Efficient Compression of Medical Images Based on Adaptive Histogram Modification

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Abstract – **In this paper is presented one new method for efficient compression of visual medical information, based on adaptive histogram modification. After that the images are losslessly compressed and saved in a new format. The restored images are then processed so that to enhance their contrast. In result of the pre-processing the compression ratio is significantly increased, retaining the visual quality of the image.**

Keywords – **Image pre-processing, Lossless image processing, Archiving of medical images.**

I. Introduction

Governments worldwide are pushing to computerize paper-based medical records in order to make them available for easy and reliable exchange. Paper-based medical record serves all the essential issues of medical care. They are used to record each patient's health status, and allow caregivers to offer the appropriate treatment to patients.

Although paper-based medical records played an important role in health care, it has several significant limitations like:

- Fragmented.
- Limited availability - only at one place at a time.
- Poorly indexed.
- Often illegible.

In many countries, the current implementations of inter-institutional transfer, share and use of patient's data, the information exchange is still performed mainly manually. This process is tedious, time consuming, error-prone and therefore expensive. In addition, the importance of linking medical specialists lies in speeding up the extraction of comprehensive patients' information where the time is critical in the medial care process. Since Electronic Medical Records (EMR) are independently developed, they often have different structure and semantics. There is a lack of communication and integration between these heterogeneous information systems. Current Health Care Information Systems (HIS) provide only local data within the medical institute. This situation creates a reality in which the medical record is scattered in various locations, different structures and semantics, and among many different caregivers. Beside, patient's can only be given care after reviewing its medical history. This would lead to a situation where patient can only get medical care in institutions that obtain a medical record, even in case of emergencies. Increasingly, healthcare organizations are considering moving to an EMR. EMR is a computer-based patient medical record that serves as the primary source of information for effective patient care. The purpose of an EMR is to gain the benefits of paper-based medical record and overcome its limitations. Thus, EMR is a single, permanent, legal document. Thus, a first step in integrating EMR is to identify and characterize their inter-schema and semantic relationships, which involves ontology mapping.

Recent scientific literature suggests that Electronic Health Record (EHR) implementation will optimize healthcare delivery to individual patients [1]. It is expected that EHRs will decrease the cost of care, increase the quality of life and allow the portability of records, while maintaining privacy of some medical information. Such systems would connect hospital patient data with clinical data as the patient moves between providers and patient care establishments. Interoperable EHRs have the potential to promote access to more detailed and accurate patient information at the time of treatment, to reduce medical errors and to improve the overall healthcare quality.

Considering the importance of the patient's medical information for the caregivers to ensure that patients receive the appropriate treatment in light of their medical history, sharing distributed medical information among caregivers is essential. On the other hand, these caregivers suffer from communication gaps and the heterogeneity of their medical records. As a solution, there has been proposed new approach for archiving and standardization of medical records. Other techniques are proposed to achieve partial automation of interoperability based on medical record schema or semantics.

The prevailing part of the information, stored in the medical databases is visual. In correspondence to the contemporary trends and requirements, the hospitals and other healthcare institutions have to maintain significant number of electronic files, comprising various kinds of information: images (ultrasound, CT, X-Ray etc.), ECGs, EEGs, scanned documents, prescriptions, and many others. Two main problems arose when all this information is archived and stored: how to archive all this information efficiently in order to create databases of size as small as possible, retaining the visual quality unchanged, and how to ensure the needed confidentiality for the patients' information.

The first problem is solved using some kind of image and data compression. The most famous standard, used for medical imagery, is DICOM, based on the JPEG standard [2,3]. As it is very well known, the JPEG-based compression is highly efficient and offers restored images with retained visual quality.

The paper presents one new approach for image pre- and post-processing aimed at the efficient compression of the medical images. The paper is arranged as follows: in Section 2 is presented the method for adaptive histogram modification

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and the adaptive contrast enhancement of the restored images; in Section 3 are given some experimental results and Section 4 contains the Conclusions.

II. Adaptive histogram modification

Typical medical images (X-ray, MRI, etc.) are of low contrast and possess significant noises. The visual quality of the medical images is not high and for the better image understanding various techniques aimed at the improvement of their visual quality are used. In this paper is offered a method for image preprocessing, which results in high compression ratio with retained visual quality. Besides, the restored image could be processed in order to enhance the image contrast also.

An Example medical ultrasound image is shown on Fig. 1. The image is of size 350×432 pixels, 24 bpp. The image contrast is relatively low. The image histogram is shown on Fig. 2.

As it is seen from Fig. 2, the brightness values, which comprise the meaning information in this test image, are in the range 37-168, i.e. about 50% of the standard 255 values.

Fig. 1. Test ultrasound image “Axial 2” of size 344× 430 pixels

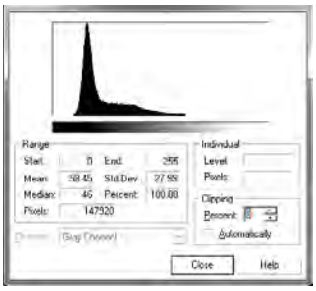

Fig. 2. The histogram of the test image from Fig. 1

The histogram modification, proposed in this work, comprises the following steps.

