Crowd-sourced Mobile Phone Images for Heritage Conservation Monitoring

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***Abstract*—We propose quantifying color in crowd-sourced images from mobile phones to monitor built heritage over time. Time-lapse color movies in CIE color space can provide information on a large range of deterioration mechanisms, including soiling, biofilm growth, weathering and vandalism. Citizen science can create large-scale geographical coverage of sites difficult to obtain any other way. We show that the color accuracy of current phones is sufficient for this purpose and demonstrate image registration, color calibration and change detection using mobile phone cameras. For accurate color, a calibration target of known, stable colors need to be in the image field of view.**

***Index Terms*—built heritage, imaging, conservation monitoring, change detection, image calibration, self-calibration.**

I. Introduction

Built heritage, no matter how defined, is exposed to the elements and under constant attack from rain, biofilms, pollution, and other processes that degrade it. Conservators and site managers have an unmeet need for ways to detect, image and map changes over time for these effects. We propose using crowd-sourced images from mobile phones to create a fine- grained, time-stamped, and geolocated image dataset of calibrated color images. Using this dataset, we can create time- lapse movies showing quantitative changes in color, such as soiling rates on cathedrals.

A real-world project requires a significant computational backend to handle large amounts of data properly. Turning crowd-sourced images into quantitative data involves automating (1) image registration, (2) corrections for camera lens distortion, and (3) color calibration and transformation from sRGB to CIE L*a*b*. We will show our approaches and solutions to each.

The concept is to partner with site managers and conservators to pose specific questions about individual sites. Cell phone cameras do a lot of scene specific processing and thus each image must be calibrated before it can be added to the database. We shall show that for consistent quantification a target that contains suitable known colors for calibration must be included in the image. To that end, a small calibration module or kiosk will be placed in the field of view of interest. It will contain robust color targets, a small weather station, and Citizen Science signage.

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To reduce image registration burden and improve quality and usability, the citizen scientist will have the option to be guided to the correct image by a transparent image overlay in a camera app. So, the image stream will be approximately the same. For comparison, tourist images taken at the same location can be harvested from sites such as Flickr, Snapfish, and Instagram.

Citizen science has gained traction [1] and many projects with a significant level of user interaction go beyond use of idle PC cycles. Ongoing citizen science projects take advantage of the extensive geographic distribution of smart phones and collect large numbers of geotagged and time stamped images, as we anticipate doing. Examples include the Bud Burst Project (BudBurst.org), which uses collected images to map changes in the growing season caused by climate change; and the Loss of the Night project monitors degradation of the night sky from light pollution (lossofthenight.blogspot.com). These projects indicate that we would not be asking anything of the participant beyond what is already in place. Further, we will use social media and games to create an engagement loop to make it easy and fun for participants.

The components of built heritage are all subject to deterioration from a large range of processes driven by weathering, light, salts and biology. In addition, built heritage often suffering much more rapid levels of change than objects in museum environments. A recent example in San Antonio, Texas is the 5-7 cm of exterior surface loss since 1960 suffered by particular areas of the Alamo façade [2].

Our data are color images and there are several natural questions to ask. One is what sort of change processes in built heritage can we expect to see and detect with a color image, calibrated or not? A second question is how good are cell phone cameras, i.e., are they good enough to measure realistic color changes in built heritage? Third, do we know anything about measured color changes in built heritage; i.e. if we look at L*a*b* values, do these change over time and how much? Are these changes comparable to what we can measure with calibrated mobile phones?

We will calibrate and transform the sRGB mobile cell images into the CIE L*a*b* color space. L* is lightness, similar to luminance or intensity, while a* and b* provide chromatic information; a* is the red-green axis and b* is yellow-blue. The CIE color space is an orthogonal 3-coordinate space that can provide quantitative measurement of color changes and can also be related to human color perception of changes.

