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ENHANCEMENT OF SCREEN CONTENT IMAGES BY JUST NOTICEABLE DIFFERENCE MODEL

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Abstract: Now we can observe the rapid development of cloud computing services are influenced by the transmission of screen content images (SCI). While transmitting the images they are going to be compressed to decrease the computational time. The visual quality of screen content images will be reduced at this time. To overcome this we introduce a new just noticeable difference (JND) model for the enhancement of screen content images before transmitting through remote systems. JND model adopts a local parametric edge model to generate edge profile, which is an enhanced screen content image. This parametric edge model predicts the luminance, contrast and sensitivity of an edge profile by making the use of luminance adaptation, contrast masking and structural sensitivity algorithms. By using these parameters proposed model evaluate the visibility threshold. This just noticeable difference model estimates on and near edge pixel transitions. If we see the visual quality of screen content images exhibited by the parametric edge model outperforms the existing JND models

Index Terms—local parametric edge model, edge profile, just noticeable difference, screen content image.

I. INTRODUCTION

Screen content image may have only textual content or both textual content and pictorial regions. Screen content images have discontinuity between the content while the natural images consist continuous content. Up to now the existing JND methods are designed for natural images but for the enhancement of screen content images there is no specific method exists. So we developed a parametric edge model especially for screen content images.

Our Human Visual System (HVS) cannot diagnose the low level pixel variations. The just noticeable difference provides minimum visibility threshold at this low level pixel variations. There are two types of JND models exists which are named as pixel domain JND model and transform domain JND model.

Pixel domain JND models use the effect of luminance adaptation and contrast masking to evaluate the visibility threshold value. Whereas transform domain JND models uses contrast sensitivity function (CSF) to identify the base threshold values. Pixel domain JND models perform operations on each and every pixel, but Transform domain JND models perform operations on particular region of interest in an image. The overlapping effect of luminance adaptation and contrast masking gives the visibility threshold in conventional pixel domain JND model, where the exact structure of the image may not achieved.

These screen content images have unique characteristics such as Frequency energy falloff statistics, sharpness of edges and free energy principle. Here we are introducing JND model based on the sharpness of edges characteristic because SCI having sharp edges and thin lines. Due to these unique characteristics these SCIs results in different behaviours of human visual system while viewing the text documents. To demonstrate the sharp edges of SCIs we have introduced a just noticeable blur metric which takes the advantage of edge width computation. This proposed JND model uses luminance adaptation, contrast masking and structural sensitivity to evaluate the visibility threshold of SCIs. With this visibility threshold we can reconstruct the edge profile of original image.

Further, we incorporate the proposed JND model in perceptually lossless compression to preserve the visual quality of an image. To obtain better visual quality of an image in screen content coding, we have to incorporate the proposed JND model in screen content coding extension. From the subjective results the proposed JND model is efficient in predicting the visual quality of an image at the same coding bits.

II. EXISTING METHODS

The just noticeable difference estimation plays an important role in all JND models. The JND models which are existed till now are designed for natural images. There are four conventional methods existed. Those are Yang et al.'s [8], Liu et al.'s [2], Zhang et al.'s [5] and Wu et al.'s methods [3]. Here we are using Liu et al.'s method to compare with the proposed JND model performance. This existing model is just noticeable difference for images with decomposition model [2], here they have used luminance adaptation and contrast masking factors to calculate just noticeable difference. Because of the distinct properties of SCIs the existing models still quite limited in preserving the visual quality of the

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images. This model calculate the just noticeable difference based on the on edge pixel values, due to this there may be some inconsistency presents while reconstructing the edge profile which results in distortions at the JND profile.

