

Increased depth perception with sharpness enhancement for stereo video

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ABSTRACT

Three-D (3-D) stereo video is becoming widely available and one need to consider depth effects when extending the 2-D video processing algorithms to 3-D stereo set-up. Depth is the additional attribute which contributes to overall visual quality of the 3-D stereo video. Sharpness enhancement algorithm is commonly applied in 2-D video processing chain; the effect of depth perception when sharpness enhancement algorithm is applied to the 3-D stereo video is studied. A subjective experiment is presented to study the relation between blur/sharpness and depth. A concept of just noticeable blur (JNB) at different depths is introduced for the stereo image pairs. Based on the results of the experiment an adaptive sharpness enhancement algorithm is proposed. The visual quality results, of the proposed depth aware sharpness enhancement algorithm, are presented.

Keywords: 3D, 3-D stereo video enhancement, sharpness enhancement, blur metric

1. INTRODUCTION

A typical video processing chain will have pipelined algorithm stages such as color/contrast enhancement, sharpness enhancement, and noise reduction. In the video processing chain different artifacts [11] get introduced during capturing, coding, transmission and visualization steps. In most of the cases the 2-D video post processing steps are applied directly to the 3-D stereo video. But, Depth is an additional attribute in stereo set-up which needs to be considered when mitigating the artifacts and enhancing the 3-D stereo video.

In 3D stereo setup two separate views are presented to each eye. The brain fuses these two images and uses the disparity between the two views as the binocular clue to perceive the depth. Monocular cues [6] such as texture gradients, interposition, and knowledge of the world also play important role in perceiving the depth. The dominant cue contributes to the final depth perception. In [12] unsharp masking sharpness enhancement is applied to the depth maps but the images are rendered without any post-processing step. In this work we have studied the sharpness enhancement algorithm applied to the 3D stereo video. A subjective experiment is conducted to formalize the relation between depth and perceived blur/sharpness in a stereo set-up.

In Section 2, details of the subjective experiment are presented along with the results. In Section 3, adaptive sharpness enhancement algorithm is presented along with the visual quality results of the proposed method. Conclusions and future work are presented in Section 4.

2. SUBJECTIVE EXPERIMENT

A subjective study is conducted to find the relation between blur/sharpness and depth for 3-D stereoscopic images. The goal of the experiment is to find out whether the perceived blur/sharpness varies with the disparity. Since, blur and sharpness are inversely related, in the proposed experiment blur is used as the variable instead of sharpness. Blur metric for 2-D video has been extensively studied in the literature [1-4]. In [5] “just noticeable blur” (JNB) is defined for the 2-D images where JNB is the minimum amount of perceived blur around an edge given a contrast higher than the just noticeable difference (JND). In the current experiment JNB is extended to 3-D stereo setup with depth as the additional attribute. Three variables were defined in the subjective experiment, namely: *Blur*, *Depth* and *Contrast* (Figure 1). *Blur* is measured by the standard deviation of the Gaussian filter applied to the image. *Contrast* is measured as the difference between the foreground and background image intensities. *Depth* is measured by the disparity between the left and right

eye images. In these experiments, a parallel camera model is assumed; hence, the disparity is just the shift in the horizontal direction.

In Figure 2, perceived depth in the case of a parallel camera model is shown. Perceived depth in humans is function of many factors including monocular and binocular clues. In our experiment since we have used rectangular boxes without any textures, disparity is the only source of the depth clue. In terms of disparity [6], the perceived depth is given by:

$$\begin{aligned} Depth_{in} &= Disparity * Distance / (IOD - Disparity) \\ Depth_{out} &= Disparity * Distance / (IOD + Disparity) \end{aligned} \quad (1)$$

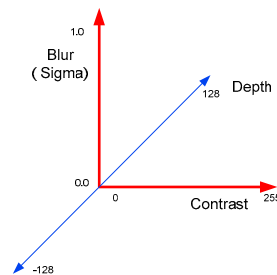


Figure 1. Variables of the experiment.

