

Guetzli: Perceptually Guided JPEG Encoder

J. Alakuijala, R. Obryk*, O. Stoliarchuk, Z. Szabadka, L. Vandevenne,
and J. Wassenberg

Google Research Europe

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Abstract

Guetzli is a new JPEG encoder that aims to produce visually indistinguishable images at a lower bit-rate than other common JPEG encoders. It optimizes both the JPEG global quantization tables and the DCT coefficient values in each JPEG block using a closed-loop optimizer. Guetzli uses Butteraugli [1], our perceptual distance metric, as the source of feedback in its optimization process. We reach a 29-45% reduction in data size for a given perceptual distance, according to Butteraugli, in comparison to other compressors we tried. Guetzli's computation is currently extremely slow, which limits its applicability to compressing static content and serving as a proof-of-concept that we can achieve significant reductions in size by combining advanced psychovisual models with lossy compression techniques.

1 Introduction

Two thirds of the average web page size are spent on representations of images: JPEGs, GIFs and PNGs; almost half of the image requests are JPEGs, which tend to be much larger in byte size than PNGs and GIFs [2]. Given that many clients and particularly mobile clients are limited by transfer bandwidth, we can make websites load faster by reducing the size of JPEG images. Standard JPEG encoders allow trading off visual quality against size by tuning the *quality* parameter. In this work we look into how to reduce the size of JPEG images without impacting the perceived visual quality of the images.

*robryk@google.com

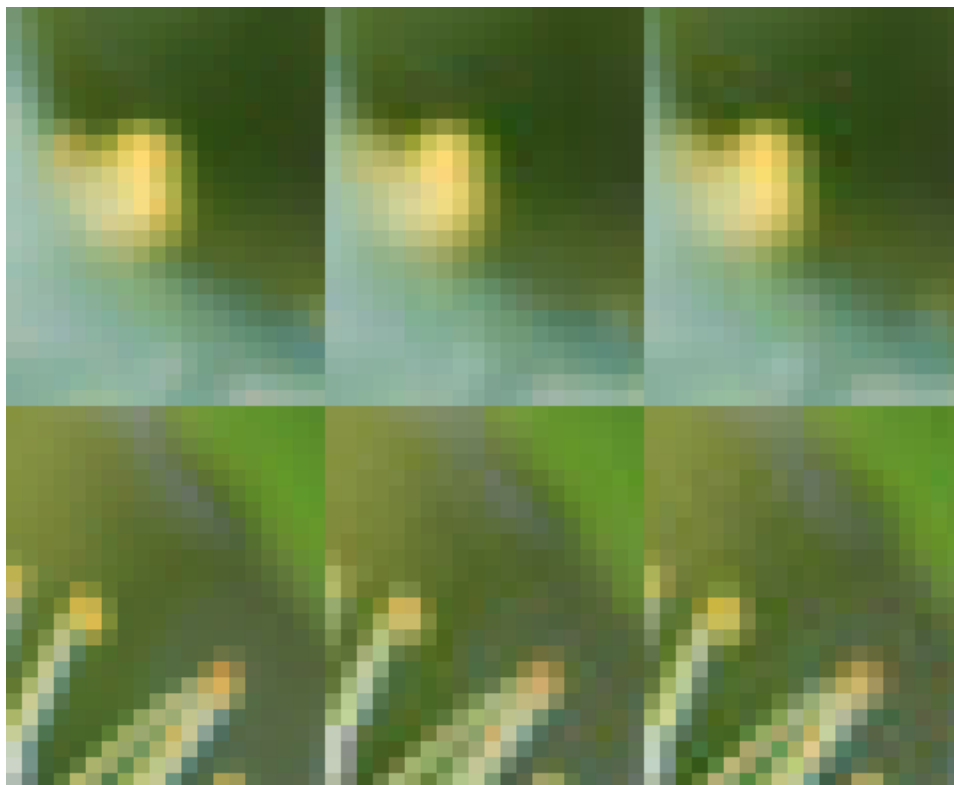


Figure 1: Visualization of two details in an image, original in the left column, Guetzli in the middle, libjpeg on the right. Libjpeg shows more ringing artifacts than Guetzli.

