Improving 'Objective' Digital Images with Neuronal Processing: A Computational Approach

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This paper describes an experiment where an image recorded with a digital camera is processed using an electro-physiological model of a neuron. The luminosity level of each pixel of the source image is treated as the stimulus for an individual neuron, and the source image is transformed into a response image based on the processing behavior of the Hodgkin-Huxley neuronal model. It is seen that transformation of the image through neuronal processing yields (i) more evenly balanced levels of luminosity and (ii) a more 'subjective' rendering of the environment than what was photographed with the digital camera. The CCD (charge coupled device) – based digital camera reveals its limitation as a linear recording device that does not have a balanced dynamic range. The neuronal processing of the image adds non-linearity and a balanced range to the luminosity levels in the image, rendering it closer to a 'subjective' perception of the scene.

1. Introduction

The use of digital media by design professionals has become widespread. Design professionals such as architects and interior designers are using digital images to make design decisions about built environments at different scales. Many of these design decisions are based on the luminosity levels in the images, and the levels of contrasts between the luminosity levels. If these levels, and their differences, are based on what a CCD sensor 'sees' rather than an 'eye-brain' perceptual mechanism, then the design decisions made using objective digital representations of images may lead to unanticipated and unintended subjective experiences of the built environment. These objective digital images are generated based on computational models that are physics-based. They provide an accurate rendering of the built environment based on objective measurements of luminosity levels. In that sense, they represent 'ideal' mathematical visions of the environments they portray. These renderings do not reflect the subjective processing of the scene that occurs when the neuronal cells in the brain process the 'raw' sensory data.

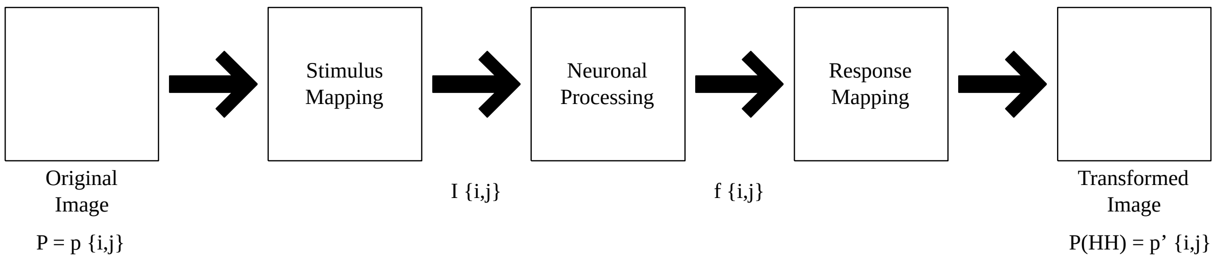
A common problem that occurs when one takes a grayscale photograph (commonly referred to as a black and white photograph) with a digital camera is that the image produced by the digital camera does not reflect our perception of the scene. This is because the digital camera uses a CCD sensor that records luminosity levels in an objective manner. In keeping with the scientific method, these levels are objective measures that are recorded by the instrument without any subjective interference.

One cannot predict if one is going to get a balanced image when one takes a grayscale photograph with a digital camera by just surveying the scene. The skills of photographers like Ansel Adams lay predominantly in their ability to survey a scene and deduce that the scene would indeed produce a brilliantly balanced grayscale photograph. One of the challenges we addressed in our experiments was to see if we can account for this discrepancy between an 'objective seeing' and a 'subjective seeing,' at least in the narrow realm of luminosity levels of digital representations of images.

In our experiments we took digital images and processed those using electro-physiological models of neurons to see what emerges when a digitally encoded image is processed 'neuronally.' Our results revealed that the neuronal 'adjustment' to the objective luminosity levels in the source image presented a much more balanced and clearer image that was in tune with subjective perceptions.

2. Methodology

The methodology we employed is illustrated in Fig. 1. It is a multi-stage process that is implemented in the software package MATLAB.



▲ Figure 1. Model of method used in the experiment.

