Adaptive Crossed Reconstructed (ACR) K-mean Clustering Segmentation for Computer-aided Bone Age Assessment System

Hum Yan Chai, Lai Khin Wee, Tan Tian Swee and Sh-Hussain Salleh

Abstract-- The development of computer-aided design (CAD) system for clinical usage has been given excessive attention in recent years. Nonetheless, many problems still remain unsolved in the CAD field especially the segmentation problem in digital image processing. In order to increase the accuracy and efficiency in Bone age assessment (BAA), CAD system has been developed to assist the doctor and radiologist. The crucial step in the system is the bone segmentation before proceeding to the subsequent analysis and comparison with atlas. Therefore, in this paper, a method proposed to solve the problem based on grey-level co-occurrence matrix (GLCM) and k-means clustering, namely adaptive crossing reconstruction (ACR) k-mean clustering method. The method begins with bands separations into vertical and horizontal direction. Next, the pixels of each section are clustered and performed with GLCM texture analysis. At last, all the sections will be reconstructed based on the texture analysis. The resulting outcome shows that this method could segment the bone from the soft-tissue region and background effectively compared to global clustering method.

Keywords **--** bone age assessment, image processing, textural segmentation, Gray level co-occurrence matrix, skeletal segmentation

I. Introduction

BONE age assessment (BAA) or Bone maturity assessment is an examination of ossification development on mainly the left-hand wrist and deduce the age of the bone by comparing to a standard atlas [5,6].The result from this assessment that indicates a different in the age of the patients and the age of the bone can be used as prediction of adult height [3,4], endocrine disorders [8,9], pediatric syndromes, multitude of growth retardation factors and skeletal dysplasias [5,6]. This assessment has been used excessively globally. Two main methods in the Bone age assessment by hand and wrist are by using the Greulich-Pyle [1] and Tanner-Whitehouse atlas [2, 7].

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The procedure of the assessment relied on the visual inspection of the skeletal development of hand and wrist which involves tedious and subjective process of examination by repetitive comparison with atlas [1, 10].Therefore, numerous of investigations have been conducted to create an accurate computer-aided system to replace the visual evaluation especially from E.Pietka al et [11-17]. The first step in most of the computer-aided bone age assessment is bone segmentation which separates the bone from the background and the soft-tissue region. The separation of the soft tissue region from the bone is not an easy task as some part of the trabecular bone (Cancellous bone) pixel's intensity in this region is similar to the soft tissue region in digital radiographic image and this has greatly reduced the effectiveness of the conventional clustering segmentation method. Furthermore, the variability of images contrast has increased the difficulty of this hand bone segmentation where global thresholding method will fail.

Different methods have been done to remove the background of the radiograph digital image as preprocessing [12, 18, 27-33] .The more challenging part is to remove the soft tissue region, in [19], the soft tissue area is removed by firstly constructing the two dimensional gradient image by using sobel operator, then remove the soft tissue region by an empirically determined threshold value. This method has limitations where the result of the gradient image might not suitable for subsequent segmentation and the threshold value subjective and difficult to be determined for digital radiograph that computed from different devices. G. Manos et al [20] uses the information from the region and edge of the image and segment the hand from background using the predetermined threshold. This method involves processes like region growing, region merging, edge information extraction and threshold setting. The procedure involves many steps that are full of uncertainties and the rule-based setting is subjective. Same problems happen on other methods [21, 22, 23, 24] that contains steps involving the calculation of edge information like active contour where edge energy is computed and objective function is optimized to find the contour of the anatomy.

David J.Michael and Alan C.Nelson [25] have proposed a model-based system in the hand segmentation which involves determining the model parameters that used in modifying the histogram in order to use it in other digital radiographs in the system and in subsequent steps like bone contour detection by thresholding, bone location detection, feature extraction and measurement. The procedure involves multitude steps and is relatively complicated. During the process, assumptions like the pixel's intensities of the image possessing Gaussian distributions and average illuminations in all the images. Thresholds are needed in steps during preprocessing which is considered as a drawback in image segmentation. The texture analysis will implement the Gray Level Co-occurrence Matrix (GLCM) which proposed by Haralick [27], Haralick suggested statistics equations that can be calculated from the co-occurrence matrix and be used in describing the image texture. It is a statistical way to describe image texture structure by statistically sampling the pattern of the grey-levels occurs in relation to other grey levels. There are mostly weighted averages of the normalized co-occurrence matrix contents by multiplying a weighted average multiplier with the intent of expressing the relative significance of the value.