We visually observed that JPEGs encoded with existing encoders typically have inhomogeneous quality; they often exhibit disturbing artifacts only in a few places on the image. Often areas close to sharp edges or lines exhibit more visible artifacts (e.g. as in Fig. 1). This led us to think that further optimization is possible. We assume that when an encoder throws away information in an efficient manner, the JPEG image should start to degrade roughly evenly everywhere when the degradation starts to become visible. With Guetzli we attempt to cause a degradation in visual quality that is both more homogeneous and yields smaller JPEG images.

Guetzli is an open source JPEG encoder [3] that targets very high perceptual qualities. It performs a closed-loop optimization, with feedback provided by Butteraugli, our model of human vision [1]. Its goal is to find the smallest JPEG which cannot be distinguished from the original image

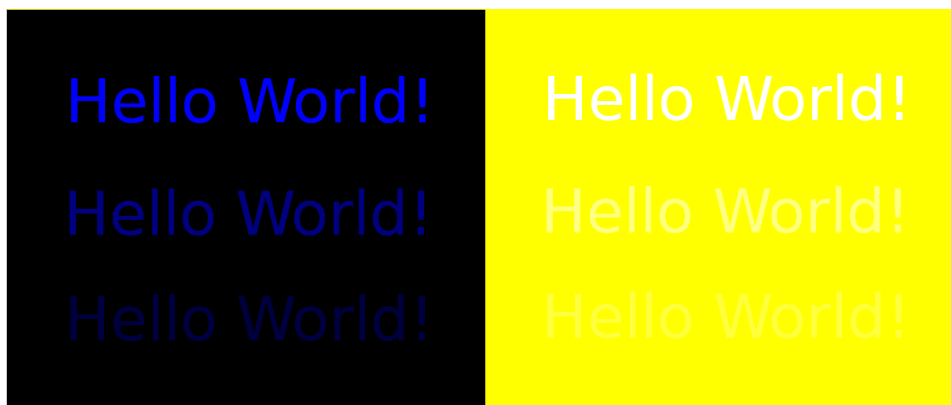


Figure 2: Experiment with additive blue channel signal on black and yellow backgrounds shows that blue changes are more difficult to see on the yellow background. Receptors (cones) at retina receive the colors in such a way that different components can mask changes in other components. Here, we show how changes in the low intensity blue component are masked by the high intensity levels in the red and green components. The same differences in blue are more difficult to see against a yellow background than against the black background. By using Butteraugli, Guetzli detects the lesser importance of blue on a yellow background and stores it with less accuracy.

by the human eye according to Butteraugli. Butteraugli takes into account three properties of vision that most JPEG encoders do not make use of. First, due to the overlap of sensitivity spectra of the cones, gamma correction should not be applied to every RGB channel separately. There is some relationship between e.g. amount of yellow light seen and sensitivity to blue light. Thus, changes in blue in the vicinity of yellow can be encoded less precisely (Fig. 2). YUV color spaces are defined as linear transformations of gamma-compressed RGB and thus are not powerful enough to model such phenomena. Second, the human eye has lower spatial resolution in blue than in red and green, and has next to no blue receptors in the high-resolution area of the retina. Thus, high frequency changes in blue can be encoded less precisely. Third, the visibility of fine structure in the image depends on the amount of visual activity in the vicinity. Thus, we can encode areas with large amount of visual noise less precisely (see example in Fig. 3). In Guetzli we model all these aspects in a way that leads to homogeneous loss in the image. We achieve this by guiding the encoder with Butteraugli, our psychovisual metric.



