Development of an automated Moon observation system using the ALTS-07 Robotic Telescope: 2. Progress report on standard contrast enhancement of Moon crescent image with OpenCV

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Abstract. Vision is a continuous two-dimensional (2-D) image that can be perceived by human visual system. Mathematically, image is a 2-D function that expresses the intensity of light. This research introduces the fundamental ideas of computer vision. We used OpenCV (Open-Source Computer Vision) to solve automatic image processing techniques, especially enhancement of contrast crescent visibility. We described an image using feature vectors to characterize and numerically to quantify the contents of an image. Then, we compared several techniques for increasing image quality, such as Basic contrast, Binary thresholding, Otsu thresholding, Histogram equalization, and Adaptive Histogram equalization. Finally, we calculated the statistical features of the image before and after enhancement process, and also decided to choose the best enhancement technique that will be implemented on a self-constructed cascade classifier in the future.

1. Introduction
Astronomical observations are currently heavily reliant on three key factors: Optics, image processing, and robotic systems. While the use of machine learning, especially using computer vision techniques in the field of astronomy is not new, but still uncommon especially when apply in crescent detection. Several recent astronomical studies that have used machine learning include: Star-galaxy detection and classification of optical galaxy morphologies [1-4]. The detection of celestial bodies related to a focus on computer vision, has been performed especially on crater detection [5-6]. As a result, we propose
Computer Vision (CV) as one of the simplest approaches to integrate the four factors and become a good potential research prospect in the future. Computer Vision is a program that allows a computer to automatically analyze images and videos like emulating how humans' brains and eyes work to visually objects around them to gain an understanding of the information contained in an object as a basis for decision making, data processing, and object detection [7-8]. Image Processing [9-10] is the collective term given to techniques or procedures used to process an image for analysis, feature extraction, object detection, etc. Previously, image processing relied on human visual abilities to assess and analyze objects. As a result, each person may give different assessment and interpretation.

In this paper, we provide a comprehensive case study of advanced image processing technique using computer vision applied to Crescent images to improve analysis, to make accurate inferences, and to carry out faster analysis. This project contributes to the development of imaging techniques used so far to analyze crescent moon and provides technological updates to develop an automatically crescent moon detection and recognition by implementing an artificial intelligence system program, namely Computer Vision. The system acts as a decision support system that uses Computer Vision to support the ALTS-07 (Astelco Lunar Telescope System) robotic telescope at Obervatorium Astronomy ITERA Lampung (OAIL), Institut Teknologi Sumatera, Lampung, so that it can detect the crescent moon more quickly and precisely.

2. Method
We applied the program that has been developed to reduce the images from crescent moon observations at OAIL on October 7, 2021, using ITERA Robotic Telescope (IRT) with focal length of 900 mm, diameter of 102 mm, and focal ratio F/8.82. A total number of 5 crescent moon images with different sky conditions have been acquired (see figures 1–5).

![Figure 1](image-url) Figure 1. The first case: Crescent looks faint, obscured by very thin clouds.
Figure 2. Second case: Crescent is partially obscured through thin clouds. It is difficult to distinguish cloud strokes from object.

Figure 3. Third case: Thick clouds cover the entire crescent moon, only the tip of the crescent moon is still visible.

Figure 4. Fourth case: Crescent is completely invisible.
Figure 5. Fifth case: Although thick clouds cover crescent, the curved part of the crescent can still be seen.

We used the Open-Source Computer Vision (OpenCV) library to carry out the process. The OpenCV library, originated from an Intel research project of 1998, is “aimed at providing the tools needed to solve computer vision problems. It contains a mix of low-level image-processing functions and high-level algorithms” [11]. We tested the five crescent cases using various contrast enhancement methods based on the distribution of histogram equalization methods such as Histogram Equalization (HE) and Limited Contrastive Adaptive Histogram Equalization (CLAHE). The contrast enhancement process is illustrated in the flow chart displayed in figure 6.

