

# Optimal Halftoning for Network-Based Imaging

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## Abstract

In this contribution, we introduce a multiple depth progressive representation for network-based still and moving images. A simple quantization algorithm associated with this representation provides optimal image quality. By optimum, we mean the best possible visual quality for a given volume of information under real life constraints such as physical (network load, connection speed), psychological (viewer's expectation and patience), or legal constraints (access privileges). A special variant of the algorithm, multi-depth coherent error diffusion, addresses a specific problem of temporal coherence between frames in moving images. The output produced with our algorithm is visually pleasant because its Fourier spectrum is close to the “blue noise”.

**Keywords:** Network-based Imaging, Image Quality, Halftoning, Error-Diffusion, Multiple Resolution

## 1 Introduction

What is the optimal representation for network-based imaging? At first glance, the answer seems obvious: the representation that provides the best visual quality for a given volume of information. But what is the reality of network-based imaging? During peak hours, a typical web page like that in Fig 1 may appear for long seconds while loading before it switches to normal resolution. A logical argument behind this obviously insufficient representation is the following: it's better than nothing, patience, in a short instant the image will be better. The problem is that very often the viewer has no patience to wait for this better image and will skip the page, thereby missing some essential information. A typical user connected to the network via a modem line faces the dilemma between



Fig 1 We are so accustomed to see such a web page that sometimes we don't even notice that something is wrong with it.

switching all images off, and endless wait for high-resolution images.

We claim that there is no fatality to rely on inappropriate image format or representation. In our eyes, the notion of optimum for network-based imaging should contain human factors like the viewer's patience or expectations, coupled with physical factors, such as the network load, connection speed, visualization device characteristics, etc. In many cases, access privilege considerations may play an important role as well. For example, the same image representation may contain all the needed information for different types of image consumers having different access privileges, ranging from previewing to full privileges.

In this contribution, we propose a multiple depth progressive quantization scheme for network-based still and moving images. This representation tends to satisfy some of the human/physical/legal factors mentioned above. Namely, it provides the best possible quality at each stage of a multi-stage visualization process, starting from the very first (rough) depth level. Our representation is progressive: every additional depth level enriches the previous image, without sending any redundant information.

This image representation is well-suited for the client-server network architecture where a unique version of the image/sequence is available from the server. The consumer requests the image/sequence of appropriate depth according to available connection bandwidth, access privileges, and perhaps according to his/her patience at this particular moment. One may imagine a scenario in which the uploading depth varies dynamically, following the network resource availability. The details of the multiple depth quantization are presented in section 2.

In section 3, we complete the multiple depth representation by an additional feature intended to increase temporal coherence in row image sequences: multi-depth coherent error-diffusion.

The proposed quantization schemes rely on any available error-diffusion algorithm such as, for example, the universally used Floyd-Steinberg algorithm.

## 2 Multiple depth image quantization

Let us introduce multiple depth image quantization in comparison to alternative progressive image quantization schemes, as illustrated in Fig 3. It shows the three simplest progressive image representations: straightforward  $n$ -bit quantization (left column), multi-resolution block-based representation (middle column), and the multiple depth representation (right column). Each horizontal row contains the same volume of information. In each vertical sequence, the image is progressively enriched by adding only the modifier with respect to the previous stage. For example, in the  $n$ -bit quantization (left column), consecutive bits starting from the most significant one are used for progressive enrichment of the image. In our multiple depth quantization scheme, we combine usage of the most significant bits of information, as in the left column with the spatial distribution (error-diffusion). The point here is that every consecutive image in the progression (vertical column) reuses the information contained in the previous image of the progression, generating a set of modifiers only.

The comparison between the three quantification schemes shows a clear advantage of the third one. In fact, already the second image of the progression (2 bits/pix per color) shows a pretty decent quality, whereas the third one (3 bits/pix per color) may be considered as satisfactory for most interactive visualization tasks.

