

Comparison of Image Enhancement Methods for the Effective Diagnosis in Successive Whole-Body Bone Scans

Chang Bu Jeong,¹ Kwang Gi Kim,¹ Tae Sung Kim,² and Seok Ki Kim²

Whole-body bone scan is one of the most frequent diagnostic procedures in nuclear medicine. Especially, it plays a significant role in important procedures such as the diagnosis of osseous metastasis and evaluation of osseous tumor response to chemotherapy and radiation therapy. It can also be used to monitor the possibility of any recurrence of the tumor. However, it is a very time-consuming effort for radiologists to quantify subtle interval changes between successive whole-body bone scans because of many variations such as intensity, geometry, and morphology. In this paper, we present the most effective method of image enhancement based on histograms, which may assist radiologists in interpreting successive whole-body bone scans effectively. Forty-eight successive whole-body bone scans from 10 patients were obtained and evaluated using six methods of image enhancement based on histograms: histogram equalization, brightness-preserving bi-histogram equalization, contrast-limited adaptive histogram equalization, end-in search, histogram matching, and exact histogram matching (EHM). Comparison of the results of the different methods was made using three similarity measures peak signal-to-noise ratio, histogram intersection, and structural similarity. Image enhancement of successive bone scans using EHM showed the best results out of the six methods measured for all similarity measures. EHM is the best method of image enhancement based on histograms for diagnosing successive whole-body bone scans. The method for successive whole-body bone scans has the potential to greatly assist radiologists quantify interval changes more accurately and quickly by compensating for the variable nature of intensity information. Consequently, it can improve radiologists' diagnostic accuracy as well as reduce reading time for detecting interval changes.

KEY WORDS: Successive whole-body bone scans, Image enhancement, Exact histogram matching, Similarity measure

INTRODUCTION

Whole-body bone scan or bone scintigraphy is one of the most diagnostic procedures in nuclear medicine. It plays a significant role in important procedures such as the diagnosis of

osseous metastasis and evaluation of osseous tumor response to chemotherapy and radiation therapy. It can also be used to monitor the possibility of any recurrence of the tumor. Most patients with bone metastases regularly receive a whole-body bone scan within 6 months to 1 year, in order to identify the extent of the increase or decrease in bone abnormalities by detecting and/or quantifying any changes in successive bone scans. Therefore, it can assist in a more accurate diagnosis of the development of a new bone abnormality or any changes to the existing abnormality.

However, a major drawback to the diagnosis of successive bone scans is that they display variations in intensity and/or morphology, due to the difficulty of maintaining the same exact conditions of the patient and/or the gamma camera throughout the entire series of scanning sessions. This variation in intensity is caused by changes in the accumulation of radioisotopes during each examination, the image quality of the gamma camera, and the volume of water intake or the response to drug treatment of each patient. The variation in morphology is caused by changes in the image

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resolution of the gamma camera and the imaging pose of the patient. Since image intensity is of paramount importance in the diagnosis of successive bone scans, image enhancement must be used to acquire acceptable consistency in intensity.¹⁻³

Most previous studies regarding whole-body bone scans aimed to detect abnormalities in single bone scans, using conceived methods to segment a image into bone and soft tissue such as fuzzy sets,^{4,5} neural network,⁶ and support vector machine.⁷ However, as these are not appropriate for successive whole-body bone scans, recent studies have analyzed the detection of interval changes in successive whole-body bone scans using temporal subtraction images, which were obtained using a nonlinear image-warping technique, and the use of histogram normalization for consistency of intensity in those studies could not guarantee effective detection of interval changes for the images with large variations in intensity.

Histogram processing is one of the most important digital image processing techniques, and it is widely used for increasing medical image's quality. Because of the simplicity and better efficiency of the histogram-based algorithms, these algorithms are widely used for contrast enhancement of images. Histogram equalization (HE) is a very popular technique for image enhancement based on histogram due to its simplicity and comparatively better performance on almost all types of images. HE performs its operation by remapping the gray levels of the image based on the probability distribution of the input gray levels. It flattens and stretches the dynamic range of the image's histogram, resulting in overall contrast enhancement.⁸

However, since HE results in a significant change of the mean brightness of the image, it may distort the original image outlook, especially for low-contrast images. It may also result in over-enhancement and saturation artifacts due to the stretching of the gray levels over the entire gray level range. Many techniques have been proposed to deal with these problems. Brightness-preserving bi-histogram equalization (BBHE) has been proposed to overcome the first problem. It divides the histogram into two sub-histograms and then performs a HE operation on each sub-histogram independently. Adaptive histogram equalization (AHE), which is one of basic local histogram equalizations, has been proposed to adapt with the local contrast features of the input image. It divides

the original image into several non-overlapped sub-blocks and then performs a HE operation on individual sub-blocks.⁹

In this study, we propose a method of image enhancement based on histograms to assist radiologists in interpreting successive whole-body bone scans effectively. Our aim is to make the intensities of the bone scan images consistent for effective comparison and/or analysis, while ensuring that any visual evidence of abnormality remains untouched. We have used six histogram-based methods for image enhancement and identified the most effective method to improve radiologists' diagnostic accuracy in detecting interval changes and reducing reading time by using three methods of measuring intensity similarity.

MATERIALS AND METHODS

In this section, we will discuss the performed whole-body bone scan images, the histogram-based methods of image enhancement, and the methods of measuring the similarity between the images.

Whole-Body Bone Scans

Whole-body bone scan image was acquired using a gamma camera (GE, Infinia Hawkeye) about 3 h after intravenous injection of a radiopharmaceutical agent (Tc-99m MDP). The scan speed was 10/min without zooming. The whole-body field was used to record anterior and posterior views digitally with resolution $256 \times 1,024$ pixels pixel spacing 2.209×2.209 . Images represent counts of detected gamma decays in each spatial unit with 16-bit grayscale depth. We obtained 48 pairs of successive bone scans from 10 patients, in which each scan included both anterior and posterior views obtained simultaneously by use of a set of two gamma cameras placed face to face. That is, the average number of successive bone scans per patient was 4.8.