First, the image contrast is evaluated. As a rule, the image contrast enhancement is performed in cases, when the corresponding contrast coefficient K is low. This coefficient is calculated in accordance with the relation [4]:

$$K = \frac{k_{\max} - k_{\min}}{k_{\max} + k_{\min}} ,$$

where k_{max} and k_{min} are correspondingly the maximum and the minimum brightness levels in the processed image.

In case, that for some image $K<K_0$ (where K_0 is a threshold value, defining the image as one with low contrast), its brightness histogram $h(k)$ is strongly distorted and has an outlined maximum, h_{max}. The medical images (ultrasound, X-ray, MRI, etc.) are of low contrast and need corresponding processing. The processing is described below.

The image histogram is calculated in accordance with the relation:

$$h(k) = n(k)/n \quad \text{for } k = 0, 1, 2, \ldots, k_{max} ,$$

where $n(k)$ is the number of the pixels in the discrete brightness level k, n is the total number of the image pixels and k_{max} is the maximum number of brightness levels.

Then, (for $K<K_0$, which is the case of the low-contrast images) is performed image segmentation, using the thresholds k_1 and k_2, in result of which the brightness range is divided into three segments (A, B, C). The algorithm for the calculation of the thresholds is presented as follows:

- The maximum of the histogram is defined:

  $$h_{max} = max\{h(k)\} \text{ for } k = 0, 1, 2, \ldots, k_{max},$$

- The value of the segmentation boundary is calculated as $t = \alpha h_{max}$, where $\alpha < 1$ (0.01%).
- The values of the thresholds k_1 and k_2 are defined in accordance with he relations:

$$h(k) \leq t \quad \text{for} \quad k = 0, 1, 2, \ldots, k_1\text{-}1,$$

$$h(k) \geq t \quad \text{for} \quad k = k_2+1, k_2+2, \ldots, k_{max},$$

The histogram is then modified as follows:

The brightness values, placed in parts of the histogram, outside the "meaning" parts of the histogram are strongly reduced - for every 10 or 12 values one representative only is selected. The belonging to the closest representative is done following the rule for arithmetic rounding.

Similar approach is used for the "meaning" part of the histogram, but in this case the representatives are usually placed at a distance of 4 or 5 values.

With this, the preprocessing is finished. In result of the preprocessing the visual quality of the processed images is retained (the PSNR remains higher than 38 dB, which means, that the histogram modification is practically unnoticeable.

After the preprocessing, the image is losslessly compressed using the Adaptive Run-length Coding, developed by the authors [5].

After decoding the image is restored with retained visual quality. For better image representation is used adaptive image histogram enhancement. For this, the gray-level k for every pixel in the already defined histogram segments A, B and C is transformed in accordance with an individual table, as follows:

$$g(k) = \begin{cases} g_A(k) & if \quad 0 \leq k < k_1; \\ g_B(k) & if \quad k_1 \leq k \leq k_2; \\ g_C(k) & if \quad k_2 < k \leq k_{max}. \end{cases}$$

Here $g_A(k)$, $g_B(k)$ and $g_C(k)$ are the corresponding tables for brightness transformation in the segments *A*, *B* and *C*. In order to improve the image quality of the low-contrast image areas the thresholds k_1, k_2 of the segment *B* are widened (stretched) up to $(k_1-\delta_1)\geq 0$ and $(k_2+\delta_2)\leq 255$ shrinking the segments *A* and *C*. In this case δ_1 and δ_2 are parameters, which define the contrast enhancement for the segment *B* and correspondingly – the change of the contrast range for segments *A* and *C*. Each table for brightness transformation is defined in accordance with the condition for histogram equalization for the corresponding image segment *A*, *B* or *C* with changed (stretched or skewed) dynamic range:

$$g_A(k)=(k_1-\delta_1)\sum_{l=0}^{k}h_A(l),$$

$$g_B(k)=(k_2-k_1+\delta_1+\delta_2)\sum_{l=k_1-\delta_1}^{k}h_B(l)+(k_1-\delta_1),$$

$$g_C(k)=(k_{\max}-k_2-\delta_2)\sum_{l=k_2+\delta_2}^{k}h_C(l)+(k_2+\delta_2).$$

In particular, in case that the histogram of the corresponding segment is constant, i.e. for:

$$h_A(k)=\frac{1}{k_1}\quad for\quad k=0,1,..,k_1-1;$$

$$h_B(k)=\frac{1}{k_2-k_1}\quad for\quad k=k_1,k_1+1,..,k_2;$$

$$h_C(k)=\frac{1}{k_{\max}-k_2}\quad for\ k=k_2+1,k_2+2,..,k_{max},$$

the table for the brightness transform for each segment is linear and the relations are defined as:

$$g_A(k)=\left(\frac{k_1-\delta_1}{k_1}\right)k\,;$$

$$g_B(k)=\left(\frac{k_1-k_2-\delta_1-\delta_2}{k_1-k_2}\right)k+\left(\frac{\delta_2k_1+\delta_1k_2}{k_1-k_2}\right);$$

$$g_C(k)=\left(\frac{k_{\max}-k_2-\delta_2}{k_{\max}-k_2}\right)k+\left(\frac{\delta_2k_{\max}}{k_{\max}-k_2}\right).$$

In this case the brightness levels in the range (k_1, k_2) are stretched in accordance with a linear relation and corresponding inverse operations are performed for the two remaining histogram segments (0, k_1-1) and (k_2+1, k_{max}).

