Algorithm comparison for histogram matching in MRI/CT

First Assignment in Advances in Digital Imaging and Computer Vision

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Contents

Abstract

With the rapid development of technology and medicine, there is a greater need for image analysis. A methodology that helps a lot in the analysis of medical images, MRI and CT, is the histogram matching. This method is used to match the histogram of an image with another to improve the intensity for example. There are different algorithms used to histogram matching. This article compares two algorithms for histogram matching in OCTAVE. The same images are used for original MRI and for CT reference image. These images depict a brain without any underlying disease. The comparison is based on the pixel error rate, root mean square, correlation and intersection. The algorithm with the best performance is the second because it had a better result in pixel error rate and root mean square. Also, both algorithms had the same effect on the intersection.

Keywords

Histogram matching, Histogram specification, CT, MRI, Brain CT, Brain MRI, Histogram matching with MRI and CT brain images.

Introduction

Over time, we have noticed that there is a strong emphasis on the histogram matching to images and specifically to medical images. Histogram matching is used to match the histogram of an image with the histogram of another image. In this way, an image that has noise or high intensity can be corrected. In the field of medicine, we see it very often in the tomographic images. Many studies have been done on the brain by examining its MRI and CT images. The use of this method helps in the research of the tumour and even comparison of mechanisms to determine that the images have common results. For all of the above, algorithms need to be evaluated to histogram matching to find the one that best match. The present article examines the comparison of two algorithms that are for histogram matching to investigate the algorithm that best match. The two algorithms use the same images as for the original MRI image and the CT reference image. After extracting the results, the comparison is made based on the pixel error rate, root mean square, correlation and intersection.

Review of Literature

From time to time, many articles have been written about histogram matching. Article [2] states that the histogram matching to the maximum possible extent of the source signal compared to low image distortion methods will be detrimental to subsequent image processing functions. Consequently, Article [3] presents a methodology for creating a histogram matching for digital images because the histogram for digital images is considered a problem because of the pixels that have the same values. Article [1] presents a method for MRI images to enhance the contrasts using the image histograms and compares the results with the histogram specification method. As in Article [4], it examines MRI images, noting that the histogram matching significantly helps to normalize the images in order to provide biologically interpretable units. The importance of normalizing the histogram for magnetic resonance imaging based on the histogram is emphasized in Article [5], which proposes a method for MRI brain imaging. In addition, Article [6], for its part, gives its importance to the histogram matching for medical imaging to make the analyzes more effective and proves it through the MATLAB program. Article [7] uses a deep learning algorithm to create synthetic computed tomography based on TRI and MRI. In their method, the histogram matching is used to normalize the images CT and MRI in order to have a similar intensity scale. Finally, in article [8] the histogram matching for the images with cancer is used. In summary, the histogram matching is of particular importance for the images and especially for the medical images such as MRI and CT for the extraction of the results.

Theoretical Background

In this section, an analysis is made on the Histogram matching, for the MRI and CT images.

Histogram Matching

Histogram matching or histogram specification of a is a technique in image processing. Used to normalize images. Each image has a histogram. With the histogram of an image we can normalize another image. So, it is the transformation of the image of a picture to match a defined histogram. This method is used for example in two same images when one of them has noise, shadows or different lighting.

To apply the algorithmic histogram matching, we first set the images to gray X input scale. The gray scale sets the value of each pixel of an image to be a single sample that only counteracts a quantity of light. It only transmits black-intensity information which is the weakest contrast intensity to white which is stronger. Subsequently, you look at the density function you calculate from the histogram of the image that is the image we want to transform and the image we have as a reference. The mathematical formula for probability is as follows:

$$p_r(r_j) = \frac{n_j}{n}$$

Figure 1:Mathematical formula for probability

Where n_j is the frequency of the gray scale value r_j, and n is the total pixel number in the image. Finally, we match the sum distribution function and find the transformed image. The mathematical formula for matching the probability density function with the cumulative distribution is as follows:

$$S(r_k) = \sum_{j=0}^{k} p_r(r_j), \qquad k = 0, 1, 2, 3, \ldots$$

$$G(z_k) = \sum_{j=0}^{k} p_z(z_j), \qquad k = 0, 1, 2, 3, \ldots, L$$

Figure 2:Mathematical formula for cumulative distribution

Where L is the total number of gray levels.

MRI

Magnetic Resonance Imaging (MRI) form images of normal body processes and anatomy. It is a medical technique for imaging and is used in radiology. It uses radial waves, magnetic field inclinations and strong magnetic fields. The imaging is done without radiation. In particular, magnetic resonance imaging (MRI) scans are used to visualize organs and soft tissues in internal structures. In addition, it gives the possibility of the emergence of the difference of the tissue between the normal and the abnormal.