Images (a) and (b) from Figure 1 are images of bone scans conducted with an interval of 6 months. The objects (patients) within images are different sizes, positions, and brightness due to variations in the settings of the gamma camera, so the object in concern (the skeleton) was cropped and the image was normalized. Images (c) and (d) are the inverted images of (a) and (b), individually. Bone

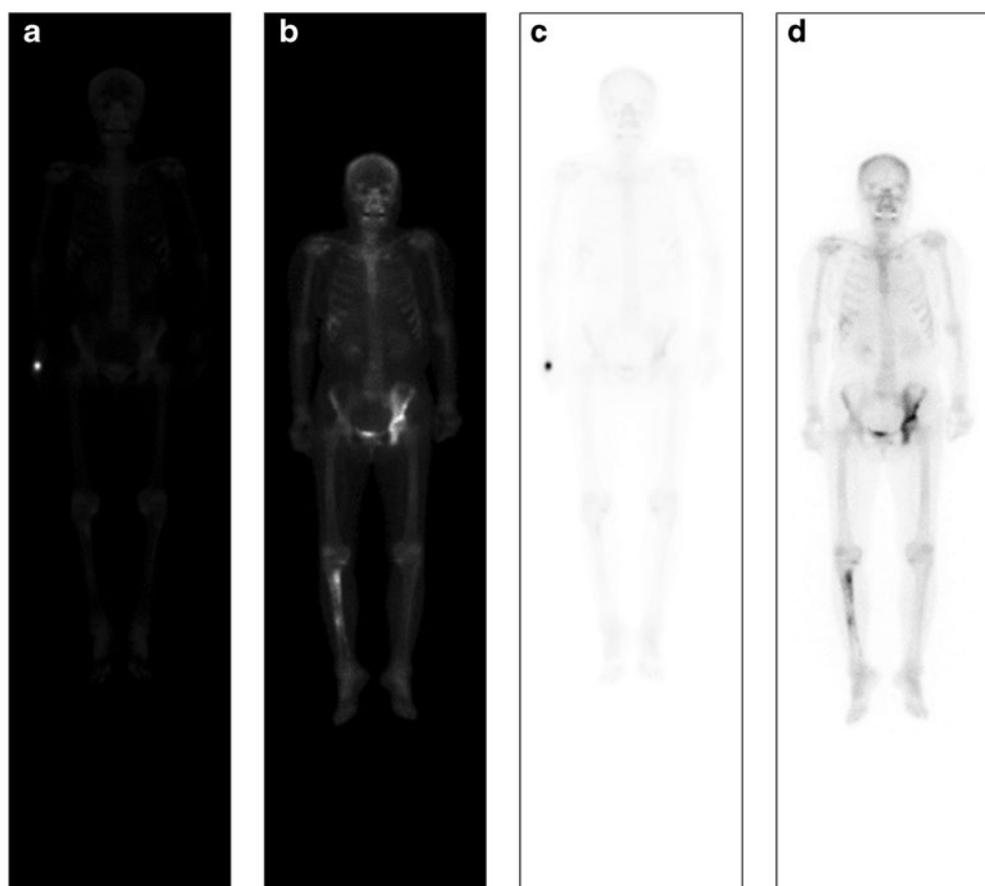


Fig 1. Sample images of whole-body bone scans: a previous image, b current image (after 6 months), c inverted previous image, and d inverted current image.

scan images used in this investigation are (a) or (b), which were inverted like (c) or (d) for effective analysis and comparison.

Image Enhancement Based on Histogram

The main representative histogram-based methods of image enhancement are HE, histogram stretching (HS), and histogram matching (HM). HE makes the histogram as uniform as possible, effectively increasing the contrast within an image. In order to minimize the artifacts that may be caused, other procedures such as BBHE and contrast-limited adaptive HE (CLAHE) have been proposed. HS, on the other hand, enhances image contrast by stretching a histogram of an input image within a range of a preset maximum expansion level and a preset minimum expansion level; ends-in search (EIS) is a more complex version of HS. The other main method, HM,

modifies the histogram of a set of data to match a given desired histogram, and exact histogram matching (EHM) has been proposed as a more precise matching method of the histograms.

In this section, we describe the algorithms of HE, BBHE, CLAHE, EIHS, HM, and EHM in greater detail and the three similarity measures used to determine the best method for the diagnosis in successive bone scans.

Histogram Equalization

HE usually increases the global contrast of the image by assigning the intensity values of pixels in the input image so that the output image contains a uniform distribution of intensity. HE computes the normalized cumulative distribution from the intensity distribution of the image and uses it as a transformation function. We can see that after applying HE to Figure 2a, the distribution is spread

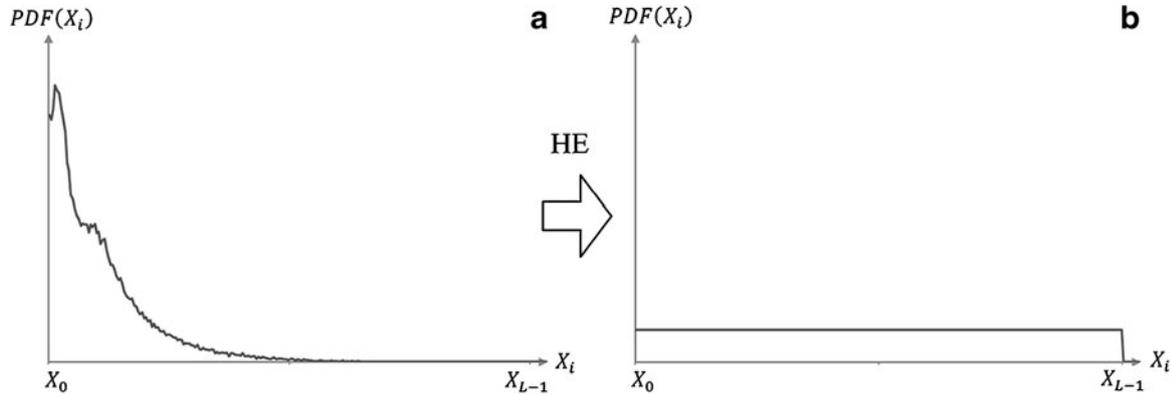


Fig 2. Histograms a before and b after histogram equalization.

out uniformly as seen in Figure 2b, where $PDF(X_i)$ denotes the probability density of the gray level, and $X_i \in \{X_0, X_1, \dots, X_{L-1}\}$ and L denote the total number of discrete gray levels of the image.

