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A CENTRE OF EXCELLENCE IN SCIENCE & TECHNOLOGY BY THE CATHOLIC ARCHDIOCESE OF TRICHUR

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NBA accredited B.Tech Programmes in Computer Science & Engineering, Electronics & Communication Engineering, Electrical & Electronics Engineering and Mechanical Engineering valid for the academic years 2016-2022. NBA accredited B.Tech Programme in Civil Engineering valid for the academic years 2019-2022.

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

SEMINAR REPORT

Structural Similarity Index by using different edge detection approaches on live video frames for different color models

Submitted by

MUHAMMED AFTHAB V U
JEC17CS070

Supervised by

Ms. NINU FRANCIS
Ass. Prof., Dept. of CSE

---

in partial fulfillment for the award of the degree

of

BACHELOR OF TECHNOLOGY (B.Tech)

in

COMPUTER SCIENCE & ENGINEERING

of

A P J ABDUL KALAM TECHNOLOGICAL UNIVERSITY

DECEMBER 2020

Jyothi Hills, Panjal Road,
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CREATING TECHNOLOGY LEADERS OF TOMORROW

DECEMBER 2020

Department of Computer Science and Engineering

JYOTHI ENGINEERING COLLEGE, CHERUTHURUTHY

THRISSUR 679 531

DECEMBER 2020

BONAFIDE CERTIFICATE

This is to certify that the seminar report entitled **Structural Similarity Index by using different edge detection approaches on live video frames for different color models** submitted by **Muhammed Afthab V U (JEC17CS070)** in partial fulfillment of the requirements for the award of **Bachelor of Technology** degree in **Computer Science and Engineering** of **A P J Abdul Kalam Technological University** is the bonafide work carried out by her under our supervision and guidance.

Ms. Ninu Francis	**Mr. Shaiju Paul**	**Dr. Vinith R**
Seminar Guide	Seminar Coordinator	Professor
Assistant Professor	Assistant Professor	Head of The Dept
Dept. of CSE	Dept. of CSE	Dept. of CSE

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3. An ability to apply design, development, maintenance or evaluation of software engineering principles in the construction of computer and software systems of varying complexity and quality.
4. An ability to understand concepts involved in modeling and design of computer science applications in a way that demonstrates comprehension of the fundamentals and tradeoffs involved in design choices.

Course Outcomes (COs)

C418.1 **Presentation Skills in terms of Content** : Students will be able to show competence in identifying relevant information, defining and explaining topics under discussion. They will demonstrate depth of understanding, use primary and secondary sources; they will demonstrate the working, complexity, insight, cogency, independent thought, relevance, and persuasiveness. They will be able to evaluate information and use and apply relevant theories.

C418.2 **Presentation Skills in terms of Organization** : Students will be able to show competence in working with a methodology, structuring their oral work, and synthesizing information. They will make a detailed study on the previous works related to their topic and will present the observations.

C418.3 **Presentation Skills in terms of Delivery** : Students will use appropriate registers and vocabulary, and will demonstrate command of voice modulation, voice projection, and pacing. They will be able to make use of visual, audio and audio-visual material to support their presentation, and will be able to speak cogently with or without notes.

C418.4 **Discussion Skills** : Students will be able to judge when to speak and how much to say, speak clearly and audibly in a manner appropriate to the subject, ask appropriate questions, use evidence to support claims, respond to a range of questions, take part in meaningful discussion to reach a shared understanding, speak with or without notes, show depth of understanding.

C418.5 **Listening Skills** : Students will demonstrate that they have paid close attention to what others say and can respond constructively. Through listening attentively, they will be able to build on discussion fruitfully, supporting and connecting with other discussants.

C418.6 **Argumentative Skills and Critical Thinking** : Students will develop persuasive speech, present information in a compelling, well-structured, and logical sequence, respond respectfully to opposing ideas, show depth of knowledge of complex subjects, and develop their ability to synthesize, evaluate and reflect on information.

Course Outcome							
Programme Outcomes		C418.1	C418.2	C418.3	C418.4	C418.5	C418.6
	1	3	3	3	3	3	3
	2	3	3	3	3	3	3
	3	3	3	3	3	3	3
	4	3	3	3	3	3	3
	5	3	3	3	3	3	3
	6	3	3	3	3	3	3
	7	3	3	3	3	3	3
	8	3	3	3	3	3	3
	9	3	3	3	3	3	3
	10	3	3	3	3	3	3
	11	3	3	3	3	3	3
	12	3	3	3	3	3	3

PO - CO Mapping

PEO - CO Mapping

Course Outcome							
		C418.1	C418.2	C418.3	C418.4	C418.5	C418.6
Programme Educational Objective	1	3	3	1	1	-	2
	2	3	3	3	3	1	3
	3	1	2	3	3	1	3

PSO - CO Mapping

Course Outcome							
		C418.1	C418.2	C418.3	C418.4	C418.5	C418.6
Programme Specific Outcomes	1	3	3	3	3	3	3
	2	3	3	3	3	3	3
	3	3	3	3	3	3	3
	4	3	3	3	3	3	3

Seminar Outcome

1. Studied about the concept of Machine Learning.
2. Studied about the image classification process.
3. Analyzed the general architecture of Bag of Visual Words.
4. Studied about different machine learning algorithms.
5. Analyzed how the quantitative performance of algorithms is reported.

Seminar Outcome - CO Mapping

	Course Outcome						
		C418.1	C418.2	C418.3	C418.4	C418.5	C418.6
Seminar Outcome	1	3	3	3	1	3	3
	2	3	3	1	1	3	3
	3	3	3	3	1	3	1
	4	3	3	3	3	1	1
	5	3	1	3	3	1	1

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ABSTRACT

Structural Similarity Index (SSIM) has become a standard among image quality metrics. Structural Similarity Index is a framework for quality evaluation based on the degradation of structural information of video frame. Structural Similarity Index is used to assess the similarity between the reference video frame and the processed video frame. Structural Similarity Index is easy and well linked with subject evaluation. Measure of structural similarity index is able to provide a good approximation to perceived image quality. This procedure evaluates the visual impact of changes in luminance, contrast and structure in an image.In this paper SSIM values are calculated and compared for live video frames by applying different edge detection operators for different color models to assess the quality of the frames.

Keywords -Color Models,Edge Detection,Edge detection operators,SSIM

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List of Abbreviations

SSIM	: *Structural Similarity Index*
MSSIM	: *Mean Structural Similarity*
PSNR	: *Peak signal to noise ratio*
LCV	: *Laboratory for Computational Vision*
LIVE	: *Laboratory for Image and Video Engineering*
CIE	: *Commission Interna − tionale deI Eclairage*
MESSIM	: *Mean − Edge Structural Similarity*
PSNR	: *Peak Signal To Noise Ratio*
MAE	: *Mean Absolute Error*

(1)

CHAPTER 1
INTRODUCTION

1.1 Overview

Edges are important local intensity changes in the image and are important features to analyze an image. They are important hints to split region within an object or to identify changes in illumination or color. They are an important feature in the early vision stages in the human eye. Edge detection identifies sudden changes in an image. Primary goal is to extract information about the two-dimensional projection of a 3D scene. Secondary goal is Image segmentation, region separation, objects description and recognition etc. Edge Point is one in an image with coordinates [i, j] at the location of a significant local intensity change in the image. Edge fragment is a small line segment about the size of a pixel, or as a point with an orientation attributes. The term edge is commonly used either for edge points or edge fragments. Edge detector is algorithm that produces a set of edges from an image. Some edge detectors can also produce a direction that is the predominant tangent direction of the arc that passes through the pixel.

The Structural Similarity (SSIM) index is a method for evaluating the perceived quality of digital images and videos.Structural Similarity is used for measuring the similarity between two images.The Structural Similarity index is a measurement or prediction of image quality based distortion-free image as reference. SSIM is a perception-based model that considers image degradation as perceived change in structural information by incorporating important perceptual phenomena, including both luminances masking and contrast masking. Structural information is the design that the pixels have strong inter-dependencies when they are spatially close. These dependencies carry significant information about the structure of the objects in the visual scene.

1.2 Objective

The main objective of this seminar is to calculate SSIM values of live video frames and compared with live video frames by applying different edge detection operators for different color models to assess the quality of the frames.

