VISION IMPROVEMENT FOR PATIENTS WITH RETINAL DEGENERATIONS

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ABSTRACT

Patients with retinal degenerative disorders such as age related macular degeneration suffer from reduced visual acuity and a significant loss of contrast sensitivity. The effect is a gross blurring of the visual scene over the significant area of their field of view. In this paper we present three novel image enhancement techniques for visual augmentation systems to enhance the remaining visual capability of those with patients suffering from retina degenerative diseases. The effectiveness of these algorithms was tested on 27 patients with average visual acuity of 0.63 and average contrast sensitivity of 1.22. Results show that Advanced Scaled Chromatic Edge (ASCE), and edge overlaying algorithms are very useful in detecting motion in dynamic scenes, whereas image Cartoonization algorithms held greatest preference for determining static spatial scenes.

KEY WORDS

Low vision aid, image processing, augmented vision system

1. Introduction

According to the World Health Organization (WHO), it’s estimated that about 148 million people worldwide have a visual impairment. Of these, 38 million persons are completely blind and 110 million have partial blindness, and are said to have Low Vision (LV), and this number is expected to double over the next 25 years [1]. The low vision pathologies of the partial blindness group can be divided mainly into two functional categories; those that predominantly suffer from a loss of visual acuity (macular degeneration; diabetic retinopathy; optic atrophy, and cataracts) and those that predominantly suffer from a reduction in the overall visual field (retinitis pigmentosa, glaucoma, and higher level visual disorders of the optic nerve and brain). In the developed world, disorders such as cataracts and Glaucoma are becoming more treatable. There is an increasing prevalence of Age Related Macular Degeneration (AMD) due to our ageing societies and Diabetic Retinopathy due to expanding waistlines. Retinitis Pigmentosa (RP), an untreatable hereditary condition, has a fixed prevalence of 1 in 3500, and is major source of visual impairment in the developed world [2].

People with visual acuity impairment suffer from a range of problems affecting their mobility and quality of life [3]. In many cases, these individuals can be prescribed conventional low vision aids (LVAs) such as magnifying lenses. These will assist by providing magnification in order to compensate for reduced visual acuity, while contrast is maximized with local task lighting. LVAs are, however, highly task specific, and the patient may need several different aids to deal with the variety circumstances encountered in daily life. Electronically enhanced visual aids have been proposed which offer a number of distinct advantages over conventional LVAs in low vision rehabilitation [4]. With the development of head mounted displays and cameras for the virtual reality field, work has attempted to apply these devices to the needs of users with low vision in combination with computer image processing techniques. Prothero [5] used a head-up display, in which virtual imagery is overlaid on the real scene, to provide visual cues which improved the mobility of patients with akinesia due to Parkinson's disease. Massof and Rickman [6] developed a low vision imaging system at Johns Hopkins University known as the Low vision Enhancement System (“ELVIS”), which mainly, provides magnification and contrast enhancement. Wolffsohn [7] had developed image processing techniques to enhance the television viewing of the visually impaired by applying a simple edge overlaying algorithms on the scene. Peli has published numerous papers on the field of vision rehabilitation for visual impairment patients [8], [9],[10]. His work has concentrated on augmented vision systems to assist those with constricted visual fields using the concept of vision-multiplexing; the visual scene would be acquired, compressed to the size of the patient’s visual field, and converted to edges. These edges would then be superimposed over the original scene on a see-through display. Fernando [11], recently developed a portable head mounted aiding system for low vision patients, especially retina pigmentosa patients. Mainly, his system applied a digital image zooming and edge enhancement on the visual scene. Most of the work described above was based on two main techniques; image magnification/de-magnification and edge overlay. While edges of a demagnified image can potentially assist patients with low visual fields, non-demagnified edges overlaid on the original scene may be helpful for low-vision patients. The hypothesis is that the
contrast of high spatial frequencies should be increased to aid detection. However, such algorithms will amplify less important or irrelevant information such as noise or textural detail in addition to significant features. Everingham [12] tackled with this problem by developing a method using artificial intelligence to recognise and classify the objects in the scene into eight main objects. The limitation is that the scene can only be separated on the basis of eight pre-defined objects, so patient loses the ability to see the natural color information.