The distribution of intensity can be expressed with the use of the probability density function (PDF) and the cumulative density function (CDF). For a given image X , the PDF is defined as shown in Eq. 1.

$$PDF(X_k) = \frac{n_k}{N}, k = 0, 1, \dots, L - 1 \quad (1)$$

For $k = 0, 1, \dots, L - 1$, n_k represents the number of times that the gray level X_k appears in the input image X , and N is the total number of gray levels in the image. Note that $PDF(X_k)$ is associated with the histogram of the input image, which represents the number of pixels that have a specific intensity X_k . Let us also define the CDF corresponding to PDF as Eq. 2, which is also the image's accumulated normalized histogram.

$$CDF(k) = \sum_{i=0}^k PDF(X_i), \text{ for } 0 \leq k \leq L - 1 \quad (2)$$

HE uses CDF as a transform function and attempts to spread out over the entire range $[X_0, X_{L-1}]$ and make the distribution of intensity uniform. In order to reassign the intensity values of pixels in the input image, a mapping function $f(x)$, which is defined based on the CDF, needs to be applied to the result as shown in Eq. 3.

$$f(x) = X_0 + (X_{L-1} - X_0) \times CDF(x) \quad (3)$$

Brightness-Preserving Bi-Histogram Equalization

BBHE divides the histogram into two parts as shown in Figure 3, and the two histograms are then equalized independently to get the brightness preserved enhanced image. Hence, BBHE can overcome the problem of excessive change in brightness that may result from over-enhancement with HE.⁹ With this method, the separation intensity X_m is presented by the mean or median brightness value of all pixels that construct the input image.

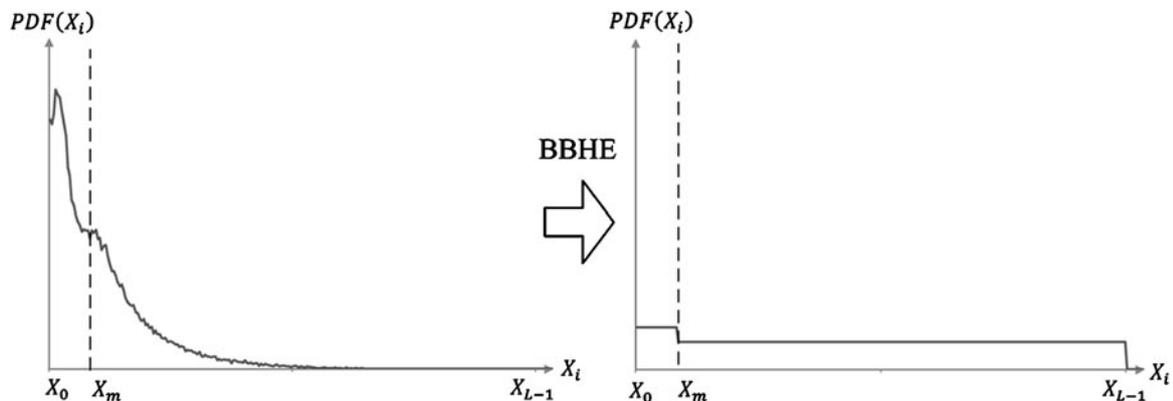


Fig 3. Histograms before and after BBHE.

Denote by X_m the median brightness value of the image X and assume that $X_i \in \{X_0, X_1, \dots, X_{L-1}\}$, and the histogram is then divided into two sub-histograms $\text{Reg}_{\text{lower}}$ and $\text{Reg}_{\text{upper}}$ based on X_m . Note that the sub-histogram $\text{Reg}_{\text{lower}}$ is composed of $\{X_0, X_1, \dots, X_m\}$, and the other histogram $\text{Reg}_{\text{upper}}$ is composed of $\{X_{m+1}, X_{m+2}, \dots, X_{L-1}\}$.

Next, define the respective PDF of the sub-histograms $\text{Reg}_{\text{lower}}$ and $\text{Reg}_{\text{upper}}$ as shown in Eqs. 4 and 5, in which n_i and n_j are the respective frequencies of grey level X_i and X_j , and N_{lower} and N_{upper} are the total number of samples in $\text{Reg}_{\text{lower}}$ and $\text{Reg}_{\text{upper}}$, respectively.

$$\text{PDF}_{\text{lower}}(X_i) = \frac{n_i}{N_{\text{lower}}}, (0 \leq i \leq m) \quad (4)$$

$$\text{PDF}_{\text{upper}}(X_j) = \frac{n_j}{N_{\text{upper}}}, (m+1 \leq j \leq L-1) \quad (5)$$

The respective CDF for $\text{Reg}_{\text{lower}}$ and $\text{Reg}_{\text{upper}}$ are then defined as shown in Eqs. 6 and 7. Similar to the case of HE where a CDF is used as a transform function, $f_{\text{lower}}(x)$ and $f_{\text{upper}}(x)$ are the respective mapping functions for and as shown in Eqs. 8 and 9. Based on these mapping functions, the divided histograms are equalized independently.

$$\text{CDF}_{\text{lower}}(x) = \sum_{i=0}^x \text{PDF}_{\text{lower}}(X_i) (0 \leq x \leq m) \quad (6)$$

$$\text{CDF}_{\text{upper}}(x) = \sum_{i=m+1}^x \text{PDF}_{\text{upper}}(X_i) (m+1 \leq x \leq L-1) \quad (7)$$

$$f_{\text{lower}}(x) = X_0 + (X_m - X_0) \times \text{CDF}_{\text{lower}}(x) \quad (8)$$

$$f_{\text{upper}}(x) = X_{m+1} + (X_{L-1} - X_{m+1}) \times \text{CDF}_{\text{upper}}(x) \quad (9)$$

Contrast-Limited Adaptive Histogram Enhancement

CLAHE was originally developed for medical imaging and has proven to be successful for enhancement of low-contrast images such as portal films. CLAHE is an improved version of AHE, and both overcome the limitations of standard HE. AHE performs local HE on the small tiles of an image and combines the neighboring tiles using bilinear interpolation, which will eliminate the artificially induced boundaries, while CLAHE includes the use of a clip limit to the AHE method. CLAHE with a clip limit can avoid over-saturation of the image specifically in homogeneous areas that present high peaks in the histogram of certain image tiles due to many pixels falling inside the same gray level range.¹⁰

A clip limit is used to limit the maximum slope in the transform function. As shown in Figure 4, it limits the maximum number of samples per bin in each tile, and the clipped samples are then redistributed uniformly because the CDF must be normalized to $[0,1]$. After that, CLAHE performs the procedure of the AHE with the reconstructed histograms.