1.3 Organization Of The Report

The report is organised as follow:

- **Chapter 1:Introduction** Gives an introduction to how SSIM is calculated by using different edge detection approaches on live video frames for different color models.
- **Chapter 2:Literature Survey** Summarizes the research on different applications of Structual Similarity Index and its importance in image processing.
- **Chapter 3: Image classification using BoVW** Discusses in depth about Structural Similarity Index and its calculation using edge detection approaches.
- **Chapter 4:Implementation & Results** Contains the implementation and results of calculated SSIM.
- **Chapter 5:Advantages & Disadvantages** List out the advantages and disadvantages of SSIM.
- **Chapter 6:Applications** List out the various applications of SSIM.
- **Chapter 7:Conclusion** The overall development and its inferred results are concluded with probable best practice.
- **References** Includes references of image quality evaluation using ssim and its applications for future purposes.

CHAPTER 2
LITERATURE SURVEY

2.1 Image quality measurement through structural similarity based on higher order moments

Structural similarity index (SSIM) considers the loss of structural information as a degradation of quality. Structure of original and distorted images are compared by using low order moments, which are mean, variance and correlation. In this paper, we extend the SSIM by incorporating shape parameters of distributions, which are the higher order moments based skewness and kurtosis. We show that skewness and kurtosis adds useful extra information to SSIM, which is relevant in quantification of local structures.

Image quality assessment means estimating the quality of an image or determining the distortion present in the image. Distortions occur in images during capturing, storing and transmitting images from one device to another or over network. Hence, image quality assessment is needed in many systems such as in measurement of service quality of networks, and in evaluation of performance of capturing devices, and various compression and processing algorithms. Subjective image quality assessment involves a lot of manpower, and is time consuming. It is not feasible for real time quality assessment as well[4]. Hence, objective image quality measurement that assesses quality automatically is of high importance.In this paper, SSIM is extended by introducing shape parameters in existing SSIM. Change in the shape of distribution is considered as degradation in quality. Higher order moments are quantitative measure of a shape of distribution. Along with the mean, variance and correlation, Kurtosis and Skewness of both original and distorted images are compared to compute new Structural similarity index. The algorithm is compared with existing techniques by taking results on over 900 images of standard CSIQ database. We have taken results for various type of distortion like JPEG, JPEG2000, Gaussian blurring, white noise, contrast, fast fading. Results are validated against Difference Mean Opinion Scores (subjective ratings) and results are depicted and tabulated. which indicates that the performance of proposed method is better than the existing SSIM.

2.1.1 Structural Similarity Index

Natural image signals exhibits strong spatial dependencies and structural similarity provides good measure for quality[15]. SSIM is based on the assumption that human visual system views and processes an image by extracting its structural information. Therefore, change in the structural information is considered as loss of quality. SSIM The approach divides structural similarity into three parts, namely, similarity in luminance, contrast and variation.

Luminance of signal is calculated by finding the average of pixels intensity.

$$\mu_x = \frac{1}{N}\sum_{i=1}^{N} x_i$$

Luminance comparison function compares mean of original and distorted signals.

$$l(x,y) = \frac{2\,\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1}$$

Standard deviation is used to determine contrast of the signal

$$\sigma_x = \left(\frac{\sum_{i=1}^{N}(x_i - \mu_x)^2}{N-1}\right)^{\frac{1}{2}}$$

Similarly contrast comparison function is given by

$$c(x,y) = \frac{2\,\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2}$$

Similarity in variation is calculated by determining correlation coefficient between original and distorted signal. The correlation coefficient is a quantitative measurement of how much one signal is varies in comparison to the other signal. One signal will equal to other when both have the same kind of variation.

$$s(x,y) = \frac{\sigma_{xy}+C_3}{\sigma_x\sigma_y+C_3}$$

$$\sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu_x)(y_i - \mu_y)$$

The resulting value of luminance, contrast, and variation comparisons are combined to give SSIM index value.

$$SSIM(x,y) = [l(x,y)]^{\alpha}[c(x,y)]^{\beta}[s(x,y)]^{\gamma}$$

Putting α=1, β= 1 and ϒ =1 we get following expression

$$SSIM(x,y) = \frac{(2\,\mu_x\mu_y+C_1)(2\,\sigma_{xy}+C_2)}{(\,\mu_x^2+\mu_y^2+C_1)(\,\sigma_x^2+\sigma_y^2+C_2)}$$

Where, and are constants equal to k1L, k2L and k3L respectively. L is a dynamic range of pixel intensities. k1, k2 and k3 are constants «1.

2.1.2 Proposed Structural Similarity:

Local and global distribution of pixel values is one way of representing local and global image structure, respectively. This representation is particularly useful as attributes of distributions like mean, variance and correlation used in SSIM represents what human visual system perceives quite well[15]. However, the moments and their orders which will most effectively relate to human perception are unknown. In addition to measurement with the lower order moments like mean, variance and correlation coefficient, measurements based on higher order moments are required to represent information about the shape of the distribution. Shape of a distribution might be an important measure for perceptual quality assessment. Obviously, quality of image is degraded when shape of image distribution is not preserved.

Higher order moments of distribution are used in our algorithm to measure the similarity between the original and distorted signals /images. These moments are descriptors of shape of a distribution. Third order central moment is normalized with respect to cube of standard deviation to get what is known as skewness. It measures the symmetry of the distribution about its mean. For a signal x.

It is given by following expression:

$$sk_x = \frac{E\left[(x-\mu_x)^3\right]}{\sigma_x{}^3}$$

Skewnesses of two signals x and y are compared by:

$$S(x,y) = \frac{2\, sk_x sk_y + C}{sk_x^2 + sk_y^2 + C}$$

Flatness (or peakness) of a distribution is measured by using fourth order central moment. It is normalized by dividing it by square of variance, to get what is known as kurtosis. For a signal x.

It is given by following expression:

$$k_x = \frac{E\left[(x-\mu_x)^4\right]}{\sigma_x{}^4}$$

Kurtosis of two distributions x and y, that is, distorted and referenced distributions, is compared by:

$$K(x,y) = \frac{2\, k_x k_y + C}{k_x^2 + k_y^2 + C}$$

Kurtosis or Skewness value may go to infinity. To deal with these pathological cases we consider the general representation as

$$\frac{2\,AB + Const}{A^2 + B^2 + Const}$$

The overall equation of SSIM is given as

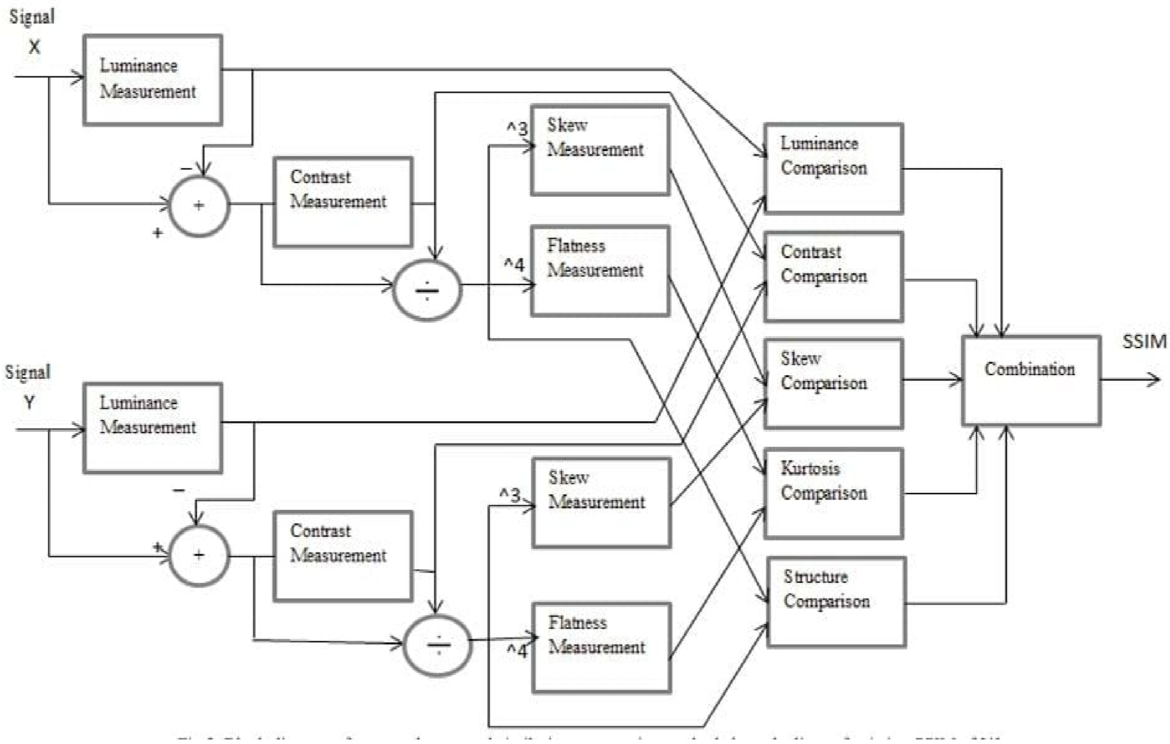

Figure 2.1: Block diagram of proposed structural similarity computation method along the lines of existing SSIM

$$SSIM(x,y) = [l(x,y)]^{\alpha}[c(x,y)]^{\beta}[s(x,y)]^{\Upsilon}$$
$$[S(x,y)]^{\pi}[K(x,y)]^{\rho}$$