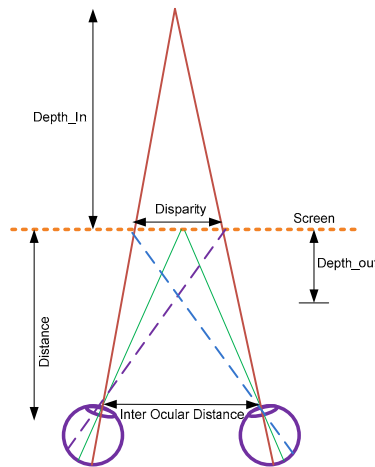


Figure 2. Perceived depth.

where *Disparity* is the unsigned disparity value, *Distance* is the viewing distance, and *IOD* is the inter-ocular distance which has an average value of 63 mm for humans. *Depth_In* is the observed depth inside the screen and *Depth_out* is the observed depth outside the screen.

In the conducted experiments, a rectangle with intensity I_R is overlayed, at different depths, on a given “background” intensity I_B . The rectangular shape is chosen to analyze the blurriness effect around horizontal and vertical edges which are commonly found in natural images. For a given contrast $|I_R - I_B|$, the edges of the rectangle are blurred using a lowpass 7x7 Gaussian mask with a standard deviation σ (*sigma*) ranging from 0.05 to 1.55. The σ values of the Gaussian filter are selected based on tuning experiments. As part of the conducted tuning experiments, subjects were allowed to vary the σ value till they see the blur. This is repeated for each considered contrast and depth. We refer to the σ values at which subjects were just able to notice blur during the tuning experiment as σ_{JNB}^T . For each considered contrast and depth, based on the mid-range of the corresponding σ_{JNB}^T value, seven *sigma* values are chosen including

four values around the mid-range σ_{JNB}^T value along with the two extreme σ values (0.05 and 1.55) as shown in Table 1. Table 1 summarizes the range of values used for each variable in the experiment. The perceived depth for the current display is calculated using (1). Image pairs were produced for the experiments based on all the possible combinations of the values (*sigma*, *contrast*, *disparity*) shown in Table 1.

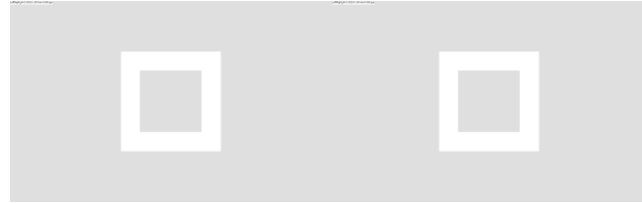


Figure 3. Concatenated left and right eye images.

Table 1. Parameter values used in the subjective experiments.

Sigma	.05	σ_{JNB}^- 0.2	σ_{JNB}^- 0.1	σ_{JNB}^T	σ_{JNB}^+ 0.1	σ_{JNB}^+ 0.2	1.55
Contrast	32	64	128	255			
Disparity (pixels)	-30	-10	+10	20			
Depth (mm)	155	46	42	82			

For the conducted subjective experiments, for each considered contrast value (Table 1), after the edges of the rectangle are Gaussian blurred at a given *sigma*, the left and right eye images are created by shifting the image by a *disparity* value. The subject was asked to evaluate the blur effect at the boundary of the object. The size of the outer larger square shown in Figure 3 was set to 520x520. The size of the smaller inner square was set to 320x320. A 1680x1050@120Hz Samsung Syncmaster 2233rz display is used with nVidia active shutter glasses to render 60Hz images for each eye. This gives the best spatial/temporal resolution present in the market without much flicker. The pixel size of the display is 0.283mm. Subjects were seated at a viewing distance of 1 meter.

The tests are conducted with seven subjects and the results have shown that there is a clear relation between the perceived JNB at different depths. The sigma JNB is calculated as the 63% probability of detecting blur. For a given contrast C and depth D pair, the probability of detecting the blur is modeled as a psychometric function [8] with the following form:

$$P = 1 - \exp \left(- \left| \frac{\sigma}{\sigma_{jnb}} \right|^\beta \right) \quad (2)$$