Histogram Stretching and Ends-in-Search

HS is a simple image enhancement technique that attempts to improve the contrast in an image by stretching the range of intensity values it contains to span a desired range of values. In order to spread the histogram range $[X_{\min}, X_{\max}]$

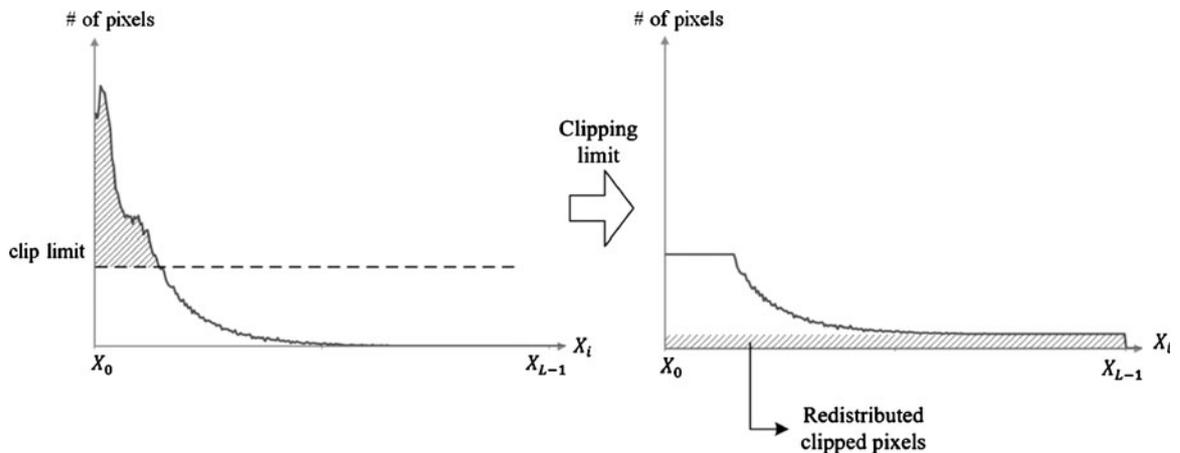


Fig 4. Clipping the original histogram to a limit.

out over the entire range $[X_0, X_{L-1}]$, application of a transformation function is utilized to map the i th pixel brightness value X_i to x'_i as shown in Eq. 10. Therefore, it works best when the histogram of an image has low contrast.⁸

$$X'_i = \frac{X'_i - X_{\min}}{X_{\max} - X_{\min}} \times X_{L-1} \quad (10)$$

EIS is another contrast-stretching technique that allows a minimum number of pixels to count as the lightest or darkest area. EIS is used to improve the drawback of HS in that a single outlying pixel with either a very high or very low value can severely affect the value of X_{\min} or X_{\max} , which can lead to very unrepresentative scaling.

In Eq. 11, these upper and lower thresholds of intensity indexes, low and high, are calculated from the image histogram by excluding certain percentage of pixels, T_{lower} and T_{upper} , from either the upper or lower end of the histogram, respectively. That is, the percentage T_{lower} of the pixels in the histogram will have values lower than the intensity X_{low} , and the percentage T_{upper} of the pixels will have values higher than the intensity X_{high} .

$$X'_i \begin{cases} 0 & \text{for } \sum_{i=0}^{\text{low}} \text{PDF}(X_i) < T_{\text{lower}}, \\ \frac{X_i - X_{\text{low}}}{X_{\text{high}} - X_{\text{low}}} \times (L-1) & \text{for otherwise,} \\ L-1 & \text{for } \sum_{i=0}^{\text{low}} \text{PDF}(X_i) < T_{\text{lower}}. \end{cases} \quad (11)$$

Histogram Matching or Histogram Specification

HM improves the contrast of the original image by specifying the histogram of the desired image, which transforms one histogram into another by remapping the pixel values to control the relative frequency of their occurrence.

Let the gray levels x and z be continuous random variables with corresponding continuous PDFs denoted by $p_x(x)$ and $p_z(z)$. In this notation, x and z denote the gray levels of the reference and output (processed) images, respectively. We can estimate $p_x(x)$ from the given input image, while $p_z(z)$ is the specified PDF that we hope the output image to have. Let s be a random variable with the property given in Eq. 12 where T is essentially the cumulative operator.

Suppose next that we define a random variable z with the property given in Eq. 13. It then follows from these two equations that $g(z)=f(x)$, therefore, that z must satisfy the condition given in Eq. 14. That is the theoretical case. In application, we would like to map each given input gray level x to

an output one, z , so that the difference between the corresponding values of the input and output CDFs is minimized as shown in Eq. 15.

$$s = f(x) = \int_0^x p_x(u) d(u) \quad (12)$$

$$g(z) = \int_0^z p_z(u) d(u) = s \quad (13)$$

$$z = g^{-1}(s) = g^{-1}(f(x)) = h(x) \quad (14)$$

$$z(x) = \arg \min_z |f(x) - g(z)|, \quad \forall x \in S \quad (15)$$

As in the discrete case, the CDFs of continuous random variables must be changed to those of discrete random variables as shown in Eqs. 16 and 17. In application, HM creates a histogram matched image by using the look-up table modified to reassign each given input gray level x to an output one, z .

$$\text{CDF}_x(l) = \sum_{i=0}^l \text{PDF}_x(i), \quad \text{CDF}_z(k) = \sum_{i=0}^k \text{PDF}_z(i) \quad (16)$$

$$z(k) = \arg \min_k |\text{CDF}_x(l) - \text{CDF}_z(k)|, \quad \forall l \in X \quad (17)$$

Exact Histogram Matching

While the previously stated HM are supposed to provide exact results in the continuous case, it is difficult to exactly implement the HM in the discrete case. Since the number of pixels in an image is usually much larger than the number of intensity levels and there are many pixels with the same intensity level, they could not be assigned different intensity levels to match the histogram of the resulted image to the matched histogram because the latter CDF is not exactly invertible. In Figure 5, an original histogram was transformed to a desired histogram using HM, but the stair-step effect was caused by the aforementioned reasons in the transformed histogram. To improve the HM's problem, EHM divides each set of pixels of the original image with the same intensity into two or more subsets, each to be assigned a different new intensity.¹¹