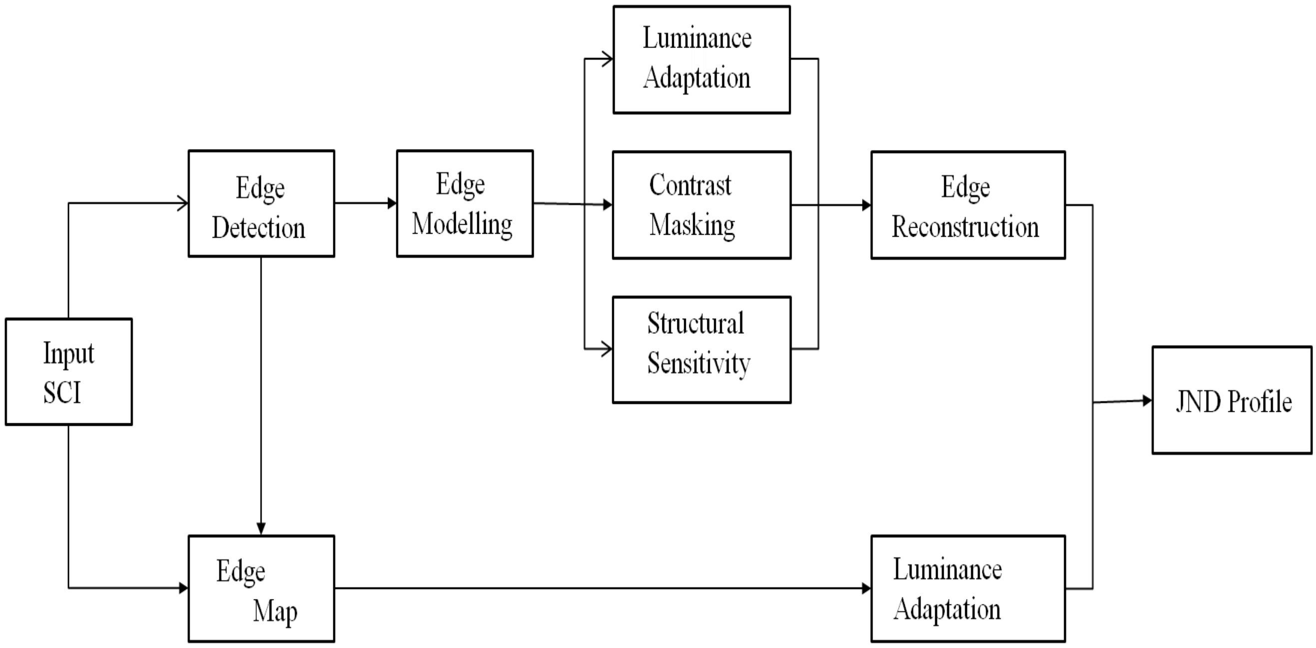
Drawbacks of existing system:

- Limited in predicting the visual quality of SCIs.
- High noticeable distortions present in conventional JND methods.
- These models cannot distinguish the pixels on and near sharp transitions leads to same JND value.

III PROPOSED SYSTEM

A) System Description:

Fig1: Block diagram of proposed method

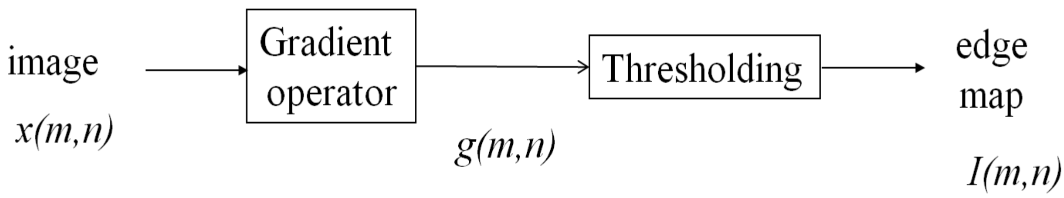


B) Edge detection:

It is a fundamental tool for all the segmentation methods in image processing. Some common edge detection algorithms are sobel, prewitt, Roberts, canny and fuzzy logic algorithms. Here the edge detection process adopts canny edge detection to identify the edges.

C) Edge Map:

Here we map the edge pixels after edge detection. This mapping is done based on the gradient operator. By using this gradient operator we can examine how the pixels are changing their colour from one direction to another direction. This edge map will map the pixels where the colour is changing abruptly.



$$I(m,n) = \begin{cases} 1 & |g(m,n)| > th \\ 0 & otherwise \end{cases}$$

C) Edge modelling:

The edge modelling adopts a parametric edge model where the luminance, contrast and structure of an image are calculated. Based on the luminance, contrast and structure values the visibility threshold values of an image will be calculated by making use of luminance adaptation, contrast masking and structural distortion sensitivity. A parametric

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edge model can offer simultaneous representation of intensity, strength and width of each pixel variations which represents the luminance, contrast and structure values. Here one-dimensional notation is adopted to describe the edge model. To characterize the step edge x_0 we use step function with edge basis as,

$$u(x;b,c,x_0) = c \cdot U(x - x_0) + b$$

Where $U(x - x_0)$ denotes the unit step function, b denotes edge basis means luminance and c denotes contrast, Here we can observe that sharp edges do not exist in practical images even for textual blocks in SCIs. So the edge is treated as distorted version of the isolated step edge with a point spread function,

$$s(x;b,c,\omega,x_0) = u(x;b,c,,x_0) * psf(x:\omega)$$

Usually Gaussian function is treated as appropriate point spread function and Gaussian function is denoted as $g(x,\omega) = (1/\sqrt{(2\pi\omega^2)})\exp((-x^2/2\omega^2)$. So the edge will have smooth transitions and it is represented as

$$s(x;b,c,\omega,x_0) = b + \frac{c}{2}\left(1 + erf\left(\frac{x - x_0}{\omega\sqrt{2}}\right)\right)$$

Luminance adaptation:

This luminance adaptation method calculates the visibility sensitivity based on the background luminance values. It makes the use of N x N patch to derive visibility threshold value. In this method edge pixels are separated from the pixels in pictorial regions, So we can easily calculate the background luminance. While calculating the background luminance we concentrate more on homogeneous content than the edge pixels of textual contents. So we are excluding the edge pixels to measure the background luminance.

