An Agent-Search Strategy for Contrast Enhancement in Medical Images

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Abstract

Image Contrast Enhancement (ICE) is one of the most used techniques in image processing for image quality improvement at preprocessing stages; However, common ICE implementations like Histogram Equalization (HE) or Contrast-Limited Adaptive Histogram Equalization (CLAHE) often introduce noise or result in information loss, which negatively impacts overall image processing. This paper shows an implementation of recently introduced technique Agent-Search-based ICE (AS-ICE) which effectively reduces these undesired side effects. A comparative study shows how AS-ICE outperforms CLAHE in multiple image quality criteria. Furthermore, original images and images enhanced with CLAHE and AS-ICE are fed into a CV system for tuberculosis diagnosis, with AS-ICE images leading to the most accurate results, getting an improvement by reduce error classification from 28

1. Introduction

As image processing has found its way to more diverse applications, the demand for techniques that improve image quality, and allow for relevant information to be extracted, has increased. One of the most used techniques for this aim is Image Contrast Enhancement (ICE), which redistributes the pixel values of a gray-scale image according to the structural distribution to ease the differentiation of objects or areas of interest in the image. Among the techniques for ICE are: Histogram Equalization (HE), Contrast-Limited Adaptive Histogram Equalization (CLAHE), sigmoid function, gamma correction, and fuzzy logic operation (Ariateja et al., 2018).

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Proceedings of the 40th International Conference on Machine Learning, Honolulu, Hawaii, USA. PMLR 202, 2023. Copyright 2023 by the author(s).

Although well-spread ICE techniques, like HE or CLAHE, improve image quality, usually, this comes at the cost of noise addition and information loss. Newer techniques, such as the adjacent-blocks-based modification method, maximum intensity coverage, or recursive HE algorithm (**?**), have not fully overcome HE limitations.

In the medical field, several studies report using ICE at the preprocessing stage before analyzing the images with classification algorithms to diagnose different diseases, such as tuberculosis or breast cancer. Classification of digital images to diagnose diseases could be difficult because many variations occur at the time of image capture, due to the environment or the device used to digital image capture. These variations can cause misclassification, leading to a false diagnosis, digital images preprocessing helps feed more uniform images to the classification algorithm, reducing the chances for misclassification due to variations in the environment where the image is captured or the device that is used for this purpose (Murtaza et al., 2020; Castro & Cabrera, 2020; Hwa et al., 2020).

This paper presents an application of a recent method for ICE based on Agent Search (AS-ICE), where the pixels are treated as agents. The method increases the differences between the image sections, improving the image quality while losing less information than other popular ICE techniques (Luque-Chang et al., 2023). This method will be applied in the improvement of digital images of a rapid test for the detection of M. tuberculosis and the performance of digital image of positive or negative real samples test photographed with different devices will be evaluated.

2. Motivation

The work presented is part of a series of tests that are being carried out in the working group for the improvement of the images. When the same object in the same space is captured by different devices, digital images are generated with variations between them, in the medical area these variations can compromise the result and obtain a false positive or false negative as diagnosis, so, in this work, the performance of an agent-based contrast enhancement algorithm is presented to reduce the variations of digital images captured with 3 devices of different quality's before introduce to classification algorithm, from a rapid test for

the detection of tuberculosis diseases.

3. Contrast enhancement

In its simplest form, contrast enhancement changes the pixel values of a grayscale image to increase the number of graylevels in the image. this technique is called pixel-by-pixel adjustment, examples of which are generalized superimposition and HE, among others (Joseph & Periyasamy, 2018).

