Incremental Color Quantization for Color-Vision-Deficient Observers Using Mobile Gaming Data

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The sizes of compressed images depend on their spatial resolution (number of pixels) and on their color resolution (number of color quantization levels). We introduce DaltonQuant, a new color quantization technique for image compression that cloud services can apply to images destined for a specific user with known color vision deficiencies. DaltonQuant improves compression in a user-specific but reversible manner thereby improving a user’s network bandwidth and data storage efficiency. DaltonQuant quantizes image data to account for user-specific color perception anomalies, using a new method for incremental color quantization based on a large corpus of color vision acuity data obtained from a popular mobile game. Servers that host images can revert DaltonQuant’s image re-quantization and compression when those images must be transmitted to a different user, making the technique practical to deploy on a large scale. We evaluate DaltonQuant’s compression performance on the Kodak PC reference image set and show that it improves compression by an additional 22%–29% over the state-of-the-art compressors TinyPNG and pngquant.

Images account for a large fraction of the data transmitted on the Internet (1). The sizes of these images, when compressed for storage and transmission, depend on their spatial resolution (number of pixels) and color resolution (number of color quantization levels). Existing image compression methods such as JPEG take into account human visual perception but assume an individual with normal color vision (2). Because compression algorithms can provide improved compression when they target a smaller number of distinguishable image colors, these algorithms could in principle use information about color vision deficiencies in observers to improve compression ratios. Approximately 8% of males and about 0.5% of females have color vision deficiencies (3–5). There is therefore a missed opportunity to harness information about color vision deficiencies to improve image compression and thereby to deliver improved network speeds and improved file storage efficiency.

Users of mobile devices spend over 70% of their time in applications such as web browsing and productivity, as opposed to gaming and multimedia (6). This observation, together with the personal usage model of mobile devices and the popularity of user-specific sites and web applications therefore makes it practical to transcode images on a server to deliver improved performance customized to individual users. Today, the fraction of almost 9% of mobile device owners with color vision deficiencies is missing out on the opportunity for improved network performance and reduced data storage requirements.

A. DaltonQuant: Higher compression rates by exploiting human color vision deficiencies. We introduce DaltonQuant, a new method for bespoke (user-specific) image compression. DaltonQuant uses incremental color quantization to improve image compression for observers with color vision deficiencies, reducing file sizes by up to 29% more than the state of the art. DaltonQuant builds a user-specific model for the color acuity of its target users. This model characterizes the colors which each target observer considers to be visually equivalent. We provide two different instantiations of DaltonQuant’s user-specific function for quantifying color equivalences, constructed from a dataset of 28 million color comparisons performed by humans on modern mobile displays. The dataset used was collected through the mobile game Specimen (7).

We use an analysis of the data collected by the Specimen game, across all its users, to identify individuals in the mobile game data who demonstrated game behavior consistent with color vision deficiencies. We use the data from 30 of these individuals to construct and evaluate the two concrete instantiations of our technique. We evaluate compression performance for these 30 individuals and show that DaltonQuant enables average improvements of 22%–29% file size reduction (i.e., a compression ratio of 1.28 – 1.40) over state-of-the-art compressors TinyPNG and pngquant for the Kodak PC image benchmark suite. DaltonQuant’s improvements result from undoing conservative decisions made by TinyPNG and pngquant, neither of which customize compression for observers with color vision deficiencies.

Color quantization reduces the number of colors used to represent an image and is a standard component of mainstream lossy image compression techniques (8–10). To avoid unacceptable image degradation, successful color quantization techniques replace a large set of existing colors with a smaller set that is perceived by most human observers to be similar to the original set. All existing color quantization techniques assume a viewer with normal color vision and no vision deficiencies when constructing their reduced color palette. Because an image compression algorithm may fail to combine colors that an observer would not easily distinguish, this assumption leads to a missed opportunity to provide improved compression ratios for color vision deficient observers.

B. The Specimen color matching data corpus. We use data from Specimen (7), an iOS game designed to explore color perception. Players of the Specimen game make color comparisons

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by selecting colored objects (specimens) and matching them against a target background color (Figure 1). Specimen anonymously records each of these color selection events using the Flurry (11) cloud analytics service. We use these anonymized per-user game histories, which constitute 28 million color comparisons as of the time of writing, to determine which color pairs are consistently confused by a specific player of the game. We then use these color pairs as candidates for color mergers in the final quantized color palette for image compression. We are working with the developers of the Specimen game to make both the data and our analysis tools publicly available.