Our aim is to develop portable augmented vision system to patients with retinal dystrophy diseases with considerable power consumption [13]. Our proposed system will be consisting of an eye tracking unit to track the position of eye, an image enhancement unit and a display. The system will be fitted in a fashionable head mounted unit as shown in figure 1. In this paper we are predominately concerned with enhancing the remaining visual function of those with macular degenerative conditions. We present three novel image enhancement algorithms, which have been tested on patients with retina dystrophy diseases. The image enhancement methodology will be discussed in section 2. Results of testing the algorithms on patients will be shown in section 3. Discussion will be given in section 4 followed by a conclusion in section 5.

![Fig. 1. Our proposed augmented vision system.](image)

2. Methodology

Human vision has its highest visual acuity in the central macula and fovea. In addition, much of the spatial processing of the visual cortex is designated to these regions. Thus, patients with degeneration of the macula and fovea perceive an extreme blurred vision. Our intention is to enhance the key features in the scene according to the nature of the scene. As transferability to portable processing platforms is important, we do not attempt any form of saliency. Instead we use processing functions similar to those carried out by the retina and lower levels of the visual cortex in order to achieve useful enhancement. Our image enhancement algorithms are:

2.1 ASCE Algorithm

Low vision patients need a tool that assist them in detecting moving objects normally without any delay or blurring effect. The Advanced Scaled Chromatic Edge Enhancement (ASCE), an algorithm which creates and edge-like image but maintains some chromatic content of the visual scene, aims to increase the contrast between objects by highlighting the edges of the moving objects and the edges between distinguish objects while suppressing the other homogeneous pixels in the scene. It is performed in three steps:

- **Simplification of the scene, using anisotropic filtering.**
- **Extraction of the significant spatial derivatives.**
- **Boosting the original scene.**

Image simplification is an important step before performing spatial derivatives (edge extraction) so as not to extract high frequency noise and textures [14]. Common filtering methods include Gaussian kernels [15]; however, as it is effectively a low pass filter, it removes all the high frequency information, thus blurring the edges of the significant object boundaries. We use a Non-linear anisotropic smoothing technique to eliminate noise and low importance textures, while avoiding smoothing across object boundaries. It is an iterative process which progressively smooths the image while maintaining the significant edges by reducing the diffusivity at those locations having a larger likelihood to be edges [16]. The process is defined as follows:

$$\frac{\partial I_t(x)}{\partial t} = \text{div}[c(x)\nabla I_t(x)]$$

(1)

$I_t(x)$ denotes the image intensity at position $x$ and time $t$ ($I_0(x)$ is the image at time $t = 0$ which is the original); $\nabla$ is the gradient operator, and $\text{div}$ is the divergence operator; $c(x)$ is the diffusion coefficient ($c(x)$ approaches 0 near edges, whereas it approaches 1 in homogeneous regions). The equivalent equation in the discrete domain is:

$$I^{n+1} = I^n + \Delta t[\nabla(C.\nabla I_H) + \nabla(C.\nabla I_V) + \nabla(C.\nabla I_{D1}) + \nabla(C.\nabla I_{D2})]$$

(2)

Where $n$ denotes the iteration number, $\Delta t$ is the time step (it controls the accuracy and the speed of the smoothing) and $\nabla I_H, \nabla V, \nabla D1, \nabla D2$ represents the gradient in four directions.

