Applying Image Quality in Cell-Phone Cameras: Lens Distortion

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ABSTRACT

This paper describes the framework used in one of the pilot studies run under the I3A CPIQ initiative to quantify overall image quality in cell-phone cameras. The framework is based on a multivariate formalism which tries to predict overall image quality from individual image quality attributes and was validated in a CPIQ pilot program. The pilot study focuses on image quality distortions introduced in the optical path of a cell-phone camera, which may or may not be corrected in the image processing path. The assumption is that the captured image used is JPEG compressed and the cell-phone camera is set to 'auto' mode. As the used framework requires that the individual attributes to be relatively perceptually orthogonal, in the pilot study, the attributes used are lens geometric distortion (LGD) and lateral chromatic aberrations (LCA). The goal of this paper is to present the framework of this pilot project starting with the definition of the individual attributes, up to their quantification in JNDs of quality, a requirement of the multivariate formalism, therefore both objective and subjective evaluations were used. A major distinction in the objective part from the 'DSC imaging world' is that the LCA/LGD distortions found in cell-phone cameras, rarely exhibit radial behavior, therefore a radial mapping/modeling cannot be used in this case.

Keywords: CPIQ, image quality, objective metric, subjective evaluation, photospace.

1. INTRODUCTION

The I3A Camera Phone Image Quality (CPIQ) Initiative Group is developing a multi-phase project that identifies key camera phone attributes that affect image quality, objective and subjective test methods to measure these attributes — ultimately resulting in a consumer-oriented rating system that will allow the public to choose the best camera phone for their particular needs. CPIQ's advertised goal is to remove poor image quality as the top barrier to the utilization and enjoyment of camera phone images by consumers, and to provide a standardized means of measuring and communicating image quality for vendors. Ultimately, the group will produce a complete set of image quality testing metrics and methodologies, enabling a consumer-oriented image quality rating system. CPIQ will enable manufacturers and carriers to make comparisons between capture devices handsets and components and to communicate a substantiated product quality rating to consumers through an Image Quality Testing and Performance Rating System.

Phase1 starts with an evaluation of existing best practices and industry standards, and identifies key measures/metrics in each of several critical CPIQ areas. The camera phone photospace is described and an initial subjective evaluation method for CPIQ is discussed. [1] presents an overview of this phase while a white paper is publicly available with detailed findings [2].
For Phase2, the following objectives were identified:

- Identify and define image quality metrics that affect overall image quality:
- Separate the objective and subjective components of these image quality metrics;
- Focus on the metrics that have direct impact on image quality performance;
- Develop and validate test methods for image quality metrics.

Ultimately the purpose of CPIQ is to develop a preliminary consumer oriented rating system to enable the clear communication of image quality to consumers by vendors and to promote adoption of standard measurement techniques and specifications.
To successfully reach CPIQ goal, the group decided to formulate a framework that could be applied to each image attribute identified. To validate this framework, several pilot programs were started, each addressing a specific image attribute. This paper describes such a framework that was used in one of the pilot programs.

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The purpose of the pilot program was to develop and validate a framework that could be used for different image quality attributes. The main assumption in the CPIQ initiative is image quality evaluation through multivariate formalism allows different image quality attributes to be estimated in isolation. Validating a common framework that would evaluate different image quality attributes represents a central task.