Although we take advantage of Specimen’s large-scale dataset, DaltonQuant is independent of the source of data on which colors an observer consistently confuses. A mobile device user could choose to quantify their color resolution capabilities through alternative applications and DaltonQuant could use such data in its color quantization algorithms. As we show in our evaluation (Section C), the larger this color resolution dataset, the better the color merger decisions and compression that DaltonQuant can provide.

C. Contributions. In this work, we make the following contributions:

- **DaltonQuant** is the first compression method to purposefully exploit color vision deficiencies: We introduce a new image compression color quantizer, DaltonQuant. DaltonQuant is built on a user-specific function derived from mobile game data and a quantization algorithm that exploits properties of the user-specific function. The user-specific function quantifies colors which an observer will perceive to be equivalent (despite potential numeric differences)*. We implement two concrete instantiations of this function in DaltonQuant in order to evaluate our approach. To the best of our knowledge, this is the first compression approach explicitly targeting users with color vision deficiencies and taking advantage of their differentiated color perception to reduce file sizes.

- **DaltonQuant outperforms production compressors**: Our empirical evaluation of the DaltonQuant quantizer relative to popular PNG lossy quantizers shows that DaltonQuant on average yields an additional file size reduction of 22%–29%. We validate our color confusion quantification functions and show that our proposed color mergers conform to expectations.

1. Use Cases for Bespoke Image Compression

Online services, such as Google Photos (12), Flickr (13), Dropbox (14), and Microsoft OneDrive (15), provide cloud-based storage for user images. The file sizes for images affects storage requirements and transfer performance on all of these server platforms as well as the performance witnessed by mobile device clients. These services may use lossy compression to reduce file sizes, subject to an acceptable threshold on image quality degradation. For example, Flickr extensively explored lossy compression of image thumbnails: "The slight changes to image appearance went unnoticed by users, but user interactions with Flickr became much faster, especially for users with slow connections, while our storage footprint became much smaller." (16)

DaltonQuant produces a user-specific function to quantify color confusions for color–vision-deficient users. Compression algorithms can use this function to reduce image file size beyond what is possible with state-of-the-art lossy PNG compressors such as TinyPNG and pngquant. Any platform, such as Google Photos, Flickr, or a personal mobile device, which constructs user profiles and requires users to login to interact with their platform, can store the DaltonQuant color confusion quantification function and incorporate our technique to improve compression ratios.

For large-scale services, color–vision-deficient users can constitute a relatively large population. For example, as of May 2017 Google Photos had 500 million monthly active users (17). Given the accepted color blindness rates of 8% in males and 0.5% in females (4) and assuming equal gender proportions in the user population implies up to 21 million users of Google Photos could have their server-side data significantly compressed by our approach. In addition to the storage benefits, the image size reductions will translate directly into improved download speeds for these users.

In this work, we consider two main use cases for our compression approach, both of which assume a personalized datastore, whether cloud-based or local such as a personal mobile device:

- **Storage**: Compressed images, along with a de-quantization map, reduce the storage requirements for server-side images as well as for locally-stored images such as those on a mobile phone. The de-quantization map allows us to undo the incremental quantization for sharing the images with color–vision-normal individuals.

- **Transfer**: When constraints favor network transfer improvements over storage concerns, the original image can be stored and server-side compression performed prior to transfer to the color–vision-deficient user, thereby improving network performance.

2. Specimen: A Mobile Game About Color

Specimen (7) is an iOS game designed to allow users to explore color perception. It was purposefully designed to be fun to use to enable wider deployment. Its large user base and extensive game histories make it an appealing post-hoc data source for research exploring color perception. We use data from users of Specimen to construct user-specific functions which quantify colors that are numerically distinct but which a given user cannot distinguish visually. These functions allow us to systematically reduce (i.e., re-quantize) the color palette of a PNG image for compression while reducing the likelihood that the target observer will notice image quality degradation.

A timer, indicated by the dots on the periphery of the black circular region in Figure 1, places an upper bound on
the duration available for a color matching decision in the game. If a player of the game incorrectly selects a specimen, the game greys out the specimen, preventing it from being subsequently re-selected. If the correct specimen is selected, it disappears and increases the player’s score. Players advance through the game by correctly matching colors in this manner. As players advance through the game, the specimen and target colors presented to them by the game become increasingly difficult to distinguish (as observed by a color-vision-normal individual).