Here we are using 5 x 5 mask to calculate the luminance masking effect.

$$T_l(p) = \begin{cases} \alpha_1 \cdot \left(1 - \sqrt{\frac{\overline{I(p)}}{127}}\right) + \beta & \text{if } \overline{I(p)} \le 127 \\ \alpha_2 \cdot \left(\overline{I(p)} - 127\right) + \beta & \text{otherwise,} \end{cases}$$

Here $\overline{I(P)}$ is the average background luminance from 5 x 5 mask which is shown below

Fig2: Mask to calculate average background luminance

1	1	1	1	1
1	2	2	2	1
1	2	0	2	1
1	2	2	2	1
1	1	1	1	1

edge pixel

If there is only edge pixels present then $\overline{I(P)}$ is calculated as $\overline{I(P)} = b + c/2$. To calculate the visibility threshold, the α_1,α_2 and β values are taken from parameter set index as shown below.

$$\psi_1 = \{8, 1, 1/128\}, \quad \psi_2 = \{10, 1, 1/128\}$$
$$\psi_3 = \{13, 2, 2/128\}, \quad \psi_4 = \{15, 2, 2/128\}$$
$$\psi_5 = \{17, 2, 2/128\}, \quad \psi_6 = \{19, 3, 3/128\}$$
$$\psi_7 = \{21, 3, 3/128\}, \quad \psi_8 = \{23, 3, 3/128\}$$
$$\psi_9 = \{25, 4, 4/128\}, \quad \psi_{10} = \{27, 4, 4/128\}.$$

Contrast masking:

In this method we calculate the visibility threshold based on noticeable edge contrast variations, So we go for divisive normalization framework to achieve this. In this framework contrast change is depended on the normalized contrast. Let us assume $c(p)$ and $c'(p)$ are the original contrast and changed contrast of an image. The perceived contrast change is

$$f = \frac{|c(p) - c'(p)|}{c(p) + c'(p)}$$

From the subjective tests the f values set is observed as [0.02 0.3] with an interval of 0.04. The appropriate value for visibility threshold is observed as 0.14 from the plot between perceived contrast change and percentage of preference on original SCIs. From the visibility threshold calculate the tolerable changed contrast as shown below

$$T_{c+}(p) = \frac{1-f_{th}}{1+f_{th}} \cdot c(p)$$

$$T_{c+}(p) = \frac{1-f_{th}}{1+f_{th}} \cdot c(p)$$

Where $T_{c+}(p)$ indicate the threshold corresponding to increased contrast and $T_{c-}(p)$ indicate the threshold corresponding to decreased contrast.

Structural distortion sensitivity:

The structure of the edge profile is controlled by the edge width factor which corresponds to a specific shape of the edge profile. The edge profile becomes sharper when edge width becomes smaller. Like natural images SCIs does not have homogeneous content, so we cannot assign a constant threshold. SCIs may have different high contrast edges, so we investigate the visibility threshold based on the relative change of edge width.

$$\Delta(\omega) = \omega_t - \omega,$$

Where ω_t is calculated from parameter estimation on the distorted version of SCIs. These distorted versions are generated from Gaussian smoothing which is convolved by 2D convolution on the original SCIs. The standard deviation values for the Gaussian function is given below

$$\sigma = [0.3, 0.5, 0.65, 0.8, 1, 1.2],$$

From the plot between $\Delta(\omega)$ and percentage in favour of original images, the relative change of edge width is set around 0.1. at standard deviation of 0.65.

D) Edge reconstruction:

Here we demonstrate how to incorporate the three masking effects into a unified JND model to reconstruct the edge profile. First of all we choose luminance adaptation masking effect to find out the visibility threshold, To do this we adopt one dimensional notation of parametric edge model for finding visibility threshold for pixel ‘p’ can be calculated as,

$$T_{el}(P) = s(p; T_l(p) + b, c, \omega, x_0) - s(p; b, c, \omega, x_0)$$

In similar fashion, the contrast making effect is accounted for finding the visibility threshold on contrast,

$$T_{ec}(P) = \min\{|s(p; b, T_{c+}, \omega, x_0) - s(p; b, c, \omega, x_0)|, |s(p; b, T_{c-}, \omega, x_0) - s(p; b, c, \omega, x_0)|\}$$

From this we can achieve minimum value as just noticeable threshold.

