Enhancement of CT images for visualization

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ABSTRACT

Modern medical science strongly depends on imaging technologies for accurate diagnose and treatment planning. Raw medical images generally require post-processing – like edge and contrast enhancement, and noise removal – for visualization. In this paper, a clustering-based contrast enhancement technique is presented for computed tomography (CT) images.

CCS CONCEPTS

• Image processing→ Computed tomography Enhancement

KEYWORDS

Clustering algorithm, Computed tomography, Contrast enhancement, Tone Mapping, HDR

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1 INTRODUCTION

Medical images play an essential role in diagnosis and monitoring of the patient's health condition. Despite advancement in the capturing techniques of CT images, the images generated are not be of satisfactory quality for accurate diagnosis. Environmental noises, special condition of patients in photography, lighting conditions and technological limitations of imagining hardware are the main reasons of lower quality. Moreover, various type of artifcats in imaging modalities debase the quality. Many techniques have been proposed for contrast enhancement to improve visual information of CT images. [Kallel et al. 2017] proposed the use of discrete wavelet transform with singular-value decomposition (DWT-SVD) for adjusting the intensity distribution of dark CT images. The result is enhanced CT image, however the method is computationally expensive. Anisotropic diffusion filters and unsharp masking technique were used for edge enhancement and noise smoothing of CT images in [Vincent et al. 2018]. Unsharp masking however excessively enhances the high-contrast areas. Therefore, some unpleasant overshoot artifacts occur in the resultant enhanced images. Several other sophisticated techniques for CT image manipulation can be found in recent literature [Al-Ameen et al. 2012, Gandhamal et al. 2017]. CT images in most of the formats (like DICOM) encode the pixel intensities as 16-bit integers. For visualization, these need to be converted to 8-bit images. Therefore, techniques used for tone-mapping of natural and synthetic high dynamic range (HDR) images [Shan et al. 2010, Liang et al. 2018, Reinhard et al. 2005] can also be used for enhancement of CT images.

In this paper, we propose a divisive clustering-based algorithm for enhancement and better visualization of CT images. The algorithm is extremely fast and effective as will be shown in the results section.

2 PROPOSED METHODOLOGY

CT images generally store the pixel intensities using 16 bits per pixel. The proposed algorithm quantizes them to 8 bits for visualization on standard hardware. A divisive clustering approach is used for this. Starting with all image pixels in a single cluster, we keep splitting until 256 clusters are obtained. Pixels in each cluster are assigned a unique integer label in [0, 255] range, resulting in an 8-bit grayscale image. The goal is to keep similar pixels in the same cluster so that the labeling step does not flatten the details. The optimal k-means algorithm is very slow and sensitive to initialization. Our divisive algorithm uses an intuitive approach for clustering with good results. Moreover, it is independent of initialization and is extremely fast.

To explain the algorithm, we first describe our method of splitting a cluster into two. Assume that the cluster has a set of data points $S_j, 1 \leq j \leq N$, sorted in ascending order. If each point in this cluster is represented by the mean value $\bar{S}$, the loss of information expressed as the sum of squared differences can be written as:

$$error = \sum_{j=1}^{N}\left(S_j - \bar{S}\right)^2 \tag{1}$$

The rationale behind splitting the cluster into two is to enhance the precision by providing two candidate values instead of one to represent the points in the cluster. Our goal is to select the point of split that would minimize the overall combined error of two sub-clusters. With N points in a cluster, there are $N-1$ ways to split it. Assume that the first sub-cluster gets first M elements and second gets the remaining $N-M$. Characterizing $\bar{S}_1$and $\bar{S}_2$ as mean values of the sub-clusters respectively, the total error after splitting can be calculated as:

$$e = \sum_{j=1}^{M}\left(S_j - \bar{S}_1\right)^2 + \sum_{j=M+1}^{N}\left(S_j - \bar{S}_2\right)^2 \tag{2}$$

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Selection of M, the point of split and the boundary between the sub-clusters, is important as it determines the errors in (2). Since the data is sorted, error in the left sub-cluster will increase if M moves from left to right, while it will decrease in the right sub-cluster. By calculating the combined error of both sub-clusters for all possible values of M, we can pick the optimal point of split that would minimize the error. However, this brute-force approach is not required. For sorted data, the error function given by (2) results in a parabolic curve, which has a single minimum. Using binary search, this point can be found with $O(\log_2 N)$ complexity as described below.

Assuming that the cluster to be divided is defined by an interval [a, b], we check the slope of the error function (2) at the middle of this interval $(a + b) / 2$. A negative slope would mean that the minima lies in the right half of the interval, and we can exclude the left half from the search. Similarly, a positive slope would suggest that the right half of the cluster can be discarded. This is done iteratively, and each iteration reduces the search interval to half. We stop when a point with zero slope is found or the interval size becomes equal to one.