2.1.3 Conclusion:

This paper extends the SSIM measure by introducing distribution shape parameters in the existing measure. Higher order moments based skewness and kurtoses are used as the distribution shape descriptors. It is shown that use of skewness and kurtosis adds useful information to SSIM relevant to structural similarity between image regions. Experimental results are taken on various types of distorted images from the publicly available CSIQ dataset which contains more than 900 images. Subjective rating by users is used as ground truth to compare the proposed SSIM to MSE and existing SSIM. From the outcome of the comparison, it is found that the proposed technique is an effective method of evaluating the image quality with better correspondence with human perception.

2.2 Structural Similarity Index with Predictability of Image Blocks

Structural similarity index (SSIM) is a widely used full-reference metric for assessment of visual quality of images and remote sensing data. It is calculated in a block-wise manner and is based on multiplication of three components: similarity of means of image blocks, similarity of contrasts and a correlation factor. In this paper, two modifications of SSIM are proposed. First, a fourth multiplicative component is introduced to SSIM (thus obtaining SSIM4) that describes a similarity of predictability of image blocks. A predictability for a given block is calculated as a minimal value of mean square error between the considered block and the neighboring blocks.[5] Second, a simple scheme for calculating the metrics SSIM and SSIM4 for color images is proposed and optimized. Effectiveness of the proposed modifications is confirmed for the specialized image databases TID2013, LIVE, and FLT. In particular, the Spearman rank order correlation coefficient (SROCC) for the recently introduced FLT Database, calculated between the proposed metric color SSIM4 and mean opinion scores (MOS), has reached the value 0.85 (the best result for all compared metrics) whilst for SSIM it is equal to 0.58[8].

SSIM is calculated in a fast and simple manner using small size image blocks with further averaging of the obtained results. For each pair of distorted and reference images, similarities of intensity, contrast and correlation factor are considered. SSIM takes into account effects of intensity and contrast masking (in indirect way) whilst MS-SSIM also incorporates CSF. Thus, MS-SSIM utilizes three main peculiarities of intensity and contrast masking of HVS [11]. However, this indirect way of accounting of masking effects (it is impossible to regulate the value of these effects) alongside with neglecting peculiarities of color perception by HVS has led to the fact that, according to data for the database TID2013[12], the metrics SSIM and MS-SSIM perform worse than many objective visual quality metrics proposed recently. Meanwhile, even for the best among them, SROCC between the metrics and MOS does not exceed 0.9[12] which is far from being acceptable for most of applications.

2.2.1 Conventional SSIM

In a slightly simplified form, a calculation of the metric SSIM for blocks x (of a reference image) and y (of the corresponding distorted image) can be written as:

$$\frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1} \times \frac{2\sigma_x\sigma_y + c_2}{\sigma_x^2 + \sigma_y^2 + c_2} \times \frac{\sigma_{xy} + c_3}{\sigma_x\sigma_y + c_3}, \qquad (1)$$

where x and y denotes mean values, and x2 and y2 are variance values in blocks x and y, respectively; xy denotes a covariance of blocks x and y, c1 = (0.01*L)2, c2 = (0.03*L)2,c3=c2/2, L is a dynamic range of pixel values. Being estimated for all block pairs, the SSIM values (1) are then averaged to get the final value.

2.2.2 Measure of block predictability

As the measure of predictability A2 of a given image block A, we use a minimal MSE between A and blocks in the neighborhood:

$$\varepsilon_A^2 = \min_{D \in U}(E(A,D)),$$
$$E(A,B) = \frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}(A_{ij} - B_{ij})^2 \qquad (2)$$

where U is an image area in some neighborhood of the block A, and N,M denotes the block size.

2.2.3 Proposed four-component modification of SSIM

Analyzing expression (2) for $\varepsilon A2$, one can see that $\varepsilon A2$ has the same dimensionality as $\sigma A2$. Therefore, introducing the fourth component, let us use the same methodology as for the second component of the original metric SSIM in expression (1). Then,the proposed modification SSIM4 has the following form:

$$\frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1} \times \frac{2\sigma_x\sigma_y + c_2}{\sigma_x^2 + \sigma_y^2 + c_2} \times \frac{\sigma_{xy} + c_3}{\sigma_x\sigma_y + c_3} \times \frac{2\varepsilon_x\varepsilon_y + c_4}{\varepsilon_x^2 + \varepsilon_y^2 + c_4}, \quad (3)$$

2.2.4 Multiscale color modifications of SSIM and SSIM4

The authors of the original metric SSIM recommend to calculate it for images preliminarily downscaled by the factor of two. This makes the metric more robust (in some degree) to some types of distortions, such as, e.g., spatially correlated noise with partial accounting for

Figure 2.2: Example of better correspondence of the proposed metric CSSIM4 to HVS for FLT database

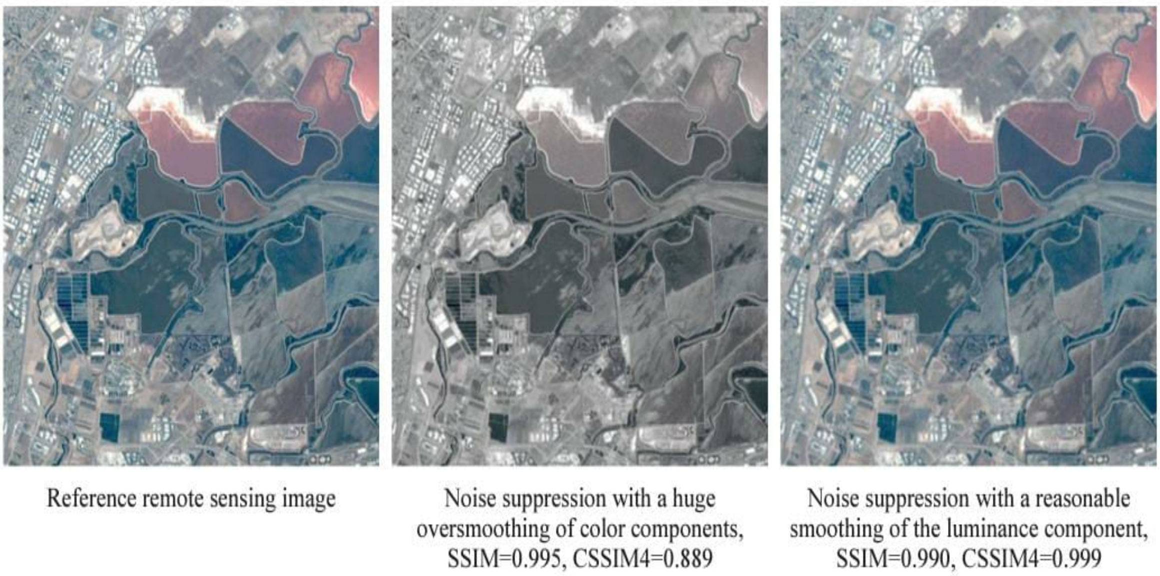

Figure 2.3: Example of better correspondence to HVS of the proposed metric CSSIM4 for the airborne remote sensing image Moffett Field

CSF of humans. For color images, the metric SSIM is calculated for only intensity component whilst color components are neglected. This leads to reduced correlation of SSIM and MSSIM with MOS for color images from color databases such as TID2013. We propose a simple modification of the metrics SSIM and SSIM4 that presumes calculations of these metrics for several image scales simultaneously in the color space YCbCr and the weighted average of the obtained partial metrics. The weights for the proposed metrics color SSIM and color SSIM4 have been optimized by maximizing SROCC values for these metrics with MOS for databases TID2013, LIVE, and FLT.