To overlap these two effects we choose nonlinear additivity model for masking which results in common threshold as,

$$T_{ns}(p) = T_{el}(p) + T_{ec}(p) - C_{ns} \cdot \min\{T_{el}(p), T_{ec}(p)\}$$

Where $C_{ns} (0 < C_{ns} < 1)$ is a constant that represents the overlapping between $T_{el}(p)$ and $T_{ec}(p)$.

Similarly the visibility threshold of structural distortion is calculated as

$$T_s(p) = |s(p; b, c, \omega + \Delta(\omega), x_0) - s(p; b, c, \omega, x_0)|$$

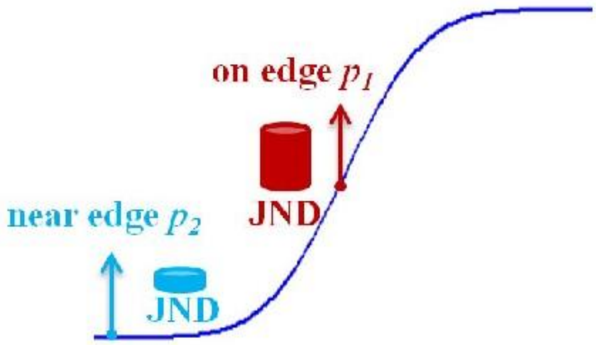
Sometimes pixels in different positions of edge profile results in different structural and non-structural visibility thresholds. This combination leads to overall edge profile (JND model),

$$T_e(p) = T_s(p) + T_{ns}(p) - C \cdot \min\{T_s(p), T_{ns}(p)\}$$

Finally the edge and pictorial JND profiles are established and merged together to form the reconstructed JND profile.

$$T(p) = \begin{cases} T_e(p) & p \in S_E \\ T_l(p) & \text{otherwise} \end{cases}$$

Fig3: Illustration of on edge and near edge pixels.



The proposed method distinguishes the pixels on and near the sharp transitions which is illustrated in above figure. The on edge pixels treated as p_1 belongs to edge pixel set S_E and near edge pixels treated as p_2 belongs to background pixel set. Therefore proposed model is applied to derive the JND, such that $T(p_1)=T_e(p_1)$ and $T(p_2)=T_l(p_2)$ .After applying all masking effects, this proposed JND model shows that $T(p_1)>T(p_2)$.

IV. EXPERIMENTAL RESULTS

Here extensive experiments are conducted to evaluate the proposed JND model performance based on comparisons on distortion masking ability. To do these experiments noise is injected into the SCIs. The distorted image is generated by injecting JND noise to original pixel in pixel domain,

$$I_1(p)=I(p)+r\cdot T(p)$$

Where $I_1(p)$ is the distorted image, $I(p)$ is the original image and $T(p)$ is just noticeable difference. We can evaluate the performance of proposed JND model from two factors. First factor is error tolerance ability which can be evaluated in terms of energy of the JND signal. Second factor is a subjective study conducted to examine the quality of noise contaminated SCIs. After that the performance of the JND model is compared with one of the existing JND model which is *Liu et al.'s*. These results are tabulated below.

Fig4: Demonstration of SCIs in validation

These SCIs are taken from the database [4]. For these images we calculate the error tolerance ability in terms of energy and perform subjective test to examine the performance of proposed system.

A) Energy:

The energy is calculated by averaging the $T(p)^2$ over the whole SCI .

$$energy=\sum T(p)^2 \Big/ totalpixels$$

TABLE I: Results of Energy calculation for two methods

Image number	*Liu et al.'s*	Proposed
1	28.2715	65.1317
2	31.6542	63.9462
3	21.6246	45.9848
Average	27.1470	58.3578

The experimental results shows that the proposed method yield higher JND energy, So this method shows stronger ability in error tolerance .

B) Subjective Test:

Here the quality of the images is being examined. The subjective scores are converted with unified order. The average subjective values are calculated to demonstrate the image visual quality.

TABLE II: Results of subjective test for two methods

Image number	*Liu et al.'s*	Proposed
1	0.4090	0.4093
2	0.4240	0.4238
3	0.4489	0.4488
Average	**0.4274**	**0.4273**

The experimental results shows that the proposed JND model has lower mean value than the *Liu et al.'s* method. From this result the proposed method has better distortion masking ability.

V CONCLUSION

Screen content images have unique characteristics such as thin lines and sharp edges. Because of these different properties of SCIs, we have proposed a specific JND model for SCIs to evaluate the visibility threshold. This JND model computes the just noticeable estimation factor by introducing the parametric edge model. This helps in computing the visibility thresholds of three components luminance, contrast and structure based on three masking effects. This JND model can be used in screen content coding for acquiring the lossless compression at transport of SCIs through web services, mobile browsers and desktop sharing systems. The proposed JND model performance is evaluated by using the factors of energy and subjective test. By considering the two factors it is observed that the proposed JND model has better performance than the conventional JND model.

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