This paper demonstrates digital hand bone radiographs segmentation by designing a gray level co-occurrence (GLCM) based adaptive crossed reconstruction (ACR) k-means method. This method integrates the strength of adaptive thresholding approach, k-means clustering and texture analysis.

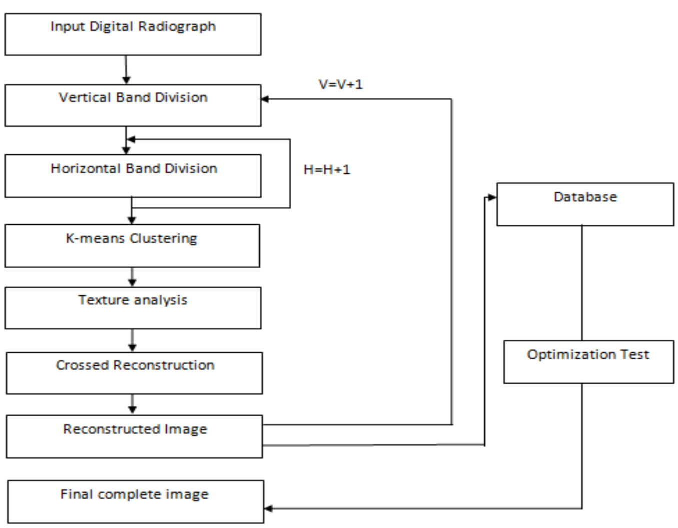

Fig. 1 Flow chart of Texture based Adaptive Crossed Reconstruction (ACR) K-means clustering segmentation
*(*H= number of horizontal band * V=number of Vertical band)*

II. Methodology

This method begins with an image region separation procedure by dividing the input image into a number of horizontal bands; each band of the image is subsequently divided into a number of vertical bands. Each region obtained undergoes k-means clustering to separate the region into maximum three clusters and minimum two clusters. The three clusters represent the bone, soft tissue region and background. Due to the region obtained might include only bone and soft tissue region, the two clusters k means is also computed. At the end only one of them will be chosen to reconstruct the complete result based on the texture analysis using GLCM. Figure 1 is the flow chart for the mentioned method.

A. Input Digital Radiographs

A gray scale 441 x 316 hand radiograph is used as demonstrative purpose.

Fig. 2 Input images

B. Vertical band division

The image is then divided into a number of horizontal bands begins with two horizontal bands for the first iteration. The number of horizontal bands will increase by one in each loop.

Fig.3 Vertical bands division

C. Horizontal band division

Each region is then divided into a number of horizontal bands begins with two vertical bands. The number of vertical bands will increase by one in each loop for every number of horizontal bands.

Fig. 4 Horizontal bands division

D. K-means clustering

A primary section heading is enumerated by a Roman numeral followed by a period and is centered above the text. A primary heading should be in capital letters. With the K-means unsupervised clustering technique [26], the x-ray image will be clustered into two and three groups which represent bone, soft tissue region and bone, soft tissue region and background with ‘k’ value equals to two and three respectively. The implementation of this clustering process is carried out by optimizing an *objective function*, in this case, to minimize a squared error function, as shown in Equation (1).

$$\sum_{j=1}^{K}\sum_{i=1}^{n}||x_i^{(j)}-c_j||^2 \qquad (1)$$

Where n is the number of data, K is the clusters number, $||x_i^{(j)}-c_j||^2$ is the distance measurement between the data point $x_i^{(j)}$ representing the intensity value of image pixels and the cluster center c_j computed from calculating the mean of each group of pixels. it indicates the distance difference from the data point to the cluster centre. First, the histogram of the input image is computed. Two clusters centre will be chosen randomly among the data points followed by constructing the distance difference between each data point and the cluster centre. Subsequently, each data point will be assigned to one of the two clusters centre depends on the distance difference. When all the data points are assigned to cluster centre, the new cluster centre is then recalculated by computing the mean of each cluster group. These steps iterate until the objective function achieve a minimum value.