The diffusion coefficient is then calculated from the following equation.

$$C = \frac{1}{1 + \sqrt{\nabla I_H^2 + \nabla I_V^2 + \nabla I_{D1}^2 + \nabla I_{D2}^2}}$$

(3)

After simplification, the next step is to obtain the gradient map. We use an algorithm described previously by Fleck [17] which based on a modified Canny filter [18]. Briefly, simple masks [-1, 0, 1] are used to compute the first derivative in four directions: $H$ (horizontal), $V$ (vertical), $D1$, and $D2$ (diagonal). The $X$ and $Y$ gradients are then computed by projecting the diagonal differences on both axes.
The amplitude of the gradient is:

\[ G = \sqrt{X^2 + Y^2} \]  

As simple high frequency (small kernel) derivatives of this form can be lossy in their boundary detection, we use a multi-scale pyramidal approach to obtain lower frequency (large kernel) derivatives. This is equivalent to using multiple higher order kernels, but is more efficient in processing terms [19].

The final stage in the ASCE algorithm to rescale the original image according to a weighting function \( W \) based on the gradient map. The gradient map is normalized to a fractional dynamic range between 0:1. We then define a threshold value \( K \) below which all the pixels will be raised to \( K \). The original image is multiplied by the weighting function as given by:

\[ ASCE \text{ Image} = \text{Input Image} \times W \]

Figure 2(c) shows the outcome of this algorithm compared to basic edge detection from a first order derivative. The advantages of this technique over edge only images, is that it is more robust vs. noise and textures, and it maintains some of the chromatic information of the visual scene. By controlling the threshold \( K \) value we can increase or decrease the color information.

### 2.2 Cartoonization Algorithm

When we look at a scene, our brain tries to interpret what we see and reorganize the perceptual visual information into coherent regions to group them together as manifestations of meaningful objects [20]. Reducing the perceptual and cognitive effort required to understand an image can makes images easier and faster to understand for low visual perception patients, which can be done by image Cartoonization. It is a technique used to create stylized images that facilitate viewer recognition of the shapes by reducing visual clutters such as shadows and textures details [21], [22].

We use this method to modify the contrast of visually important features, by simplifying and reducing contrast in low-contrast regions (i.e. making them salient) and artificially increasing contrast in higher contrast regions. Our version of the algorithm has four main steps:

- **Simplification of the image with anisotropic filtering**
- **Calculating the spatial derivatives of the image**
- **Quantization of the colors of the simplified image**
- **Combining the quantized image with the negative of the gradient map**

The Algorithm starts by smoothing the original image using the above anisotropic diffusion filter as described in equations (1) to (3), above. The gradient image calculated as given in equations (6) above, and normalized between 0 and 1. We then define two threshold values, \( \tau_{\min}, \tau_{\max} \) and we set all pixels of the normalized gradient image below \( \tau_{\min} \) to 0 and all the pixels above \( \tau_{\max} \) are set to 1. To make paint like effect on the image we quantize the colors in the image into bins according to the following relationship:

\[ Q(x) = q(x)_{\text{nearest}} + \frac{\Delta q}{2} \tanh \left( \phi_q (f(x) - q(x)_{\text{nearest}}) \right) \]  

\( Q(x) \) is the quantized image, \( \Delta q \) is the bin width, \( q(x)_{\text{nearest}} \) is the closest bin color to the current pixel \( f(x) \) and \( \phi_q \) is a parameter used to control the sharpness transition between one bin to another. The full description of this method was described previously by Winnemoller et al [23].

To increase the visual distinctiveness of high contrast regions in the image we combined the negative of the corresponding extracted spatial derivatives described in equation (6) above. This negative gradient map overlay gives a notable edge enhancement. Figure 2(d) shows the outcome of the cartoonized image.

![Fig. 2. Low contrast image (a) and its first order gradient (b) compared to the output of the ASCE algorithm (c), the cartoon image (d) and the edge overlay on the cartoon image (e).](image-url)
watching TV. The difference here is that Walffsohn extracted the contour map with and without Gaussian smoothing. Thus, with the smoothing, the image is slightly blurred compared to anisotropic simplification, and without results in the highlighting of many unwanted gradients. Additionally, the Wolfsohn algorithm only used a 3x3 kernel, which makes it difficult to highlight the relevant contours over the irrelevant ones. In this paper we apply a simplification preprocessing step, as described in equations (1) to (3) above, to extract only the relevant spatial derivatives. Additionally, we use a pyramided approach to obtain the spatial derivatives across a range of spatial frequencies. Figure 2(e) shows the outcome of the edge overlaying on the cartoon image.