Although the main idea of combination of straightforward  $n$ -bit quantization with error-diffusion appears trivial, its implementation may clash with other simple principles which make its realization almost impossible. Let us explain this. Imagine that we would like to produce two consecutive representations for a flat gray patch of intensity  $15/16$  (light gray), using 1- and 2-bits depths by applying error-diffusion, as shown in Fig 2. Everything is straightforward with the 1-bit representation. But, when we examine the 2-bits representation, there are two possibilities. For every pixel, we may decide what will be its 2-bit representation value based on the 1-bit representation value: 1-bit zeros become 2-bit  $0/3$  or  $1/3$ , 1-bit ones become 2-bit  $2/3$  or  $3/3$ . As the 1-bit image was composed of 0 (black) and 1 (white) pixels, the resulting 2-bit image will necessarily contain  $1/3$ ,  $2/3$  and  $3/3$ , as shown in Fig 2b. Such an image is visually disturbing and unpleasant. Please note that this harmful phenomenon is not specific to highlights or to the 1- to 2-bit quantization step: it happens through entire dynamic range of the image, at every  $n$ - to  $(n+1)$ -bit quantization step. Another possibility would be to perform, when producing the 2-bit representation, an independent 2-bit error-diffusion. This produces a much better, visually pleasant image as

shown in Fig 2c. The problem with this independent error-diffusion is that the 2-bits image does not use any information from the 1-bit representation, thus increasing the volume of information needed for transmission of both of them. Consequently, we lose all advantages of progressive enrichment.

Is it possible to get an image that resembles the image in Fig 2c while still retaining the advantages of progressive enrichment? In the rest of this section, we shall show a method, which brings a positive answer to this question.

Let us suppose that we already have an image  $B^n(x,y)$ , in  $n$ -bit representation. Our task is to find a simple function  $f$  that would provide  $(n+1)$ -bit representation  $B^{n+1}=f(B^n)$ . We propose to use a modified error-diffusion algorithm as follows:

- the image is processed pixel-by-pixel, following a serpentine path (e.g. left-to-right for each even line and right-to-left for each odd line). For each pixel  $(x,y)$ , we perform the following operations:
- O1• we calculate a predictor  $P^{n+1}(x,y)=(\sum N_8)\gg 3$ , where  $N_8$  are 8-connected neighbors of the pixel  $B^n(x,y)$  in the  $n$ -bit representation, and  $\gg$  denotes a binary shift. Neighbors lying outside the image are considered as equal to on-border ones;
- O2• the predictor  $P^{n+1}(x,y)$  defines two closest quantization levels  $Q^{upper}$  and  $Q^{lower}$ , belonging to the set  $\{0, 1/(2^{n+1}-1), 2/(2^{n+1}-1), \dots, 1\}$  of available quantization levels;
- O3• a threshold  $T(x,y)$  is placed half-way between  $Q^{upper}$  and  $Q^{lower}$ ;
- O4• an error-diffusion is performed: the input signal at point  $(x,y)$  is compared to the threshold  $T(x,y)$  thus generating the resulting output signal  $R(x,y)$  which is necessarily either  $Q^{upper}$  or  $Q^{lower}$ . The quantization error between the input and output signals is distributed to unprocessed neighbors. Any error-diffusion scheme may be applied at this point.

The calculations presented above can be hardware-assisted. For example, the calculation of predictor by doing binary shift  $(\sum N_8)\gg 3$  can be implemented on a simple specialized hardware.

As we have seen,  $n$ -levels depth image representation needs  $n$  consecutive passes of error diffusion. This may be considered as a drawback. Nevertheless, the evolution of computer resources during the last years has shown a clear tendency of increasing computational speed while network bandwidth does not evolve at the same pace. In this context, we expect that the benefit of compactness offered by our multiple depth representation largely justifies additional *local* computational resources.

### 3 Multi-depth coherent error-diffusion

The multiple depth representation presented in the previous section is perfectly applicable on both still and moving images. In the case of moving images, an additional temporal coherence can be achieved thanks to a very simple modification to the basic algorithm. The threshold calculated according to operation O3 is readjusted according to the quantification value of the same pixel in the previous frame:

- if the resulting quantization level  $R(x,y)$  of the corresponding pixel in the previous frame is equal to actual  $Q^{upper}$  (operations O2 to O4 of the previous section), then we lower the threshold  $T(x,y)$  for the current frame by amount  $\delta$ ;
- if  $R(x,y)$  is equal to actual  $Q^{lower}$ , we raise the threshold  $T(x,y)$  by amount  $\delta$ ;
- otherwise, we maintain  $T(x,y)$  as defined in O3 of the previous section.