Let's approach these in order. Our end product will be a color-calibrated time-lapse movie: What sort of processes and events show up as color changes in built heritage? Color is a proxy for a variety of processes, including soiling, material loss and erosion and pollution-driven surface chemistries, such as salts. For example, material loss at the surface through spallation or vandalism exposes a brighter, fresh interior material of a color different than the unweathered surface. Oxidation, reduction, acidic leaching, dust and soiling have all been shown to change the surface color of built heritage and its components. Even surface roughness changes from weather, and erosion of features can change color [3]. Color illuminates biodeterioration via moss/lichen/biofilms with photosynthetic pigments. While we may not able to *identify* each change mechanism with a set of color images, we should be able to differentiate and segment these processes and measure their rate of change. Studies shows that weathering and soiling primarily change L* and b*, rather than a* [4, 5, 6, 7].

II. CALIBRATION

We have to do three calibrations on each image: (1) camera lens distortion, (2) registration of each image to a standard format, and (3) color calibration. In the experiments reported here we used a standard X-Rite ColorChecker for calibration and a raw potato slice as our "built heritage." Wanting a proxy that would change color over a relatively short period, we tried a variety of fruit and vegetables.

The first calibration required is to correct for camera lens distortion -- barrel and pincushion. We do not need to do this for each individual camera; since cell phone cameras are commodity items, we assume we can take all cameras of any one model to be the same. We printed out a checkerboard pattern and imaged it, filling the field of view. Using Matlab tools we calculate the (www.vision.caltech.edu/bouguetj/calib_doc/) distortion coefficients and apply that to all images taken with that model. This is easy to do since the EXIF data in each image identifies the camera and phone model.

The second step is to register the images taken over time into a single time-lapse movie with all images aligned so we can compare the same pixels over time. Since the camera and object are fairly close, we used a projective geometry. The color checker included in each image provided plenty of fiducial points for the transformation (we used the corners of the color patches and implemented the registration with the MATLAB function *fitgeotrans)*. Figure 1 shows an example of how an oblique and distorted image is rectified into a format suitable for our purposes.

Mobile phone cameras do a lot of image processing before the images are available to the user. Among other things, such processing includes (1) auto white balance; (2) auto gain adjust on each of the RGB channels, (3) gamma adjustment, and (4) edge sharpening and image compression that lead to loss of data. Worse, this processing depends on the dynamics of the scene, so there is no way to back out the processing using a fixed protocol.

Fig. 1. Registration results. Left image is taken at an angle; the bottom has been corrected for projection. All of the images are registered, so they can be aligned and overlaid to compare targets.

Thus we must color calibrate each image individually, requiring a calibration target or known colors within *each* image. Since processing is image-dependent, we cannot image the calibration kiosk and then pivot to take an image of the built heritage -- the illumination changes between images are enough that the color calibration matrix from the kiosk will not work for the very next image of the object.

Color calibration is the final step and it is the most important part for the calibration process. We use a ColorChecker (X-Rite ColorChecker Classic card) to do the color calibration, which has 24 standard colors with known L*a*b* values. The calibration process transforms the sRGB tristimulus values to the true CIELAB values. This is a non- linear process.

If one looks at the X-Rite ColorChecker with a mobile phone camera, the images often contain saturated pixels (color value is 255 for an 8 bit image) in the bright color patches with high values of a* and b*. Mobile phone cameras are designed to create bright images that appeal to the human visual system and they often stretch color data to fill the available dynamic range. One approach to reducing color errors is to exclude saturated color patches or pixels from the color calibration transform.

The first step is gamma correction. The RGB values of the photos captured by our cell phone camera are non-linear RGB values called sRGB values. So, it is necessary to linearize sRGB prior to applying the correction matrix to transform the RGB values to the true CIE XYZ color space values. The linearization process is called gamma correction. As a demonstration of how much the phone software adjusts the image, recovered gamma ranges from 1.5-2.3, so we clearly cannot assume a fixed gamma for any image and we have to derive the gamma curve from several known grays in each image.

