Biomimetically Inspired Algorithm for Noise Reduction in Low Light Imaging

Adam J Winslow
Stanford University
Electrical Engineering
winslowa@stanford.edu

Abstract

Over the last half-century, night vision device (NVD) technology has revolutionized the way humans operate within the nighttime environment. Incremental improvements to hardware over time have increased light capturing ability and resultant image representation. While future hardware improvements aim to reduce weight and increase field of view, the introduction of image processing software holds the key to future improvements in image resolution, contrast, and overall low light acuity. This work draws from physiological observations of nocturnal insect adaptations to low light conditions. The resulting algorithm demonstrates powerful low light image enhancement with possible future applications to NVDs.

Introduction

Night vision devices achieved wide use near the end of the twentieth century. In particular, night vision goggles (NVG) are essential to aviation, where formation flying (multiple aircraft together in flight) and operations into and out of restricted airfields or landing zones at night is extremely dangerous. Military applications are numerous, but NVDs have also found widespread use among rescue helicopters and other emergency medical services as well as law enforcement. Affordability has allowed a small private industry to grow with offerings for the consumer market as well. NVDs have unquestionably made operations at night safer for professionals, but improvement, especially under low light conditions, would provide an even greater margin of safety. The sections below provide an overview of NVG hardware and function, biomimetic inspiration for the proposed algorithm, and related work. Next, the algorithm and methods are explained followed by examination of results and a discussion of future applications.

1.1. Night vision devices

Night vision devices (NVD) include both night vision goggles (NVG) and forward looking infrared (FLIR) technology. These devices collect and amplify energy from visible light out to far infrared, coinciding with the bulk of reflected energy present at night (Figure 1). The rest of this paper will be devoted to improving low light imaging capabilities of NVGs.

Night vision goggles are passive devices that collect, amplify, and display available illumination, both emitted and reflected. They are far more sensitive than the human eye in the visual spectrum and add the near infrared portion of the spectrum to provide imaging capability at night. For pilots, NVGs provide increased situational awareness, improve navigation capabilities, and make formation flying and obstacle avoidance far safer [1].

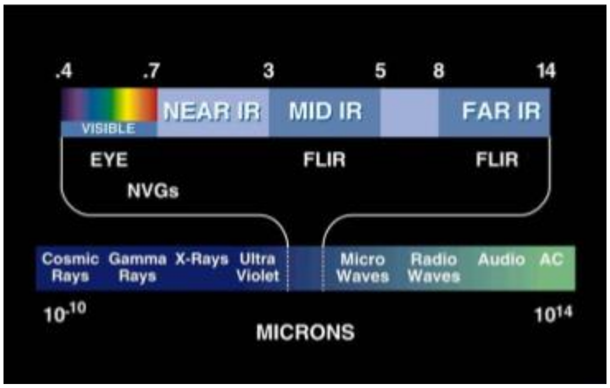

Figure 1: NVD operating portion of the EM spectrum. [1]

The key components of NVGs are the image intensifier tubes (Figure 2). Each tube collects light through an objective lens that focuses incoming photons onto a photocathode coated with gallium arsenide (GaAs) for sensitivity in the aforementioned portions of the spectrum. When photon energy is absorbed by GaAs, a proportional number of electrons are emitted and accelerated across an electric field through the microchannel plate (MCP). The MCP is a thin wafer constructed of millions of tubes coated internally with a material that, when struck with electrons from the photocathode, produce secondary electron emissions. This cascading effect along the length of the tubes leads to an increase in the number of electrons leaving the MCP of nearly three orders of magnitude. This is the "intensification" of intensifier tubes. At the back of the intensifier tube, electrons exiting the MCP are again accelerated in their relative spatial positions toward a positively charged phosphor screen. Here, the process described for the photocathode is carried out in reverse. Electrons strike the screen and their energy is dissipated in the form of emitted photon light. This light is inverted and forms the image viewed by the NVG user [1].