The EHM proposed¹¹ used the new ordering obtained by the vector operator $\Phi = \{\phi_1, \phi_2, \phi_3, \phi_4, \phi_5, \phi_6, \phi_1\}$ instead of the usual ordering obtained by the intensity of each pixel. The vector operator is computed to include the average intensities of pixels over those neighborhoods by using the kernels below, and is defined as $\phi_1 \prec \phi_2 \prec \phi_3 \prec \phi_4 \prec \phi_5 \prec \phi_6$. In Figure 6, it is

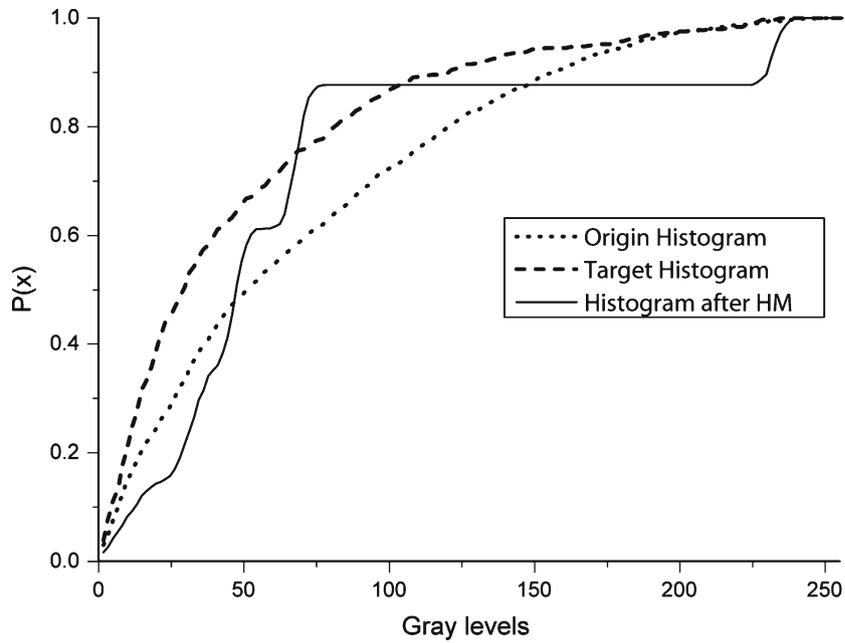


Fig 5. The result of histogram matching.

shown that the transformed histogram using EHM almost matched the desired histogram.

Similarity Measures

The similarity measure is usually derived using relevant features regarding brightness, textures, shapes, or any other information that can be derived from the image itself. A common measure is the brightness-based similarity measure, and the existing representative one is the peak signal-to-noise ratio (PSNR). PSNR is most commonly used

as a

$$\phi_1 = [1]$$

$$\phi_2 = \frac{1}{5} \begin{bmatrix} 0 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$

$$\phi_3 = \frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

$$\phi_4 = \frac{1}{13} \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

$$\phi_5 = \frac{1}{21} \begin{bmatrix} 0 & 1 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 1 & 0 \end{bmatrix}$$

$$\phi_6 = \frac{1}{25} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{bmatrix}$$

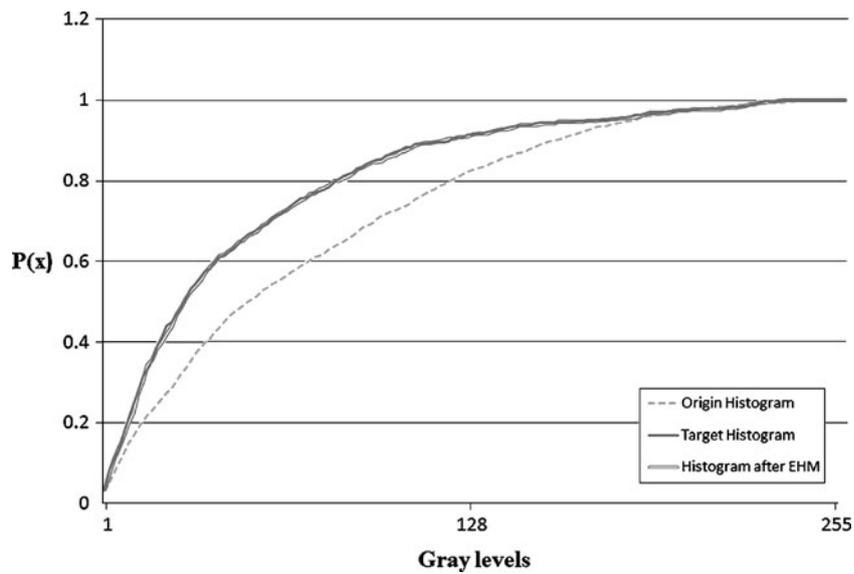


Fig 6. The result of exact histogram matching.

measure of the quality of reconstruction of lossy compression codecs (e.g., for image compression). While in the case of image compression, the signal and noise are the original data and the error introduced by compression, respectively, and in the case of the similarity measure, they are the reference image and the enhanced image, respectively.

Denoting a reference image by $R(i,j)$ and an enhanced image by $E(i,j)$, we first define the mean square error (MSE) between the two images as Eq. 18, which is the average of the square of the pixel differences of them. PSNR is defined via the MSE as Eq. 19, where MAX_i is the maximum possible pixel value of the image.

$$\text{MSE} = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} (R(i,j) - E(i,j))^2 \quad (18)$$

$$\text{PSNR} = 10 \times \log_{10} \left(\frac{\text{MAX}_i^2}{\text{MSE}} \right) \quad (19)$$

A histogram is a useful feature for analyzing the overall image brightness, and the histogram intersection (HI) is a general method based on histogram analysis to measure the similarity of images. The conventional HI algorithm computes the intersected section of the corresponding brightness

histograms in order to measure the matching rate between two histograms.¹² Denoting the histogram functions of the images R and E by $H_R(k)$ and $H_E(k)$ respectively, the similarity between two images is defined as $\text{SIM}_{\text{HIM}}(R, E)$ from Eq. 20.

$$\text{SIM}_{\text{HI}}(R, E) = \frac{2 \times \sum_{i=0}^N \min(H_R(i), H_E(i))}{\sum_{i=0}^N H_R(i) + \sum_{i=0}^N H_E(i)} \quad (20)$$

Although PSNR and HIM have an advantage in simple computation and have physical meaning, these do not keep coherence with the human visual system (HVS) in many cases. We assume that the HVS is not built for detecting absolute, exact intensities but adapted for extracting structural information (relative spatial covariance) from images. The structural similarity (SSIM) index has been proposed¹³, which successfully incorporates HVS characteristics without much added complexity.