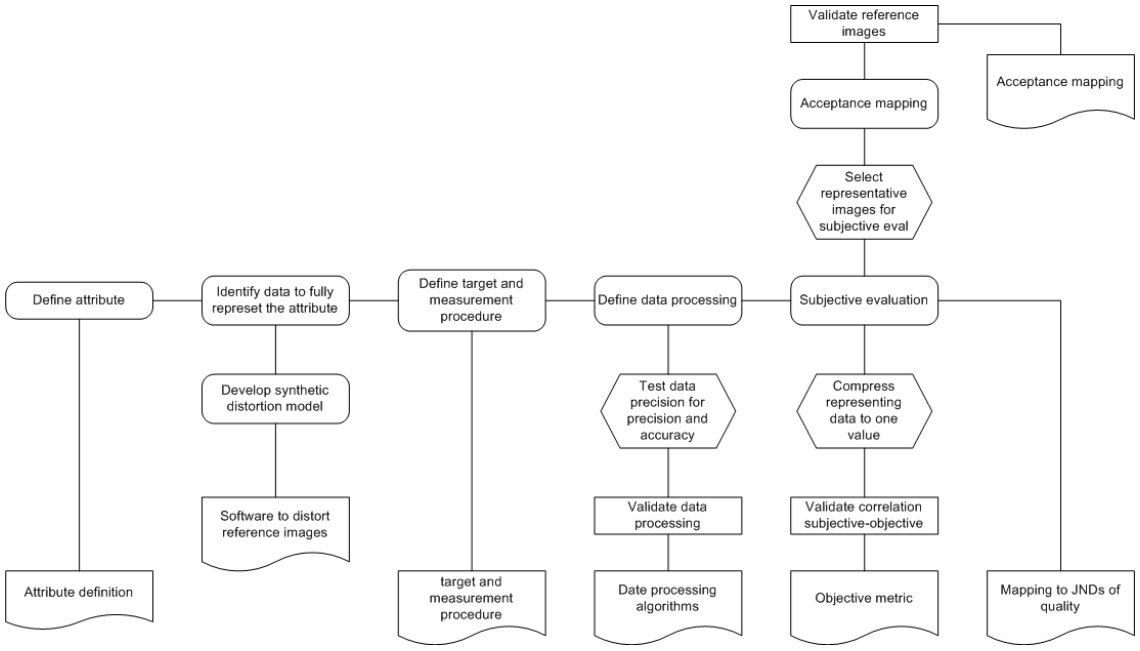


Figure 1 Image quality attribute development framework

Using the above framework, the target of the pilot program is to deliver the following:

- image attribute definition
- a software that would use a distortion model to apply different grades of distortion to reference images (group internal target)
- a measurement target and procedure
- data processing algorithms that satisfy both precision and accuracy
- reference images that are relevant to the attribute evaluated (group internal target)
- an objective metric that correlates with subjective evaluations of the attribute
- a mapping function between the objective metric and JNDs of quality

After each attribute gets developed, the envisioned framework for quantification of that specific attribute by the user is:

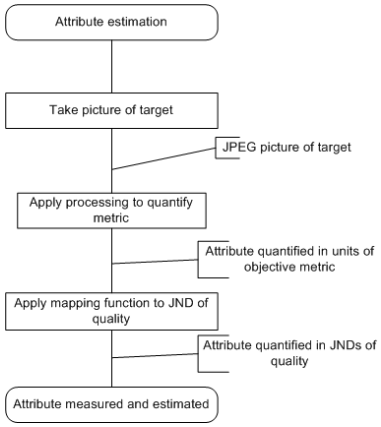


Figure 2 Image quality attribute evaluation framework

2. METHODOLOGY AND IMPLEMENTATION

2.1 Identification of individual attributes

As a requirement of multivariate formalism, first step was to find attributes that are relatively perceptually orthogonal that is to say attribute A and B are perceptually orthogonal if varying level of A does not affect perception of B. Since lens distortion is a field that is well known, the attributes were selected based on apriori knowledge and their orthogonality is intuitively plausible. The attributes selected were lateral chromatic aberrations and lens geometric distortions. It was a group decision to disregard longitudinal aberrations based on the complexity and implications of this attribute.

Lateral chromatic aberration is due to variation of magnification of the lens with the wavelength different wavelengths are focused at different positions in the focal plane). The major effect of lateral chromatic aberration is seen as color fringes around sharp edges in the image. Lateral chromatic aberration is usually, though not always, stronger on the borders of the field. Although lateral chromatic aberrations are radial symmetric for a single lens, this assumption may not hold for cameraphones optics, because of off-centering and tilt between the different optical elements and the sensor plane.

The effect of lens distortion is a non uniform magnification in the image field. The major effect of distortion is that straight lines in the scene are not straight in the image. Distortion is usually stronger on the border of the field. Two major types of distortion are usually observed:

- Barrel distortion where the lines are curved outward.
- Pincushion distortion where the lines are curved inward

Barrel distortion is visually less annoying than pincushion distortion. This classification is rough still, since camera modules can have distortions with no real definition shape.

2.2 Objective quantification

First step was to define a test target and the conditions under which the attributes would be evaluated. The major factors influencing the choice were:

- target should be very similar for both measurements.
- As the initial assumption in this project was that little or no control is available in terms of configuration of camera, the target should be able to offer consistent response with a camera operated in ‘auto’ mode. Specifically, the concern was on auto-exposure algorithms and auto-white balance algorithms that were assumed on. Under these assumptions, the target should be uniform in color and reflectance, pointing towards a ‘gray average’.
- target should allow measurements of distortions that are radial as well as non radial.

The conclusion was to choose a dot chart (black dots on white background) that would satisfy the above conditions.

2.2.1 Target definition and measurement conditions

The test chart contains black circular dots placed on a perfectly regular square grid on a uniform white background. It must be perfectly planar. It can be either a printed reflection test chart (in which case it is front illuminated) or a transparency test chart, if rear illuminated. Printed charts can be glued on glass for a better planarity. The size and the number of dots should depend on the resolution of the camera and the shooting distance. As a matter of fact, the resulting image should be such that

- the number of dots on a 4/3 image should be no less than 20x15 dots
- the diameter of each dot should be no less than 10 pixels

A suggestion is that the dots represent xx% of the total surface of the image (this is related to common behavior of auto-exposure algorithms).