3. Identifying Color-Vision-Deficient Users

Color-vision-deficient individuals perceive parts of the visible spectrum differently from color-vision-normal individuals. These differences can make it harder for color-vision-deficient individuals to distinguish between two colors which color-vision-normal individuals would perceive as distinct. To identify users that are potentially color-vision-deficient, we define a heuristic based on decisions that we believe correlate with color-vision-deficient users playing Specimen.

Let \( i \) be the \( i \)th turn in the history of Specimen selections made by some user. Let \( Y_i \) be the target color in RGB space observed by the user during turn \( i \), and \( \hat{Y}_i \) be the specimen color in RGB space selected by that user in the same turn. Let \( \text{HUE} \) define a mapping from RGB to the Hue dimension in the Munsell Color System \([18]\). \( \text{LAB} \) define a mapping from RGB to CIE-LAB color space, and \( \text{DIST} \) compute Euclidean distance. Then we define the heuristic, \( H \), as:

\[
H = \frac{\beta}{n} \sum_{i} \text{HUE}(Y_i) \neq \text{HUE}(\hat{Y}_i) + \frac{(1 - \beta)}{n} \sum_{i} \text{DIST}(\text{LAB}(Y_i), \text{LAB}(\hat{Y}_i))
\]

[1]

The heuristic \( H \) is a weighted sum of: ① the fraction of color selections where the specimen \( (\hat{Y}_i) \) and target \( (Y_i) \) colors were in distinct Munsell hues; ② the average distance in the CIE-LAB color space, for all color selections. In our experiments we set the combining weight \( \beta \) to 0.5, as this balanced both portions of the heuristic and retrieved multiple individuals for evaluation.

We compute the score \( H \) for players of the Specimen game who have made at least 1000 color comparisons (i.e., specimen selections). We rank the users in descending order using \( H \) and select the top 30 users for evaluation. We refer to these users as possibly color vision deficient (PCVD) and refer to them as PCVD User 1 through PCVD User 30 in the following sections.

We validated the chosen users by visually inspecting a sample of their color confusions, focusing on color choices where the target and specimen colors correspond to different Munsell hue buckets. Figure 2 shows the color confusions for the highest ranking user based on the heuristic \( H \). The average Specimen selection accuracy across the 30 PCVD users is 80.9% (4.11% standard deviation) compared to the aggregate selection accuracy of 84% observed in the overall Specimen dataset. Figure 3 shows the selection accuracy in the Specimen game for each of the 30 individuals along with the aggregate selection accuracy in the dataset.
4. Color Quantization With PCVD Data

We present our approach for incremental image quantization based on the color selection data for PCVD Users extracted from the Specimen Game.

A. \( \delta_u \): A Bespoke Function for Quantifying Color Equivalence. We define a new user-specific function, \( \delta_u \), that is a continuous measure of color equivalence. We use this function to implement a color quantization algorithm that purposefully exploits a user’s inability to visually distinguish between certain pairs of colors that are numerically distinct. We first introduce an abstract definition for the function \( \delta_u \) below then we provide two possible concrete definitions in Section 4.D for evaluation of our approach.

We build a user’s \( \delta_u \) function from that user’s history of color confusions. The function takes two colors in the display’s native color space, usually the 24-bit RGB color space, and produces a real value that correlates with the user’s color confusions. A user’s \( \delta_u \) will score a pair of colors higher the more likely that pair is to be confused by the user. We use \( \delta_u \) to guide the search for colors that may be combined in an image palette during compression.

After constructing \( \delta_u \) for a given user, we can take an already quantized image and further reduce the image’s color palette.

B. Color Quantization Optimization Formulation. We formulate the problem of incremental quantization as an optimization problem over two goals: \( \theta \) increasing the number of pixels that are modified to a given color in the output image and \( \theta \) merging colors that are more likely to be perceived as equivalent by the user. The first goal serves as a proxy for the more complex goal of merging neighboring pixels, which lend themselves to better encodings. The second goal exploits color perception to remove the visible effects of more aggressive color mergers.