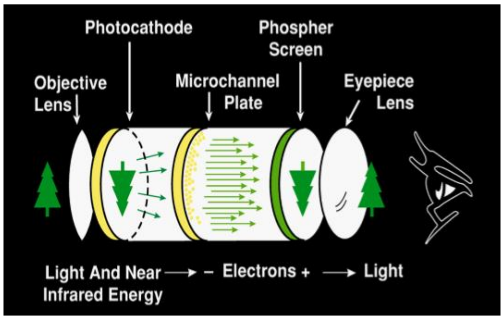

Figure 2: Image intensifier components. [1]

There are limitations to NVGs, however. They are only as good as the quality of light they collect. At times of little moonlight and far from cultural lighting, ambient reflected energy is minimal and NVGs have to elevate gain in order to maximize the signal. Consequently, noise levels are also raised. Poor weather conditions, absorption due to humidity, and scattering due to particulate obscurants also contribute to elevated noise levels and decreased contrast and resolution in the final image [1]. Very little can be done to change these environmental factors. Improving NVG hardware is possible but would likely increase system weight. On the other hand, advancements in image processing algorithms and processor speed provide opportunities to improve image signal strength while reducing noise. Interestingly, research in this area has turned to the natural world for answers.

1.2. Biomimetics

Humans seem to have an affinity for creations that reflect what is seen and experienced in the natural world. Biomimetics (also biomimicry) is the application of adaptations found in nature to complex problems. Velcro® is a well-known example. This paper draws extensively from the biomimetic ideas of Warrant et al. among others, to test an algorithm as a proof of concept for future application to NVGs [2].

2. Related work

In their paper, Warrant et al. use the visual adaptations to low light conditions at night found among insects as inspiration for a low light video enhancement algorithm. Their biomimetic reasoning is briefly recapped here as is research related to tone mapping and image denoising [2].

2.1. Biomimetic reasoning

Warrant et al. surveyed a body of research devoted to nocturnal animals, specifically insects. They focused on photoreceptive adaptation to low light conditions. Photoreceptors act as a transduction mechanism by which incoming photons are registered as electrical signals of proportional amplitude. This should sound familiar as it is the same (biomimetic) concept applied by the NVG photocathode. Under low light conditions, photoreceptors in the eye suffer from the same noise contamination as the photocathode. Noise is fundamentally signal uncertainty and is thus described by Poisson statistics. For a number of absorbed photons, N, the magnitude of this uncertainty is given by:

$$\frac{N}{\sqrt{N}} = \sqrt{N} \qquad (1)$$

Therefore, as the number of absorbed photons decreases, uncertainty, or noise, increases. In other words, signal to noise ratio (SNR) decreases [2].

The insects studied were found to have two adaptations that were applicable to image processing. The first adaptation takes us back to the photoreceptor. Ideally, the photoreceptor would perfectly replicate the same received signal every time. Noise has already been shown to inhibit this. Instead, nocturnal insects, such as the Central American bee, *Megalopta genalis*, display a higher transduced signal amplitude, or "bump." In the case of *Megalopta*, that bump is nearly five times greater than its diurnal cousin (Figure 3). This higher voltage response in the receptor means greater contrast gain and thus, greater signal. Unfortunately, the resultant signal increase comes at the expense of an equally increased level of noise. So now have to solve the problem of increased noise [2].

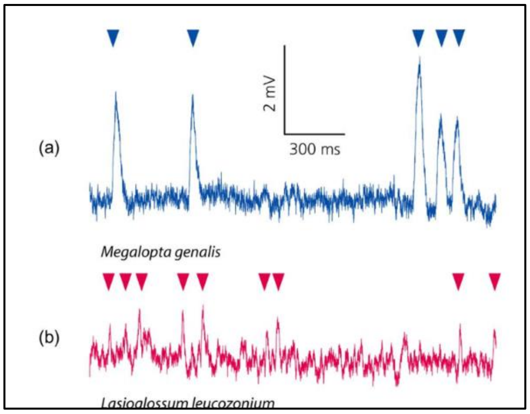

Figure 3: Photoreceptor response to photons in closely related (a) nocturnal and (b) diurnal bee species [2].

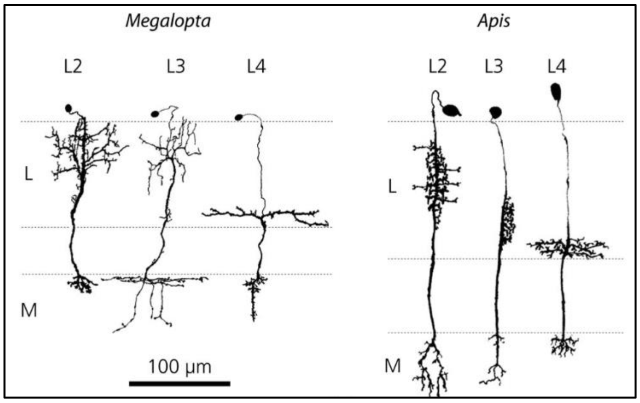

Figure 4: Optic ganglion fibers in nocturnal (Megalopta) and diurnal (Apis) species [2].