2.2.5 Conclusion

This paper presents the four-component version SSIM4 of the metric SSIM. As the fourth component, similarity of predictability of reference and distorted image fragments was used. Simple schemes for calculation of multiscale color versions of the metrics SSIM and SSIM4 have been proposed and optimized. We have demonstrated that the proposed metric CSSIM4 on average provides the best correspondence (among the considered metrics) to human perception for the databases TID2013, LIVE and FLT.

2.3 A Mean-Edge Structural Similarity for Image Quality Assessment

Image quality assessment plays an important role in various image applications, such as video image acquisition and transmission, the choice of parameters in coding systems, and the performance comparison of different image compression algorithms. Generally, image quality assessment methods can be classified as subjective methods and objective methods [6]. Although subjective methods can identify the difference of image quality more properly, but it is time consuming, laborious and only applied in some specified fields. Currently, most of objective methods are pixel error based, including mean squared error (MSE), peak signal to noise ratio (PSNR) and mean absolute error (MAE) etc. Considering the low computation complexity of PSNR, it is widely used until now. But in many cases, PSNR does not keep coherence with humans' visual system [2]. In order to seek more reasonable assessment metrics, many researchers have put great efforts into involving the human visual properties and some prior knowledge into image quality assessment. As a result, they proposed many algorithms based on error-sensitivity and visual mask effect [12], expecting to keep coherence with subject method as much as possible. However, none of these complicated image quality measures can show convincing advantage over traditional measures, such as PSNR, under strict testing conditions and different distortions.

Recently, a new image quality metric, mean structural similarity index(MSSIM)[2], is widely noticed, based on the philosophy that the most important information to the human eyes is to extract the structural information from a scene. It changes the traditional image quality assessment methods based on pixel error[9]. The simulation experiment results illustrate that it is more consistent with human visual properties. Besides, it has low computation complexity. However, further analysis has found that MSSIM method failed to evaluate the quality of blurred image or Gaussian noise image because of inaccuracy in the measurement of the structural information. To resolve the problems, this paper is to introduce an innovative improved image quality metric that is based on mean-edge structural similarity (MESSIM). The method considered different visual sensitivity to the image edges and then divided the image edges into large edges and subtle edges[11]. The experiment results have demonstrated that the MESSIM method achieved better consistency with subjective perception for a wide range of image types.

2.3.1 Measurement of structural similarity

Generally, natural images have strong structure characteristics. The neighboring pixels have great correlation, which provides important information about the object structure in the viewing scene. The traditional image quality assessment methods define the image distortion as the pixel error between the reference image and distortion image. However, such definition is not reasonable in many cases. For example, a contrast enhanced image will present better visual effect compared with the original image, although there is obvious difference. The reason lies that the structural information is preserved completely. Therefore, an ideal image assessment method should measure the regression of structural information, but not the pixel wise difference. The MSSIM method was proposed just based on above ideas. In fact, the object structural information has no relation with the brightness of the scene. In order to measure the structural similarity of object in the scene, the structural information is defined firstly. The MSSIM method divides the whole image into NxN sized image blocks. The total number of the image blocks is M, denoted as x i , y i , i = 1 , 2 , M . The structural similarity (SSIM) of the image block is the combination of three parts: luminance measurement l(x,y),contrast measurement c(x,y),and structure management[14].

$$\begin{aligned} \mathrm{SSIM}(x, y) &= [l(x, y)]^{\alpha}[c(x, y)]^{\beta}[s(x, y)]^{\gamma} \\ &= \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \end{aligned} \qquad (1)$$

here xu and yu are the mean gray value of the image block x and y, respectively; xand y are the variance of the image x and image y, respectively; xy is the covariance between the image x and image y. Parameters 0>0> and 0>are used to adjust the relative importance of three parts. Thus, the mean structural similarity of the entire image is defined as

$$\mathrm{MSSIM}(\mathrm{X},\mathrm{Y}) = \frac{1}{M}\sum_{j=1}^{M}\mathrm{SSIM}(\mathrm{x}_j,\mathrm{y}_j) \qquad (2)$$

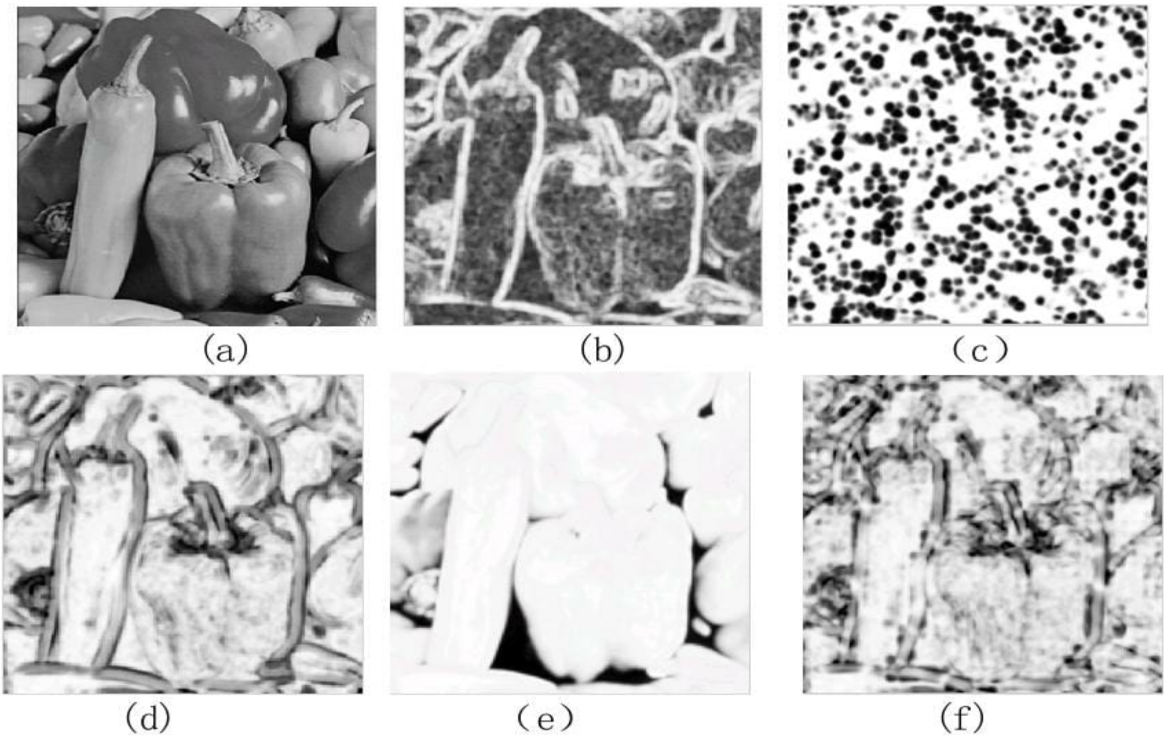

Figure 2.4: The evaluation of "Pepper" images distorted by different means: (a) Original image; (b) Gaussian noise image; (c) Pepper and salt noise image; (d) Blurred image; (e) Contrast stretch image; (f) JPEG compressed image.

2.3.2 Mean-Edge Structural Similarity

The important contribution of image quality assessment method based on structural similarity is to propose a new kind of assessment framework. Instead of taking pixel wise difference as the image quality metric, perseverance of image structure is used. This makes defining the image structure flexible. Our study has found that MSSIM method failed in evaluation of blurred images or noise images.

Figure 2.5: Comparison of "Lena" images with different types of distortions, all with MSE = 300: (a) Original image, 256 x 256, 8bits/pixel; (b) Blurred image, MSSIM=0.6750; (c) Gaussian noise image, MSSIM=0.5740.