3.1. Contrast-Limited Adaptive Histogram Equalization (CLAHE)

Histogram equalization is an image enhancement technique where a redistribution of the pixel value is performed based on the full histogram of the image, this technique can lead to image enhancement, however, it can lead to the formation of artifacts. On the other hand, the Contrast-Limited Adaptive Histogram Equalization (CLAHE) technique performs a redistribution of the pixel value considering the accumulated value of the histogram, account the value of its nearest neighbors to achieve a distribution with better balance (Pizer et al., 1987). Finally, the contrast is more homogeneous than in HE, but it is still a limited technique that can generate noise in the image. image to calculated as follows:

$$P_x(i) = P_{(x=i)} = \frac{n_i}{n}, \rightarrow 0 \leq i < L \tag{1}$$

Where P is the new pixel value to be calculated, variable n is the number of pixels from dataset the image and L consist of 256 shades of gray. CLAHE is a well-known technique in image processing for different tasks (Pizer et al., 1987).

3.2. Evaluation criteria

A series of quality tests are run to compare the traditional contrast enhancement method with the proposed approach. These tests were chosen because they are well-known in the field of image processing: MSE, SSIM, FSIM, and STD.

Median square error (MSE) The mean square error is a measure that evaluates the similarity between an image I processed, concerning an original image R, by subtracting the pixel values of the processed image from the pixels of its reference and then calculating the mean value of the total error (Li et al., 2019).

Structural similarity (SSIM) The structural similarity index metric is a method that evaluates the perceived quality of a digital image. It allows the measurement of the quality of a processed image concerning its original version (Wang et al., 2004).

Feature similarity (FSIM) The FSIM metric evaluates the similarity characteristics between two images, a previously processed image, and a raw image. It has two stages, local similarity mapping, and simple similarity score classification (Zhang et al., 2022).

Standard deviation (STD) The sample standard deviation s is represented by (2).

$$s = \sqrt{\frac{1}{(n-1)} \sum_{i=1}^{n} (xi - \bar{x})^2} \tag{2}$$

4. Agent-Search-based ICE technique

Multiple ICE techniques are used to improve the quality of images before processing for a specific task. This is necessary when the information on the pixel distribution is grouped into a close neighborhood (Luque-Chang et al., 2023).

In this section, contrast enhancement employing search by agents is carried out. Each pixel $p_{(i,j)}$ is associated with an agent $A_{(i,j)}$ that represents a cooperative or competitive environment in its immediate neighborhood of n×m elements. The proposed model characterizes interactions of agents by intensity differences among them. So, the behavior of agent $A_{(i,j)}$ is determined by a set of rules between $A_{(i,j)}$ and the elements within its neighborhood N(i,j) which allows to increase or decrease the grayscale of the agent $A_{(i,j)}$.

Our contrast enhancement method consists of two operating rules. First, the agents or pixels that show higher intensity differences concerning the average are modified to increase these differences further. On the other hand, agents or pixels that maintain a small difference are altered to obtain a homogeneous intensity value.

4.1. Rule 1: feature highlights

This rule states that pixels or agents that present sufficiently high differences in their intensity values are modified to increase these differences. Therefore, assuming a neighborhood N(i,j) of 3×3 elements and a configuration pixel, each difference is calculated as follows:

$$s_q = sign(s_0 - s_q) \tag{3}$$

Where $q \in (1, ..., 8)$. Therefore, S is computed by (4):

$$S = sign\left(\sum_{i=1}^{8} s_q\right) \tag{4}$$

Finally, a value of $S = 0$ implies two cases. The first is that all pixels $N_{(i,j)}$ present the same intensity value as the agent $A_{(i,j)}$.The second involves that half of the elements $N_{(i,j)}$ are larger than $A_{(i,j)}$ while the other half are smaller. Therefore, each search agent is modified according to the

equation (5).

$$A^{k+1}_{(i,j)} = \begin{cases} A^k_{(i,j)} * 0.9, & S = -1 \\ A^k_{(i,j)}, & S = 0 \\ A^k_{(i,j)} * 1.1, & S = 1 \end{cases} \quad (5)$$

4.2. Rule 2: Pattern smoothing

In this rule, the pixels or agents that maintain a small difference in intensity are averaged. The rule that describes this behavior, behaves as follows:

$$A^{k+1}_{(i,j)} = \begin{cases} A^k_{(i,j)} * 1.05, & S = -1 \\ A^k_{(i,j)}, & S = 0 \\ A^k_{(i,j)} * 0.95, & S = 1 \end{cases} \quad (6)$$

5. Results and Discussion

This section reports a comparative study of the experimental results achieved by AS-ICE and CLAHE for digital images used in M. tuberculosis diagnosis.