where σ is the standard deviation of the Gaussian blur filter and corresponds to the blur strength at the considered edge, σ_{jnb} is the standard deviation which corresponds to the JNB threshold, and β is a model parameter. In (2), at $\sigma = \sigma_{jnb}$ the probability of detecting blur is equal to 63%. The subjectively obtained data is modeled using (2) with σ_{jnb} and β as the model parameters. Figure 5 shows an example plot of the probability of blur detection as a function of the sigma values, for a contrast value of 32 and a disparity value of -30. Table 3 summarizes the σ_{jnb} values for the contrast and disparity ranges used in the experiment. It is observed that σ_{jnb} varies with the depth for the same contrast values. It is also observed that, for the same contrast value, σ_{jnb} increases as we move away from the screen (screen corresponds to zero disparity), apart from one outlier. It can also be noticed that the σ_{jnb} increased as the contrast is increased. It is found that the outliers are created when the σ_{jnb} falls outside the observed σ values. It can be concluded from the above experiments that perceived blur/sharpness depends on the depth of the object. The objects closer to the observer look sharper than the ones farther away. Hence depth map has to be considered in the application of the sharpness

enhancement to the 3-D stereo images. As a part of our future work we would like to develop a JNB metric for stereo images which can predict the blur metric at different depths.

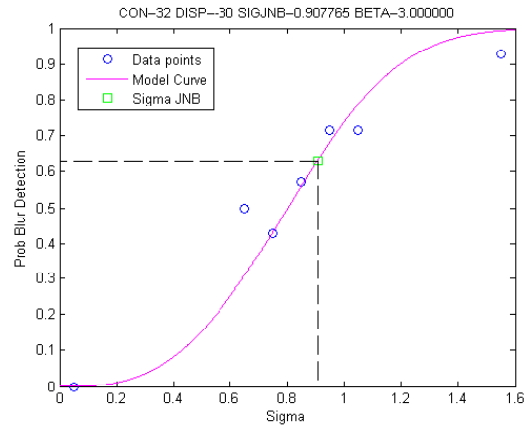


Figure 4. Probability of blur detection and corresponding sigma JNB for a contrast of 32 and a disparity of -30.

Table 2. Sigma values for just noticeable blur at different contrast and disparity values.

Contrast	Disp	σ_{JNB}	Contrast	Disp	σ_{JNB}
32	-30	0.907765	64	-30	0.946718
32	-10	0.760658	64	-10	0.960845
32	10	1.001128	64	10	1.028565
32	20	1.078524	64	20	0.868373
128	-30	0.980948	255	-30	1.186565
128	-10	0.948571	255	-10	1.207066
128	10	0.972172	255	10	1.111234
128	20	1.158324	255	20	1.184083

3. PROPOSED ADAPTIVE SHARPNESS ENHANCEMENT ALGORITHM

The subjective test in Section 2 concluded that perceived sharpness at different depths is different. The objects closer to the observer will appear sharper than the objects which are further away. Based on these observations a disparity aware sharpness enhancement algorithm is proposed. The block diagram of the proposed algorithm is shown in Figure 5. The gain of the unsharp masking sharpness enhancement algorithm is controlled by the disparity map. The disparity map is represented by value between 0-255. A value of 255 represents object closer to the observer and a value of 0 represents the object at infinity. In the unsharp masking algorithm fraction of the high pass filtered image is added back to the original image to boost the edge transitions. The gain of added image controls the amount of sharpness enhancement applied to the image.

$$Y_{i,j} = X_{i,j} + \alpha * LUT(DisparityMap) * HP(X_{i,j}) \quad (3)$$

In Equation 3, $X_{i,j}$ is the input image and $HP(X_{i,j})$ is the output of the high-pass filtered image and α is the scaling factor which determines amount of sharpness enhancement applied to the image. The value $LUT(DisparityMap)$ provided by the look-up table is used to vary the strength of sharpness enhancement based on the disparity map. The proposed algorithm is tested on the Middlebury stereo test data [9, 10]. Figure 6 shows the two of the example test sequences namely “Cloth” and “Aloe”. The depth maps provided in the data set are used to control the gain of the sharpness enhancement algorithm. In the subjective tests a linear look-up table (shown in Figure 5) is used which maps

the disparity of 255 to 1.0 and disparity of 1 to 1/255 in equation 3. The outputs for the “Cloth” and “Aloe” sequences are shown in Figure 7 & 8 respectively.