K-means Algorithms used in this paper:

Input: Data set (image pixels intensity)= $\{x_i\}_1^n$, where n represents the total number of pixels in the image.

Process:

1: (a) Set the clusters number ‘k’, 2≤ $k \leq 3$ where k is an integer.
(b) Initiate the cluster center, $C_j(T)$, $1 < j \leq k$, T=0
(c) Set the tolerant error value ‘∂’

Where T = number of k-means iteration, Initiation value: k=2, T=0, j=1 and i=1

2: Euclidean Distance between intensity value and cluster center value is computed:

$$D_{ji}^{(T)} = \sum_{j=1}^{K}\sum_{i=1}^{n} w_{ji}\left\|x_i^{(j)} - C_j^{(T-1)}\right\| \qquad (2)$$

3: Assign each data point (pixel’s intensity value) to the cluster center:

$$\mathrm{w_{ji}} = \begin{cases} 1, \mathrm{argmin}_{j=1}^{k}\, \mathrm{D_{ij}^{(T)}} \\ 0, \mathrm{Otherwise} \end{cases} \qquad (3)$$

4: Recalculation of the cluster center:

$$C_j^T = \frac{\sum_i^n w_{ji}^T x_i}{\sum_i^n w_{ji}^T} \qquad (4)$$

5: Stopping criteria testing: Iterate until E(T) is less than tolerant error value ‘∂’

$$\mathrm{E\,(T)} = \left\|C_j{}^{T} - C_j{}^{T-1}\right\| \leq \partial \qquad (5)$$

6: Repeats with T←T+1 in step 2 if stopping criteria is not achieved

7: Fill the pixels belong to cluster with lower value of cluster center with zero intensity and remain the pixels intensity that belong to cluster with higher value of cluster center.

$$x_i^{(j)} = \begin{cases} 0, \mathrm{argmin}_{j=1}^{2}\, \mathrm{Cj} \\ x_i\ \ , \mathrm{otherwise} \end{cases} \qquad (6)$$

8: Repeat the process with k=3

9: Fill the pixels belong to clusters with lower value of cluster center with zero intensity and remain the pixels intensity that belongs to cluster with highest value of cluster center.

$$x_i^{(j)} = \begin{cases} x_i\ \ , argmax_{j=1}^{3}\mathrm{Cj} \\ 0, otherwise \\ 0, \mathrm{otherwise} \end{cases} \qquad (7)$$

Output : K-means clustering with k value of two and three will be implemented on each region in Fig.4.

Fig. 5 K-means clustered image with k equals to two

Fig.6 K-means clustered image with k equals to three

E. Texture analysis

Grey Level Co-occurrence Matrix (GLCM) proposed by Haralick [27] suggested a way to describe texture of image by statistical measurement. A GLCM is a matrix that contains the probability of gray scale i occur together with the gray level j at a specific distance, in a specific direction. The distance and direction are named offset at times and different value of offset will give different indication for the texture of image. Gray scale levels used in this paper is divided into four in order to increase the algorithm computing speed:

$$I(x,y)=\begin{cases} 1, if\ 0 \le I(x,y) \le \frac{argmax_x^{column}{}_y^{row} I(x,y)}{4} \\ 2, if\ \frac{argmax_x^{column}{}_y^{row} I(x,y)}{4} \le I(x,y) \le \frac{argmax_x^{column}{}_y^{row} I(x,y)}{2} \\ 3, \frac{argmax_x^{column}{}_y^{row} I(x,y)}{2} \le I(x,y) \le \frac{argmax_x^{column}{}_y^{row} I(x,y)}{\frac{4}{3}} \\ 4, if\ \frac{argmax_x^{column}{}_y^{row} I(x,y)}{\frac{4}{3}} \le I(x,y) \le argmax_x^{column}{}_y^{row} I(x,y) \end{cases}$$

Where I(x,y) represents pixels gray level intensity at coordinate (x,y) where x represent column and y represent row. The second order statistical measure relevant in this paper is shown in (8) and (9).