We define a function \( f_{\text{color}} \) that combines these two goals by using a weight, \( \alpha \). Let \( c_i \) stand for different colors in the image palette \( P \). Let \( \text{pixels}(c_i) \) count the number of pixels with color \( c_i \) in the original image.

\[
f_{\text{color}}(\alpha, c_i, c_j, \delta_u) = \\
\alpha \frac{\delta_u(c_i, c_j)}{\max_{c_k, c_l \in P} \delta_u(c_k, c_l)} + (1 - \alpha) \frac{\text{pixels}(c_i)}{\max_{c_k \in P} \text{pixels}(c_k)}.
\]

Let \( m \) be a function that maps colors in the original palette to a smaller palette, representing the quantization decisions. Let \( X_m \) be the set of colors that are removed from the palette based on the quantization decisions in \( m \). Our optimization goal is then defined as

\[
\argmax_m \sum_{c_i \in X_m} f_{\text{color}}(\alpha, c_i, m(c_i), \delta_u).
\]

We approximate the optimization solution by performing a greedy search over a list of candidate mergers \((c_i, c_j) | c_i, c_j \in P \land c_i \neq c_j \) sorted using the value of \( f_{\text{color}} \). We take candidate mergers until we have reduced the color palette size to a predefined target size provided by the user. We then unify merged colors transitively, so that if color \( c_1 \) is merged with \( c_2 \), and then \( c_2 \) is merged with \( c_3 \), any pixel in the image that was originally colored by \( c_1 \) will be colored by \( c_3 \) in the final version. Algorithm 1 summarizes this procedure.

**Algorithm 1** Incrementally quantizing the input palette \( P \) using \( \delta_u \) for a PCVD user given a target number of colors \( n \) in the output palette and a weight \( \alpha \) that combines the two optimization goals.

1: procedure QUANTIZE(\( \delta_u \), \( \alpha \), \( n \), image)
2: \( \text{mergers} \leftarrow \{} \)
3: \( \text{palette} \leftarrow \text{PALETTE(image)} \leftarrow \text{pre-quantized palette} \)
4: Sort \((c_i, c_j) \in P \times P\) based on \( f_{\text{color}}(\alpha, c_i, c_j, \delta_u) \)
5: Take top mergers such that \(|P \setminus \text{mergers}| = n\)
6: \( \text{mergers} \leftarrow \text{TRANSITIVE-CLOSURE(mergers)} \)
7: return \( \text{RECOLOR(image, mergers)} \)

C. Our Color Quantization Optimization is Reversible. When performing the color changes, we maintain a map from the original color to the pixel location for any pixels that are recolored. This map allows us to reconstruct the original, pre-quantized input image. The reconstructed pre-quantized image facilitates use cases such as image sharing with color-vision-normal individuals.

D. Defining \( \delta_u \): Transformation-based Metrics. We explore two different concrete definitions for \( \delta_u \). We provide these definitions as examples that satisfy our \( \delta_u \) abstract definition (presented previously in Section 4.A) and provide effective compression, as shown in our empirical results, which follow in Section 6. Other such definitions may exist.

A possible approach to modeling user color vision deficiencies is to perform a transformation that takes the standard CIE-LAB color space and produces a user-customized space. Prior work (19) has used a transformation-based approach to perform tasks such as user interface adaptation for color-vision-deficient users, though no prior work has built this transform using large-scale data collected through mobile devices as we do in DaltonQuant. To implement this approach, we first construct a matrix \( Y \) where each row corresponds to a target color, converted to CIE-LAB, observed by a Specimen user. Similarly, we construct \( \hat{Y} \) with the corresponding selected colors. We can then build a transformation \( f \) such that \( f(Y) \approx \hat{Y} \). Using \( f \), colors that were perceived as close by color-vision-deficient individuals, despite potentially large distances in CIE-LAB space, will be closer in the transformed space.

D.1. A Linear Transformation. We consider a simple linear transformation, represented as a matrix \( M_{3 \times 3} \) such that \( Y \hat{M} \approx \hat{Y} \). We minimize \( \| \hat{Y} - \hat{Y} \hat{M} \| \), which we can solve as a simple ordinary-least-squares problem.

D.2. A Non-Linear Transformation. Rather than construct a set of basis functions that include non-linear transformations over \( Y \), we can provide non-linearity by instantiating \( f \) to be an off-the-shelf neural network (20). The default implementation we used has a single hidden layer of 100 units and rectified linear unit (ReLU) activation functions (21).
We evaluate our approach on the Kodak PC Set (24), which consists of 24 pictures ranging from portraits to action shots and landscapes. We applied DaltonQuant using 30 different Specimen users as observers. We chose these 30 individuals as they had at least 1000 game observations and ranked highest according to our heuristic $H$ (Equation 1) for PCVD user identification. For additional analyses, such as the impact of different game histories, we take PCVD User 1 to be our prototypical color-vision-deficient user as their game history produced the highest value for $H$.