In other words, the quality score is not consistent with human's subject perception (shown in Fig. 2.5). Different distortion images are shown in Fig. 2.5(b) and (c). These images have the same MSE but different visual qualities. The subjective quality of Gaussian noise image shown in Fig. 2.5(c) is greater than blurred image in Fig. 2.5(b). However, the quality scores for these images calculated by MSSIM method is contrary to the visual perception.

Considering the fact that human perception is very sensitive to the image edges, where the image structural information is mainly obtained from, this paper introduced an improved image quality assessment method based on dual-scale edge structure (MESSIM). Dual-scale edge means the image edge can be divided into two layers: The first layer describes the main edge information, called macro image; the second layer reflects the subtle edges, called micro edge. Macro edges present the crude contours of the objects in the scene while micro edges reflect the details edges of the objects[10]. Human have different reaction to such two kinds of edges. In general, human eyes crab a crude impression on the objects in the scene when taking a glance at the macro edges. If the observer has interest on certain object, he will keep attention on it and acquire the micro edges. The paper will compare macro edges similarity and micro edges similarity between original image and distortion image.

2.3.3 Conclusion

In this paper, we have proposed an improved image quality assessment method based on mean-edge structural similarity. The MESSIM method considered more on edge similarity during measurement of structural similarity, and overcame the shortcoming of MSSIM to the blurred image and the Gaussian noise image. Experimental work has showed the higher quality of the MESSIM images in a wide range types as they achieved better consistency with subjective perception.

CHAPTER 3

STRUCTURAL SIMILARITY INDEX BY USING DIFFERENT EDGE DETECTION APPROACHES ON LIVE VIDEO FRAMES FOR DIFFERENT COLOR MODELS

3.1 Edge Detection

Edges are important local intensity changes in the image and are important features to analyze an image. They are important hints to split region within an object or to identify changes in illumination or color. They are an important feature in the early vision stages in the human eye. Edge detection identifies sudden changes in an image. Primary goal is to extract information about the two-dimensional projection of a 3D scene. Secondary goal is Image segmentation, region separation, objects description and recognition etc.

Edge Point is one in an image with coordinates [i, j] at the location of a significant local intensity change in the image. Edge fragment is a small line segment about the size of a pixel, or as a point with an orientation attributes. The term edge is commonly used either for edge points or edge fragments. Edge detector is algorithm that produces a set of edges from an image. Some edge detectors can also produce a direction that is the predominant tangent direction of the arc that passes through the pixel[4]. Contour is list of edges of the mathematical curve that models the list of edges.

Edge linking is a process of forming an ordered list of edges from a un ordered list. Edge following is process of searching the edge image to determine line. Origins of edges are 1.Surface normal discontinuity 2.Depth discontinuity 3. Surface color discontinuity 4.Illumination discontinuity. Using Edge detection procedure major features like corners, lines, and curves can be taken out from the edges of an image. These features are used by algorithms like recognition. The ideal edge detector should discover all real edges by ignoring noise. The detected edges should be as close as possible to the accurate edges. The edge detector must return one point for each true edge point. Cues of edge detection are differences in color, intensity, or texture across the boundary and continuity and closure[12].

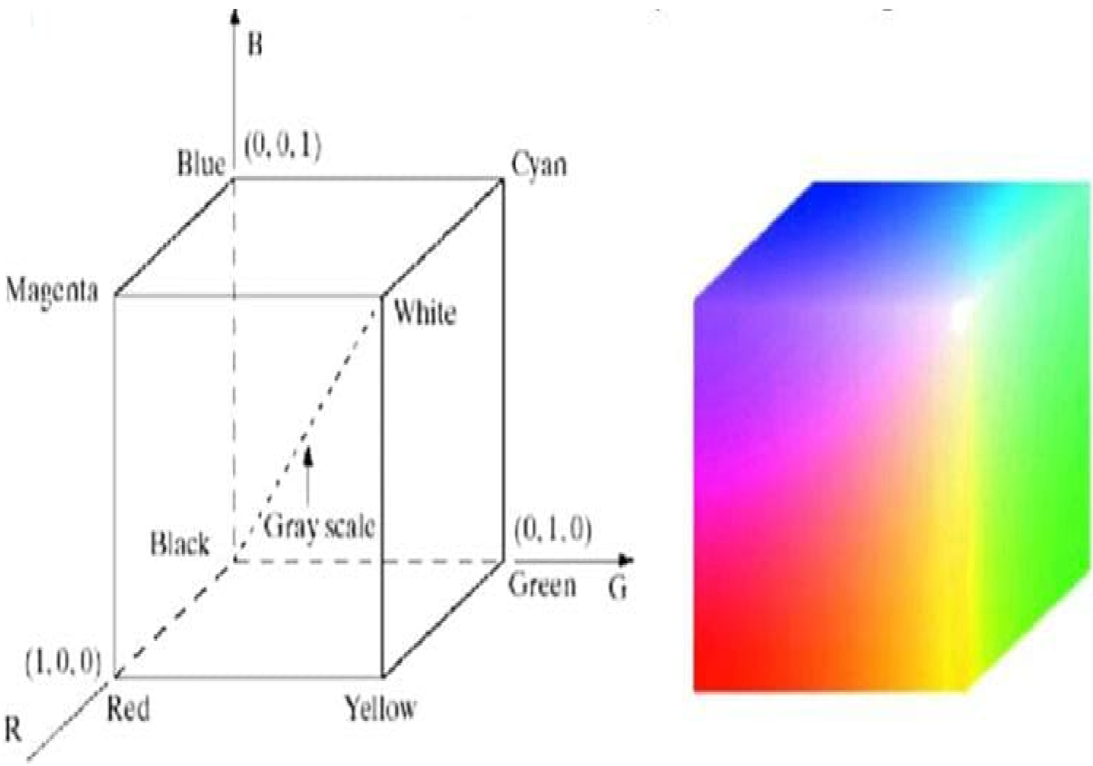

Figure 3.1: The RGB color cube. The grey scale spectrum lies on the line joining the black and white vertices

3.2 Different color models

3.2.1 The RGB Model

The RGB color model is an additive color model in which primary colors Red, Green and Blue are added together in different ways to reproduce a broad array of colors. The name of the model comes from the initials of the three additive primary colors, Red, Green and Blue. In this model, an image consists of three independent image planes Red, Green and Blue stating a particular color is by indicating the amount of each of the primary components present. Fig3.1 shows the geometry of the RGB color model for specifying colors using a Cartesian coordinate system. Red, green, and blue can be pooled in a variety of proportions to get any color in the visible spectrum.Red, Green and Blue can range from 0 to 100 percent of full intensity. Each intensity value is on a scale of 0 to 255.In hexadecimal intensity value ranges from 00 to FF[1].

3.2.2 YUV Color Model

The YUV color space is derived from the RGB color model. It consists of the luminance(Y) and two color difference (U,V) components. The luminance can be calculated as the weighted sum of the Red, Green and Blue components [2].The chrominance components are produced by subtracting luminance from Blue and Red .YUV color model generally used as part of a color image pipeline. The YUV model describes a color space in terms of one luma (Y') component and two chrominance (UV) components. Y' represents luma component i.e brightness and U and V represents the chrominance i.e. color components. Luminance is denoted by Y and luma by Y. The symbol (') indicates gamma compression with "luminance" which is perceptual brightness, while "luma" is electronic brightness[8]. Y component ranges from 0 to 1 or 0 to 255 in digital formats, while U and V components ranges from -0.5 to 0.5 or -128 to 127 in signed form or 0 to 255 in unsigned form.

