver (licensee) of copyrighted material. It usually contains copyright or licensing information, such as the identifier of the copyright holder, the creator of the material, or a link (URL) through which to fetch more related information. It may contain a serial number that uniquely identifies material to registration entities. Retrieving a public watermark requires no information but the model data itself plus a specific key, unique among the material generated by one or various creators or copyright holders. A public watermark puts heavy demands on a watermarking algorithm regarding capacity. Because a public watermark provides additional copyright-related information for receivers and doesn't aim to prove ownership or identify licensees, the requirements regarding robustness are relaxed.

COLOR COMPONENTS TRANSFORMATION

Initially, images have to be transformed from the RGB color space to another color space, leading to three components that are handled separately. There are two possible choices:

1. Irreversible Color Transform (ICT) uses the well known YCBCR color space. It is called "irreversible" because it has to be implemented in floating or fix-point and causes round-off errors.
2. Reversible Color Transform (RCT) uses a modified YUV color space that does not introduce quantization errors, so it is fully reversible. Proper implementation of the RCT requires that numbers are rounded as specified that cannot be expressed exactly in matrix form. The transformation is:

$$Y = \frac{R + 2G + B}{4}$$

$$C_b = B - G \;; \quad C_r = R - G \;;$$

$$G = Y - \frac{Cb + Cr}{4};\ R = C_r + G;\ B = C_r + G$$

TILING

After color transformation, the image is split into so-called tiles, rectangular regions of the image that are transformed and encoded separately. Tiles can be any size, and it is also possible to consider the whole image as one single tile. Once the size is chosen, all the tiles will have the same size (except optionally those on the right and bottom borders). Dividing the image into tiles is advantageous in that the decoder will need less memory to decode the image and it can opt to decode only selected tiles to achieve a partial decoding of the image.
The disadvantage of this approach is that the quality of the picture decreases due to a lower peak signal-to-noise ratio. Using many tiles can create a blocking effect similar to the older JPEG 1992 standard.

QUANTIZATION

After the wavelet transform, the coefficients are scalar-quantized to reduce the amount of bits to represent them, at the expense of a loss of quality. The output is a set of integer numbers which have to be encoded bit-by-bit. The parameter that can be changed to set the final quality is the quantization step: the greater the step, the greater is the compression and the loss of quality. With a quantization step that equals 1, no quantization is performed (it is used in lossless compression).

Packets are the key to quality scalability (i.e., packets containing less significant bits can be discarded to achieve lower bit rates and higher distortion). Packets from all sub-bands are then collected in so-called layers. The way the packets are built up from the code-block coding passes, and thus which packets a layer will contain, is not defined by the JPEG 2000 standard, but in general a codec will try to build layers in such a way that the image quality will increase monotonically with each layer, and the image distortion will shrink from layer to layer. Thus, layers define the progression by image quality within the code stream.

The problem is now to find the optimal packet length for all code blocks which minimizes the overall distortion in a way that the generated target bit rate equals the demanded bit rate. While the standard does not define a procedure as to how to perform this form of rate distortion optimization, the general outline is given in one of its many appendices: For each bit encoded by the EBCOT coder, the improvement in image quality, defined as mean square error, gets measured; this can be implemented by an easy table-lookup algorithm.

Furthermore, the length of the resulting code stream gets measured. This forms for each code block a graph in the rate–distortion plane, giving image quality over bit stream length. The optimal selection for the truncation points, thus for the packet-build-up points is then given by defining critical slopes of these curves, and picking all those coding passes whose curve in the rate–distortion graph is steeper than the given critical slope. This method can be seen as a special application of the method of Lagrange multiplier which is used for optimization problems under constraints. The Lagrange multiplier, typically denoted by λ, turns out to be the critical slope, the constraint is the demanded target bit rate, and the value to optimize is the overall distortion.

Packets can be reordered almost arbitrarily in the JPEG 2000 bit-stream; this gives the encoder as well as image servers a high degree of freedom. Already encoded images can be sent over networks with arbitrary bit rates by using a layer progressive encoding order. On the other hand, color components can be moved back in the bit-stream; lower resolutions (corresponding to low-frequency sub-bands) could be sent first for image previewing. Finally, spatial browsing of large images is possible through appropriate tile and/or partition selection. All these operations do not require any re-encoding but only byte-wise copy operations.

PERFORMANCE

JPEG 2000 gains up to about 20% compression performance for medium compression rates in comparison to the first JPEG standard. For lower or higher compression rates, the improvement can be somewhat greater (especially if altering the input resolution to the codec is not considered as a technique for effective use of the older JPEG standard). Good applications for JPEG 2000 are large images, images with low-contrast edges - e.g., medical images.

CONCLUSION

We have presented a method to remove color fluctuations among images of the same scene, taken with a single camera or several cameras of the same or different models. No information about the cameras is needed. The method works for still images and for video. It is based on the observation that the color correction operations performed in-camera (apart from gamma correction) can be cascaded into a single 3×3 matrix, and color matching among images only requires to transform one matrix into another, it's not necessary to actually estimate the matrices. This is precisely what motivated TV engineers to allow for manual modification of the colorimetric matrices of broadcast cameras, so that their colors could be matched and the transitions among them were smooth. We have shown applications of our method in a variety of settings, as well as comparisons with the state of the art in the color transfer literature. We have chosen to implement our method using reliable, classical techniques, for which there exist hardware accelerated implementations, but we also show how better numerical methods can further improve the results.

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