A. Methodology. We constructed a $\delta_u$ color equivalence function using each of the approaches described in Section 4.D for each of the 30 PCVD users presented previously in Section 3. Our experiments evaluate the additional compression provided by our PCVD-specific color quantization and our results demonstrate the benefits of our color quantization when compared to three other quantizers: pngquant, TinyPNG, and basic median-cut color quantization.

B. Our PCVD Color Quantization Outperforms State-of-the-Art CVD-Agnostic Quantization. Figure 4 presents the effects of our incremental PCVD color quantization on image 7 of the Kodak benchmark based on the $\delta_u$ functions constructed from PCVD User 1’s data. Both $\delta_u$ implementations produced smaller files than the pngquant output with the same palette size. With a target palette size of 230, the linear and non-linear transformation-based $\delta_u$ enable file size reductions of 13.9% and 15.4%, respectively, relative to the reference image. The file size reductions relative to TinyPNG are 16.6% and 17.7% for the linear and non-linear transformation-based $\delta_u$, respectively. We note
Again, we note that, when comparing to Table 1. Comparing mean file sizes for the reference systems and DaltonQuant. For image set under different palette sizes and using different initial reference image and DaltonQuant’s output for the Kodak PC reductions than the linear transformation produces more significant file size reductions for the non-linear variant.

Table 1. Comparing mean file sizes for the reference systems and DaltonQuant. Reference file sizes for Basic Median Cut and pngquant entries have the same palette size as DaltonQuant.

| Palette Size | Pre-Quantizer       | Reference (kB) | DaltonQuant (kB) |
|--------------|---------------------|----------------|------------------|
| 128          | Basic Median Cut    | 168.51         | 84.56            |
| 128          | pngquant            | 198.90         | 112.31           |
| 128          | TinyPNG             | 213.03         | 100.10           |
| 153          | Basic Median Cut    | 176.43         | 102.97           |
| 153          | pngquant            | 209.97         | 136.51           |
| 153          | TinyPNG             | 213.03         | 121.47           |
| 179          | Basic Median Cut    | 184.66         | 123.64           |
| 179          | pngquant            | 220.64         | 162.09           |
| 179          | TinyPNG             | 213.03         | 144.23           |
| 204          | Basic Median Cut    | 191.99         | 145.36           |
| 204          | pngquant            | 229.55         | 187.81           |
| 204          | TinyPNG             | 213.03         | 166.72           |
| 230          | Basic Median Cut    | 200.33         | 170.56           |
| 230          | pngquant            | 238.65         | 215.78           |
| 230          | TinyPNG             | 213.03         | 191.57           |

that, when comparing to TinyPNG, we cannot control the output palette size for the reference image.

Figure 5 presents the effects of our incremental PCVD color quantization on image 2 of the Kodak PC image benchmarks, based on the functions constructed from PCVD User 1’s data. Both implementations produced smaller files than the output with the same palette size. With a target palette size of 204, the linear and non-linear transformation-based enabled file size reductions of 26.4% and 22.2% relative to the reference image, respectively. The file size reductions relative to TinyPNG are 54.4% and 48.5% for the linear and non-linear transformation-base, respectively. Again, we note that, when comparing to TinyPNG, we cannot control the output palette size for the reference image. As expected, a smaller palette target size results in larger file size reductions.

As the number of colors for the output image decreases, the file size reductions achieved by DaltonQuant increases. In contrast to standard lossy compression, the artifacts that may arise are designed, by the formulation of the color equivalence quantization function $\delta_u$, to be less likely to be visible by PCVD users. We provide evidence supporting this assertion in Section 7.A.

Figure 6 shows a summary of incremental file size reductions achieved by applying $\delta_u$ color quantization at several output palette sizes. The data in Figure 6 are averages across the 30 PCVD users we selected for evaluation. The file size reductions in Figure 6 correspond to the percentage change in file size from the reference image to the image produced by DaltonQuant. A smaller palette size correlates with a larger amount of lossy compression. We also observe that the non-linear transformation $\delta_u$ produces more significant file size reductions than the linear transformation $\delta_u$.

Table 1 presents the average absolute file sizes for the reference image and DaltonQuant’s output for the Kodak PC image set under different palette sizes and using different initial quantizers. For pngquant and Basic Median-Cut entries, the reference image and DaltonQuant’s output have color palettes of the same size.