The original picture with $N \times N$ pixels is denoted as $P = p(i,j), i,j = 1...N$ where $p(i,j)$ represents the luminosity level of the pixel (i,j). Next, we regard the luminosity of each pixel as the stimulus to a neuron so that its effect may be represented by an input current $I^{inp}(i,j)$. The current $I^{inp}(i,j)$ is then fed as a steady input current to a neuron represented by the Hodgkin-Huxley model [1]. The neuron responds to this input current by producing an action potential with a frequency $f(i,j)$ which depends on the strength of the input current. The ability of excitable neurons to encode the strength of the input in to a firing rate is used as a preliminary attempt to capture the input-output transduction process in visually responsive neurons. The firing rates $f(i,j)$ are then mapped back to the range of luminosity levels contained in the original image to obtain the neuronally processed image $P^{HH} = p'(i,j), i,j = 1... N$.

2.1. Neuronal model

The biophysical model proposed by Hodgkin and Huxley (1954) has been one of the most important models in computational neuroscience. The Hodgkin-Huxley (HH) model is described by the time evolution of four variables *(v,m,n,h)* which represent membrane potential, activation of a sodium current, activation of a potassium current and inactivation of the sodium current respectively. The dynamical system for the model can be then described by:

$$C\, dv/dt = -g_l(v - v_l) - g_K n^4 (v - v_K) + g_{Na} h m^3 (v - v_{Na}) + I^{inp}$$

$$\tau_x\, dx/dt = x_{\infty}(v) - x$$

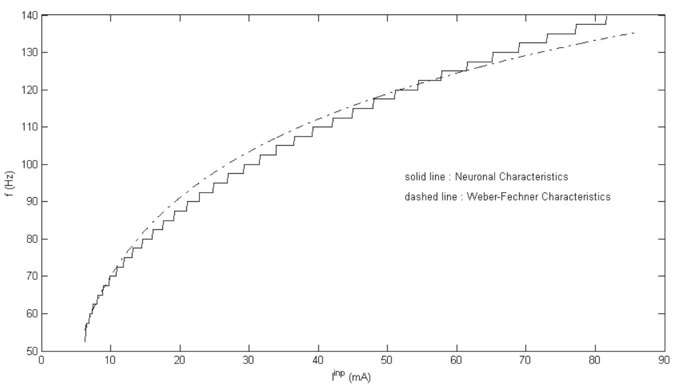
where $x \in \{m,n,h\}$. When the input current I^{inp} exceeds a certain threshold, the neuron is capable of displaying sustained oscillatory behavior. From a dynamical point of view, the bifurcation that determines the transition from a quiescent to oscillatory state determines the type of neural excitability in a given model [2]. Accordingly, we have two types of excitability [3] namely,

Type I: neural excitability occurs when the rest potential (quiescent state) disappears after a saddle node bifurcation on a limit cycle.

Type II: neural excitability results when the quiescent state undergoes an Andronov-Hopf bifurcation.

The HH neuronal model employed here displays Type-II neural excitability where the frequency of oscillations at the onset of neural excitability is distinctly non-zero. In our case, the transition from rest state to repetitive firing is seen to occur through a supercritical Hopf bifurcation at $I^{inp} = 6.265$ *mA* corresponding to a frequency of $f = 52.5$ *Hz*. As the input current is gradually increased, the frequency of oscillations increases as shown in Fig. 2. When $I^{ext} = 86.35$ *mA*, the upper limit of the frequency of oscillations is reached, which is *140 Hz*. It follows that when the input current is in the range of *[6.26 – 86.35] mA*, the neuron fires with a corresponding frequency in the range of *[52.5 – 140] Hz*. The relation between firing frequency *f* and input current I^{inp} in the model employed is shown in Fig. 2. Regarding the current I^{inp} as the input and the firing frequency *f* as the output enables us to represent the input-output transduction of the neuron by the characteristics shown in Fig. 2. Thus we have attempted to capture the selectivity of the response of a neuron to different luminosity levels in a given image by the mapping process explained. Fig. 2 also shows (in dashed line) the mapping of a stimulus to a response based on the Weber-Fechner law, which maps psychophysical responses.