5.1. Test Dataset

The test dataset was obtained from a rapid and low-cost test for the detection of antibodies against M. tuberculosis by hemagglutination. This sample test is composed of three biomarkers and one more for test control, hence it is evaluating four sites for each sample (Ayala et al., 2019). Test dataset is conformed by four samples tested, two negatives and two positives; those tests were validated for two eye experts and were classified as negative by negative sample, and positive for positive sample, that is both the negative samples have all biomarkers as negative classification and positive samples have all biomarkers as positive classification, besides all samples have approved control. Digital images were captured by photography each test with different qualities devices: high (1), mid (2), and low (3); this capture was made in control environment at same time to reduce variation for other factors.

In figure 1, biomarker of one sample positive and one negative are shown. In this dataset, positive samples must be positive in all biomarkers, and the control test site is correct in all sample tests. After processing, there are twelve original digital images, which were subsequently processed by AS-ICE and CLAHE algorithms, resulting in twelve more images obtained from each algorithm, making a total of 36 digital images. Figure 2 shows the comparison of biomarker 1 of a positive sample of the original digital image captured with each device and with the AS-ICE and CLAHE image enhancement treatment.

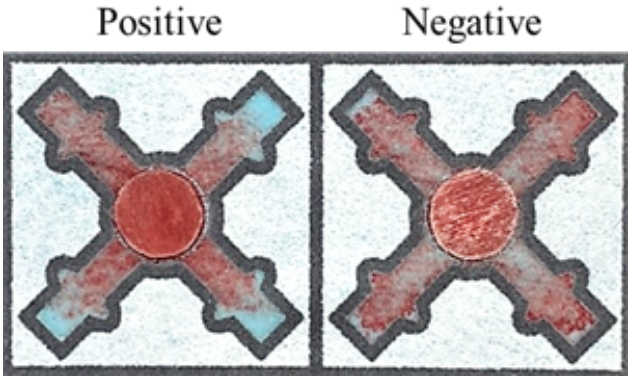

Figure 1. Representative digital images of positive and negative samples.

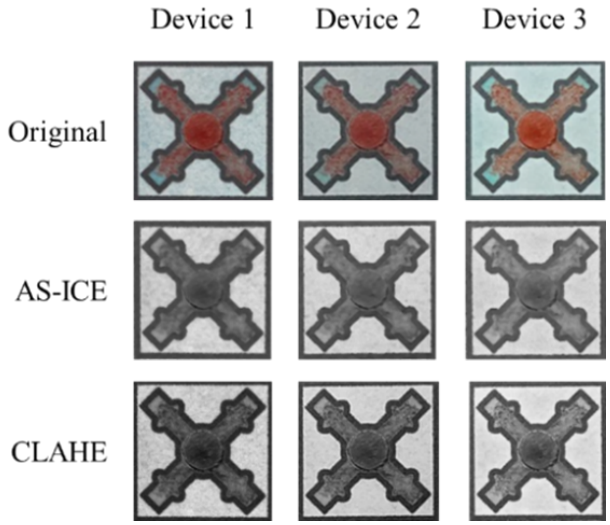

Figure 2. Comparative of digital images of positive sample obtained whit different devices and the resulting images after processed with AS-ICE and CLAHE.