In other words, if there is a correlation between the quantization results obtained for the previous frame and some of the quantization candidates for the current frame at the same depth level, we give more chances to this candidate. If this reinforcement produces wrong output, as compared to the unmodified algorithm, this error will be readjusted by the pixel's immediate neighbors, which is one of inherent benefits of error-diffusion. Fortunately, such an error happens rarely, only where there is no coherence between consecutive frames. In most cases, our algorithm empha-

sizes real inter-frame coherence, and retains it in the multiple depth representation.

The benefits of the proposed method are twofold: on one hand, the quantized images become naturally coherent, despite their “irregular” appearance due to error diffusion. On the other hand, this method tends to stabilize the sequences of images, suppressing random or thermal noise proper to many input devices such as LCD captors.

The only parameter  $\delta$  used in the coherent multiple level error-diffusion governs the degree of temporal coherence induced by the algorithm. Too small  $\delta$  (less than 10% of difference between  $Q^{upper}$  and  $Q^{lower}$ ) will produce negligible effect whereas too big  $\delta$  (more than 30% of difference between  $Q^{upper}$  and  $Q^{lower}$ ) may generate some ghosting effect. The results produced with  $\delta$  set to 20% of difference between  $Q^{upper}$  and  $Q^{lower}$ .

## 4 Discussion and Conclusions

We have presented a set of simple techniques intended to improve the quality of network-based imaging during the quantization phase. As the quality improvements meet viewer’s expectations, network physical constraints, and eventually other considerations including access privileges in a complex broadcast architecture, we consider that our representation approaches an optimal representation for network-based imaging.

Some important issues such as compression, have been left out of this article. We have tried various traditional compression algorithms such as the modified Hoffman’s, LZW or run-length compression schemes, and we found that this issue deserves further exploration. In fact, we are convinced that the best compression performance can be achieved if we take into account the specific features of presented quantifications schemes. The work in this direction is under way.

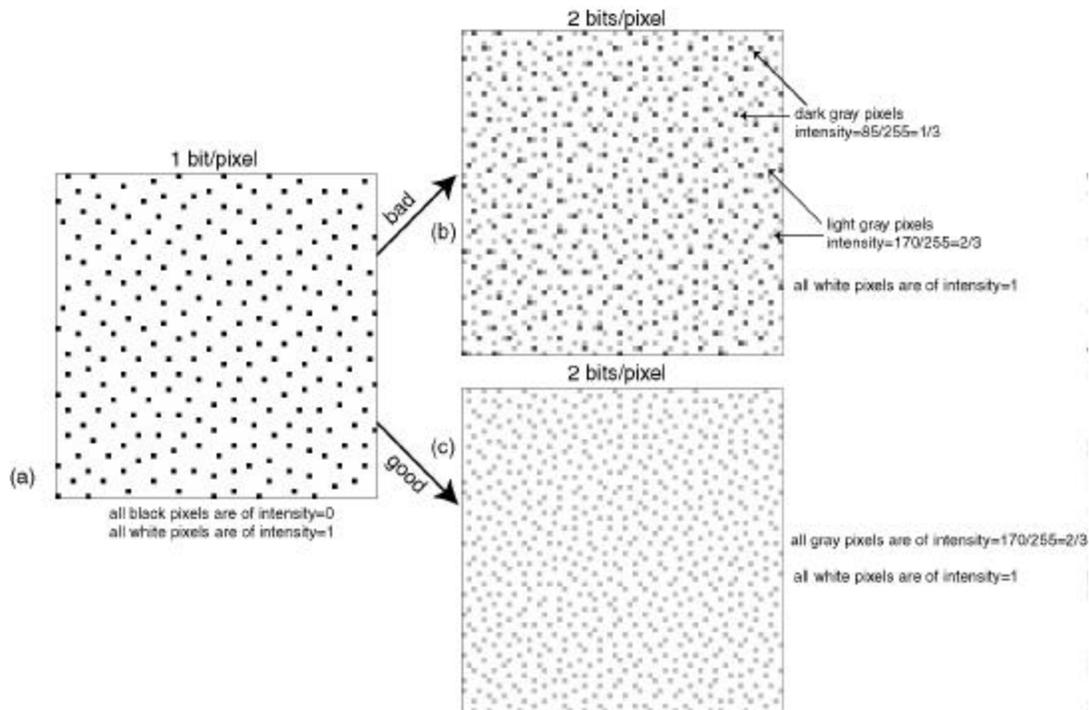
Implementation of the multiple depth quantization scheme in web browsers or similar network-based imaging applications may provide immediate benefit for many users and image providers, increasing image quality and decreasing transmission cost.