▶ Figure 2. Mapping of the stimulus current to the response firing frequency based on the Hodgkin-Huxley neuronal model and the Weber-Fechner Law



3. Results

The proposed scheme was tested by processing four images acquired through a NIKON digital camera. The images were processed using the transformation model outlined in Section 1. The original and processed images are shown in Figures 3 – 10. Histograms of luminosity levels (see Figures 11, 12, 13 and 14) in the four sets of images were constructed. A summary of the mean luminosity levels for the four sets of images is shown in Table 1.

▶ **Table 1. Mean luminosity levels of 4 sets of original and processed images**

Image	Mean Luminosity of Original Image	Mean Luminosity of Processed Image	Ratio of Mean Luminosity Levels
1	93.75	142.84	1.5236
2	59.81	100.34	1.6772
3	86.98	139.73	1.6063
4	60.21	102.55	1.7032

◀ Figure 3. Photograph of a studio environment taken with a digital camera (Image 1)

◀ Figure 4. Image 1 that has been processed neuronally

◀ Figure 5. Another photograph of the studio environment taken with a digital camera (Image 2)

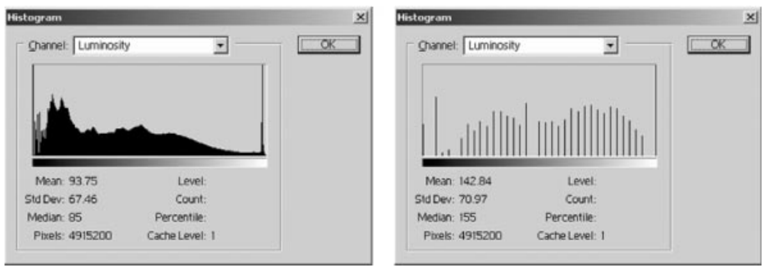
► Figure 6. Image 2 that has been processed neuronally

► Figure 7. Another photograph of the studio environment taken with a digital camera (Image 3)

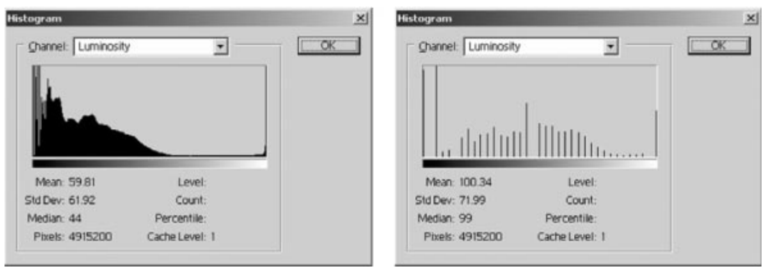
► Figure 8. Image 3 that has been processed neuronally

◀ Figure 9. Another photograph of the studio environment taken with a digital camera (Image 4)

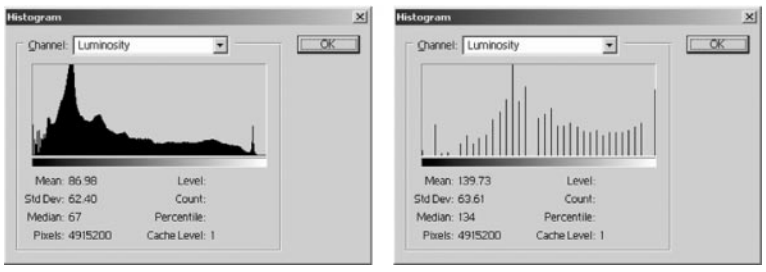
◀ Figure 10. Image 4 that has been processed neuronally