5.2. AS-ICE and CLAHE indexes evaluation

For this analysis, were considered four performance indexes: Median square error (MSE), Structural similarity (SSIM), Feature similarity (FSIM), and Standard deviation (STD), showing results in table 1. The reported result in the MES index is higher in CLAHE than in the AS-ICE approach, this means that CLAHE images have increased error, therefore, AS-ICE algorithm images have more similarity to the original digital image. The SSIM and FSIM values indicate the preservation of important details before treatment and segmented image similarity, in both measures, a high value indicates a better process.

All images processed with the AS-ICE algorithm have values of those indexes higher than CLAHE processed im-

Table 1. Indexes value of digital image treatment with different samples and different devices. Best performance is show in bold.

D*	A**	MSE	SSIM	FSIM	STD
		NEGATIVE 1			
1	AS-ICE	**0.0073**	**0.9997**	**0.9917**	**0.2470**
	CLAHE	0.0353	0.9964	0.9775	0.2932
2	AS-ICE	**0.0140**	**0.9988**	**0.9927**	**0.2456**
	CLAHE	0.0318	0.9969	0.9687	0.2935
3	AS-ICE	**0.0075**	**0.9998**	**0.9921**	**0.2386**
	CLAHE	0.0715	0.9913	0.9567	0.2935
		NEGATIVE 2			
1	AS-ICE	**0.0068**	**0.9998**	**0.9901**	**0.2495**
	CLAHE	0.0431	0.9955	0.9725	0.2939
2	AS-ICE	**0.0113**	**0.9991**	**0.9960**	**0.2409**
	CLAHE	0.0372	0.9959	0.9667	0.2934
3	AS-ICE	**0.0068**	**0.9998**	**0.9971**	**0.2576**
	CLAHE	0.0372	0.9959	0.9667	0.2934
		POSITIVE 1			
1	AS-ICE	**0.0066**	**0.9998**	**0.9914**	**0.2331**
	CLAHE	0.0435	0.9951	0.9748	0.2934
2	AS-ICE	**0.0078**	**0.9995**	**0.9940**	**0.2236**
	CLAHE	0.0418	0.9951	0.9676	0.2930
3	AS-ICE	**0.0080**	**0.9997**	**0.9921**	**0.2454**
	CLAHE	0.0623	0.9928	0.9595	0.2933
		POSITIVE 2			
1	AS-ICE	**0.0070**	**0.9997**	**0.9953**	**0.2404**
	CLAHE	0.0382	0.9958	0.9782	0.2932
2	AS-ICE	**0.0118**	**0.9990**	**0.9959**	**0.2359**
	CLAHE	0.0366	0.9959	0.9670	0.2929
3	AS-ICE	**0.0062**	**0.9999**	**0.9929**	**0.2297**
	CLAHE	0.0590	0.9931	0.9609	0.2938

D* corresponding to *Device*.
A** corresponding to used *Algorithm*.

ages. Moreover, the STD value indicates algorithm stability, where a low value denotes higher stability, AS-ICE algorithm images processed have best results than CLAHE images, getting the lowest values in the STD values.

5.3. Diagnosis comparison

Predictive positive was made using a traditional Machine Learning algorithm proprietary to the same laboratory that has developed the biomarkers (Ayala et al., 2019), this model was training with several images of positives and negatives samples to give a positive probability for each biomarker; for differences evaluation between improvement image algorithms, this predicted algorithm was used without modification.

The predictive algorithm measures the probability of a positive sample within a 0-1 scale for each biomarker, then a threshold of 0.7 determine result as positive when is upper.

Figure 3 shows the differences between the positive and negative classification of original and processed images with AS-ICE and CLAHE. The predictive algorithm struggles to accurately classify unprocessed digital images captured with different devices, yealing an accuracy of only 72%. This issue is fixed by the AS-ICE, where 100% of samples are correctly classified. In CLAHE, the accuracy was 83%, better than original images but worse than AS-ICE. Negative real samples have a correct classification in all digital images samples. Experimental results show how the proposed approach improves the image quality enough to help the correct classification in all the cases considered for this study.