CT

CT scans are a medical procedure for imaging the body. It produces cross-sectional images ("slices") from different perspectives through combinations of X-ray measurements that are processed by a computer. In particular, it is used to diagnose muscular disorders, infections, and bone fractures, to detect internal bleeding, and to study blood vessels. It has the disadvantage of not being able to display the soft molecules well. In addition, the examinee receives a large number of X-rays.

Methodology

In order to compare the two algorithms that are for histogram matching, the same images were used as the original image and as the reference image. Consequently, the results from the algorithm were compared if the images and histograms were different. Finally, correlation methods, intersection points and a square mean were used to prove the best algorithm for histogram matching.

Datasets

Two databases with brain images were used for the research. The first base was with MRI images while the second base was with CT images. The bases were from the Kaggle website with url: https: //www.kaggle.com. The website provides many databases with medical images. In addition, the images used did not show any underlying diseases, i.e. they are images of people who did not have a brain disease or a brain-related disease.

First Algorithm

The first algorithm was simple in its structure and the operations for the calculation were done with ready-made Octave commands. The steps of the algorithm are as follows:

Step 1: Upload the original MRI image to be converted and save it to the variable.

Step 2: Upload the CT image as a reference image used to match its histogram.

Step 3: Create a table with zeros. The table has 256 lines and 1 column in the form of an insight integer(uint8).

Step 4: Create the histograms of the 2 images in different variables.

Step 5: Calculate the probability for each image separately.

Step 5: Calculate the cumulative distribution from 1 to 256.

Step 6: Save the values in the table above.

Step 7: Add 1 to the table and save it to a variable for the converted image.

Step 8: Save the image to jpg.

Step 9: We display the original image, the reference image, the transformed image and their histograms.

Second Algorithm

The second algorithm is more complex in its structure and with more data. Two functions and main were created.

First method:

Step 1: Set L to 256.

Step 2: Transform an image or colourmap from red-green-blue (RGB) colour space to a grayscale intensity image.

Step 3: Find the histogram.

Step 4: Calculate the probability.

Step 5: Calculate the cumulative distribution.

Step 6: Round off the last result.

Second Method:

Step 7: Defines the original and reference images.

Step 8: Create a zero table with the size of the original image.

Step 9: For each RGB channel of the report image.

Step 10: If the channel is green and blue make a histogram and find the probability.

Step 11: Otherwise it leaves it as it is.

Step 12: When you have finished repeating, find the cumulative distribution and round it.

Step 13: For the original image, create a table with 3 columns and put the channels.

Step 14: Call the first function for the original image.

Step 15: Create a table with ideals in the size of the reference image.

Step 16: Defines minimum and minimum index.

Step 17: Calculate for each element of the original image and the reference image the magnitude.

Step 18: If it is zero it saves it.

Step 19: If they are smaller, store them in the minimum variables.

Step 20: Define a final table and save the final formatted values.

In the main program:

Step 21: Upload the original MRI image as the original image.

Step 22: Uploads the CT reference image.

Step 23: Call the second function with the original and the reference image.

Step 24: Put the final image on a variable.

Step 25: Save the image as jpg.

Step 26: Displays the original image, the reference image, the transformed image and their histograms.

Compare of two histograms

To compare the histograms and to prove which algorithm is better in histogram matching, it was first examined whether the images that were transformed have the same percentage of difference as the reference image, i.e. the average error per pixel was calculated. Consequently, the transformed images were examined by comparing them with each other to find the differences between them and the differences appear in the image and the histogram. In addition, the root mean square of each transformed image was found with the reference image. The mathematical formula to calculate the root mean square is:

$$d(H_1, H_2) = \sum_{I} \frac{(H_1(I) - H_2(I))^2}{H_1(I)}$$

Figure 3:Mathematical formula for root mean square

Their values were compared and the lowest value has the best match. Finally, correlation and intersection were calculated for each transformed image with the reference image. The values are higher having the best match. The mathematical formula to calculate the correlation is:

$$d(H_1, H_2) = \frac{\sum_I (H_1(I) - \bar{H_1})(H_2(I) - \bar{H_2})}{\sqrt{\sum_I (H_1(I) - \bar{H_1})^2 \sum_I (H_2(I) - \bar{H_2})^2}}$$

Figure 4:Mathematical formula for correlation 1/2

where:

$$\bar{H_k} = \frac{1}{N} \sum_J H_k(J)$$

Figure 5:Mathematical formula for correlation 2/2

and N is the total number of histogram bins. The mathematical formula for intersection is:

$$d(H_1, H_2) = \sum_I \min(H_1(I), H_2(I))$$

Figure 6:Mathematical formula for intersection

Results

The two algorithms displayed the original image, the reference image, the transformed image and their histograms. Below are the results of the algorithms.