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**Fig 2** A light gray patch of intensity 15/16, quantized using 1-bit representation (left) and two alternative 2-bit representations (right).

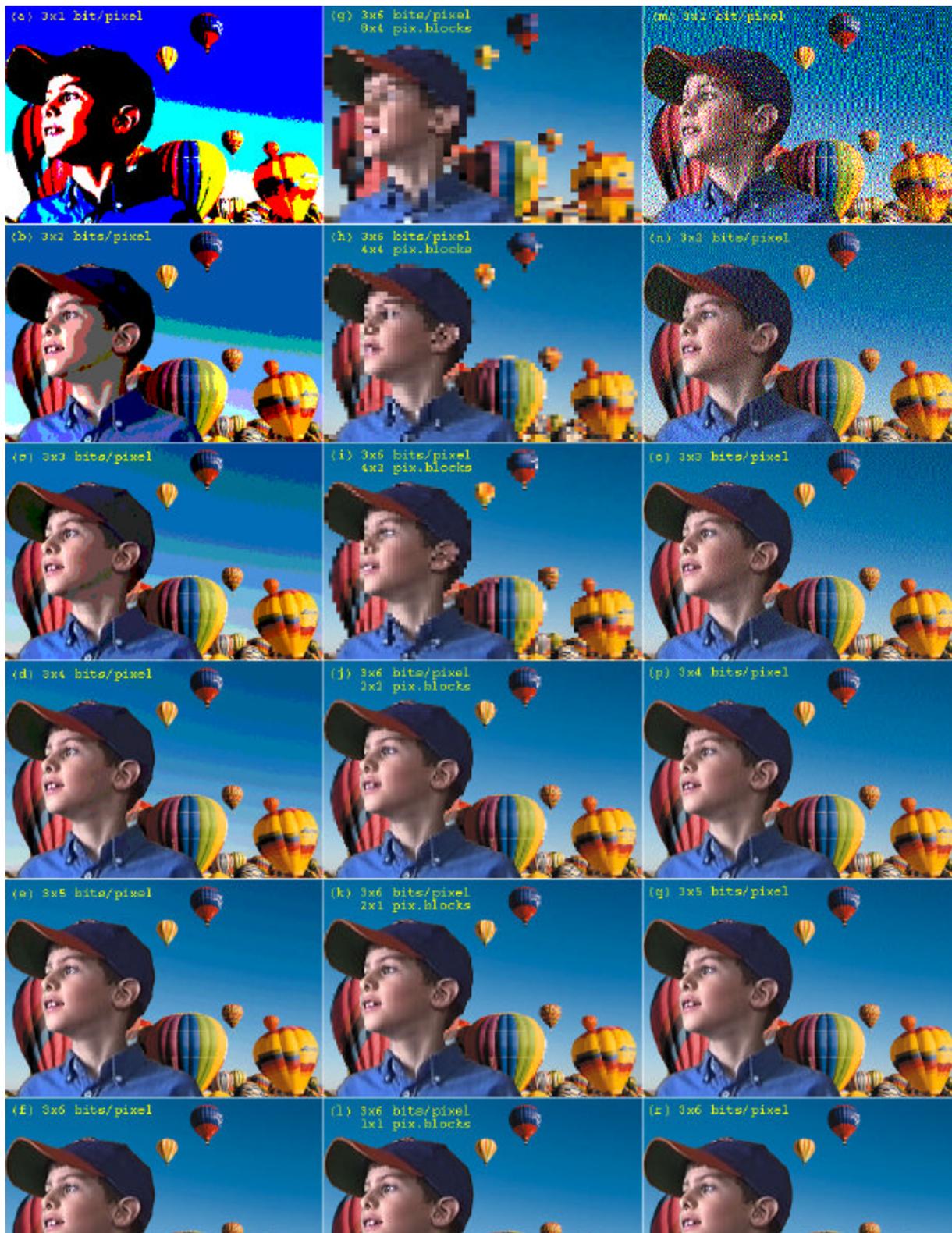


Fig 3 Three alternative progressive image quantization schemes: straightforward n-bit quantization (left column), multi-resolution block-based representation (middle column), and the multiple depth quantization (right column). Each horizontal row contains the same volume of information.