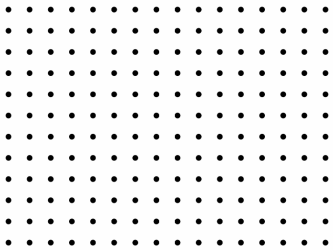


Figure 3 Dot Chart

2.2.2 Data extraction algorithms

Next step was to identify the data that would fully describe each attribute. Lateral chromatic aberration can be fully characterized using a 2D map of distances between dot centers in each color plane (R,G,B) in the distorted image. For each dot, the green channel is taken as the reference position, and the measurement reports a map of the distances between R and G, B and G, and R and B.

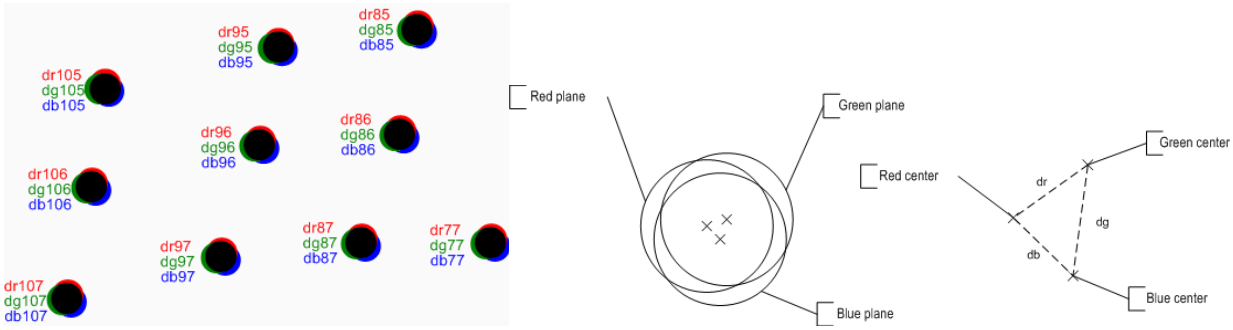


Figure 4 Lateral chromatic aberration measurement. The distortion is characterized by a 2D map of distances between dot centers in each color plane.

Using a similar approach, lens geometric distortion is fully described by a 2D map, giving the displacement from a point in an undistorted image to the point in the actual distorted image. Distortion is measured by comparing a regular square grid and the image of the same grid by the camera. The distance between the observed position of a point and its theoretical position is a measure of distortion.

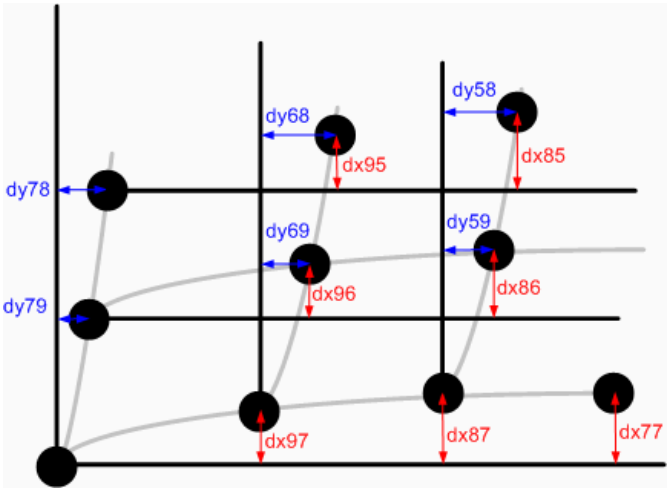


Figure 5 Geometric distortion measurement: the distortion is characterized by a 2D map giving the difference of position between the distorted image and the undistorted image

At this point, it became clear that the procedure used to extract dot centers from captured images would greatly influence the result, therefore the decision was to examine several approaches and to select one that would provide high accuracy in dot location, it would have relatively low complexity in implementation and also would be relatively insensitive to noise and other artifacts. To establish initial bounds of the required accuracy, an acceptance threshold of 0.5 pixels was considered, which is the limit below lateral chromatic aberration is considered unnoticeable. Therefore, the required accuracy for the dot centre extraction procedures was set at 0.2 pixels.

The procedures were evaluated under the following assumptions: Light exposure conditions are optimal, SNR is reasonable, camera to target is aligned, captured dot has a radius of ~20pixels, light uniformity is <10% over the target – those conditions are guaranteed through the calibration procedure recommended for measurement.

To evaluate, the following approach was used:

First, generate two synthetic images:

- one is a dot chart image, simulating the dot chart;

- the second is an image with the centre dots in the dot chart image, as both images are generated from a list of centers, there is only the quantization error in generation of circles;

Second, distort both images using the same procedure. Part of this pilot program was to create a software application that would distort input images with a predefined amount, simulating lens geometric distortion or lateral chromatic aberrations.