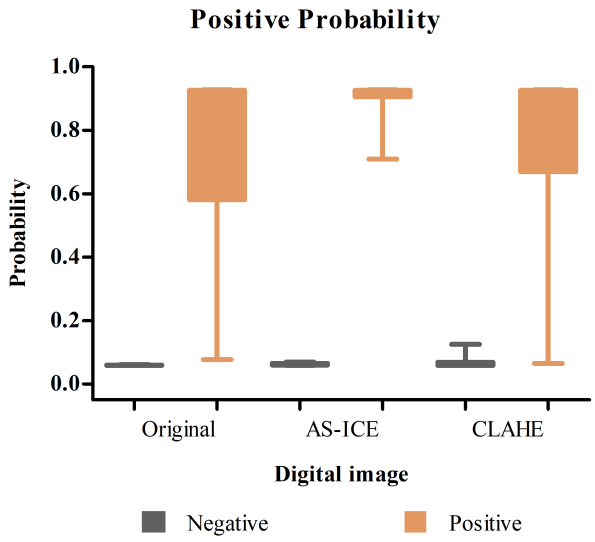

Figure 3. Positive probability comparison of images processes vs original.

Original digital images with classification error comparison with the same test before the AS-ICE and CLAHE are shown in figure 4, biomarkers 1 and 3 classification in positive 2 sample have the most significant diagnosis correction with AS-ICE algorithm, getting an improvement in all tests for AS-ICE. In the case of CLAHE, the correction of the result was made in both biomarkers in device 2 and biomarker 1 in device 3, while there was no improvement in device 1.

6. Conclusion

Image processing is a powerful tool that has several applications in different areas. One of its applications is the accurate detection of antibodies against M tuberculosis by Image Contrast Enhancement. Using the novel technique of Agent-Search-based for image contrast enhancement is

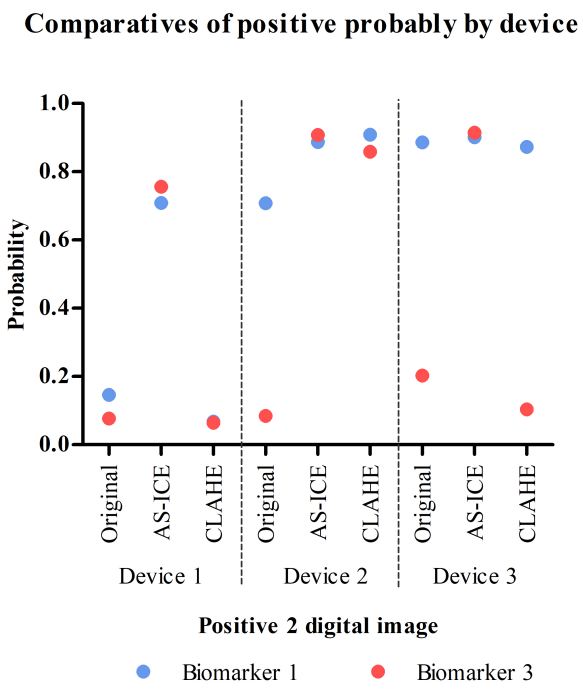

Figure 4. Positive probability results comparison by device in biomarkers 1 and 3 of positive sample.

possible to improve effectiveness in the detection of tuberculosis disease by enhancing the captured image before employing a diagnostic algorithm. With this technique, it is possible to reduce the error of classification in the actual diagnosis from 28 to 0% in this study, when the digital image of the same sample is captured with different devices, thus generating 100% of real positives and real negatives. This is an effective technique to increase the quality of digital images from different devices and thus obtain an effective diagnosis of the disease. For future work, this study can be supplemented with more digital image variety and different validation tests.

Acknowledgements

Database and probably of positive Machine Learning algorithm was issued by Unima INC.

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