Second, find the 3×3 matrix transforming the linear RGB to true XYZ values with least squares fitting. There is a linear relationship between linear RGB and XYZ values, but not between XYZ and LAB values. Since we cannot find a 3×3 matrix that could directly transform the linear RGB to LAB, we first transform from linearized RGB to XYZ and then compute the XYZ to LAB. The final step is to transform XYZ values to LAB values; a standard transformation and we leave out the details.

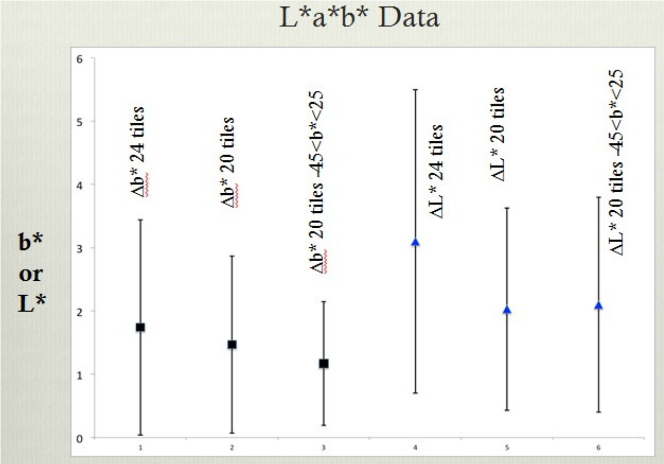

Fig. 2. Color calibration errors from an X-Rite ColorChecker Classic. The errors are the mean of the abolute value of the difference between the regressed and known CIE values.

Figure 2 shows our color calibration results for three separate sets of ColorChecker Classic patches. For the first set, we used the entire set of 24 color tiles in the ColorChecker. For the second one, we took out the four patches that were commonly saturated by camera processing. For the third analysis, we took advantage of some a *priori* knowledge about built heritage and reduced the color gamut in an attempt to reduce the color errors. In general, asking for an optimized color matrix for a smaller color space makes it easier to get better results. This is supported by the observation that the trend we see is that larger values of a* and b* have, in general, large differences between the known and regressed values. More generally, several papers have also suggested using special purpose color targets with a smaller gamut chosen to match the objects being imaged [8, 9]. This is particularly relevant for collections such as hand- colored prints, books and maps with neutrals and pastels, for which the standard colorchecker makes little sense. In fact, the ColorChecker patches were chosen decades ago to match features of color film and provide bright colors for outdoor photography [11].

Figure 3 is a scatter plot of typical values taken from the literature for a* and b* – including cement and stone with and without biofilms. In the third data point in Fig. 2 the patches were limited to -50<b*<25, values picked using Fig. 3.

Using a ColorChecker as a calibration target, we are able to detect changes in L*~2 and b*~1.5. How do these values compare with what we may expect for typical color changes of built heritage in the field? Again, there is a significant journal literature using point colorimetry to look at built heritage and its components over time, some data spanning 5-10 years, and we can set a detection level with this data. Stone colorimetry gives us data on a variety of color measurements, including L*a*b*, ⊗E76 and other parameters [12, 13]. Other studies look at changes due to soiling and weathering [4, 5, 10, 14, 15, 16] and laboratory SO2 acid aging [17].

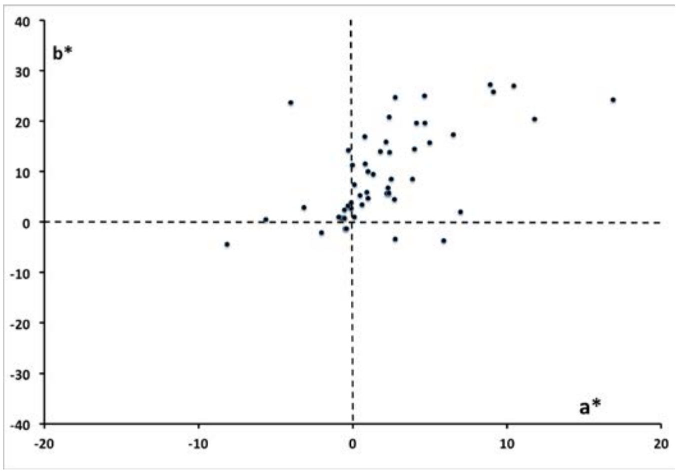

Fig. 3. Literature values for CIE L*a*b* values for built heritage. The values are point colorimetry and include cement, granite, limestone and marble, with and without biofilms.