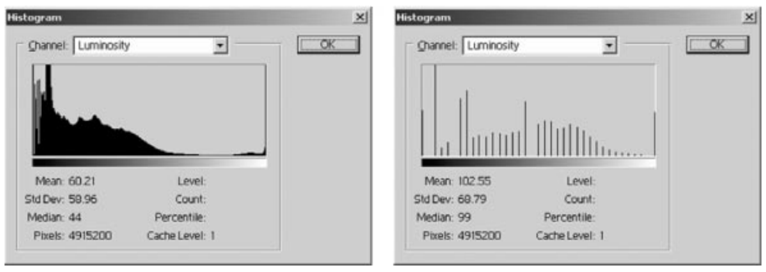
◀ Figure 11. Histograms of luminosity levels of original and processed Image 1



◀ Figure 12: Histograms of luminosity levels of original and processed Image 2



► Figure 13. Histograms of luminosity levels of original and processed Image 3



► Figure 14. Histograms of luminosity levels of original and processed Image 4

It can be noted from Figures 4, 6, 8 and 10 that the neuronal processing improves the visual appearance of the images. From Table 1, we note that the average luminosity level of the original image is increased by a minimum of 50 % upon neuronal processing. The histogram of the original Image 1 shows a concentration of luminosity levels in the "darker" ranges and a gradual waning as luminosities in the brighter range are approached. On the other hand, the processed image has a fair distribution of luminosities both in the lower and higher ranges. The histogram of the original Image 2 shows a strong concentration of luminosities from the low to midrange, and luminosities in the higher range are virtually absent. The histogram of the processed Image 2 however shows a fair concentration of luminosity levels in the entire range. A similar feature is observed from the histogram plots of the original and processed Images 3 and 4. Therefore, it is reasonable to say that the distribution of the luminosity levels is more balanced in the processed images compared to the original images. Thus, the neuronal processing model is seen to offer a marked improvement in the visual appeal of images by virtue of a balanced range of luminosities.

When we compare neuronal processing and the psychophysical response to a stimulus as predicted by the Weber-Fechner law, which is given by the relation:

$$S = k \log I$$

where S = subjective response level, k is a constant and I is the stimulus intensity level, some interesting results are produced.

We see that the results produced by the neuronal processing are superior to the ones predicted by the Weber-Fechner law (Fig. 15). In order to compare the stimulus-response (input-output) mapping curve of the

Weber-Fechner law with the stimulus-response mapping curve defined by the Hodgkin-Huxley neuronal model, we used a value for $k = 70$. Though the mapping curves seem to match rather closely (Fig. 2), the image produced by the neuronal processing is distinctly superior to the image produced by a stimulus-response mapping based on the Weber-Fechner law. This can be attributed to the difference between the continuous smooth curvature of the Weber-Fechner mapping curve and the stepped transitions in the Hodgkin-Huxley curve.

◀ Figure 15. Comparison of processed Image 1, processed according to the Weber-Fechner law (above) and the Hodgkin-Huxley neuronal model (below).

4. Conclusion

We have shown that the neuronal processing of digital images of environments produces adjustments to the images that reflect our perception of the environments more closely. This approach would be a good post processing strategy for digital images generated by digital cameras and computer-based modeling and rendering software. In our approach, images that are 'objective,' and are generated by physics-based computational models are modified into images that are 'subjective' and generated by processing with electro-physiological neuron models. This type of processing enables design professionals, who use digital images, to make design decisions based on images that are closer to subjective perceptions. In architecture, the perception of space and architectural forms depend on the distribution of luminosity levels in the scene perceived by the eye. To the extent that neuronal processing affects the perception of the luminosity levels of a scene, it indirectly affects design processes used in the creation of works of architecture.

One of the assumptions that we made in our experiment was that the individual luminosity levels in the source images were connected in exactly the same way (as a grid) in the neuronal processing model. This need not be the case. A study of the variations in connectivity in the neuronal processing model based on the neuronal firing frequencies of individual luminosity levels or 'cells' can reveal other intricacies in the neuronal processing of the images, thereby revealing a more sophisticated 'subjective seeing' of the images.

References

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