Conversion between RGB – YUV

$$R = Y + 1.4075 * (V - 128) \quad (1)$$
$$G = Y - 0.3455 * (U - 128) - (0.7169 * (V - 128) \quad (2)$$
$$B = Y + 1.7790 * (U - 128) \quad (3)$$
$$Y = R * 0.2990 + G * 0.5870 + B * 0.1140 \quad (4)$$
$$U = -0.14713 * R - 0.28886 * G + 0.436 * B \quad (5)$$
$$V = 0.615 * R - 0.51499 * G - 0.10001 * B \quad (6)$$

3.2.3 YCbCr Color Model

The YCbCr color model is extensively used for digital video. In this model luminance information is stored as a single component (Y) and chrominance information is stored as two color-difference components (Cb and Cr). Cb component corresponds to the difference between the blue component and a reference value and Cr component corresponds the difference between the red component and a reference value[8]. YCbCr data can be double precision. The data range for Y component is [16, 235] and the range for Cb and Cr components is [16, 240].

$$Y = 0.299R + 0.587G + 0.114B \quad (7)$$
$$Cb = 128 - 0.168736R - 0.331264G + 0.5B \quad (8)$$
$$Cr = 128 + 0.5R - 0.418688G - 0.081312B \quad (9)$$

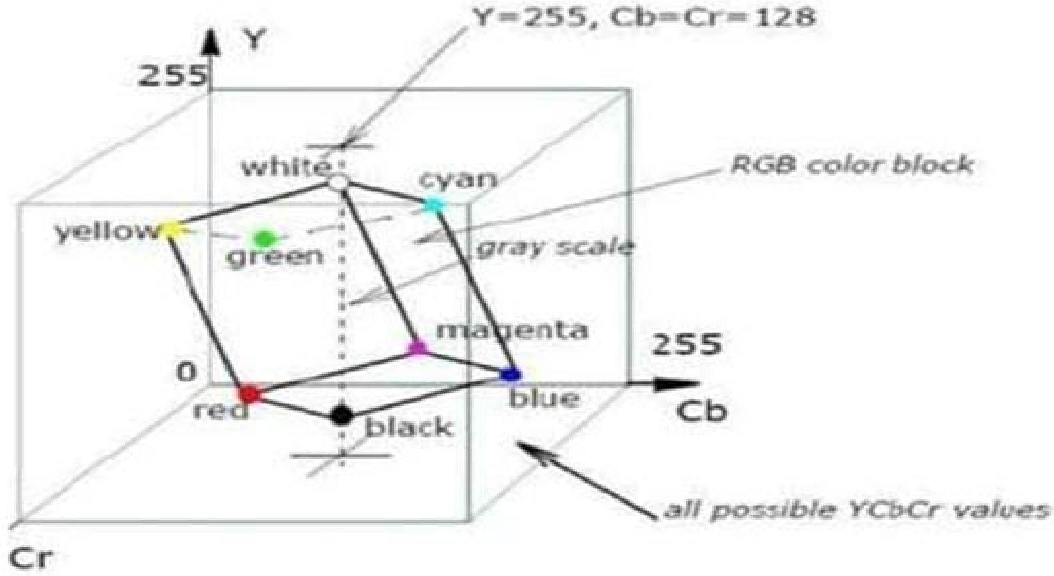

Figure 3.2: YCbCr and YUV color models

3.2.4 CIE XYZ Color Model

The XYZ color space is an international standard developed by the Commission Internationale de I Eclairage (CIE). This model is based on three hypothetical primaries, XYZ and all visible colors can be represented by using only positive values of X,Y,Z. The CIE XYZ primaries are theoretical because they do not conform to real light wave lengths. The Y primary is deliberately defined to match closely to luminance, while X and Z primaries give color information. The main advantage of the CIE XYZ color model is that this model is completely device independent. The position of the block of the RGB representable colors in the XYZ space is shown in Fig.3.3.

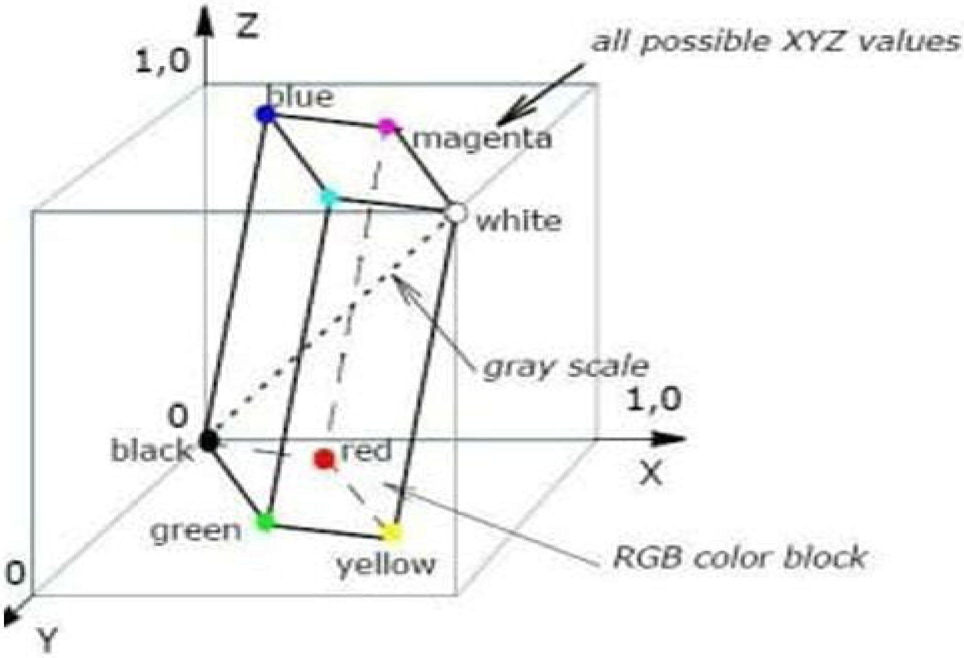

Figure 3.3: RGB colors Cube in the XYZ color space

Conversion between RGB and XYZ color space

$$X = 0.4124 * R' + 0.3575 * G' + 0.1804 * B' \quad (10)$$
$$Y = 0.2126 * R' + 0.7151 * G' + 0.07216 * B' \quad (11)$$
$$Z = 0.0193 * R' + 0.1191 * G' + 0.9502 * B' \quad (12)$$
$$R' = 3.2404 * X - 1.5371 * Y - 0.4985 * Z \quad (13)$$
$$G' = -0.9692 * X + 1.8759 * Y + 0.0415 * Z \quad (14)$$
$$B' = 0.0556 * X - 0.2040 * Y + 1.0573 * Z \quad (15)$$

3.3 Edge detection operators

3.3.1 Laplacian Operator

Laplacian Operator is a derivative operator which is used to find edges in an image. The major difference between Laplacian and other operators like Sobel, Prewitt and Robert is that these all are first order derivative masks but Laplacian is a second order derivative mask[13]. In Laplacian mask there are two types. 1. Positive Laplacian operator 2. Negative Laplacian operator. Another difference between Laplacian operator and other operators is that unlike other operators Laplacian operator didn't take out edges in any particular direction but it take out edges as Inward Edges and Outward edges.

Positive Laplacian Operator

Positive Laplacian mask contains center element as negative and corner elements as zero as shown in Fig.3.4. Positive Laplacian mask is used to take out outward edges in an image.

Negative Laplacian Operator

Negative Laplacian mask contains center element as positive value and all the elements in the corner as zero and rest of all the elements in the mask as -1 as shown in Fig.3.8.

0	1	0
1	- 4	1
0	1	0

Figure 3.4: Positive laplacian mask

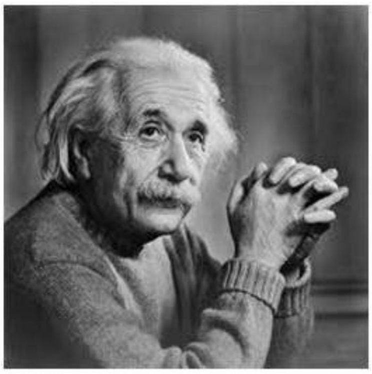

Figure 3.5: Sample image

Figure 3.6: Applying positive laplacian

Figure 3.7: Applying negative laplacian mask

0	-1	0
-1	4	-1
0	-1	0

Figure 3.8: Negative laplacian mask

3.3.2 Sobel Operator

The operator consists of a pair of 3 X 3 convolution kernels. The Fig.3.9 represents 3 X 3 mask along x-axis and 3 X 3 mask along y-axis. Kernels are designed to react to edges running vertically and horizontally relative to the pixel grid. Kernels can be applied individually to input image to produce separate measurements of the gradient component in each orientation. Kernels can be combined together to find absolute magnitude of the gradient at each point and the orientation of that gradient[12].