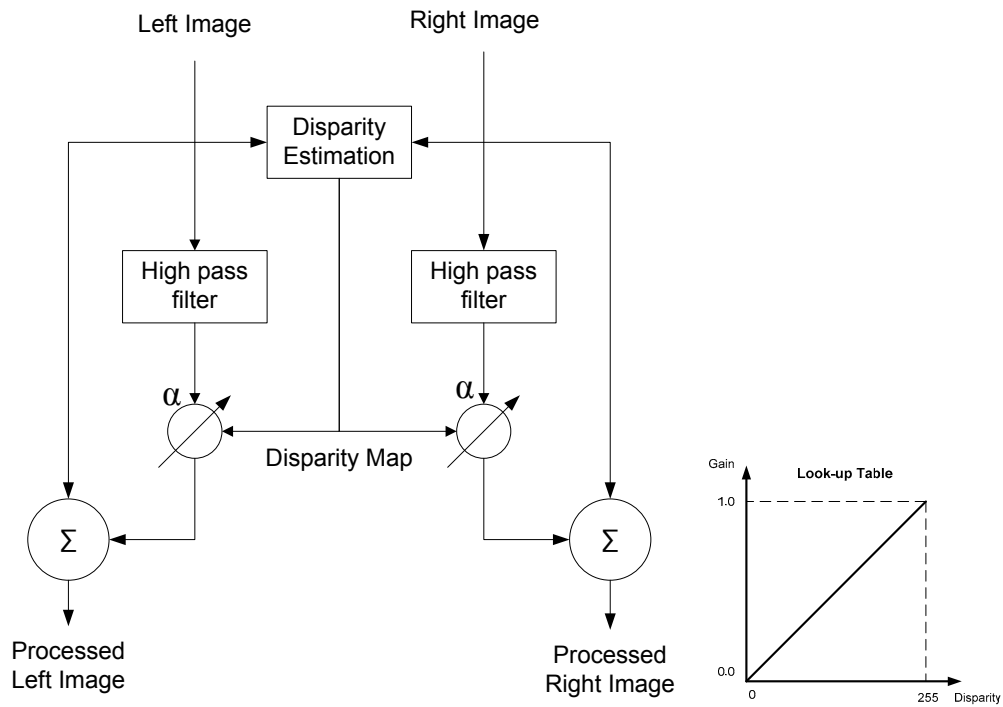


Figure 5. Disparity aware sharpness enhancement

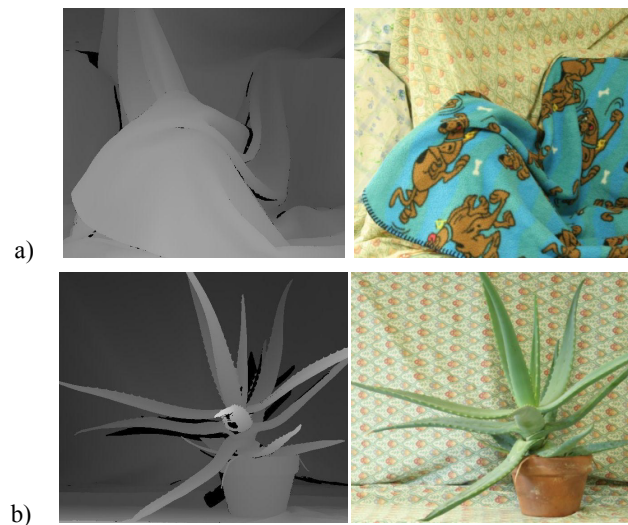


Figure 6. Disparity images and left eye test images from Middlebury stereo database – Sequence names a) Cloth & b) Aloe



Figure 7. Left eye and Right eye images of the “Cloth” sequence – a) Original images b) Sharpness enhancement applied uniformly & c) Proposed adaptive sharpness enhancement results.