Given two images R and E to be compared, three similarity functions are firstly computed as Eq. 21: Luminance similarity is estimated as the mean μ of each image, contrast similarity is estimated as the standard deviation σ , and structure similarity is estimated as the covariance σ_{RE} , by normalizing by the standard deviation. Then, the

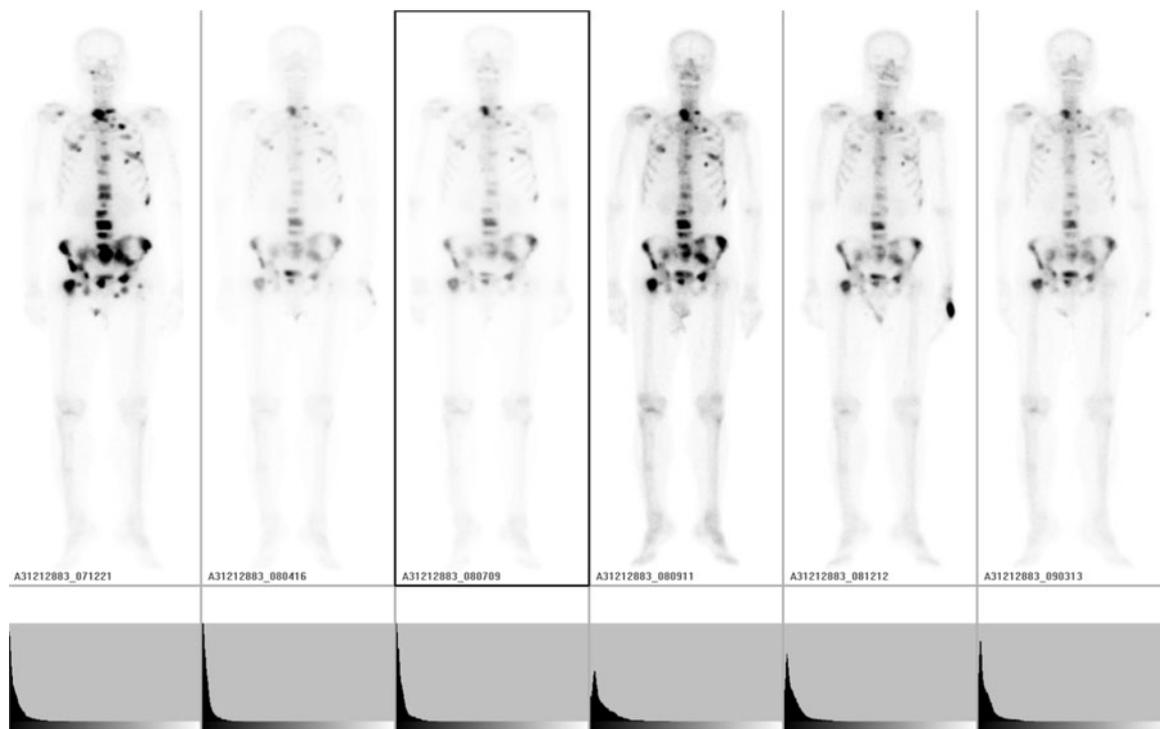


Fig 7. Sample images of successive whole-body bone scans of a patient.