7. Analyzing Compression Factors

We present an analysis of various factors affecting the compression results for DaltonQuant. We explore the validity of the $\delta_u$ functions constructed, the impact of the multi-objective weighting factor, and the effect of varying a user’s color selection history length.

A. $\delta_u$: Data-Based Validation. The large-scale vision data collected through the Specimen game can enable novel post-hoc studies such as the re-quantization we explore in this work. At the same time, being data from a game rather than a purposefully-designed user study, the Specimen dataset presents an evaluation challenge when used in place of a user study. We present several analyses that address several of the challenges to using the Specimen dataset and which provide us with greater confidence in the validity of its use in studies such as ours.

A.1. Correlation with Game Behavior. As a first step towards a data-driven validation of our hypothesis that potential artifacts produced by incremental quantization are less likely to be perceived by a PCVD user, we analyze the color changes performed by our approach in all 24 pngquant pre-quantized Kodak images, when using the two $\delta_u$ definitions. In order to isolate the effect of $\delta_u$, we set the multi-objective weight ($\alpha$) to 1.0 such that we only perform color mergers as a function of the scoring provided by $\delta_u$.

We consider each pixel in an incrementally quantized image to be analogous to an observation in the Specimen game. For example, given a pixel of color $c$, we say this is equivalent to a Specimen game turn where the target background was $c$. We therefore consider pixels that are remapped to a different color $c' \neq c$ as analogous to incorrect selections in Specimen.

For a given user, we took the Specimen game accuracies per hue-bucket, and normalized these to $[0.0, 1.0]$. The normalization is done based on the minimum and maximum values observed for that user, as follows:

\[
\text{acc} = \frac{\text{MIN}(\text{acc})}{\text{MAX}(\text{acc}) - \text{MIN}(\text{acc})}
\]

where $\text{acc}$ corresponds to the user’s accuracy for a particular hue-bucket.

We then took the recolorings in our benchmark image set, aggregated them across images, computed hue-bucket accuracies and performed a similar normalization. We refer to these values as the Kodak-based accuracies. Figure 7 and Figure 8 show the results over the different palette sizes in our experiment when using the linear and non-linear versions of $\delta_u$, respectively. Each plot shows the Kodak accuracies on the x axis, and the Specimen accuracies on the y axis (points) together with a linear regression through these points (line). The $R^2$ value for this regression is given in the title of each plot. The shaded region around the regression line in the plot is the 95% confidence interval for the regression line. When considering a given image as opposed to the aggregated results, accuracies shift lower for images when more aggressively compressing (lower target number of colors). The accuracies observed across palette sizes have good correlation with observed hue-level accuracies for PCVD User 1 in Specimen with correlation coefficients between 65% and 80% for the linear $\delta_u$ and 37% and 66% for the non-linear variant.
DaltonQuant produces an image of 179,995 bytes. With the same palette size, pngquant’s image is 209,162. This is a compression ratio of 3.15 relative to the original image, and 1.16 relative to the pngquant image with the same palette size.

Fig. 4. The transformation-based $\delta_u$ implementations for PCVD user 1 with palette size of 230.

DaltonQuant produces an image of 177,013 bytes. With the same palette size, pngquant’s image is 209,162. This is a compression ratio of 3.19 relative to the original image, and 1.18 relative to the pngquant image with the same palette size.

Fig. 5. The transformation-based $\delta_u$ implementations for PCVD user 1 with palette size of 204.

Incremental quantization yields file size decreases between 22% and 29%, on average, compared to the reference image file sizes with the same palette size. Smaller palettes lead to larger file size decreases. Evaluation is done over the Kodak PC Set.
We compare normalized hue-level accuracies for PCVD User 1 based on the Specimen data and the recolorings of our benchmark images when using the linear definition for $\delta_u$. The line is a simple linear regression and the shaded region corresponds to a 95% confidence interval.

We compare normalized hue-level accuracies for PCVD User 1 based on the Specimen data and the recolorings of our benchmark images when using the non-linear definition for $\delta_u$. The line is a simple linear regression and the shaded region corresponds to a 95% confidence interval.
A.2. Reducing Distances in Transformed Space. We do not claim that our linear and non-linear transformations will fully predict the mapping from observed target colors to the set of colors perceived by the user. However, our definition of $\delta_u$ does not require prediction of pairs of colors, but rather the ranking of colors based on perceived color equivalence.