The second adaptation found in *Megalopta* is a neural mechanism suggested by horizontal branches in the first optic ganglion where visual processing first takes place (Figure 4). This lateral spreading couples visual channels together allowing summation over a greater space. The result is greater photon capture, higher signal, and thus a reduced effect of noise [2].

These adaptations form the basis for the biomimetic algorithm proposed and described in section 3.

2.2. Tone mapping

Transforming the intensity of a target image is a product of tone mapping. This is a decades old field with numerous techniques available. For this algorithm, an adaptive histogram equalization method was chosen. Zuiderveld's work on contrast limited adaptive histogram equalization (CLAHE) was particularly useful given the control over brightness required for low light imaging [3] [4].

2.3. Image denoising

The filtering used in this algorithm is based on years of research into bilateral filtering, edge preserving anisotropic diffusion, structure-adaptive anisotropic filtering, and most importantly, block matching 3D (BM3D) techniques. The original work by Dabov et al. provides the foundation for the noise reduction effectiveness of this algorithm [2] [5].

3. Scope and design

The algorithm proposed by Warrant et al. was constructed for video processing with spatio-temporal filtering. Since NVGs are not video cameras but rather display devices, this paper explores the application of a similar algorithm to single images, again, as a proof of concept for future application in the temporal domain. The basic algorithm flow is shown in Figure 5 and explained in the sections below.

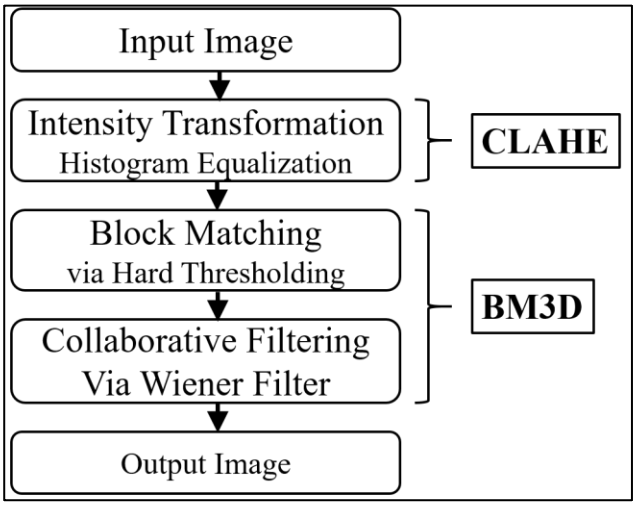

Figure 5: Algorithm flow

3.1 Signal amplification

To simulate the "bump" in signal amplitude displayed by *Megalopta*, contrast limited adaptive histogram equalization (CLAHE) is implemented. CLAHE segments an image into tiles and creates a cumulative distribution function (CDF) for each one based on its histogram. Linear and bi-linear interpolation smooths the boundaries between each tile. This procedure also enhances noise and has a tendency to over brighten images. To overcome this, a clip limit is determined. It establishes a maximum value any one histogram bin can hold. Anything in excess is distributed over the histogram of that associated tile. The process effectively limits the slope of the CDF, thereby preserving contrasting elements of the image [2] [3] [6].

While Warrant et al. chose a method without tiling, this algorithm takes advantage of improved processing speed of CLAHE in anticipation of future "real-time" applications. Additionally, the *adapthisteq*() function in MATLAB (based on Zuiderveld's work) was used and written for both monochrome and color images in LAB space to preserve color quality while enhancing image intensity [2] [6] [7].

3.2. Noise reduction

Megalopta genalis was shown above to have seemingly overcome increased noise by "casting a wider net" as it were, to collect more photons and as a result increase SNR. By filtering the amplified image, we can effectively reduce the amount of noise, also increasing SNR. BM3D is described below and is the filtering used in the algorithm. Bilateral filtering is also described below and was used for comparison purposes [2].

3.2.1. Block matching 3D

Block matching 3D (BM3D) is a widely used image denoising method that leverages an image's locally sparse representation in the transform domain. Two dimensional neighborhoods of similar signal are determined (matched), then blocked together into a 3D array, and finally filtered. Matching involves choosing a reference signal fragment and then joining that reference with other fragments with dissimilarity values below a prescribed threshold. Once matched, each fragment within a block undergoes a filtering process that is dependent on how closely matched each element originally was. The more dissimilar the matching, the less effective the filtering. This is called collaborative filtering [5]. The BM3D filter used in this algorithm follows the implementation proposed by Dabov et al. It implements hard thresholding and Wiener filtering of the blocks, and allows adjustment of parameters for each [5].