Third, extract from distorted centre chart picture the correct position of centers using the centre of mass (image is free of noise); this list of centers is the reference list towards the algorithm is benchmarked;



Figure 6 Algorithm evaluation: (a) distorted dot chart detail (b) distorted centre chart detail

Fourth, further distort the dot chart image to have evaluation conditions as close as possible to real world situations:

- Add a lens shading profile (we used a real profile to distort the image). This step will test the algorithm ability to deal with nonuniform surfaces;

- Blur the edges using a Gaussian blur to simulate a PSF degradation. This step will test the algorithm accuracy in locating dot boundary. Here, two levels of blur are used to observe also algorithm precision;

- Add noise and jpeg compression artifacts. This step will test algorithm robustness.

At this point, we were able to benchmark different dot location procedures, using the reference distorted image generated in the four steps above and the list of dot centers obtained in step three above. In this paper we'll present two such procedures as well as their performance. The first procedure comprises of two steps:

- Step1: Canny edge detection, as it generates single pixel thick and continuous edges, also it is tolerant to noise and light nonuniformity. Code is available on the internet, as this is a well known and used algorithm. We used default parameters.

- Step2: Linear least squares ellipse fitting (minimizing algebraic distance works good enough), as the result of step 1 is a continuous contour which is very close to an ellipse, performance difference between geometric fitting and algebraic fitting is below 0.1 pixels.

After applying the procedure to the reference image, in step1 the dots are isolated from the picture and in step 2 the centres are found as a result of the ellipse fitting, as illustrated in the detail in Figure 7.

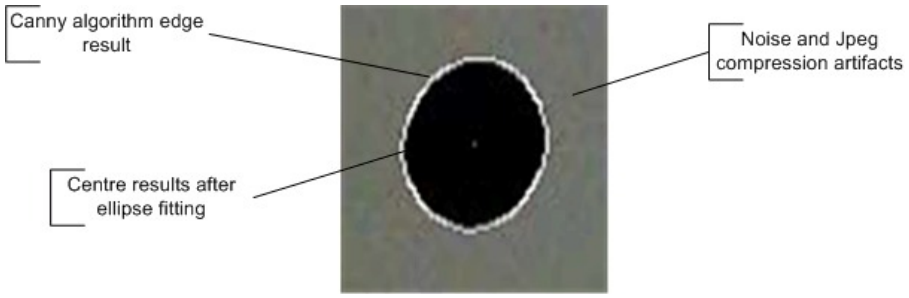


Figure 7 Dot centre location algorithm 1

To evaluate the precision of this algorithm, both reference images (with 2 different blur values) were used, and as it can be seen in Figure 8.

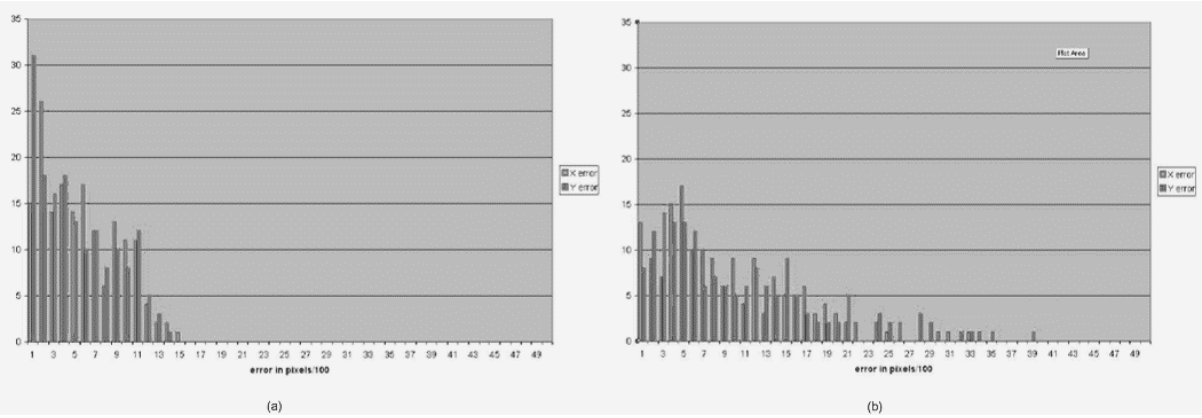


Figure 8 Dot location algorithm1 precision evaluation: (a) low blur reference image (b) high blur reference image

The second algorithm evaluated provides a better precision and was the one chosen. In this approach, the dot finding method consists of 2 distinct phases:

The first phase uses the Green channel information to determine the region of interest for each dot. Separating the dot finding into 2 steps allows each dot to pre-processing individually prior to determining the centre of mass. The following section describes the main ingredients of this algorithm:

As mentioned before, there are several issues which a robust centre finding method must manage.