With this goal in mind, we evaluate the transformations by comparing the change in distance between colors in the transformed user space relative to the original CIE-LAB color space. For each user, we take all the color confusions observed in the Specimen data and split the data into a training and test set of observations. We remove from the test set any pair of colors in which either the target or the specimen color was observed in the training set. We then fit the transformation using the training set and evaluate (using the test set) the change in distance from the original color space to the transformed color space. This process is repeated with 10 different splits of the underlying data.

Table 2 shows the results for the top three ranked PCVD users in our evaluation set of 30 users. Both the linear and non-linear transformation successfully reduce the distance despite not observing the exact pairs of colors from the test data set. The reductions in distance ranged from 54% to 80%.

| PCVD User | Transformation | Mean Change Distance (+/- Std) |
|-----------|----------------|-------------------------------|
| 1         | Non-Linear     | -0.65 (+/-0.10)               |
| 1         | Linear         | -0.54 (+/-0.11)               |
| 2         | Non-Linear     | -0.80 (+/-0.08)               |
| 2         | Linear         | -0.73 (+/-0.12)               |
| 3         | Non-Linear     | -0.64 (+/-0.08)               |
| 3         | Linear         | -0.54 (+/-0.11)               |

Fig. 9. Average file size reduction for varying values of $\alpha$, the multi-objective weighting factor, across the 24 Kodak images. File size reductions are relative to the file size when $\alpha = 1$. Evaluation done with a target palette size of 204 colors using PCVD user 1’s non-linear transform-based $\delta_u$. Lower values of $\alpha$ produce, as expected, smaller files.

B. $\alpha$: Evaluation of the Multi-Objective Weighting Factor. The multi-objective weighting factor, $\alpha$ (Equation 2 and Equation 3), can impact the file size produced by our incremental quantization technique. Larger values of $\alpha$ favor the color equivalence measure produced by $\delta_u$ over the number of pixels associated with a particular color when selecting the color pairs to merge in the new palette. We present results for PCVD User 1, as their color selection history produced the highest heuristic score for PCVD identification (see Section 3 for details) and so we consider them a good example of the color vision deficient individual that could benefit from DaltonQuant.

Figure 9 shows the average file size reduction for Kodak PC Set images when incrementally quantized using the non-linear transform-based $\delta_u$ for PCVD User 1 with a target palette size of 204 colors. We compute the file size reduction relative to the file size for the same image when $\alpha = 1$. We see that the average file size decreases as expected when we reduce the value of $\alpha$. The output file size at $\alpha = 0$ is approximately 15% smaller than the output file size at $\alpha = 1$, on average across the Kodak benchmark set for PCVD User 1.

C. History Impact: Handling New Users. The length and variety of a user’s Specimen history is important for the construction of $\delta_u$. Given that Specimen is a game, some users may play it more frequently than others, producing histories of differing length and with different target and specimen color observations.

Users with longer histories of color selections have a better chance of observing a larger variety of colors within the Specimen game and will have more observations across confusions to better estimate the appropriate transformation for $\delta_u$. So a natural question is: How can we construct $\delta_u$ for a new user? As an initial step in this direction, we consider a related question: How do limited histories affect $\delta_u$?

With limited user histories, the impact on compression is driven by the extent to which the $\delta_u$ constructed from shorter histories produces a sorted list of color merger candidates in an image that differs significantly from the list that would be produced under the $\delta_u$ constructed from the complete user history. This effect is dependent on both $\delta_u$ and the specific image to be compressed, as well as the multi-objective weighting factor $\alpha$. To evaluate this potential impact, we consider the 24 Kodak images from our evaluation set and compared the changes in sorted merger candidates. For all comparisons we set $\alpha = 1$ to isolate the impact of the change in the user history.

For the non-linear $\delta_u$ we initialize the random state for model fitting to be the same value in all experiments to consistently compare against the same original sorted candidate list. We take the top 200 color merger candidates, as ranked by the $\delta_u$ with full history, and measure the rank of these candidates in the new sorted merger candidate list produced by the limited history $\delta_u$. We then compute Spearman’s rho over the two sets of rankings. Spearman’s rho is a common non-parametric measure for rank correlation (27).