III. EXPERIMENTAL RESULTS

For the experiments were used more than 300 test images (ultrasound, X-ray and MRI) of various sizes (bmp, 24 bpp). The presented method was implemented in software (*Visual C*, *Windows* environment). The processed images were archived in a specially developed format (*tk*). For the experiments were used the image database of the Technical University of Sofia and some free medical databases accessible via Internet.

On Fig. 3 is shown the test image "Axial 2" obtained after histogram modification, and on Fig. 4 – the corresponding histogram. In spite of the histogram change (Figs. 2 and 4), the visual image quality is retained. The compression ratio obtained for the processed image after lossless compression is much higher than that for JPEG2000LS (for JPEG, which is the basis of the DICOM standard, the compression efficiency of the new approach, is better also).

Fig. 3. Test ultrasound image "Axial 2" obtained in result of the histogram modification (PSNR= 42dB)

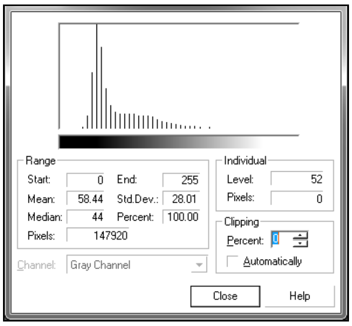

Fig. 4. The modified histogram of the test ultrasound image

The compression efficiency was compared with that of JPEG2000 LS. Some of the results obtained are shown in Table 1 and their graphic representation - on Fig. 5.

Image		Size [pixels]	$PSNR_{MH}$ [dB]	CR_{MH}	CR_{JP2K}	Size [KB]
1	Axial2	350×432	43,5	13,04	5,7	34,1
2	Axial8	344×430	42,20	12,08	5,6	36,7
3	Thorax	280×301	44,78	10,8	6,8	23,3
4	1-vh	359×283	40,44	14,1	8,81	21,57
5	1. 135	512 ×512	39,02	15,5	5,85	50,8
6	1.136	512 ×512	39,44	10,6	5,26	74
7	1.138	512 ×512	39,33	13,3	5,27	59,0
8	1.139	512×512	39,62	22,83	8,49	34,4
9	1.198	512×512	39,26	18,04	7,15	43,5
10	1.826	512 ×512	39,86	11,95	4,90	65,8

On Fig. 6 is shown the image obtained after decoding and contrast enhancement and on Fig. 7 is shown the corresponding histogram. The image histogram is widened with about 10% of the part of the histogram, corresponding to the original image. Further stretching of the histogram could produce visible distortions. The visual quality of the restored image (Fig. 6) is much better than that of the original (Fig. 3).

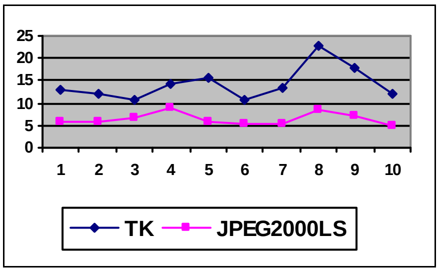

Fig. 5. Graphic representation of the results obtained after lossless compression with JPEG 2000 and the new approach (TK)

Fig. 6. Test ultrasound image (Fig. 3) obtained after decoding and contrast enhancement

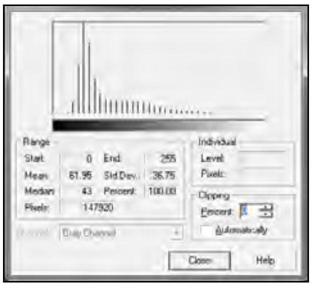

Fig. 7. The histogram of the test image after contrast enhancement

For comparison, same test image was processed with Corel Photo Paint (Contrast Enhancement). It is easy to notice that the image on Fig. 8 has visible distortions, while the images with contrast enhancement in accordance with the method, presented above, have no such changes.

IV. Conclusion

In the paper is presented one new method for preprocessing of medical images aimed at their efficient archiving with retained visual quality.

The method was implemented in software (Visual C. Windows environment). A special format was developed for the coded images, which will permit the creation of efficient contemporary medical image databases. Significant number of tests was performed with various kinds of medical images, with different statistical properties. The software implementation of the method confirmed its efficiency in all cases.

The method efficiency was compared with that of JPEG2000. Some experimental results are presented in the paper.

The visual quality of the restored images is improved after their decoding using the special method for adaptive histogram enhancement, whose basic algorithm is presented in the paper. In result, the visual quality of the images was improved.

Fig. 8. The test ultrasound image “Axial2” obtained after contrast enhancement with Corel Photo Paint

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