Figure 3: Landscape photo on the top with its visual mask shown on the bottom. Darker areas on the visual mask require less precise reproduction of details. Visual masking allows areas of the photograph to be stored at different accuracy, up to $6\times$ quantization difference for this image. According to this visual masking model, the sky needs to be compressed with less loss than the tree, lake and the buildings for a uniform experience of compression quality. Guetzli computes two separate masking models – one for low spatial frequency color modeling and one for high spatial frequency color modeling. Both models contain one mask for each dimension of the color space. The mask above is the high spatial frequency intensity mask.

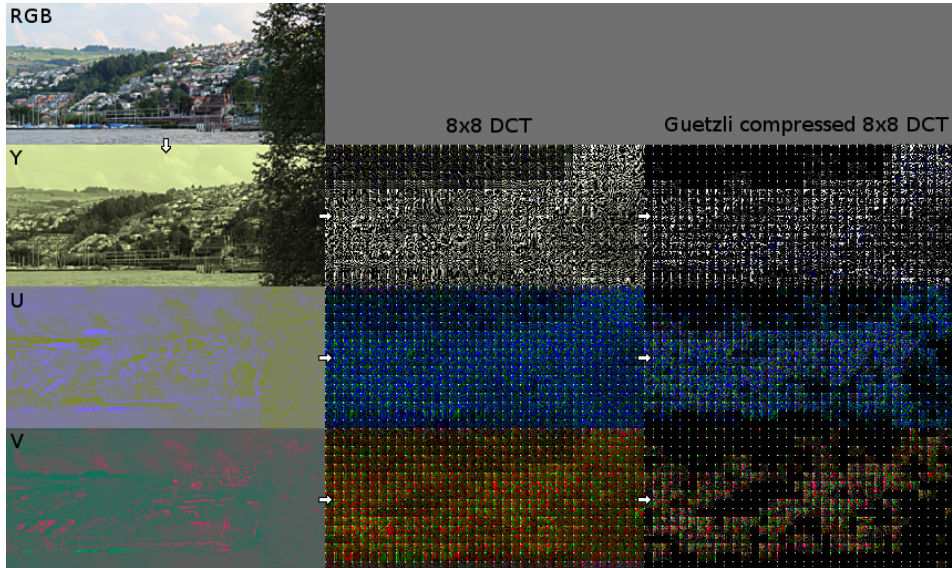


Figure 4: On the left hand, the landscape image on the top left hand corner is decomposed into three YUV planes in a JPEG. Every 8×8 square is transformed into DCT space, and the DCT values are quantized. In addition to quantizing, Guetzli zeroes out small values aggressively.

In this document we describe the optimization approaches we use and ones we have rejected, the iterative framework in which we apply those approaches, show the results in comparison to other JPEG encoders, and finally discuss their significance and further opportunities in image compression.

2 Methods

JPEG encoding consists of converting an image to YUV colorspace, breaking it up into blocks, transforming each block into frequency domain using DCT, quantizing the resulting coefficients and compressing them losslessly (Fig. 4). Guetzli looks for possibilities to reduce the size of the compressed representation without degrading the perceived visual quality. This section describes the methods used to achieve that.

2.1 Optimization opportunities

Guetzli produces a compliant JPEG file, so the optimizations that can be performed are limited strictly to the options available in this data format,

and even further limited to those that practical implementations support. We use three options provided by the format: we tune the global quantization tables, replace some DCT coefficients with zeroes and decide on using a mode in which chroma channels are downsampled (YUV420). We have decided not to use other options, either because we found them not to be beneficial, or because they cause other undesirable effects.

The first optimization opportunity we make use of is changing the (global) quantization tables to make the quantization coarser, which decreases the size of the image (by decreasing the magnitude of stored coefficients). This is similar to adjusting the quality parameter in a traditional JPEG encoder and causes distortions in the whole image.