Figure 6. Flow chart of contrast image enhancement with HE, CLAHE, and various thresholding methods.
Among the methods or techniques for increasing contrast are:
1. Histogram Equalization (HE - cv2.equalizeHist)
   Histogram Equalization is a computer image processing technique that improves image contrast. It achieves this by effectively spreading out the most common intensity values, i.e. stretching out the image's intensity range. This method typically increases the global contrast of images.
2. Limited Contrastive Adaptive Histogram Equalization (CLAHE - cv2.createCLAHE)
   CLAHE differs from adaptive histogram equalization in that it applies contrast limiting to each neighborhood from which a transformation function is derived. CLAHE was developed to prevent the overamplification of noise caused by adaptive histogram equalization.

Then, from the equalization of the histogram distribution, it is continued by increasing the Thresholding. The thresholding technique is the concept of changing the color of pixels and manipulating the pixels in an image into only two colors, namely black and white. This concept is widely used to display image objects clearly. Several thresholding methods or techniques include:
1. The simplest form of global thresholding, Binary Thresholding (cv2.THRESH_BINARY).
2. Inverse-Binary Thresholding (cv2.THRESH_BINARY_INV).
3. Truncate Thresholding (cv2.THRESH_TRUNC).
4. Threshold to Zero or the threshold close to zero (cv2.THRESH_TOZERO).
5. Inverse of Threshold to Zero (cv2.THRESH_TOZERO_INV).
6. Otsu Threshold (cv2.THRESH_OTSU).

Finally, we calculated the Root-mean-square Error (RMSE) and Peak signal-to-noise ratio (PSNR) values to determine the quality of the image reconstruction results. In general, PSNR is expressed as a logarithmic quantity using the decibel scale. The typical value for the PSNR in the lossy image and video compression is between 30 and 50 dB, provided the bit depth is 8 bits, where higher is better. The processing quality of 12-bit images is considered high when the PSNR value is 60 dB or higher [12-13]. For 16-bit data typical values for the PSNR are between 60 and 80 dB [14] Acceptable values for wireless transmission quality loss are considered to be about 20 dB to 25 dB [15].

3. Results and Discussions
We have tested the crescent contrast enhancement automation program on the results of observations carried out at OAIL, which has a geographic latitude of 5° 21' 45.9" S, longitude of 105° 18' 41.7" E (altitude = 90 meters above sea level) using the ITERA Robotic Telescope (IRT). Observations of the crescent moon determined the beginning of the month of Rabiul Awal 1443 H on Thursday (7/10/2021), which coincided with 29 Safar 1443 H. A total of five images with different sky conditions became the subjects of the application of the image contrast enhancement method. The first step before applying contrast enhancement is to convert the original image into a grayscale image. The result of the conversion from the original image to the grayscale image is shown in figure 7.

![Figure 7. Result of converting the original image to a grayscale image.](image-url)
reduction by determining the kernel matrix. It operates by assigning value into each input image pixel by the average of the kernel weighting values for each neighboring pixel and the pixel itself. Figures 8–12 show the results of the contrast changes between the two methods.

Figure 8. In the first case, the application of HE causes the crescent object to appear blurry because the sky conditions around the object experience an increase in contrast (left). The application of CLAHE improves the visibility of the crescent object, the increase in contrast, is limited to the object area (right).

Figure 9. In the second case, it is difficult to identify the crescent with our eyes because it is obscured by clouds. The results of using HE and CLAHE are not particularly significant, but they are good enough to ease us in identifying the object.
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In the third case, the use of HE and CLAHE enabled to clarification of the object even though only a small portion of it was visible from the crescent moon.

In the fourth case, the original data and the results of the HE application were still unable to make the crescent visible. The crescent is visible after using the CLAHE method. The CLAHE method has performed excellently in increasing contrast by only focusing on the area around the object.

In the fifth case, based on the original data, which is very easy to identify an object with the eye, the application of the HE and CLAHE is also capable of increasing the object’s contrast.