3.2.2. Bilateral filter

Bilateral filtering was chosen for comparison due to its simple approach that makes it relatively efficient. This process need not be iterative, so its efficiency can be maintained. Such efficient algorithms are important for future use in real-time applications [8].

A bilateral filter determines each pixel value as a weighted average of its neighbors, similar to Gaussian convolution [8]. Unlike the Gaussian model, where weights fall off as distance from the reference pixel increases and edges tend to blur, the bilateral filter adds a second weighting measure. This weight compares the range between pixel values [9]. At edges, average pixel values change rapidly. To preserve this, bilateral filters exclude pixels whose values differ from the reference below a preset margin, sigma (σ). Again, LAB colorspace is used for its physiological similarity to human perception of distance and color discrepancy [8] [9].

4. Results

All images were captured using a set of Gen III AN/ANS-9 NVGs. They depict an MV-22 tiltrotor aircraft stationary under characteristic nighttime conditions. Edges and some detail are easy to make out against the bright sky but against the ground such details are degraded.

4.1. CLAHE

The intensity transformation completed by CLAHE performed well as expected. Figure 6(b) shows an obvious increase in signal brightness over image (a). Strong signals are amplified but so too is the noise, especially in the foreground. A relatively small value for sigma (0.005) was

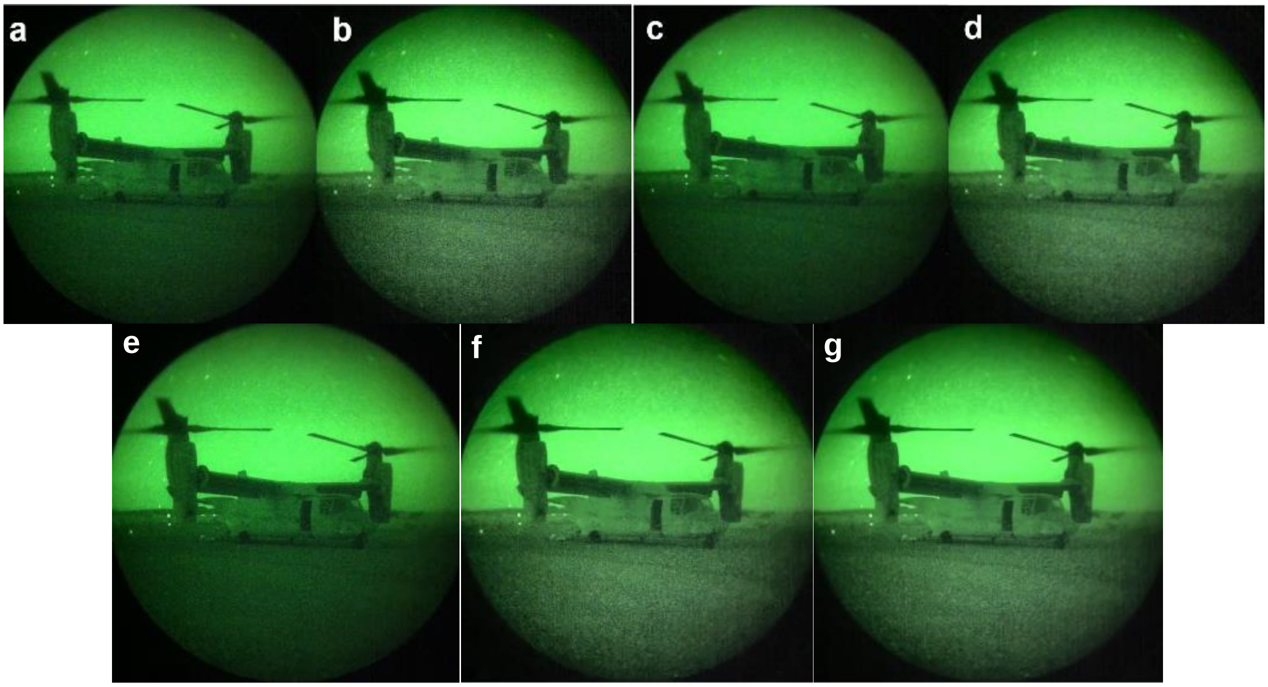

Figure 6: Results of varying algorithm parameters. Image (a) represents the original image captured from a night vision goggle. Image (b) is the result of CLAHE applied to the original. Images (c) and (d) are the result of bilateral filtering of the original and CLAHE image, respectively. Image (e) is the original image with artificial noise applied during BM3D filtering. Image (f) is the CLAHE image with additional noise added during BM3D. Finally, image (g) represents the CLAHE image filtered by BM3D without any additional noise added. Note: Blurring near outside circumference is due to optical alignment between NVG and camera used to capture image.

chosen to prevent the image from being oversaturated. An image that is too bright would impair night adaptation of the eye for other visual tasks in a night environment. In all CLAHE enhanced images, the "bump" seems to have increased both signal and noise. Greater detail and contrast result but the noise is still a significant issue in all but the BM3D filtering case (g).