-1	0	1
-2	0	2
-1	0	1

1	2	1
0	0	0
-1	-2	-1

Figure 3.9: 3 X 3 mask along X-axis and 3 X 3 mask along Y-axis

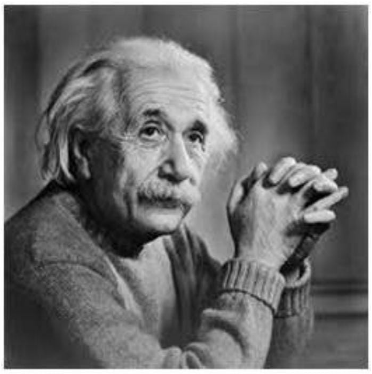

Figure 3.10: Sample image

Figure 3.11: Applying horizontal mask

Figure 3.12: Applying vertical mask

As you can see that in the first picture on which we apply vertical mask, all the vertical edges are more visible than the original image. Similarly in the second picture we have applied the horizontal mask and in result all the horizontal edges are visible.

So in this way you can see that we can detect both horizontal and vertical edges from an image. Also if you compare the result of sobel operator with Prewitt operator, you will find that sobel operator finds more edges or make edges more visible as compared to Prewitt Operator.

3.3.3 Prewitt operator

The Prewitt operator is edge model operator. This operator is made from the ideal edge sub-image composition. Detect the image using this edge model one by one and acquire the highest value of the model operator that is most similar to the detected region as the output of the operator [7]. Prewitt and Sobel operator uses the similar differential and filtering process, but the template does not use the same image. This gradient based edge detector is estimated in the 3x3 neighborhood for 8 directions. All the eight convolution masks are calculated. Then convolution mask which is having largest module is chosen. The convolution masks of the Prewitt detector are shown in Fig.3.13.

1	1	1
0	0	0
-1	-1	-1

1	1	1
0	0	0
-1	-1	-1

Figure 3.13: Prewitt masks

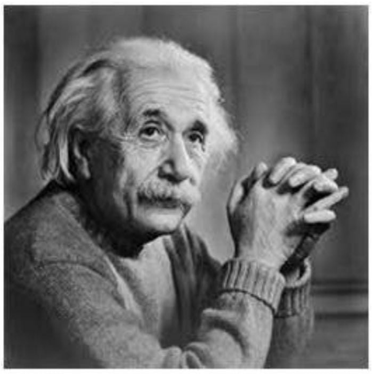

Figure 3.14: Sample image

Figure 3.15: Applying vertical mask

Figure 3.16: Applying horizontal mask

3.3.4 Robert Operator

Robert operator is a first-order operator, which uses a partial differential operator to find the edge. It uses the approximation between the two adjacent pixels of the diagonal direction of the gradient amplitude to detect edges.

Roberts's operator is defined as

$$G(x,y) = \{[\sqrt{f(x,y)} - \sqrt{f(x+1,y+1)}\,]^2 + [\sqrt{f(x+1,y)} - \sqrt{f(x,y+1)}\,]^2\}^{\frac{1}{2}}$$

Gradient size of Roberts operator represents the strength of the edge and direction of the gradient. The operator edge has higher positioning accuracy, but it is easy to lose a part of the edge. The operator with a steep low-noise image corresponds best.

1	0
0	-1

0	1
-1	0

Figure 3.17: Robert mask

3.4 Structural Similarity Index

The Structural Similarity (SSIM) index is a method for evaluating the perceived quality of digital images and videos. An early variant was developed in the Laboratory for Image and Video Engineering (LIVE) at the University of Texas at Austin and the full algorithm was developed jointly with the Laboratory for Computational Vision (LCV) at New York University. Structural Similarity is used for measuring the similarity between two images [10]. The Structural Similarity index is a measurement or prediction of image quality based distortion-free image as reference. Peak signal-to-noise ratio (PSNR) and mean squared error (MSE) have proven to be inconsistent with human visual perception. Mean squared error and Peak signal-to-noise ratio (PSNR) estimates absolute errors, where as SSIM is a perception-based model that considers image degradation as perceived change in structural information by incorporating important perceptual phenomena, including both luminances masking and contrast masking. Structural information is the design that the pixels have strong inter-dependencies when they are spatially close[3]. These dependencies carry significant information about the structure of the objects in the visual scene. Luminance masking is a phenomenon whereby image distortions tend to be less visible in bright regions, where as contrast masking is a phenomenon whereby distortions become less visible where there is texture in the image.

The SSIM index is calculated on various windows of a frame. The measure between two windows and of common size N×N is

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{\left(\mu^2{}_x + \mu^2{}_y + c_1\right)(\sigma^2{}_x + \sigma^2{}_y + c_2)}$$

μ_x the average of x
μ_y the average of y
σ_x^2 the variance of x
σ_y^2 the variance of y
σ_{xy} the covariance of x and y
$c_1=(k_1L)^2$ & $c_2=(k_2L)^2$ two variables to stabilize the division with weak denominator
L the dynamic range of the pixel-values
$K_1=0.01$ and $k_2 = 0.03$ by default

3.4.1 Proposed Algorithm

Edge detection and calculation of SSIM value based on different color models edge detection operators for live video frames can be explained by the following steps.

Step 1: Constructing a video input object.

Step 2: Select the source to use for video frames acquisition.

Step 3: View the properties for the selected video source object.

Step 4: Preview the stream of video frames.

Step 5: Acquire and display a single video frame.

Step 6: Video frame is sub divided into R, G and B layers.

Step 7: A Laplacian mask of size 3 X 3 is convolved with R layer of Video Frame to detect the edges to obtain edge detected R layer.

Step 8: Edge detected R layer and G, B layers of video frame are concatenated to obtain edge detected frame.

Step 9: The SSIM(R) parameter is measured. The same process is repeated to obtain the edge detected G layer and edge detected B layer along with SSIM (G and B) parameter.

Step 10: The average value of SSIM(R), SSIM (G) and SSIM (B) gives SSIM value of RGB frame.

Step 11: Repeat steps 6 to 10 for Sobel, Prewitt's and Robert's Operators.

Step 12: Repeat steps 6 to 11 for XYZ, YCbCr and YUV color models.