The second opportunity involves direct modification of the coefficients. We replace some of the DCT coefficient values in each block with zeros. This modification distorts the visual appearance of the block in question. Zeros are RLE-encoded, so encoding a zero that occurs next to another zero costs virtually nothing. Thus, replacing a coefficient with a zero, when there is a neighbouring zero, reduces the encoded size by the size of that coefficient. Even if there is no neighbouring zero, encoding of a zero is virtually always shorter than of a non-zero value.

Lastly, we consider an encoding in YUV420 mode, where two out of three channels are downsampled by 2×2 . Unfortunately, YUV420's handling of an area of the image does not depend on the colors involved, and so it cannot capture effects such as the one in Fig. 2 (see Fig. 5 for the distortion that Guetzli applies to that image, which still cannot be seen). In many cases encoding an image in YUV420 mode, with no quantization, already causes a visible distortion. Thus, YUV420 is rarely useful in the quality range Guetzli targets.

We have also tried to get space savings by decreasing (but not zeroing out) absolute values of some coefficients. We hoped that by doing that we can decrease the size of a coefficient at a lower cost to the image quality. However, we could not find a way to beneficially combine it with zeroing out of the coefficients.

We have also tried to modify the coefficients to compensate for distortions caused by previously-mentioned optimizations. In order to find the compensating modifications, we've computed the derivative of an approximation of Butteraugli. Unfortunately, such modifications are usually smaller than quantization intervals, so they cannot be applied.

We chose to forego some options due to undesired effects they would have. We have chosen not to resample the image to a lower resolution. Using a lower spatial resolution is often a practical approach [4], but we left it out from



Figure 5: The top part of the figure shows how `imagemagick convert --subsample-factor 1x1` stores the blue channel of the image in Figure 2. One can observe that the blue channel, which is displayed here as a grayscale image, is stored with similar accuracy in the black area and in the yellow area.

The bottom part of the figure shows how Guetzli stores the blue channel of the image in Figure 2. Guetzli compromises the quality of low blue values more when the blue perception is masked by yellow, but stores it with higher accuracy when blue modulation is on the black background.

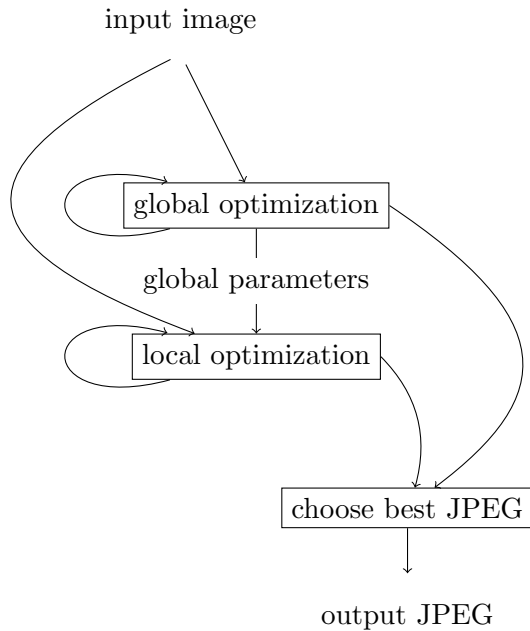


Figure 6: High-level overview of Guetzli operation. Guetzli first tunes global parameters and only then tunes local parameters, holding global parameters constant. During the whole course of tuning, candidate JPEGs are generated and the best one of them is chosen as the final output.

automated optimizations as we thought that it is somewhat orthogonal to the optimizations we do and can be implemented as a higher-level optimization. We have also decided to forego producing progressive JPEGs (we always produce sequential JPEGs). Although progressive JPEGs are 2-5% smaller, they are 17-200% slower to decode [5].

2.2 Optimization procedure

Guetzli uses an iterative optimization process. In order to make the problem simpler, the optimizer is not guided by file size. Instead, it is driven by the perceptual quality target alone. It aims to create a JPEG encoding with perceptual distance below a given threshold, as close to the threshold as possible. Each iteration produces a candidate output JPEG and, at the end, the best (not necessarily the last) one of them is selected. As mentioned previously, there are two adjustments we can make to the image: global ones (quantization table) and local ones (replacing coefficients with zeros). We

make them in order (Fig. 6): We first generate some number of proposals while tuning the global adjustments only. At the same time we decide on the final set of global adjustments. Then, while using the final set of global adjustments, we generate more proposals while tuning the local adjustments.