$$\text{Contrast} = \sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2 \tag{8}$$

$$\text{Homogeneity (HOM)} = \sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2} \tag{9}$$

Where $P_{i,j}$ represents the probability a group of spatial related pixel intensity occur in the image. Among the twelve statistical equations proposed by Haralicks [27], homogeneity is a suitable one for the purpose in this paper in order to choose a uniform region of image. Homogeneity, also called 'Inverse Difference Moment' is an inversion to the contrast .while computing the contrast, the weight of element increases when distance of element from diagonal of the GLCM increases. Inversely, the weight of element decreases as the distance of elements from diagonal increases. In short, the weight of contrast (8) is $(i-j)^2$, on the other hand, the weight of Homogeneity is $\frac{1}{1+(i-j)^2}$.

The texture analysis in the proposed ACR k-means clustering method will be conducted twice. First the texture analysis implemented on selecting the number of k in k-means clustering, both images for k equals to two and k equals to three will be computed, however only one of them will be used in reconstruction step, the criteria is based on the homogeneity value (10). Among every two images, the one with higher homogeneity will be selected.

$$R(V,H) = R(V,H)^k,\ \ argmax_{k=2}^{3}\ HOM^k \tag{10}$$

Where R (V, H) represents the adaptive region of the image with V number of vertical bands, T represents the number of horizontal bands and HOM^k represent homogeneity value in region $R(V,H)^k$.

$$I(V,T) = \sum_{V=2}^{\max\ V} \sum_{T=2}^{\max\ T} HOM\ of\ R(V,T) \tag{11}$$

$$Optimized\ Complete\ Image = argmax_{V}^{\max\ V}{}_{T}^{\max T}\ I(V,T) \tag{12}$$

Secondly, the texture analysis will be used in last stage when selecting the optimized completed image among the reconstructed images in database. The algorithm is shown in (11) and (12) where I (V, T) represents the total homogeneity of reconstructed image with regions R (V, T).

F. Crossed Reconstruction

The average homogeneity value are 0.9792 0.9732 0.9747 and 0.9560 respectively in fig.5. The average homogeneity value are 0.9763 0.9684 0.9773 and 0.9700 respectively in fig.6. Therefore, by comparing the value and take the region with higher degree of homogeneity, the first image in fig.5 will be chosen, the second image of fig.5 will be chosen, the third image of fig.6 will be chosen and lastly the forth image of fig.6 will be chosen to construct a complete reconstructed image.

Fig.7 Chosen regions based on homogeneity

Fig. 8 Reconstructed Image

The complete Image for the first iteration will be stored in a database. The process repeats, the number of horizontal bands will increase by one until a pre-set maximum number is achieved. Subsequently, the number of vertical bands will increase by one until a pre-set maximum number is achieved. All the complete images will be stored in database and undergo a global homogeneity texture analysis and the image with highest value of homogeneity will be chosen as the final output which is the complete image (6).

III. Result

In this section, we report on experiments using digital x-ray image from the clinic in Universiti Teknologi Malaysia. The size of image has been reduced to 441 x 316 pixels to ease the analysis. The algorithm explained in methodology will be implemented on this image with horizontal bands from two to ten and vertical bands from three to five in order to demonstrate the ACR k-mean clustering segmentation method. This experiment fully employed MATLAB 7.8.0 (.r2009a) as the programming tool for loading image and image processing.

