IMAGE CONTRAST ENHANCEMENT USING RETINEX PRINCIPLES

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***Abstract*:**The picture contrast is a characteristic that records the spatial variation of the picture signal. A characteristic like this is important for many computer vision applications, including object detection and picture/texture retrieval, since it helps to explain the local image structure at various sizes. Here we introduce MiRCo, a new contrast metric for images that is based on the Retinex theory. Regardless of the magnitude of the light shift or the in-plane rotation, MiRCo remains stable. Here we introduce MiRCo, a new contrast metric for images that is based on the Retinex theory. Regardless of the magnitude of the light shift or the in-plane rotation, MiRCo remains stable. These features allow MiRCo to provide a reliable and precise description of the local picture structure. We compare MiRCo to other well-known contrast metrics and go into its mathematical insights here.

***Index keys*:** Photo contrast, Retinex, Milan Color algorithms for space and Retinex.

I. INTRODUCTION

Edwin H. Land's groundbreaking Retinex hypothesis, which he put forward in 1964, untangled many essential components of human color vision. A series of investigations led to the development of the Retinex hypothesis, which states that the color seen by humans (i.e., the variety as seen by people) could shift essentially from the variety caught by a camera.The reason for this is because the final perception is formed when neighboring hues in a scene interact with the Human Vision System (HVS). For clarity, HVS processes the signal at every given observational position in the waveband of a class of cones as per the nearby spatial changes of the encompassing tones as estimated by cones in a similar waveband. Consequently, local contrasts have a significant impact on the perceived hue of a spot by humans. Specifically, minor differences further away have less of an effect on color perception than big contrasts near to the seen spot. The phrase "contrast" may mean several things depending on the surrounding circumstances. In the fields of ophthalmology and biology, the word "contrast" refers to a metric that is associated with visual acuity, or the HVS's capacity to differentiate between details. Here, we take the definition of contrast from computer vision, where it denotes regional or global variations in the color and/or intensity of an image. The image contrast, which is a measure of computer vision, is distinct from dissimilar to HVS because it fails to account for factors including viewing distance, ocular angle, stimulus and background brightness levels, frequency, and spatial masking that contribute to the creation of HVS contrast. At a given scale, a pixel's contrast value should be zero in uniform areas, but it will be different from zero in non-uniform regions. Picture contrast, in particular, has to be proportionate to the value fluctuations of pixels throughout space at various resolutions and resilient to a wide range of situations, including changes in light and geometric transformations. Three common types of picture contrasts are Michelson, root-mean-square, and multi-goal. Overall picture contrasts, which are the distinction of two power values taken from the entire picture support, don't often provide much information and can't differentiate or describe the picture structure well. Since this is the case, it is best to use proportions of power changes in picture locales or pixelneighbors. In this context, we mean the areas of the picture that are used to calculate the intensity variations in relation to the mathematical help of the differentiation. The size and type of this sort of help dictate where the picture contrast is located and, in turn, the outcome. Drawing inspiration from Retinex, we provide a new contrast metric in this study. Milano Retinex, a modification of the original Retinex model, is the source of our metric. Retinex and Milano Retinex are both members of the larger family of Spatial Color Algorithms (SCA), which includes many computer models that attempt to replicate the spatial color interaction seen in HVS. Any input picture may be improved using Milano Retinexes, making details more visible and smoothing out shadows and/or light dominated colors. This makes the material easier to read. The way based Milano Retinex calculation, or PMRA for short, utilizes a variation of the spatial variety handling proposed by the first Retinex calculation. In this worldview, the MR daintiness, or power esteem at each upgraded picture pixel x, can be elegantly described using a series of intensity changes in the x neighborhood and a conditional equation. We begin with this equation and demonstrate that the MR brilliance at x is conversely connected with the nearby vacillations in force encompassing x. From that point onward, we change theMR lightness equation and use the Milano Retinex Contrast keywords to create a new contrast measure for images, which we name MiRCo. To put it simply, MiRCo takes a random route beginning at x and averages a collection of ratios of neighboring intensity values to get the picture contrast at any given pixel x. Because of this computational technique that is inspired by Retinex, MiRCo is able to accurately describe the structure of the local picture at several scales and is resilient to in-plane rotations and light fading. The spiral conveyance of the places of its mathematical help explicitly allows MiRCo its invariance against in-plane rotations. Here, MiRCo varies significantly from other well-liked contrasts, such as those that often use a pre-characterized rectangular sliding window as its premise. The difference between MiRCo and other contrasts is that in MiRCo, just a subset of the support points, selected according to their location, contribute to the contrast, as opposed to the whole sliding window in other contrasts. MiRCo does a good job of describing the local picture structure at various resolutions as it handles both spatial and intensity parameters.