- Lens shading (radial roll of in image intensity).
- 5% lighting illumination non-uniformity.
- The different intensities of the red, green and blue channels.
- Noise.

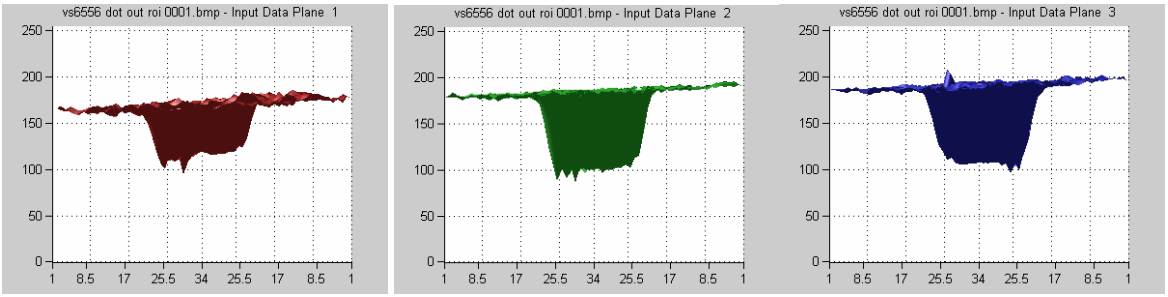


Figure 9 What a dot really looks like!

The simplest approach to find the dots is to binarize the image using an appropriately chosen threshold value. The presence of lens shading and color channel imbalance complicates matters. The result is as Figure 7 shows, the dots will have a variable depth and a variable tilt depending on where on the lens shading profile the dot is. The presence of diffraction based infra red filters in mobile phone camera modules results in the uncorrected red channel data having a faster color shading roll of than the other color channels. Management of the variable dot tilt and depths leads to an approach which individually pre-processes each dot on each color plane to correct the tilts and normalize the depths.

As the green channel is typically the strongest channel, it is used to find the region of interest of each dot. To find the region of interest for each dot the image is binarized. The effects of lens shading mean that the threshold for binarization cannot be based on the whole image. The solution to this is to calculate the threshold for an 8 x 8 grid of region of interests, each 1/8 of the image in size. The threshold used for the binarization is then the minimum of the thresholds for all of the regions of interest. This implementation uses Otsu's method to calculate the thresholds.

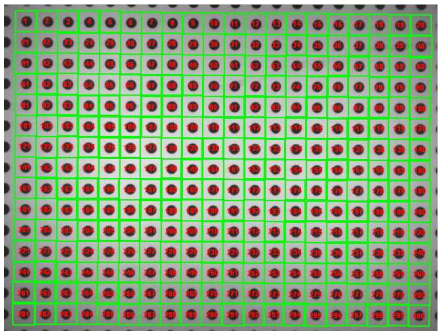


Figure 10 Region of Interest for Each Dot

The next step is to find the area, centroid and bounding box for each object (dot) in the binarized green plane data.

The 3 sets of checks below use the above information to filter out any unwanted objects. The first check is on the roundness of object. The ratio of the bounding box area to the area of the shape is used as a measure of roundness. For a circle the value should ideally be 4 / 3.14 = 1.27. The range of acceptance is 1.05 to 1.75

Typically there should be about 300 dots of similar diameter in the image, thus the median diameter of all the objects will represent the desired dot size. The assumption is that the 300 dots will be most common object in the binarized image. The diameter check looks to see if the diameter of and object is within 20% of the median For each object, a region of interest which is twice the width and twice the height of the object is generated. The final check is to reject any region of interest which touches the edge of the image. Only objects which pass of all of the above checks are considered to be valid dots.

The next step is Dot Region of Interest Processing:

The shape/profile of the dot is dependent on several factors (Noise, Lens Shading, Channel Sharpness, Spatial resolution, Matrix values). For each ROI on each colour plane the ROI data is processed using the following steps:

- Dot Pre-processing: The first step is to generate 2 masks - one for the background and a second for the dot. These masks are used to remove the unwanted regions of the ROI. The Otsu's gray threshold function is used to determine the

binarisation threshold then generate a binary mask using the above threshold. Next, define a disk filter (radius 3 pixels) this is then used to erode the masks for the background and dot to remove the edge transition data

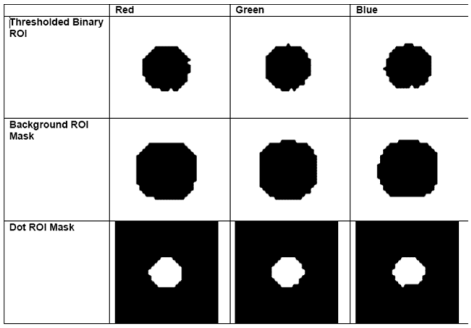


Figure 11 Mask generation

If lens shading is present then the profile of the dot can be tilted. The effects of lens shading are removed by using the white data (background) to calculate a best-fit linear plane (z = a*x + b*y + c). The ROI is normalised and has tilt removed at the same time by dividing by the best fit plane. As there is typically a 20x15 array of dots in the image and that lens shading is a low frequency variation the assumption is made that the lens shading for one dot can be approximated by a linear plane. Use background mask to remove any non background pixels.