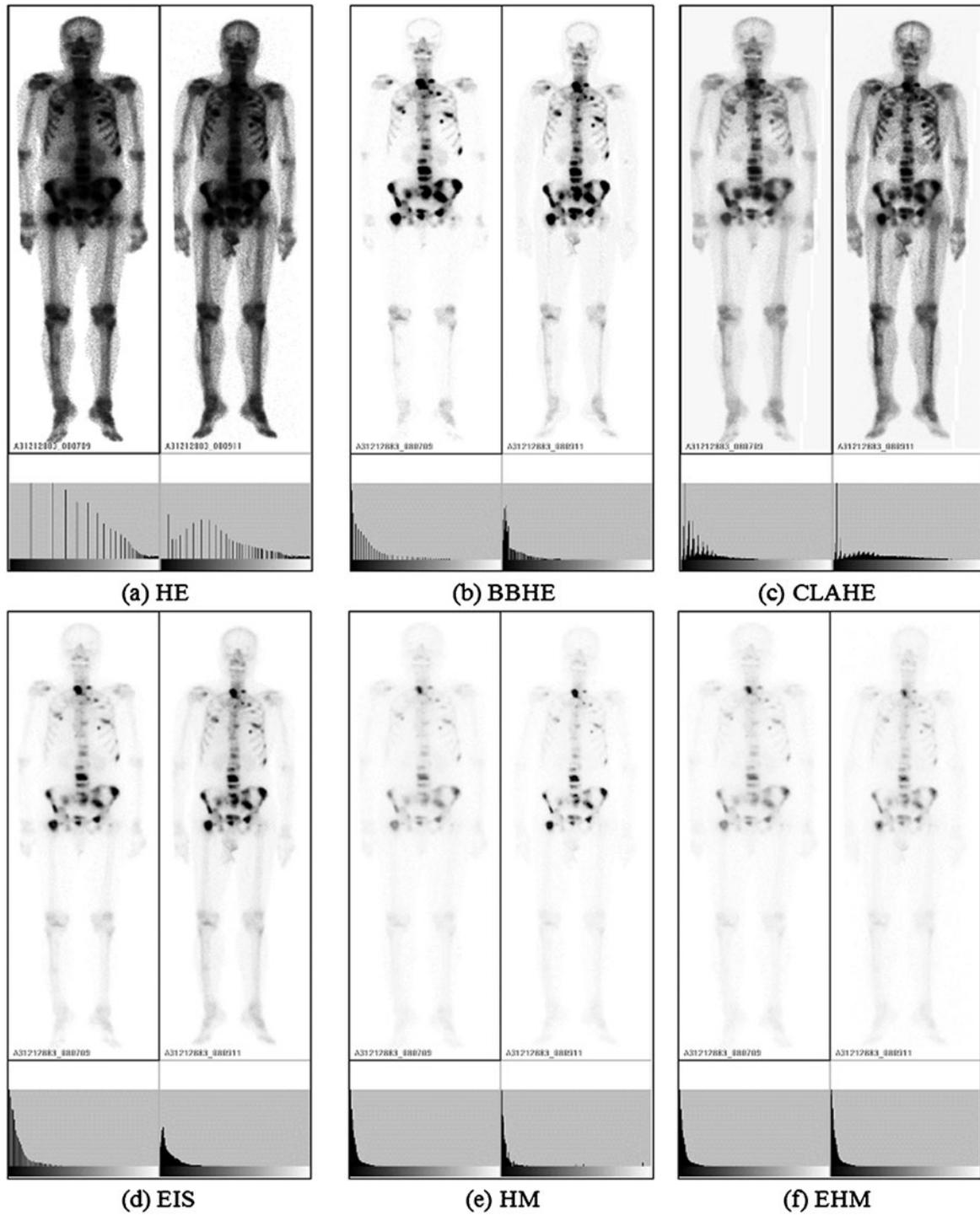


Fig 8. Results of HE, BBHE, CLAHE, EIS, HM, and EHM.

SSIM index is computed by a product of these three similarities as Eq. 22.

$$l(R, E) = \frac{2\mu_R\mu_E}{\mu_R^2 + \mu_E^2}, c(R, E) = \frac{2\sigma_R\sigma_E}{\sigma_R^2 + \sigma_E^2}, s(R, E) = \frac{2\sigma_{RE}}{\sigma_R\sigma_E} \tag{21}$$

$$SSIM(R, E) = l(R, E) \cdot c(R, E) \cdot s(R, E) = \frac{4\mu_R\mu_E\sigma_{RE}}{(\mu_R^2 + \mu_E^2)(\sigma_R^2 + \sigma_E^2)} \tag{22}$$

RESULTS AND DISCUSSIONS

In this section, we present our experimental results obtained from the histogram-based methods of image enhancement and determine the most effective method after testing them using three different measures of similarity. The bone scan images in Figure 7 are those of the same patient, taken over a certain period of time. As mentioned in the “Introduction”, although they are images of the same individual, the inconsistency of the intensity is clearly visible. The graphs below represent the probability density function of the original images before inverting.

Figure 8 shows the results of image enhancements, which are the six methods illustrated in the previous session, on the third and fourth images of Figure 7. Methods in (a) to (c) focus on evening out the distribution of intensity throughout the images, so it may lead to pixel values of the hot spots being too similar to other parts or being driven up excessively high, not preserving the information of the abnormalities in the original image. On the other hand, methods in (d) to (f) make the pixel values consistent by appropriately

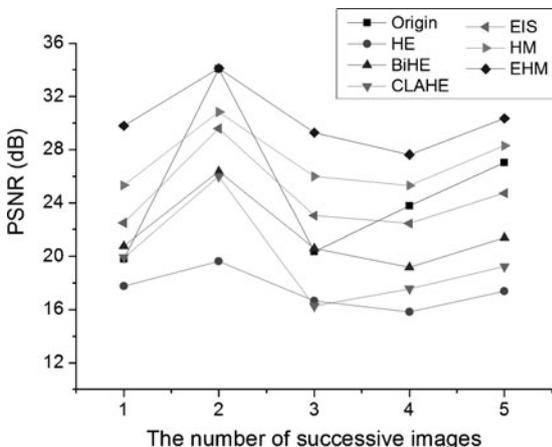


Fig 9. Comparison of similarities PSNR.

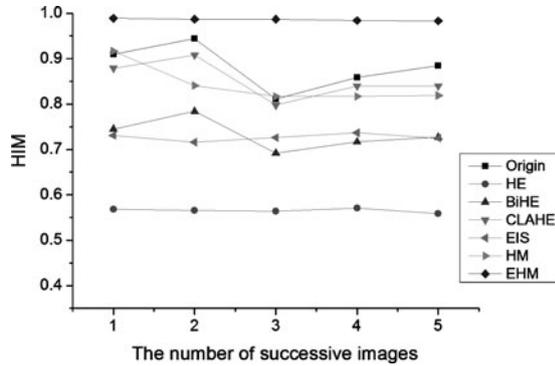


Fig 10. Comparison of similarities HIM.

modifying the histograms, and allows for an easier comparison and analysis of the two images.

The graphs show the comparison of similarities (as measured with PSNR, HIM, and SSIM) in Figures 9, 10, and 11. The six images in Figure 7 underwent image enhancement, and then the similarity measures were calculated by comparing the images with reference to the third image. A radiologist directly chooses the best reference image among successive bone scans, in which the entire bone region is quite visible, while the soft tissues are almost invisible. By observation, although the grading results for each similarity measure are a little different according to the image, we can see that the similarity value of EHM displays the highest level for all similarity measures. Figure 12 shows that EHM modified the contrast of the images by matching the histogram of the desired image, which was defined as the third image. As shown in Figure 12, we found that EHM can perform image enhancement while maintaining the relative consistency in intensity.

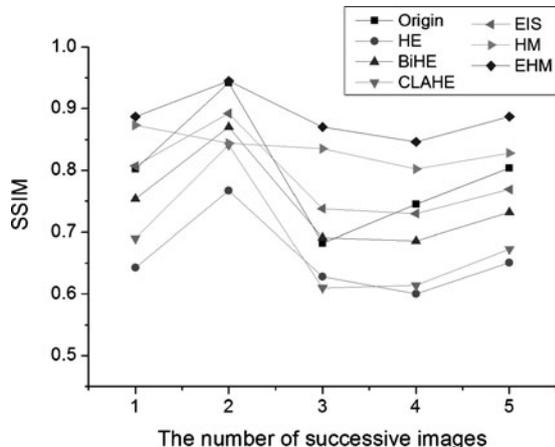


Fig 11. Comparison of similarities SSIM.