Figure 10

Figure 11

Figure 12

Figure 13 shows the histogram distributions of the various methods. The grayscale image's histogram still has a non-uniform histogram distribution. There are two peaks, one on the left that shows underexposed and one on the right that shows overexposed. The same results are shown after applying
the HE method, but with a slight smoothing of the histogram. The application of the CLAHE method yields better results, namely normal brightness and high contrast.

![Image of histograms](image.png)

**Figure 13.** Histogram distribution from various applied methods.

Following the even distribution of the histogram, contrast enhancement was carried out with the thresholding method. The thresholding technique is the concept of changing the color of pixels and manipulating pixels in an image into only two colors, namely black and white. Based on the results of the other thresholding methods (see figures 14-18), the Threshold to Zero method produced the best results. The Otsu thresholding method also sometimes gave good results, but sometimes leads the crescent object to become invisible.

Image Quality Assessment (IQA) is a tool to assess characteristic property of an image. Degradation of perceived images is measured by image quality assessment. Usually, degradation is calculated by comparison to an ideal image known as a reference image. Quality of image can be described technically as well as objectively to indicate the deviation from the ideal or reference model. It also relates to the subjective perception or prediction of an image [16]. The mean square error (MSE) is the most widely used and simplest full reference metric, calculated by averaging the squared intensity differences of distorted and reference image pixels with the peak signal-to-noise ratio (PSNR) of the related quantity [17]. Table 1 gives the result of IQA for the applied HE and CLAHE methods.

| Table 1. The values each Image Quality Assessment (IQA) in terms of RMSE and PSNR |
|-----------------|----------------|----------------|----------------|----------------|
|                | HE             |                | CLAHE          |                |
| Image          | RMSE           | PSNR           | RMSE           | PSNR           |
| First case     | 0.006          | 44.485         | 0.015          | 36.249         |
| Second case    | 0.005          | 46.188         | 0.016          | 35.780         |
| Third case     | 0.004          | 48.289         | 0.017          | 35.525         |
| Fourth case    | 0.004          | 48.291         | 0.015          | 36.594         |
| Fifth case     | 0.004          | 48.530         | 0.014          | 36.999         |

Both methods are effective for increasing the contrast of an object. HE produces smoother images with higher contrast but occasionally can make it invisible. On the other hand, the CLAHE produces image results that are more object-focused, allowing to distinguish between objects and non-objects. As
a result, a thresholding method is required to create a smoother image. Finally, we applied six thresholding methods in each case, with the following interpretation:

1. The first case, see figure 1. Crescent looks faint, obscured by very thin clouds.
2. The second case, see figure 2. Crescent is partially obscured by thin clouds. It is difficult to distinguish cloud strokes from object.
3. The third case, see figure 3. Thick clouds cover the entire crescent moon, only the tip of the crescent moon is still visible.
4. The fourth case, see figure 4. Crescent is completely invisible.
5. The fifth case, see figure 5. Although thick clouds cover crescent, the curved part of the crescent can still be seen.

Figure 14. Results of six different threshold methods that were used in the first case after applying CLAHE.

Figure 15. Results of six different threshold methods were used in the second case after applying CLAHE.
Figure 16. Results of six different threshold methods were used in the third case after applying CLAHE.

Figure 17. Results of six different threshold methods were used in the fourth case after applying CLAHE.
Figure 18. Results of six different threshold methods were used in the fifth case after applying CLAHE.

In the future, the CLAHE and Threshold to Zero methods will be used in data training to obtain image features in an automated moon detection program using a cascade classifier, as well as to object classification or object recognition using Convolutional Neural-Networks.

4. Conclusions
The best results from the application of the equalization method are CLAHE, while the best results from the thresholding technique are Threshold to Zero (objects are clearly visible) and Otsu thresholding (objects are clearly visible but sometimes objects are lost or not visible). We prefer to use the Threshold to Zero technique to extract features and as an input to the object training program for automatic detection using a cascade classifier in future studies. This paper is an initial part of an endeavor to obtain image features or characteristic information of the crescent. The image features obtained will be used as training data to create an automatic detection program for crescent objects, so that it will make it easier for observers to distinguish between the crescent and other objects such as cloud strokes.

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