4.2. Bilateral filter

The bilateral filter was chosen as a comparison. While it performed fairly quickly, the results were not of a quality necessary for NVGs. Edges in high contrast areas began to break up, especially in (d). In darker areas of less contrast, as in (c), there was a fair amount of edge softening and blurring. Though the bilateral filter wasn't expected to perform well under these low light conditions, it did provide an important contrast to what is possible with BM3D.

4.3. BM3D

The BM3D filter managed to preserve the signal in both original and CLAHE enhanced images while effectively reducing noise. The differences between the original image (a) and the same image with BM3D applied with additive noise (e) are subtle. Drastic effects are seen after CLAHE is applied. With signal "bumped" up, the BM3D filter is better able to distinguish locally sparse signals in the transform domain. Image (g) shows the best improvement by far. Noise has been drastically reduced while edges are preserved, and details in the shadows have been brought out. PSNR for (g) was calculated at 35.459 dB. This figure was somewhat lower than (e) who's calculated PSNR was 37.956 dB, but (g) stands out for aesthetic.

5. Future applications

Imaging performance under low light conditions with NVDs is fertile ground for further research. Expanding to the spatio-temporal dimension where it will be useful for video is a step already being investigated. With the processing power of today's ICs, software enhanced real-time display is here. Applications already exist in the commercial and defense worlds and with the inherent safety benefits of NVDs, it's only a matter of time before wider use in, for example, passenger vehicles.

6. Conclusion

Ingenious environmental adaptations surround us. One such adaptation, that of *Megalopta genalis,* provided the biomimetic motivation for investigating image enhancement algorithms for low light imagery. The results above seem to suggest an opportunity for these new image processing techniques to greatly improve NVG displayed images. Hardware changes are focused on improving the physical characteristics of NVGs such as weight and field of view. Incorporation of image enhancement techniques would help image quality keep up with hardware advancements and further build upon the safety margin provided by NVD's.

References

[1] MAWTS-1 Night Vision Device (NVD) Manual, 9th Edition. pp. 3-78, 2011.

[2] E. J. Warrant, O. Magnus, H. Malm. The remarkable visual abilities of nocturnal insects: neural principles and bioinspired night-vision algorithms. Proc. of the IEEE, vol. 102, no. 10, pp. 1411-1426, 2014.

[3] S. M. Pizer et al. Adaptive histogram equalization and its variations. Comput. Vis. Graph. Image Process., vol. 39, pp. 355-368, 1987.

[4] K. Zuiderveld. Contrast Limited Adaptive Histogram Equalization. In: P. Heckbert: Graphics Gems IV, Academic Press 1994.

[5] K. Dabov, A. Foi, V. Katkovnik, K. Egiazarian. Image denoising by sparse 3D transform-domain collaborative filtering. IEEE Trans. On Image Proc., vol. 16, no. 8, 2007.

[6] P. D. Ferguson, T. Arslan, A. T. Erdogan, A. Parmley. Evaluation of Contrast Limited Adaptive Histogram Equalization (CLAHE) Enhancement on a FPGA. IEEE, pp. 119-122, 2008.

[7] S. K. Naik, C. A. Murthy. Hue-Preserving Color Image Enhancement Without Gamut Problem. IEEE Trans. On Image Proc., vol. 12, no. 12, pp. 1591-1598, 2003.

[8] S. Paris, P. Kornprobst, J. Tumblin, F. Durand. Bilateral Filtering: Theory and Applications. Foundations and Trends in Computer Graphics and Vision, vol. 4, no. 1, pp. 1-73, 2008.

[9] C. Tomasi, R. Manduchi. Bilateral Filtering for Gray and Color Images. Proc. of the1998 IEEE International Conf. on Comp. Vision, pp. 839-846, 1998.

[10] G. Yadav, S. Maheshwari, A. Agarwal. Contrast Limited Adaptive Histogram Equalization Based Enhancement For Real Time Video System. 2014 International Conf. on Advances in Computing, Communications and Informatics (ICACCI), pp. 2392-2397.