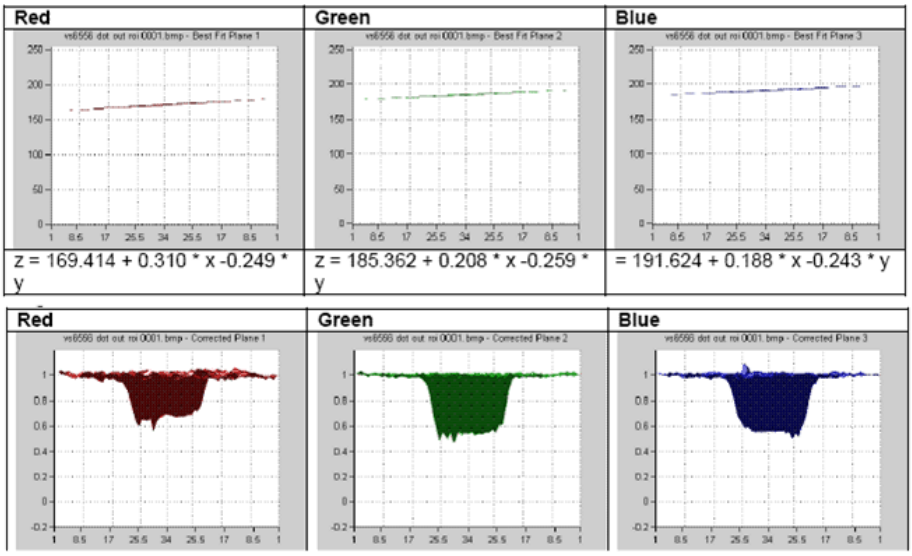


Figure 12 Best Fit Dot Tilts

Next, correct lens shading and normalize image data. After correcting the lens shading the average background level will be 1.0. The next step is to stretch the dot so that the average dot value is zero. The average dot value is mean of the pixels selected by the dot mask

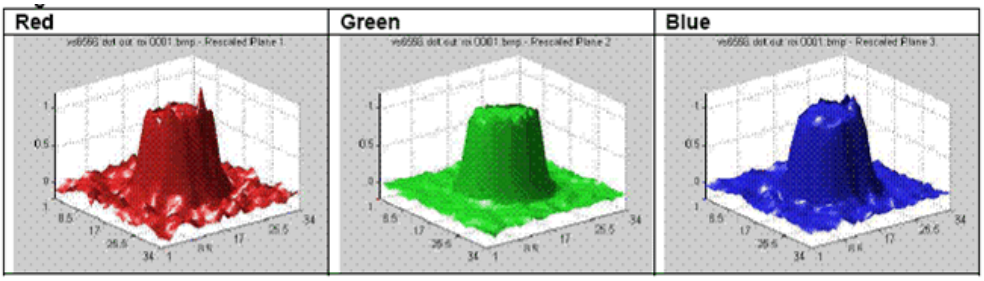


Figure 13 Dot data after inversion and re-scale

As the objective is to measure the lateral color shift in the image, any contributions due to either the background or non-uniformity in blackest region of the dot needs to be removed. The aim is to isolate the white to black transition ring around the dot. This is performed using the background and dot binary masks The background mask is used to force all of the pixels out size the dot to 0.0 and the dot mask is used to force the central dot pixels to 1.0. Define a smaller disk for eroding the image mask to generate the background mask - smaller as need to ensure that the background is removed. The larger erosion earlier was necessary to ensure that the black to white transition was completely remove for the finding the best fit plane.