Starting with all the image pixels in a single cluster, we keep repeating the split operation until we segment the data into 256 clusters. In each iteration, the cluster that has maximum individual error is picked for splitting, as this results in maximum reduction of overall error. Note that the cluster size becomes smaller and splitting operation becomes faster after each iteration.

After completion of clustering, each pixel is assigned a value equal to the index number of the cluster to which it belongs. This gives us an 8-bit image with enhanced contrast.

3 RESULTS

We conducted some experiments using several publically available 16 bits CT test images. For comparison, we picked some recent methods developed specifically for enhancement of CT images, as well as some general-purpose tone-mapping operators for HDR images. Results for a typical CT image are shown in Fig. 1 whereas more results are presented in the auxiliary file.

As can be seen in Fig. 1, [Shan et al. 2010] adds artifacts in image regions with high intensity values, while [Liang et al. 2018] keeps the edges but has lower overall contrast. The tone-mapping operator [Reinhard et al. 2005] preserves information in darker areas to some extent, however, the detail become invisible in high intensity regions. The CT image enhancement techniques [Al-Ameen et al. 2012] and [Gandhamal et al. 2017] maintain good contrast and brightness level, but suffer loss of local texture information in low intensity regions. In contrast, our algorithm sufficiently enhances both low and high intensity regions and well-reserves the edges, resulting in clear view of image details.

Note that the splitting operation in our algorithm is applied at the point of minimum error. This results in grouping similar pixels residing in the same cluster, and hence getting assigned the same label. Pixels far from each other in intensity are likely to be in different clusters and hence get different labels. This ensures that a good contrast is maintained in the entire image.

We compared the computational efficiency of our algorithm with the rest. The results presented in Table 1 show the time taken by each algorithm to enhance the test image. Our algorithm beats the rest with a very clear margin.

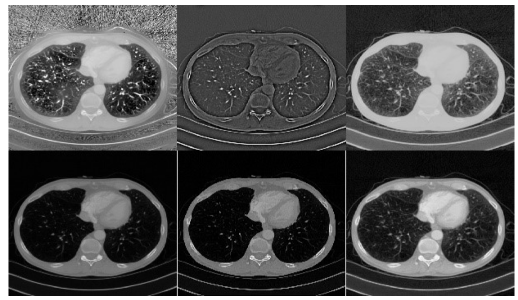

Figure 1: *A test CT image of lung (copyright @ The Cancer Imaging Archive) enhanced by [Shan et al. 2010], [Liang et al. 2018], [Reinhard et al. 2005], [Al-Ameen et al. 2012], [Gandhamal et al. 2017], and the proposed method (in reading order).*

Table 1: *Comparison of the execution time of different methods.*

Shen	Liang	Reinhard'05	Al-Ameen	Gandhamal	Proposed
3.73	2.70	0.19	0.83	0.09	0.04

REFRENCES

F. Kallel and A.B. Hamida. 2017. A New Adaptive Gamma Correction Based Algorithm Using DWT-SVD for Non-Contrast CT Image Enhancement. IEEE transactions on nanobioscience, 16(8), pp.666-675

D. J. Vincent, and A.M. Reshin. 2018. Edge Enhancement and Noise Smoothening of CT Images with Anisotropic Diffusion Filter and Unsharp Masking. In 2018 IEEE Recent Advances in Intelligent Computational Systems (RAICS) pp. 55-59.

Q. Shan, J. Jia, and M. S. Brown. 2010. Globally optimized linear windowed tone mapping. IEEE transactions on visualization and computer graphics, 16(4), pp.663-675.

Z. Liang, J. Xu, Zhang, Cao, Z. D. and L. Zhang, 2018. A hybrid l1-l0 layer decomposition model for tone mapping. In Proceedings of the IEEE conference on computer vision and pattern recognition. pp. 4758-4766.

E. Reinhard and K. Devlin. 2005. Dynamic range reduction inspired by photoreceptor physiology. IEEE transactions on visualization and computer graphics, 11(1), pp.13-24.

Z. Al-Ameen, G. Sulong and, M.G.M. Johar, 2012. Enhancing the contrast of CT medical images by employing a novel image size dependent normalization technique. International journal of Bio-science and bio-technology, 4(3), pp.63-68.

S. Gandhamal., S. Talbar, Gajre, A.F.M. Hani and D. Kumar, 2017. Local gray level S-curve transformation–a generalized contrast enhancement technique for medical images. Computers in biology and medicine, 83, pp.120-133.