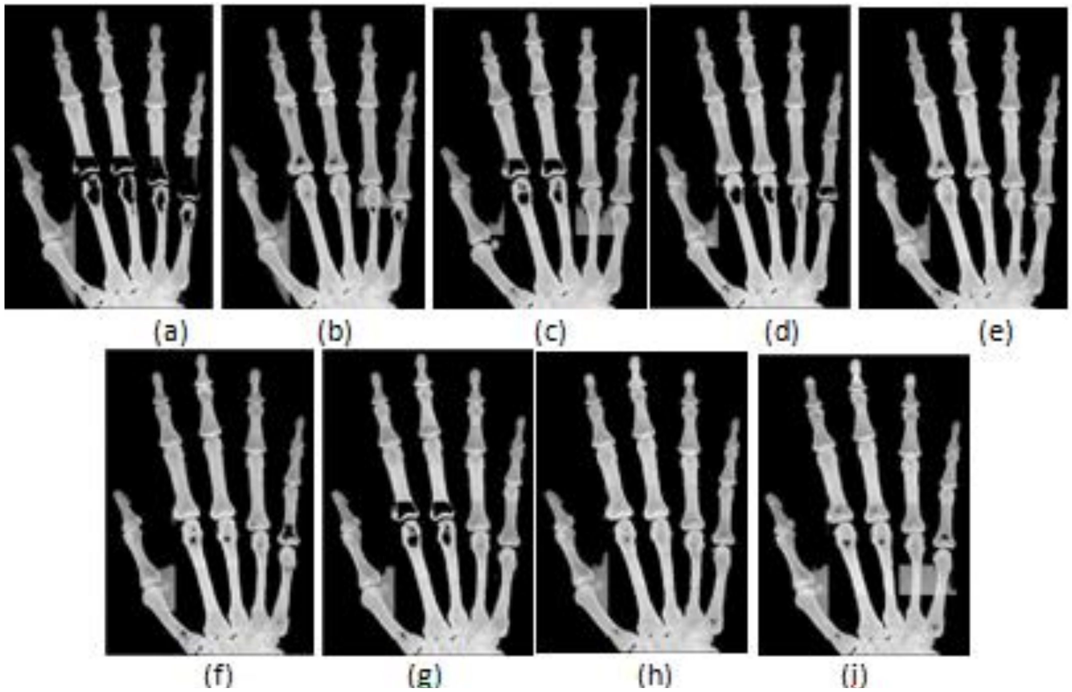

Fig. 9 Reconstructed images with three vertical bands and (a) Two horizontal bands (b) Three horizontal bands (c) Four horizontal bands (d) Five horizontal bands (e) Six horizontal bands
(f) Seven horizontal bands (g) Eight horizontal bands (h) Nine horizontal bands (i) Ten horizontal bands

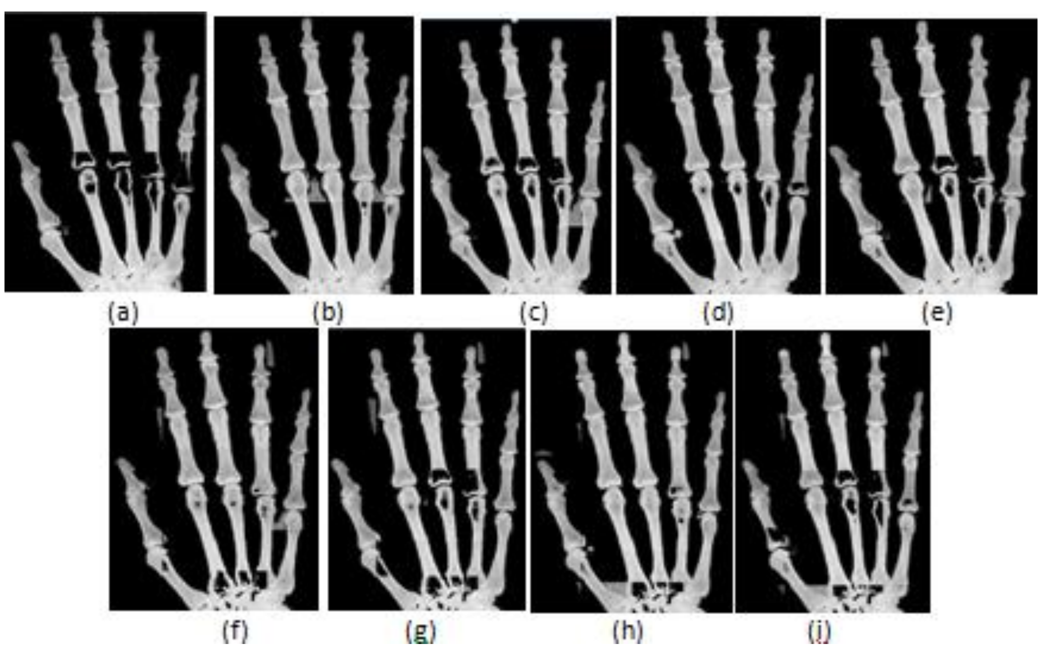

Fig. 10 Reconstructed images with four vertical bands and (a) Two horizontal bands (b) Three horizontal bands (c) Four horizontal bands (d) Five horizontal bands (e) Six horizontal bands
(f) Seven horizontal bands (g) Eight horizontal bands (h) Nine horizontal bands (i) Ten horizontal bands