II. LITERATURE SURVEY

Last but not least, MiRCo is resilient to light fading since it models intensity fluctuations by ratios, much like other contrasts. You may use MiRCo on grayscale or color pictures; when applied to color photographs, it also makes them resistant to changes in lighting. We derive MiRCo's condition from the way based Milano Retinex softness andexplain it in this paper. We also compare its features with various contrast measures and discuss them. We evaluated MiRCo's functionality on a publicly available dataset of multi-exposure images, where variations in the camera's exposure time lead to varying degrees of light dimming. Many computer vision real-world applications include working in environments with varied levels of illumination, hence it is important to evaluate MiRCo's performance in these settings. Additionally, an illustration of MiRCo's application in image retrieval is showcased. We should mention that although MiRCo does have some foundation in HVS, its primary goal is not to mimic human perception of contrast but rather to quantify local variations in image intensity that are relevant to machine vision applications.

SNo.	Author Name and Title	Journal	Year	Domain/Measuring Parameters	Advantages	Disadvantages
1	"Introduction to a Contrast Entropy-Based Image Enhancement Algorithm" by Sos Agaian and Karen Panetta”	Article published in March 2007 in the IEEE Transactions on Image Processing, Volume 16, Issue 3.	2007	Frequency Domain/EME	Good visual representation of the original scene.	Computationally complicated due to log transform
2	The article "A new combined technique for automatic contrast enhancement of digital images" was written by Ismail A. Humied and colleagues.	Journal of Egyptian Informatics (2012) 13, 27–37	2012	Spatial Domain/PSNR, MSE, AMBE	Effective and robust enhancement for various images, fully automated	Complex, computational time not specified
3	"Contrast enhancement of sports images using two comparative approaches." by Kannan, P., S. Deepa, and R. Ramakrishnan	Journal of Intelligent Systems in the United States 2.6: 141–147	2012	Spatial Domain/Sigmoid Function and Measure of contrast	A flexible method for contrast enhancement	Suitable only for dark spot images, no standard quality parameters
4	"Image enhancement using fuzzy technique." (Mahaashwari, Tarun, and Amit Asthana, 2015).	Number two of the International Journal of Research in Engineering Science and Technology, published in June 2013, pages one to four.	2013	Spatial Domain/Fuzzy and defuzzy concept	Effective for fingerprint enhancement	No specific measuring parameters provided
5	Authors: Professor K. Rajeswari and Professor	The second issue of the international journal of	2013	Spatial Domain/BMD/DMD	Good visual representation of low contrast	Computationally complicated due to fuzzy logic

	Preethi S.J1. "Membership Function modification for Image Enhancement using fuzzy logic."	computer science trends and technologies (IJETTCS)			images	
6	G. Raju and Madhu S. Nair: "A fast and efficient color image enhancement method based on fuzzy-logic and histogram"	International Journal of Electron Communications (AEÜ) 68 (2014) 237–243	2014	Spatial Domain/CII, Tenemgrad, Time	Less computational time, suitable for real-time applications	Applicable only to low contrast and low bright color images

III. METHODOLOGY

Existing System: The existing system includes several algorithms for image contrast measurement. The algorithms are:

1**. Local Michelson Contrast (ML):** Measures contrast based on the distinction between the best and least force values inside a nearby area. Formula:

$$ML = \frac{I_{max} - I_{min}}{I_{max} + I_{min}}$$

Useful for detecting edge contrasts in images.

2. Local Standard Deviation (RMSL): Uses the standard deviation of pixel intensities within a local neighborhood to measure contrast.Formula:

$$RMSL = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(I_i - \bar{I})^2}$$

Captures the variation in intensity values, making it effective for detecting texture.

3. 8-Neighbor Contrast (NC): Measures contrast by comparing the intensity of a pixel with the average intensity of its 8 neighboring pixels.Formula:

$$NC = \frac{1}{8}\sum_{i=1}^{8}|I - I_{neighbor_i}|$$

Simple and effective for local contrast assessment.

4. Edge-Based Contrast Measure (EBCM): Focuses on the strength of edges within an image by detecting significant changes in intensity.Often implemented using gradient-based methods like the Sobel or Canny edge detectors.Effective for images with distinct edges and boundaries.

5. Tadmor and Tolhurst Contrast (CMO): A perceptual contrast measure designed to align with human visual perception.Thinks on the picture's local and global contrast levels.Often used in visual perception studies and image quality assessments.