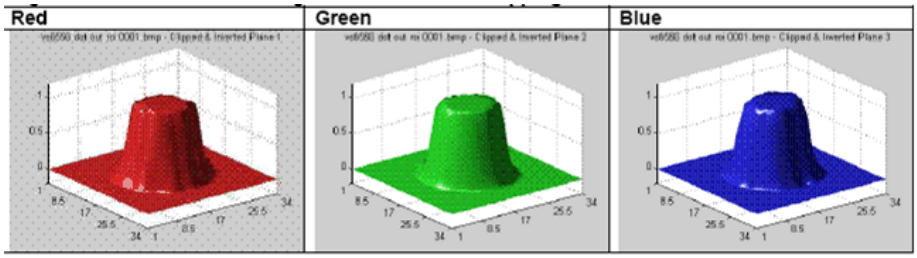
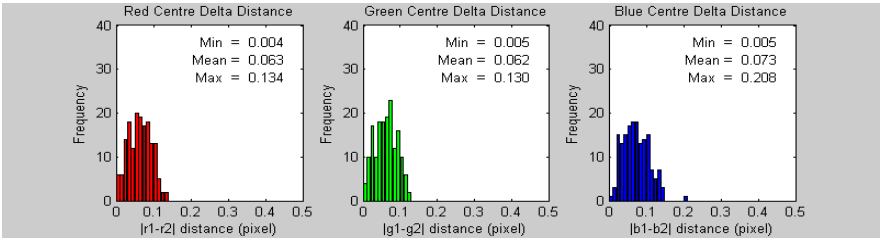


Figure 14 Dot data after background removal and clipping

And finally, the dot centre is obtained by calculating the centre of mass.

To evaluate the precision of this algorithm, both reference images (with 2 different blur values) were used, and as it can be seen in .results below the mean center error for both blur cases was < 0.1pixel. The max error was in the 0.2 to 0.26 pixel range. This is consistent with the 0.2pixel target mentioned earlier in this paper.

a) low blur image comparison



b) high blur image comparison

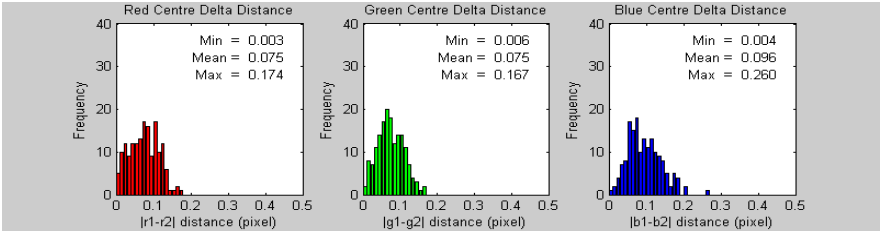


Figure 15 location algorithm2 precision evaluation: (a) low blur reference image (b) high blur reference image

2.3 Subjective evaluation

The subjective evaluation was conducted in a separate group under CPIQ, and as can be seen in the framework in Figure 1, the additional steps needed were:

- a software simulator was written to distort reference images with various degrees. The simulator was also used to explore different types of distortion: ie. for lens geometric distortion, the group evaluated pincushion, barrel, positive wave and negative wave geometric distortions. Each distorted image was paired with it's corresponding version of the distorted dot chart. This approach provided means of extracting the objective metric used to correlate the subjective measurement.

- a subjective acceptance test was conducted in order to establish the reference pictures that are relevant to the attribute investigated. For this study, a preliminary selection of pictures was made intuitively, and then based on the result, pictures were selected for the subjective mapping to JNDs of quality.
- selection of a single number metric that corresponds with the 2D maps described in 2.2.2. and correlates well with the result of subjective evaluation. The concern here is that some types of distortions (ie. positive wave or negative wave) are misrepresented by current existing metrics even though the distortion is quantifiable using the 2D maps (ie. TV distortion) but are identified in a subjective evaluation.

At the time of this paper the subjective evaluation was still underway, but the methodology used in this pilot program is presented in [4] according with the reference [7] and the methodology used to correlate an objective metric with the subjective evaluation is detailed in [5].

However, the results of the subjective acceptance show that, as expected, the images where the attribute degradation is visible the most are the best choices for subjective evaluation.