2.2.1 Global quantization table optimizations

Changes to the global quantization table impact the distortion of the whole image, usually in a different manner and with a different magnitude in different areas. A global quantization table is an array of 192 values. It is infeasible to perform anything that approximates an exhaustive search of that space. Instead, we have selected a set of predefined quantization tables and we use tables from that set only.

We try to find a quantization table in that set that will produce psychovisual distance not larger than $\alpha < 1$ times the desired maximal distance, when no other distortions are applied. The multiplication factor α was chosen experimentally to be 0.97, because this value yielded the smallest possible final output images. This small amount of slack allows for local optimizations to be done everywhere in the image.

2.2.2 Replacing individual coefficients with zeros

The JPEG format is extremely efficient in coding zero DCT coefficients, as it has a joint-entropy RLE approach to coding zeros together with DCT value prefixes. At the same time cost savings achievable by any other coefficient modification are much smaller. In practice, the more zeros we have, the smaller the resulting JPEG. Because of this, much of Guetzli's power depends on choosing the correct coefficients to zero out.

The choice of coefficients to zero out in far away blocks is essentially independent. However, the choice in nearby blocks has to be coordinated for two distinct reasons. Most obviously, the choices in both blocks that share an edge impact artifacts on that edge. In some cases it appears that introducing distortion on both sides of the edge causes the distortion to be less visible than if one of the blocks was unchanged. Secondly, the visual impact of many small artifacts in the same vicinity is additive.

In order to take these dependencies into account, we adjust the zeroing-out choice in all blocks simultaneously. Similarly to the global optimization phase, after each such adjustment we produce a candidate output image. We then compute the psychovisual distance between the original and candidate image and use it to decide on the next adjustment. Thus the feedback

loop, which uses a block-agnostic distance metric, provides the required coordination across nearby blocks.

In order to simplify the adjustments, we first determine the relative importance of coefficients in each block. This is done using a Butteraugli-derived heuristic. We then zero out some number of the least important coefficients in each block, according to our importance estimation. Before producing each subsequent candidate, we simply adjust the number of coefficients zeroed out so that the psychovisual error is below the threshold, as close as possible to the threshold, everywhere.

The zeroing out is by far the most powerful part of Guetzli. The reduction in size gained by using global and local optimization over just using local optimization (with some reasonable defaults for quantization tables) is only about 10%.

3 Results

We evaluate the Guetzli compressor and compare its performance at the same psychovisual distortion measured by Butteraugli. Butteraugli is the metric Guetzli optimizes for. Thus, this experiment tests Guetzli’s optimization abilities and, in itself, does not measure visual quality of the results. We will separately publish results of a human rating study that does compare visual quality, as perceived by humans.

Our image corpus ([6]) has been created by taking photos with a Canon EOS 600d camera, storing them using highest quality JPEG settings and downsampling the resulting images by 4×4 using Lanczos resampling, as implemented in GIMP. Some of the images had unsharp masking applied to them before the 4×4 resampling.

We have compared Guetzli to libjpeg and mozjpeg. We ran libjpeg and mozjpeg at quality 95, both with and without chroma downsampling. Additionally, for mozjpeg we have tried three values of the tune parameter (hvs-psnr, ssim and ms-ssim). The procedure we used to generate the results is detailed in Algorithm 1. The script used to implement that procedure can be found at <https://goo.gl/j0N21C>.