3.4.2 SSIM Flowchart

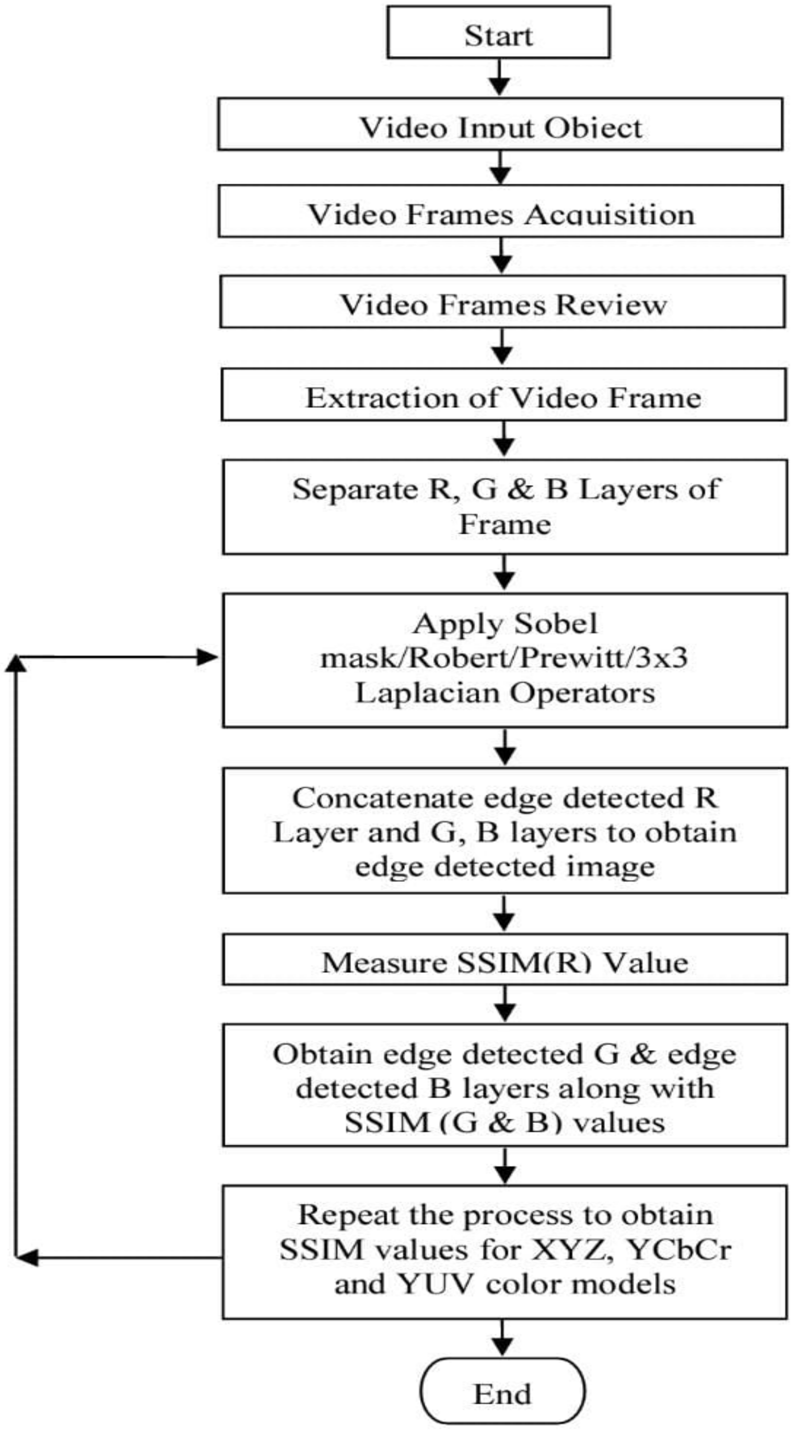

Figure 3.18: SSIM Flowchart

CHAPTER 4

RESULTS

The proposed algorithm has been applied to Live Video frames for different color models by applying Sobel, Robert, Prewitt's and Laplacian operators. The edge detected video frames are obtained for RGB, XYZ, YCbCr and YUV color models. The detected edges are more exact based on the XYZ color model and are detected effectively when compared with RGB, YCbCr and YUV color models. Mean SSIM values are obtained and shown in Table. Based on the SSIM metrics, XYZ color model is having high similarity index which indicates low data loss during transformation.

The video frames obtained through YUV color model are losing structural information and highly distorted when compared with the RGB, XYZ, YCbCr color models. Only a set of sample video frames are presented here for display from among 240 video frames.

VIDEO FRAME NO	COLOR MODEL	Mean SSIM Values			
		SOBEL	***ROBERT***	***PREWITTS***	***LAPLACIAN***
FRAME 1	**RGB**	*0.1271*	*0.1303*	*0.1323*	*0.1250*
	XYZ	*0.9958*	*0.9937*	*0.9967*	*0.9966*
	YCbCr	*0.0232*	*0.0916*	*0.0906*	*0.0912*
	YUV	*0.0410*	*0.0967*	*0.1094*	*0.1079*
FRAME 2	**RGB**	*0.1113*	*0.1139*	*0.1123*	*0.1106*
	XYZ	*0.9961*	*0.9941*	*0.9969*	*0.9969*
	YCbCr	*0.0503*	*0.0936*	*0.0929*	*0.0934*
	YUV	*0.0345*	*0.0799*	*0.0921*	*0.0883*
FRAME 3	**RGB**	*0.1144*	*0.1171*	*0.1147*	*0.1138*
	XYZ	*0.9958*	*0.9937*	*0.9967*	*0.9967*
	YCbCr	*0.0694*	*0.0956*	*0.0953*	*0.0955*
	YUV	*0.0393*	*0.0865*	*0.1009*	*0.0965*
FRAME 4	**RGB**	*0.1100*	*0.1186*	*0.1173*	*0.1158*
	XYZ	*0.9961*	*0.9941*	*0.9969*	*0.9969*
	YCbCr	*0.0690*	*0.0958*	*0.0956*	*0.0958*
	YUV	*0.0365*	*0.0885*	*0.1018*	*0.0989*
FRAME 5	**RGB**	*0.1196*	*0.1226*	*0.1194*	*0.1196*
	XYZ	*0.9958*	*0.9937*	*0.9967*	*0.9967*
	YCbCr	*0.0698*	*0.0959*	*0.0956*	*0.0958*
	YUV	*0.0393*	*0.0914*	*0.1040*	*0.1009*
FRAME 6	**RGB**	*0.1230*	*0.1261*	*0.1260*	*0.1236*
	XYZ	*0.9964*	*0.9944*	*0.9972*	*0.9972*
	YCbCr	*0.0705*	*0.0961*	*0.0959*	*0.0961*
	YUV	*0.0292*	*0.0807*	*0.0954*	*0.0941*
FRAME 7	**RGB**	*0.1078*	*0.1103*	*0.1075*	*0.1072*
	XYZ	*0.9963*	*0.9940*	*0.9969*	*0.9969*
	YCbCr	*0.1589*	*0.1595*	*0.1597*	*0.1598*
	YUV	*0.0291*	*0.0656*	*0.0757*	*0.0737*
FRAME 8	**RGB**	*0.1113*	*0.1141*	*0.1111*	*0.1111*
	XYZ	*0.9961*	*0.9941*	*0.9970*	*0.9969*
	YCbCr	*0.1435*	*0.1604*	*0.1602*	*0.1606*
	YUV	*0.0782*	*0.1149*	*0.1312*	*0.1234*
FRAME 9	**RGB**	*0.1065*	*0.1090*	*0.1055*	*0.1058*
	XYZ	*0.9960*	*0.9941*	*0.9969*	*0.9970*
	YCbCr	*0.1304*	*0.1582*	*0.1576*	*0.1582*
	YUV	*0.0011*	*0.0399*	*0.0482*	*0.0457*
FRAME 10	**RGB**	*0.1097*	*0.1121*	*0.1075*	*0.1090*
	XYZ	*0.9959*	*0.9937*	*0.9967*	*0.9967*
	YCbCr	*0.1011*	*0.1532*	*0.1521*	*0.1531*
	YUV	*0.0114*	*0.0724*	*0.0882*	*0.0848*

Figure 4.1: Mean SSSIM values for video frames for different operators.

CHAPTER 5
ADVANTAGES AND DISADVANTAGES

5.1 Advantages

1. SSIM offers superior performance to PSNR in many cases and that it is relatively simple to implement.
2. SSIM has been repeatedly shown to significantly outperform MSE and its derivates in accuracy.
3. SSIM instead of MSE is suggested to produce better results for the decompressed images.
4. SSIM mimics aspects of human perception.

5.2 Disadvantages

1. SSIM suffers from a number of problems, particularly that it is sensitive to relative scalings, translations, and rotations.
2. Instabilities in regions of low variance and insensitivity in regions high intensities.

CHAPTER 6

APPLICATIONS

1. Image Compression: In lossy image compression, information is deliberately discarded to decrease the storage space of images and videos.

2. Image Restoration: Using an SSIM variant, specifically Stat-SSIM, is claimed to produce better visual results, according to the algorithm's authors.

3. Pattern Recognition: Since SSIM mimics aspects of human perception, it could be used for recognizing patterns.

CHAPTER 7

CONCLUSION

SSIM is a perception-based model that considers image degradation as perceived change in structural information, while also incorporating important perceptual phenomena, including both luminance masking and contrast masking terms. SSIM actually measures the perceptual difference between two similar images. It cannot judge which of the two is better: that must be inferred from knowing which is the "original" and which has been subjected to additional processing such as data compression. Similarity Index is used to assess the similarity between the reference video frame and the processed video frame. Structural Similarity Index is easy and well linked with subject evaluation. This procedure evaluates the visual impact of changes in luminance, contrast and structure in an image. Here we are calculating SSIM by using different edge detection approaches,edges are the important local intensity changes in the image and are important features to analyze an image. They are important hints to split region within an object or to identify changes in illumination or color.Edge detection identifies sudden changes in an image. Primary goal is to extract information about the two-dimensional projection of a 3D scene. Secondary goal is Image segmentation, region separation, objects description and recognition etc.Here we are using edge detection approaches on different color models. A color model describes how colors can be represented as set of values of numbers, typically as three or four values.The color models are RGB color model,YUV color model,YCbCr color model and CIE XYZ color model. The edge detection operators we use are Laplacian Operator,Sobel Operator,Robert Operator and Prewitt Operator.

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