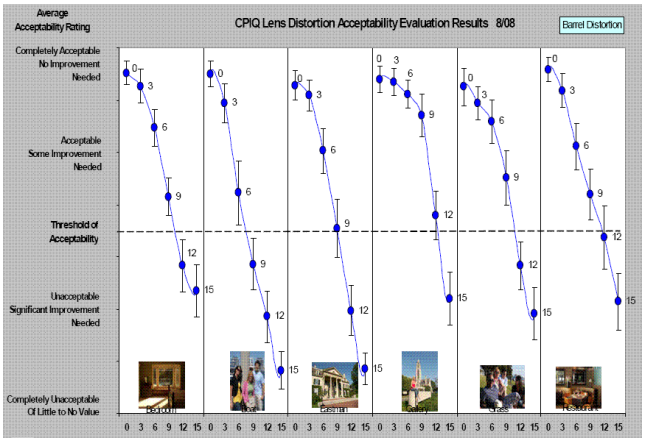


Figure 16 Subjective acceptance test results

3. CONCLUSIONS AND FUTURE WORK

The framework proposed in this paper was applied to different image attributes and proved to be usable. To proceed further towards a single number that would quantify the image quality of a cameraphone, a possible solution is using the multivariate formalism approach proposed in [6]. This approach offers the advantage of predicting the overall image quality of a image based on the impact that each image quality attribute would have in isolation. An essential aspect is that each individual attribute needs to be expressed in a common metric, which is defined as just noticeable differencies (JNDs) of quality. More precisely, the units are 50% JNDs as they correspond to a stimulus difference that is distinguished 50% of the time[3]. The distinction between JNDs (which is a measure of detectability of differences in appearance, regardless the cause) and JNDs of quality is quite important, as it is the distinction between JNDs of quality and JNDs of an individual attribute. A JNDs of quality refers to a particular image attribute, and quantifies a just noticeable difference in quality of only that attribute. It is also important to make the distinction that a JND is observed in quality of a particular attribute and a JND occurred because of a change of the attribute. This distinction is important because JNDs of quality offer the way of combining unrelated image quality attributes on the same scale. Or in other words JNDs of individual attributes are not necessarily equal to JNDs of quality, as equal detectability of different attributes does not imply equal impact on image quality[3].

Once that all the image quality attributes are identified and quantified in JNDs of quality according to the framework presented in Figure 1, a user can follow the path presented in Figure 2 to evaluate all those attributes. At this point, it is possible for the user to predict an overall number representative for image quality of the system evaluated, using the metric proposed in [3] which is a variable power Minkowski metric. The conditions that were used to generate this metric are (the conditions are intuitively plausible):

- contribution of an element equal to 0 does not change the final value, or the contribution to overall quality of an attribute that does not influence the quality is none.

- quality attributes that have small differences approximately sum.
- the attributes that manifest major degradation in quality will dominate (the suppression requirement). Intuitively, if a system has one major flaw and several minor, improving on the minor flaws won't help.

One remark is that while the result of computing the quality in this way gives an absolute value of quality regardless the use case, in some use cases some attributes can be ignored, and this could relax system constrains in terms of image quality, if the usage of the image system is for those use cases. To illustrate use case distribution a reference is made to photospace, a concept introduced in [6] and used in [2]. Photospace represents a statistical distribution of the frequency of picture taking as a function of illumination level and subject to camera distance, it also can be used to cluster various use cases of picture taking. One modality to incorporate this aspect in the metric used to estimate the image quality of a system is by weighting each attribute according to it's significance prior to its usage in the final metric. The weighting factor could be a masked area of photospace, the area relevant to that specific attribute. In case of lens geometric distortion a reasonable assumption is that in pictures captured indoor with a cameraphone, this attribute would have a lower significance. Based on this, the metric significance factor can be build. This factor can also be specific to different media presentations (ie. soft copy on a phone display or on a desktop display or hard copy). A subjective evaluation would confirm the distribution of metric significance in photospace. To weight the specific attribute, both photospace and the metric significance need to be normalized before multiplication to satisfy the following conditions:

- A flat photospace (equal probability distribution for all cases) should generate a unity weight, regardless of the metric significance, as all cases are equally relevant in terms of image quality;
- A flat metric significance (equal metric significance for all conditions) should generate a unity weight, regardless of the photospace distribution, as the attribute has equal significance to image quality regadless of conditions;
- After normalization, both photospace and metric significance should sum unity.

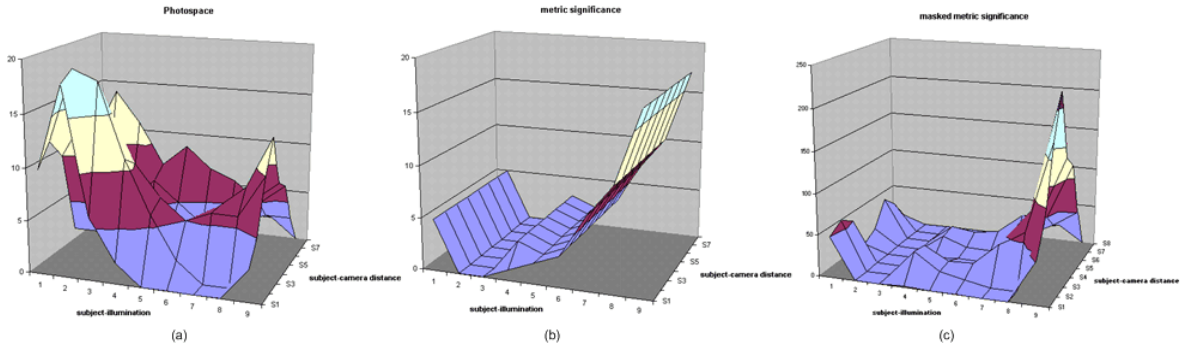


Figure 17 Attribute weighting based on photospace: (a) photospace distribution (b) attribute significance (c) attribute weighting factor

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