Fist Algorithm:

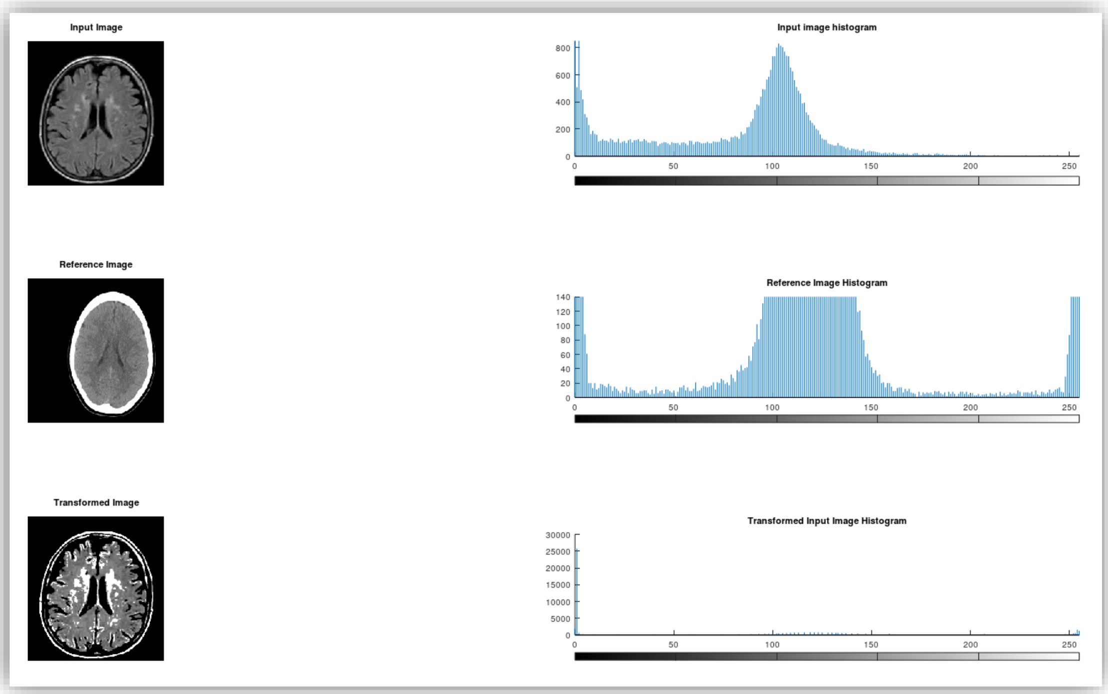

Figure 7:Output for First Algorithm

Second Algorithm:

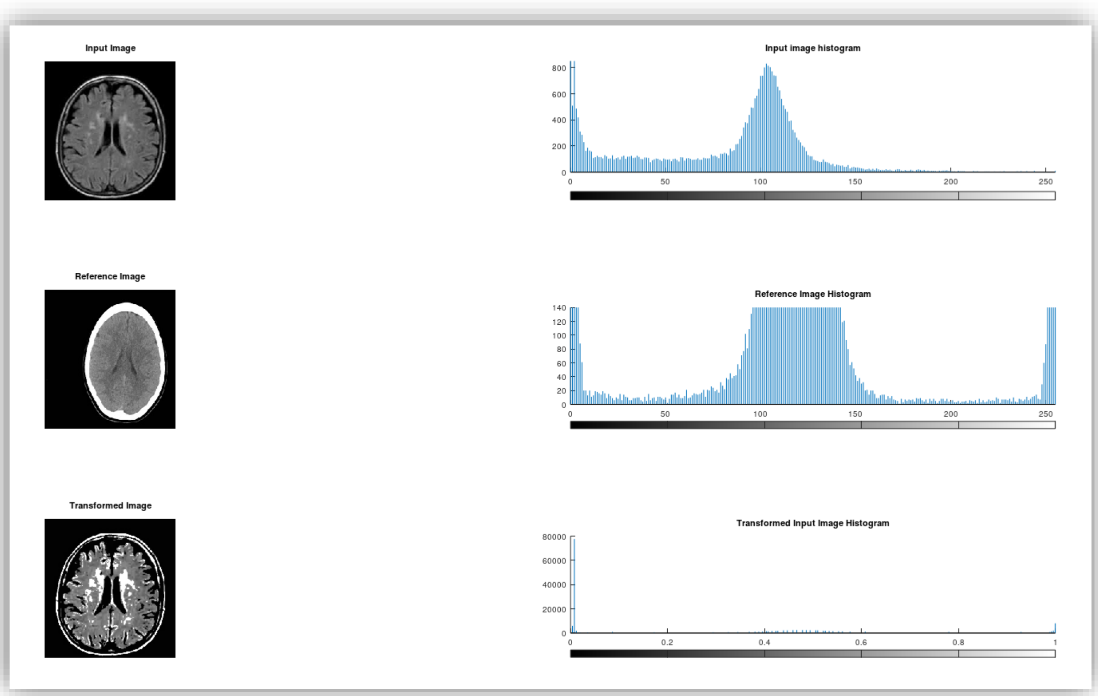

Figure 8: Output Second Algorithm

Initially, the first to be examined was the error rate per pixel. The first algorithm had a result of 26,949 compared to the second algorithm had 0.019659. Consequently, with the help of the algorithm created for their comparison examined the difference of the images and the difference of their histograms. As can be seen in the picture below, they were different and at this point it appears that both algorithms did not have the same result.

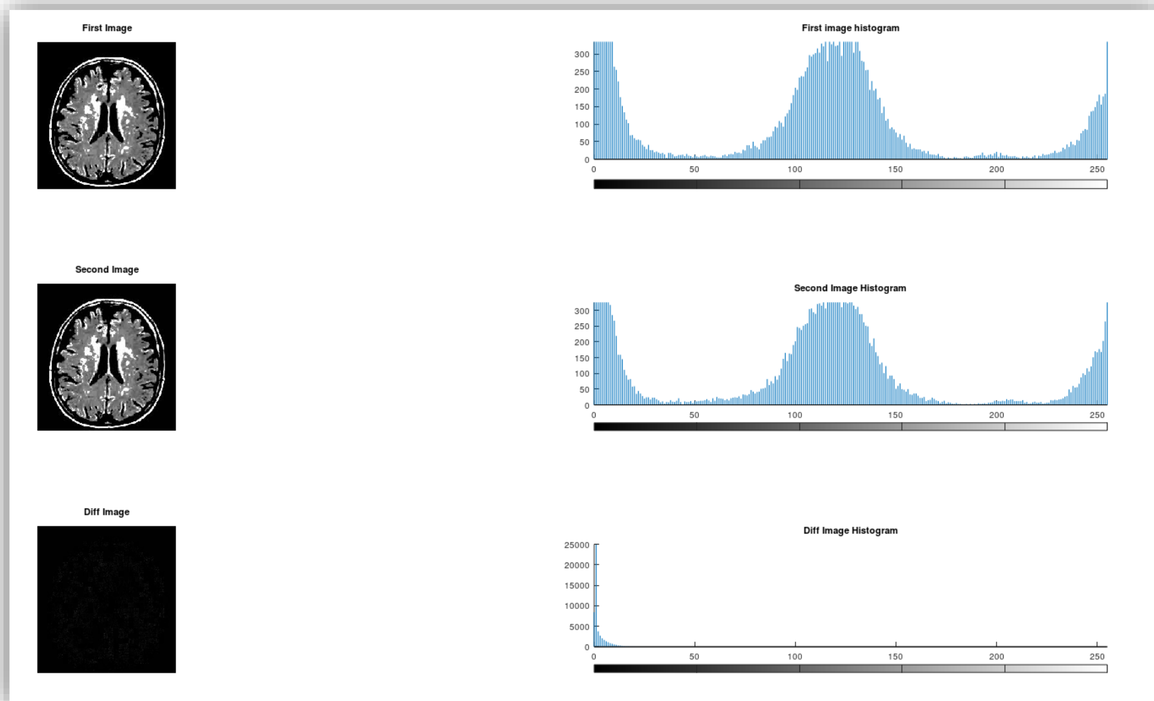

Figure 9:Differences for two transformed images

The Octave command window gave the commands for square mean, correlation and intersection. The results are as follows:

- For root square mean it was done for first algorithm compared to the reference image it had a result of 1321.9 while the second algorithm had a result of 1312.7. Second algorithm had the lowest value and as mentioned it has the best match.
- For correlation first algorithm had an effect of 2.7070 while the second algorithm had 2.7044. So, the first algorithm had the best match.
- For intersection the first and second algorithms had the same effect as 32640.

Conclusion

In conclusion, the article described two algorithms for histogram matching. For both algorithms the same images were used which were MRI for original image and CT for reference image which depicted a brain without disease. Then the final results of both algorithms were compared and it was found that they have differences in the images and the histograms. Checks were performed to demonstrate the best algorithm based on pixel error rate, root mean square, correlation and intersection. It turned out that the second algorithm had better results in the pixel error rate and root mean square. While the first algorithm had a better result in correlation. Finally, intersection was a common number for both algorithms. Based on the above results, it turns out that the second algorithm has better results.

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