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RETINEX-INSPIRED METHODS FOR IMAGE CONTRAST IMPROVEMENT

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***Abstract*:**
Picture contrast records the spatial variation of an image signal, a key characteristic for numerous computer vision applications such as object detection and texture retrieval. Contrast metrics help to describe the local image structure at different scales, aiding in these tasks. In this work, we introduce MiRCo, a new contrast metric for images based on Retinex theory. MiRCo is invariant to light shifts and in-plane rotations, making it stable across varying lighting conditions and orientations. These properties enable MiRCo to deliver a reliable and precise representation of local image structure. Here, we present MiRCo's mathematical foundations and compare its performance to other widely-used contrast metrics.

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, MiRCois 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

Finally, MiRCo demonstrates resilience to light fading by modeling intensity fluctuations through ratios, similar to other contrast metrics. This adaptability allows MiRCo to be applied to both grayscale and color images; in color images, it further enhances resistance to lighting changes. We derive MiRCo's formulation based on a modified version of Milano Retinex softness, detailing the approach in this paper. A comparison of MiRCo's features with other contrast measures is also provided. MiRCo's effectiveness is evaluated on a publicly available dataset of multi-exposure images, where variations in exposure times result in differing levels of light dimming. Many real-world computer vision applications operate in environments with varying illumination levels, making it essential to test MiRCo under these conditions. We also demonstrate MiRCo's application in image retrieval. It is important to note that, although MiRCo is partially inspired by the human visual system, its primary goal is not to replicate human contrast perception but rather to quantify local intensity variations critical for machine vision.

1. HuanjingYue,Jingyu Yang, Xiaoyan Sun, Feng Wu :Contrast Enhancement Based on Intrinsic Image Decomposition,2017

Split Bregman algorithm and CLAHE to enhance images by estimating illumination and reflectance layers through intrinsic image decomposition Good enhancement Designed only for CE. Cannot be used for methods like surface re-texturing, object insertion etc.

2. Cheolkon Jung, Tingting Sun Optimized Perceptual Tone Mapping for Contrast Enhancement of Images,2017 .

Optimized Perceptual Tone Mapping (OPTM) Focuses on the human visual attention by constructing a saliency histogram and performs Contrast Enhancement Improves the performance without over enhancement Needs more time for CE compared to HE,CLAHE.

3. Daeyeong Kim, ChangickKim Contrast Enhancement Using Combined 1-D and 2-D HistogramBased Techniques,2017

Histogram stretching technique ,quadratic programming To preserve the shape of the 1-D histogram the statistical information on the gray-level differences Enhanced images and perceptual image quality Processing time is slower.

4. Anil Singh Parihar, Om Prakash Verma, Chintan Khanna Fuzzy-Contextual Contrast Enhancement,2017

Fuzzy dissimilarity histogram (FDHE), Fuzzy Contextual Contrast Enhancement (FCCE) Captures the intensity level differences in the neighborhood of the pixels Global and local CE. No parameters are used. Original shape of histogram is preserved EME measure is low.

5. Shilpa Suresh, Shyam Lal, Chintala Sudhakar Reddy, Mustafa Servet Kiran A Novel Adaptive Cuckoo Search Algorithm for Contrast Enhancement of Satellite Images,2017

Novel Adaptive cuckoo search based enhancement algorithm (ACSEA) Contrast enhancement for satellite images Improved convergence rate. Good efficiency and robustness Complex in its execution

6. M.Shakeri, M.H.Dezfoulian, H.Khotanlou, A.H.Barati, Y.Masoumi Image contrast enhancement using fuzzy clustering with adaptive cluster parameter and sub-histogram equalization,2017

Contrast enhancement algorithm based on local histogram equalization Determination of the number of sub-histograms and density based histogram division Natural appearance of images and enhanced the contrast Loss of details in high brightness levels of the image. Noise in the output image.

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.

Implemented System: The implemented 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: TheMiRCo 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.

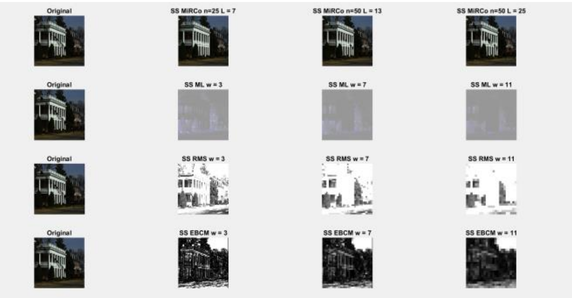

Figure 1: Single-scale contrasts

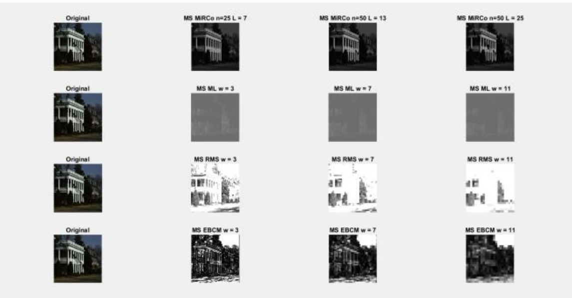

Figure 2: Multi-scale contrasts

Table 1: Results of the One-Scale Contrast Intervals

Single Scale Contrast Measures	
MiRCo(L=7)	0.43064
MiRCo(L=13)	0.43771
MiRCo(L=25)	0.44977
ML (w=3)	0.93534
ML (w=7)	0.951
ML (w=11)	0.95929
RMS (w=3)	1.9563
RMS (w=7)	2.1721
RMS (w=11)	2.2579
NC	0.35718
EBCM (w=3)	2.0341
EBCM (w=7)	2.0304
EBCM (w=11)	2.2355
CMO	5.6983
RME	9.5155

Table 2: Multi-Scale Contrast Measure Result Values

Multi Scale Contrast Measures	
MiRCo(L=7)	0.58594
MiRCo(L=13)	0.59115
MiRCo(L=25)	0.60008
ML (w=3)	1.376
ML (w=7)	1.3858
ML (w=11)	1.3905
RMS (w=3)	2.0617
RMS (w=7)	2.2527
RMS (w=11)	2.3285
NC	0.34837
EBCM (w=3)	2.4409
EBCM (w=7)	2.4364
EBCM (w=11)	2.6826
CMO	4.1142
RME	16.1167

While msMLisn'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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