6. Region-Based Contrast Measure (RME): Measures contrast by evaluating the difference in intensity between different regions of an image.
Can involve segmenting the image into regions and calculating contrast based on region properties.
Useful for images with distinct regions or objects.

Proposed System: The proposed system implements the MiRCo algorithm, which stands for Multi-scale Integrated Region-based Contrast. The MiRCo algorithm is designed to address the limitations of existing algorithms by providing more accurate and robust contrast measurements.

MiRCo Algorithm

1. Multi-scale Analysis: The MiRCo algorithm operates at multiple scales to capture contrast information at different levels of detail.This is achieved by applying a series of filters or transformations to the image, each focusing on a different scale.

2. Region-based Contrast: MiRCo divides the image into regions and measures contrast within and between these regions.This allows for a more comprehensive assessment of contrast, especially in images with complex structures.

3. Integration of Local and Global Contrast: The algorithm integrates both local and global contrast measures to provide a balanced contrast evaluation.This integration ensures that the algorithm captures fine details as well as broader patterns in the image.

Experimental Setup:

We compare MiRCo against known algorithms at single and multiple scales to assess its performance. These algorithms include ML, RMSL, NC, EBCM, CMO, and RME. To speed up computer processing, the photos in the collection are shrunk and turned to grayscale. For each image, we compute the contrast using both single-scale and multiple-scale approaches for all algorithms, including MiRCo. The performance is then assessed based on various criteria, such as accuracy, robustness, and computational efficiency.

IV. RESULTS

Tables and figures demonstrate the performance of MiRCo compared to other algorithms.

Figure 1: Single-scale contrasts

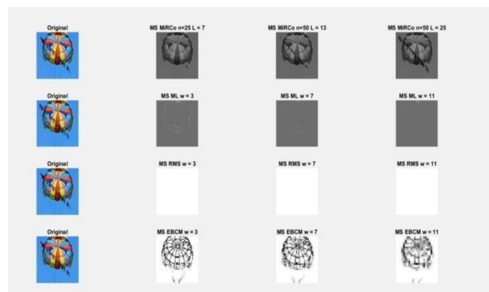

Figure 2: Multi-scale contrasts

Figure 1: Results of the One-Scale Contrast Intervals

Single Scale Contrast Measures	
MiRCo(L=7)	-0.35083
MiRCo(L=13)	-0.3414
MiRCo(L=25)	-0.32239
ML (w=3)	0.97505
ML (w=7)	0.98309
ML (w=11)	0.9852
RMS (w=3)	2.55
RMS (w=7)	2.55
RMS (w=11)	2.55
NC	0.44257
EBCM (w=3)	5.8391
EBCM (w=7)	6.4268
EBCM (w=11)	7.1834
CMO	13.5434
RME	12.6028

Table 2: Multi-Scale Contrast Measure Result Values

Multi Scale Contrast Measures	
MiRCo(L=7)	0.057251
MiRCo(L=13)	0.064217
MiRCo(L=25)	0.077731
ML (w=3)	1.4015
ML (w=7)	1.4072
ML (w=11)	1.4083
RMS (w=3)	2.55
RMS (w=7)	2.55
RMS (w=11)	2.55
NC	0.40202
EBCM (w=3)	7.0069
EBCM (w=7)	7.7122
EBCM (w=11)	8.6201
CMO	9.557
RME	21.38+3.69089e-05i

While msML isn't the best option, msMiRCo and msEBCM both provide comparable results. MiRCo demonstrates robustness to changes in light and provides consistent performance across various illumination conditions.

V.CONCLUSION

Here we introduced MiRCo, a new contrast metric for images developed specifically for use in machine vision. We update the state-of-the-art on picture contrast with two major contributions in our study. To start, one significant correlation between contrast and MR lightness is brought to light by the mathematical elaboration of MiRCo from a little variation of Retinex. For PMA lightness, the negative image is the point-wise MiRCo. The second benefit is that MiRCo gives a way to quantify local spatial intensity fluctuations; this metric is distinguished by three qualities that are important for many machine vision applications: multi-resolution edge retention, resistance to changes in light and low-intensity noise, and invariance to in-plane rotations. As shown by the studies given here, MiRCo's feature set allows for a precise depiction of an image's local structure and effective contrast-based picture retrieval, particularly for low-light images. Lastly, as previously stated in the research, it is important to note that MiRCo is an image contrast specifically created for computer vision tasks and is not a perceptual contrast, meaning it does not attempt to mimic or replicate the contrast that people experience.

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