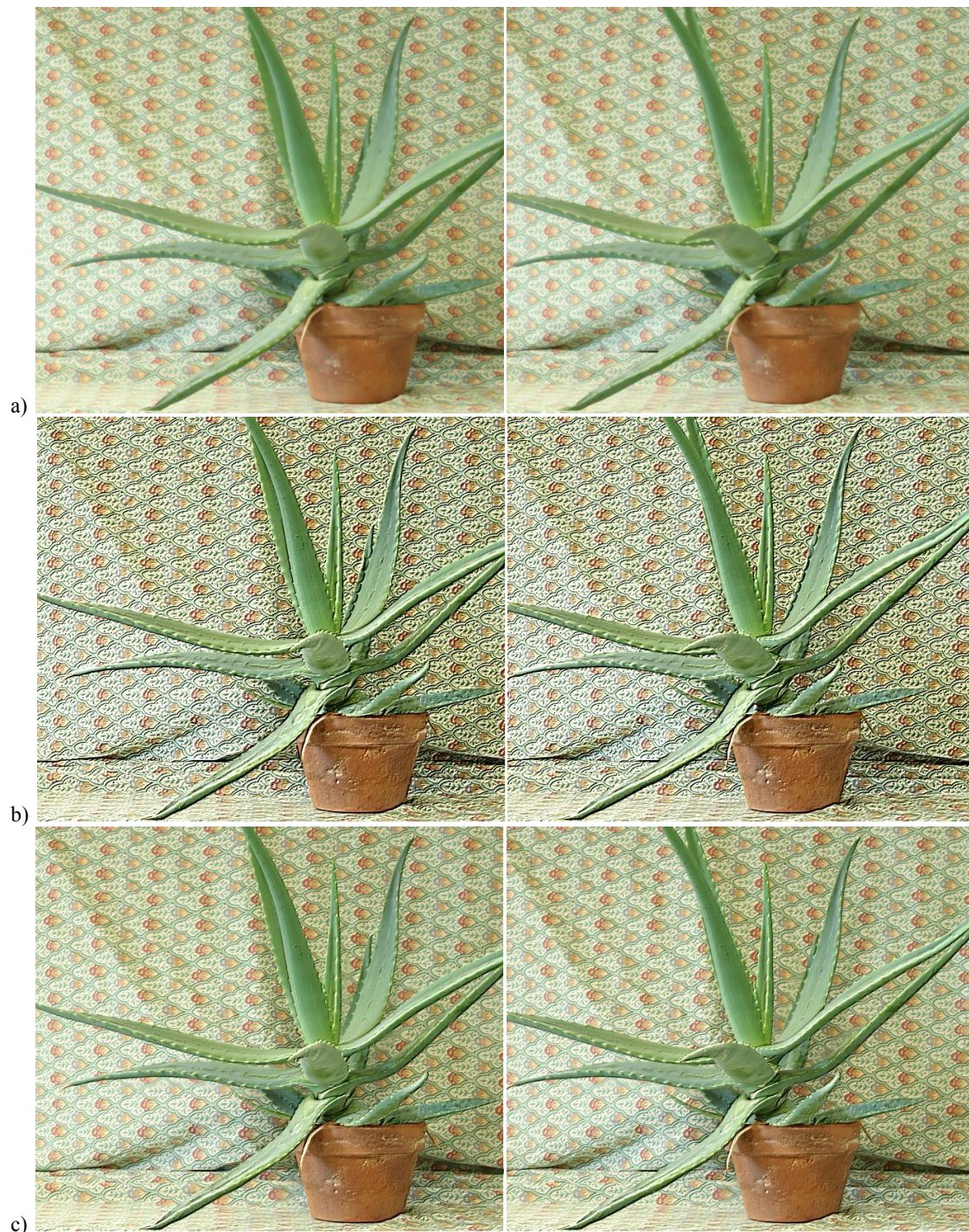


Figure 8. Left eye and Right eye images of the “Aloe” sequence – a) Original images b) Sharpness enhancement applied uniformly & c) Proposed adaptive sharpness enhancement results.

The visual quality tests of the generated outputs are conducted on stereoscopic display with active glasses (similar to the setup used for the subjective experiments in Section 2. It is observed the outputs with uniform sharpness enhancement have difficulty in fusing the images and provides an incorrect depth effect.

4. CONCLUSION

In this work a subjective experiment is presented to study the relation between blur/sharpness and depth. The concept of just noticeable blur (JNB) at different depths for 2-D video is extended to the 3-D stereo video. The results of the subjective experiment indicated that perceived blur/sharpness varies with the depth in the stereoscopic setup. Hence an adaptive sharpness enhancement algorithm is proposed where gain of the sharpness enhancement is controlled by the depth map. As a part of our future work, we would like to propose JNB metric for stereo images which can be used to control the maximum gain of the sharpness enhancement algorithm.

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