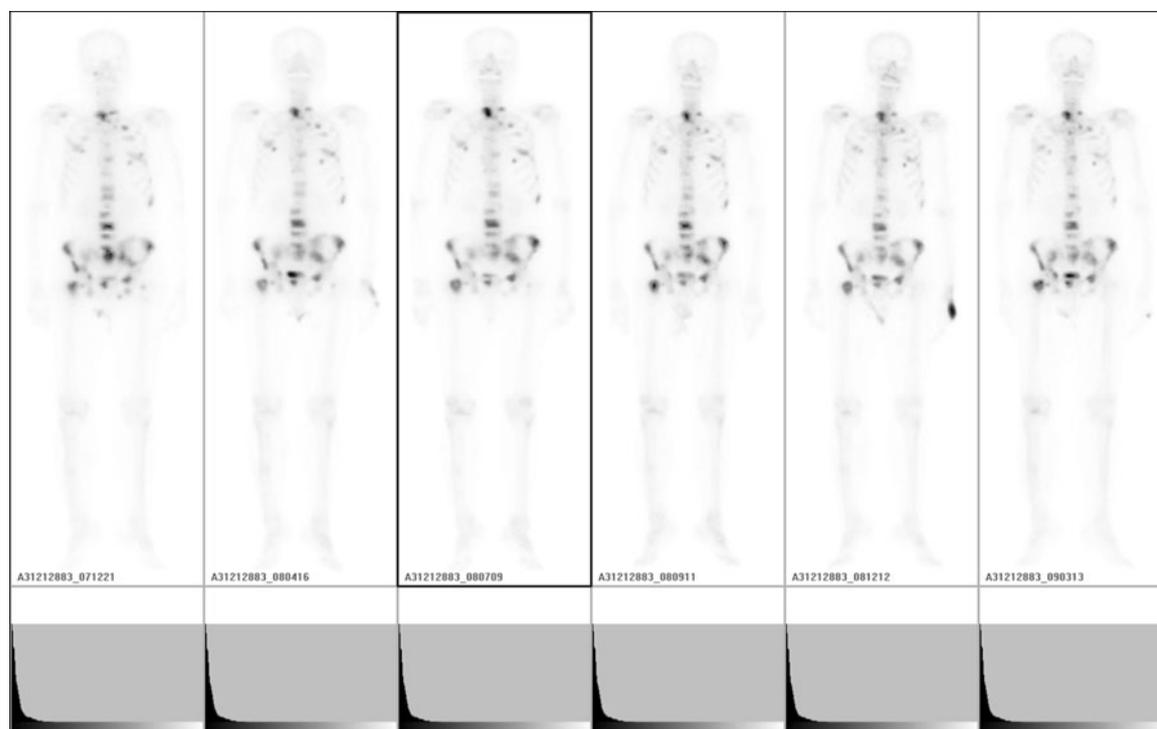


Fig 12. Result of EHM for test images in Figure 7. EHM modified the contrast of the images by matching the histogram of the desired image, which was defined as the third image in Figure 7.

In order to confirm the effectiveness of EHM, we obtained results from the bone scan images of 10 other patients. Table 1 shows the average similarity value of 48 images for each of the six histogram-based image enhancement methods. It is quite evident from the grading that EHM is indeed the most effective method.

CONCLUSIONS

This research compared and determined the most effective histogram-based method of making the pixel values of bone scan images consistent for effective detection of osseous metastasis by a radiologist.

Existing contrast-enhancement methods for medical images are focused on the enhancement of the relative difference in intensity between ROI and background for detection of specific pathologies in an image. However, these are not always effective for detecting interval changes in successive bone scans, since the main aim of them is not to compare the difference between images. Therefore, we have tested various methods of image enhancement on successive bone scans, such as fuzzy-set, multi-scale wavelet decomposition, Fourier transform, Gabor filters, etc. As a result, most methods may lead to over-enhancement or other artifacts such as flickering, contouring, etc., because bone scans are low contrast. Among these, the histogram-based enhancement method showed the better outcomes for comparing successive bone

Table 1. Comparing the Average Values for Three Similarity Measures Obtained from Whole-Body Bone Scans of 10 Patients

Similarity	Methods						
	Origin	HE	BBHE	CLAHE	EIS	HM	EHM
PSNR	25.01	17.45	21.66	19.80	24.46	27.15	30.24
HIM	0.84	0.57	0.73	0.85	0.73	0.88	0.99
SSIM	0.79	0.66	0.75	0.69	0.80	0.83	0.89
Grading	-	6	5	4	3	2	1

scans. Consequently, we have presented image enhancement methods based on histogram for detecting interval changes in successive bone scans.

The main method for image enhancement, histogram equalization, has the effect of transforming the data distributions such that the most frequent values are distributed more uniformly than the least frequent data values. Therefore, the brightness in areas of bone and soft tissue, which are of lower intensity and higher density, improves greatly to the naked eye. However, it is difficult to detect abnormal hot spots because it makes the brightness in areas of normal bone to be similar to the abnormal hot spots. On the other hand, BBHE, CLAHE, and EIS overcome these limitations of standard histogram equalization, though it cannot completely remove false abnormal hot spots.

Histogram matching and EHM perform image enhancement while maintaining the relative consistency in intensity. However, in histogram matching, the stair-step effect in the matched histogram was caused by not exactly matching the hot spot pixels with lower intensity and higher density, and then led to the connection of neighbor pixels of discontinuity. EHM has finally been proven as the best method by using not only the brightness similarity but also the structural similarity, considering HVS, and we propose it as the best image enhancement method for the effective diagnosis of abnormalities and interval changes in successive whole-body bone scans. Nevertheless, one of the major drawbacks of HM and EHM is that these are highly dependent on the selection of reference image. In other words, the results of them can be changed by radiologist selection of reference images. It is difficult to define a consistent model selection criterion for radiologists, since they are not similar in skill, experience, and preference for bone scans. Whereas HE, BBHE, CLAHE, and EIS use the histogram of an image, so these are independent on reference images. Even though these methods are not better than EHM and HM, these methods have the advantage of being able to perform consistent image enhancements.

The five methods except CLAHE method were also negatively affected by an abnormally large hot spot, which cannot be found in different bone scans, since these used global grayscale distributions. Most cases result this way because of a urine

bag, where there is radioactive urine. That is, the urine bags will appear as larger hot spots due to the radioactive urine. Normal urinary bladder can also appear as a hot spot due to much accumulation of radioactivity tracer. Finally, the most common artifact on bone scans is attributed to contamination with radioactive urine. The artifact usually overlies soft tissues but may overlie bony structures. Although it will have no negative effect on the image enhancement, it will be misdiagnosed as a bone lesion.

Despite difficulty in definition reference images and an abnormally large hot spot, the method proposed in this research allows the radiologist to expedite the analyzing process and improve the accuracy of his/her diagnosis. Ultimately, this method should facilitate the detection of osseous metastasis, and we can expect more accurate diagnosis and treatment.

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