Figure 10 and Figure 11 shows the Spearman’s rho results for PCVD User 1. The changes in ranking correlation are not uniform across images, as the candidate list produced directly depends on the original image palette. More complex transformations, such as the non-linear transformation, produce lower rank correlations with limited history. One simple solution for addressing this effect of limited user histories is to employ a simpler $\delta_u$ until the user accumulates enough...
Spearman's rho over top 200 color merger candidates

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technique accounts for human perception exclusively by consid-

al. (29) quantize an image's color palette and apply dithering

and maximize the distance across colors mapped to different

the distance of the original colors to the quantized palette

objective optimization formulation of incremental quantization,

Hu et al. (28) propose to address the quantization decision

8. Related Work

Hu et al. (28) propose to address the quantization decision

as a multi-objective optimization problem, which they solve

using an evolutionary approach. While we also propose a multi-

objective optimization formulation of incremental quantization,

our objectives differ from theirs. We aim to maximize the score

of the quantization map as a function of existing user-specific

confusions and the number of pixels associated with a color in

the original image. Their objective function aims to minimize

the distance of the original colors to the quantized palette and

maximize the distance across colors mapped to different

elements in the output palette.

Using a swarm-based optimization algorithm, Kubota et

el al. (29) quantize an image's color palette and apply dithering
to reduce the perceived degradation in image quality. Their

technique accounts for human perception exclusively by consid-
ering a weighted distance between the original and quantized

images. In contrast to their approach, we account for human

perception by empirically constructing a function that effec-
tively ranks colors that a user on a mobile display repeatedly

crossed while playing a game focused on color comparisons.

In order to produce re-colorings of images with fewer colors,

Rasche et al. (30) explore a technique that preserves image
details. Their target recoloring aims to preserve contrasts in

the original image and maintain luminance consistency. They
extend this technique to recolor images for observers with color

vision deficiencies. In contrast, DaltonQuant’s goal is not to
correct images for improved viewing by color-vision-deficient

users, but rather to exploit their perceptual differences to
produce a more aggressive compression that provides access
to improved storage and network communication. Similar to
this work, we start with a quantized image, which allows
our approach to scale to standard images with large palettes
and to preserve compression benefits for color-vision-normal
individuals when reverting incremental compression.

Perceptual image compression aims to improve compression
ratios while minimizing the impact on the perceived image
quality (31, 32). Recent work (33) proposed a new image
compression algorithm based on contrast sensitivity in the
human visual system. In contrast to our approach, existing
work has not targeted color-vision-deficient viewers.

Existing work in computation for color blind users has fo-
cused on accessibility. The authors in (19) present a system
to adapt a digital image for a color-vision-deficient individual.
They show that their transformation reduces the error in a
user study using Ishihara plates (23). The interface presented
relies on a color vision model that transfers stimulus across
RGB channels based on the type of color vision deficiency:
protanopia, deuteranopia, and tritanopia. DaltonQuant in-
stead relies on a history of color comparisons (collected through
a game for our implementation) to build a bespoke quantifica-
tion of color equivalence.

The technique presented in (34) adapts website content for
color-vision-deficient viewers. Their algorithm is customizable
and opens up personalized transformations. Similarly, our
work provides a technique that can be customized for a given
user. In contrast, our compression algorithm does not focus on
accessibility but instead on exploiting color vision deficiencies
for more efficient image representation.

Stanley-Marbell et al. (35) exploit the inherent approxima-
tion in human visual perception to transform image shapes
and colors to improve power dissipation on OLED displays.
We similarly exploit the human visual system, but focus on
a subset of the population (color-vision-deficient users) and
develop a novel approach that can reduce storage and improve
client communication for remote image services or mobile
devices.

9. Conclusion

This paper provides results for incremental quantization target-
ing color-vision-deficient users. We introduced a user-specific
function (δ, ), empirically constructed from mobile game data,
that quantifies perceived color equivalence for color-vision-
deficient individuals. We evaluated two possible implementa-
tions of δ, based on a dataset of 28 million color comparisons
collected through a mobile game. We produced implementa-
tions for 30 distinct users in our data and showed that we can
achieve incremental compression over state-of-the-art methods.
DaltonQuant, an implementation of our incremental quantization algorithm, on average reduced file sizes in our benchmark by 22% to 29% over outputs with the same palette size produced by popular compressors. Our quantization algorithm also produces a simple mapping of quantization decisions that recovers the original image, which allows standard viewing by color-vision-normal individuals.

Our analysis shows that our δ_u definitions correlate well with users’ game history and that the transformations they are based on successfully reduce the distance ratio for colors in the transformed space relative to the original color space. We explored the impact that limited user history has on the outputs of δ_u and show that the impact of limited history changes depending on the user and the image being quantized.

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