3. Results

27 patients were tested at the Oxford Eye hospital, John Radcliffe Hospital UK. Average visual acuity (VA) in the better eye for the sample was 0.63±0.07 (Range: -0.26: 1.14) and the median contrast sensitivity (CS) in the better eye was 1.22±0.08 (Range: 0.15:1.65). The heterogeneity of the patient conditions was to broadly determine the effect of different levels of macular degeneration on the effect of our enhancement methods.

Patients were presented with 25 sets of images and 4 sets of videos sequences. Images and videos enhanced with our algorithms were randomly interspersed to even out the effect of memory. For each image patients were asked to identify key scene features and were asked to rank different version of each image for helpfulness in identification of major features, as well as willingness to use in everyday life. In the case of the video sequences, these were placed next to each other and the patients asked to give viewing preference.

Patient data was divided into two groups: Those (11 patients) who preferred to see more than 70% of the images in the processed version, these patients had average maximum contrast sensitivity of 1.02±0.12 compared to 1.35±0.09 for the remaining 16 patients who preferred unprocessed images; and average VA of 0.8±0.06 in the better eye compared to 0.52±0.11 for patients who preferred unprocessed images.

Figure 3 (a), shows the patients preference to the enhanced images over the original version for the two groups of patients; the one who preferred the 70% of the images in the processed format and the others who preferred the enhanced images less than 70 %. Figure 3 (b) shows the ranking of each algorithm to those patients who preferred to see more than 70% of the images in the processed format. We found that image Cartoonization was the most preferable for those patients, especially for images with low contrast, luminance and feature size. Edge overlay, was preferred for scenes with high luminance, high contrast and large-major features.

Figure 4, shows the result of patient preference in the motion detection tests. We can see that ASCE algorithm is the most useful one in detecting motion followed by the edge overlaying algorithm.

4. Discussion

The selection of image Cartoonization to be the most preferable for RP patients in testing still images was expected. This is because Cartoonization increases the contrast between the foreground objects and background. Not only that, the added negative edges in the Cartoonization process added more contrast enhancement to the relevant features. Alternatively, edge overlay was preferred for scenes with high luminance and large-major features. One possible explanation is that high luminance can cause glaring and in that case, the differentiation between scenes objects will be difficult. Hence, by making a separation between foreground objects and background with different color can be more convenient for these patients. ASCE was least chosen because the ASCE suppresses most of the natural and colour information on the scene. However, in dynamic scenes the ASCE algorithm was the most useful in detecting objects which are moving. This is because that ASCE suppresses low frequency information and emphasizes high frequency information, so that it keeps very high contrast difference between moving objects and background.

From these observations we can conclude that presently there is no single algorithm which can be used for all the patients in all the circumstances. However, if implemented on a wearable augmented vision headset, patients can select the appropriate algorithm given the personal preference and visual situation. For example, ASCE was the most preferable algorithm for fast detection of moving objects, so may be most appropriate for navigation. Alternatively cartoonization and edge overlay are most helpful in recognizing objects so they may be
most appropriate for watching television or more static scenes.

5. Conclusion

In this article we developed three different image enhancement algorithms for patients suffering from retina dystrophy diseases. These three algorithms have been tested on group of patients with macular degeneration diseases. Results show that Cartoonization algorithm was picked more frequently than other algorithms for aiding recognition of features, while the ASCE (Advanced Scaled Chromatic Edges) algorithm show the highest performance in detecting motion. The results we had got from this study were very useful for us in determining the most efficient algorithm according to the scene characteristics and in determining the working range of CS and VA for the highest benefit from these algorithms. We are now progressing with the use of these algorithms in real time processing systems [13] to check their efficacy in real world situations and tasks. In the long run these algorithms will also be useful for our development of optogenetic retinal prostheses [24], [25] for patients who are completely blind.

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