In general, literature values are ⊗E76 ~[1-20] ~⊗L*[5-20], ⊗a* ~[3-10] and ⊗b* ~ [4-20]. Our conclusion is that the current accuracy of cell phone cameras is sufficient to be a useful tool for automated monitoring of change in built heritage. As mobile phones go to RAW images, where we can get access to the images before processing, things can only improve.

We show some L* and b* change maps from our “built heritage” potato slice. The time scale for this potato movie was about 10 hours. Figure 4 is the b* near the end of the time course and Fig. 5 is the corresponding change map for L*.

The advantage of citizen science for image acquisition is it really does not matter if most of the received images are not useable. We need only one usable image per day or week, depending on the time scale required. Photography is the world’s most popular hobby and we can reasonably assume that any tourist with a mobile phone has a camera, suggesting the great potential inherent in this method of turning “photos” into data.

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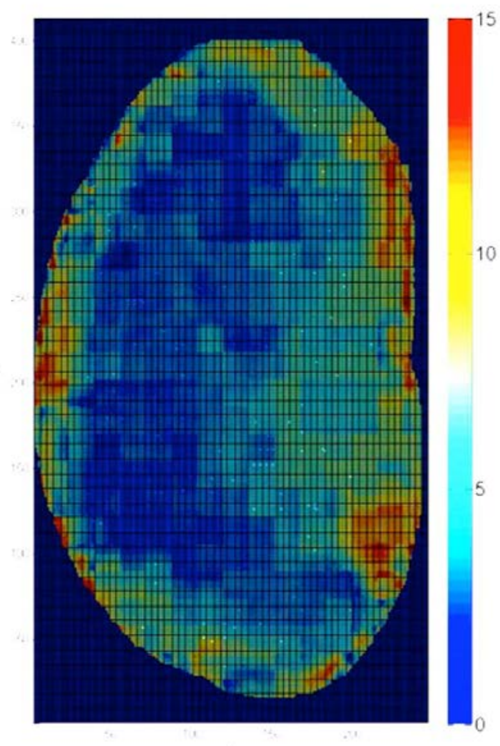

Fig. 4. A map of the changes in b* for a raw potato slice exposed to the air, slowly oxidizing, and changing color over time.

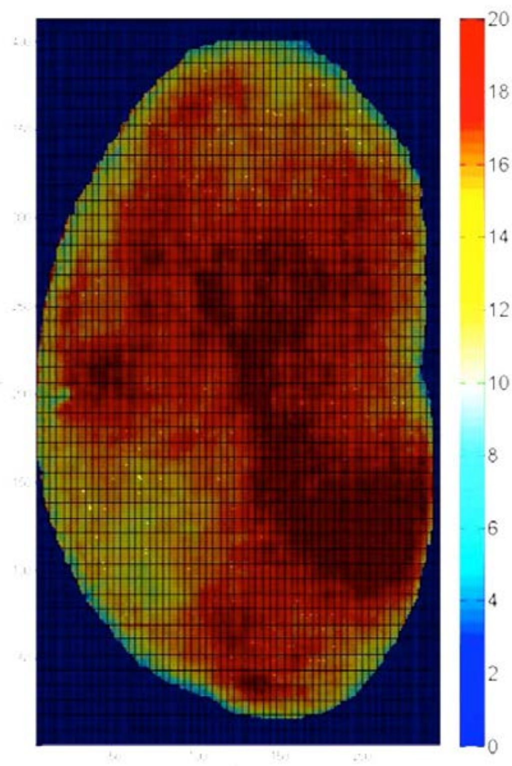

Fig. 5. Map of changes in L* corresponding to the same time point as in Fig. 4