The results are summarized in Table 1. When comparing Guetzli to another compression algorithm at the same Butteraugli score, we can reach savings in size between of 29-45% savings in file size.

```

foreach other compressor, settings of other compressor do
  foreach image do
    Compress the image with the other compressor and measure
    the Butteraugli distance. Let us call this JPEG file the other
    compressor's JPEG.

    Compress the image with Guetzli targeting the Butteraugli
    distance measured in the previous step. Let us call this JPEG
    file the Guetzli JPEG.
  end
  Compute total size of other compressor's JPEGs.
  Compute total size of Guetzli JPEGs.
end

```

Algorithm 1: Comparison procedure

JPEG Encoder	Corpus size (bytes)		Savings
	Other encoder [†]	Guetzli [*]	
libjpeg -quality 95	5 197 681	2 952 897	-43.19%
libjpeg -sample 1x1 -quality 95	7 049 784	4 639 276	-34.19%
mozjpeg -quality 95	4 195 574	2 968 525	-29.25%
mozjpeg -sample 1x1 -quality 95	6 502 510	4 177 354	-35.76%
mozjpeg -quality 95 -tune-ssim	6 498 433	3 740 070	-42.45%
mozjpeg -sample 1x1 -quality 95 -tune-ssim	10 133 646	6 721 080	-33.68%
mozjpeg -quality 95 -tune-ms-ssim	4 122 235	2 775 398	-32.67%
mozjpeg -sample 1x1 -quality 95 -tune-ms-ssim	6 481 197	3 539 223	-45.39%
mozjpeg -quality 95 -baseline	4 375 890	2 968 554	-32.16%

Table 1: Comparison with other JPEG encoder at same Butteraugli distances.

[†]—Size of corpus compressed using the other encoder

^{*}—Size of corpus compressed with Guetzli at a quality that matches the other encoder's Butteraugli distance

4 Discussion

The JPEG format does not support spatially adaptive quantization – the quantization arrays are constant across the whole image. However, one can simulate this by creating more zeroes in areas with intended coarser quantization. Using this poor substitute for adaptiveness, we can get partial benefit out of exploiting visual masking phenomena (Fig. 4). We also use it to approximate nonuniform quantization in sRGB space. Format-level support for spatially adaptive quantization and different colorspace and/or value-based adaptive quantization would make these optimizations much simpler and more powerful.

It can be interesting to note that the effect in Fig. 3 is not captured in the JPEG format. The colorspace conversion from RGB to YUV is linear, and cannot reduce accuracy of blue in a certain color mixtures. Similarly, the change between YUV444 and YUV420 does not make a difference in the representation accuracy of blue in different color environments – the spatial reduction happens similarly in black and yellow backgrounds. This partially explains why YUV420 artifacts can be easily observable in images with color details and dark backgrounds.

The results presented in this paper do not provide direct evidence of perceived visual quality of results. We will separately publish results of a human rating study designed to provide such evidence.

Some of our results are apples to oranges comparison as we compare progressive JPEGs (mozjpeg) against sequential JPEGs (Guetzli). This puts Guetzli at a disadvantage, but in a Butteraugli-based measurement we still get overall savings for Guetzli (−29.95%). It is questionable whether the savings at transfer time are worth the slowdown at decoding time. We did not make an attempt at progressive encoding with Guetzli, so we cannot be sure how much smaller such images would be, but very likely we would get significant further size savings from progressive encoding.

As with zopfli [7], our similar effort for the gzip/deflate/PNG format, Guetzli is rather slow to encode. Getting a significant savings on static image content on popular image heavy websites can be a possible actual use case. Although Guetzli may be too slow for many practical uses, we hope that it can show direction for future image format design.

We have shown that even despite the deficiencies of the JPEG format, we can still greatly benefit from a complex psychovisual score such as Butteraugli, and the approach we have chosen produces significantly smaller (29-45%) file sizes at a given psychovisual error score. The same approach can be applied to a format that lacks these deficiencies (e.g. allows spatial adaptive

quantization, admits a richer description of quantization that can capture the effect from Fig. 3) at a much smaller computational cost and, likely, significantly larger compression ratio benefit.

References

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