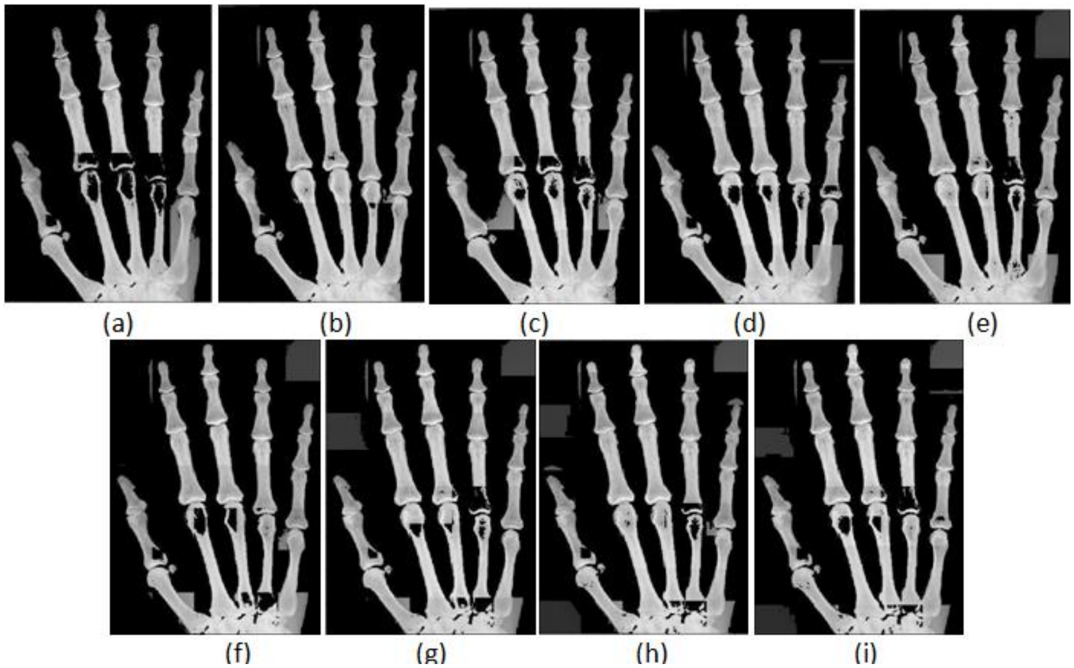

Fig. 11 Reconstructed images with five vertical bands and (a) Two horizontal bands (b) Three horizontal bands (c) Four horizontal bands (d) Five horizontal bands (e) Six horizontal bands (f) Seven horizontal bands (g) Eight horizontal bands (h) Nine horizontal bands (i) Ten horizontal bands

TABLE I
HOMOGENEITY VALUE OF THE IMAGES IN DATABASE FOR 3 HORIZONTAL BANDS

Vertical bands	2	3	4	5	6	7	8	9	10
Corresponding Homogeneity value	0.9733	0.9730	0.9736	0.9712	0.9753	0.9734	0.9735	0.9738	0.9734

TABLE II
HOMOGENEITY VALUE OF THE IMAGES IN DATABASE FOR 4 HORIZONTAL BANDS

Vertical bands	2	3	4	5	6	7	8	9	10
Corresponding Homogeneity value	0.9735	0.9730	0.9737	0.9736	0.9733	0.9713	0.9717	0.9717	0.9734

TABLE III
HOMOGENEITY VALUE OF THE IMAGES IN DATABASE FOR 5 HORIZONTAL BANDS

Vertical bands	2	3	4	5	6	7	8	9	10
Corresponding Homogeneity value	0.9737	0.9726	0.9730	0.9731	0.9731	0.9734	0.9732	0.9711	0.9722

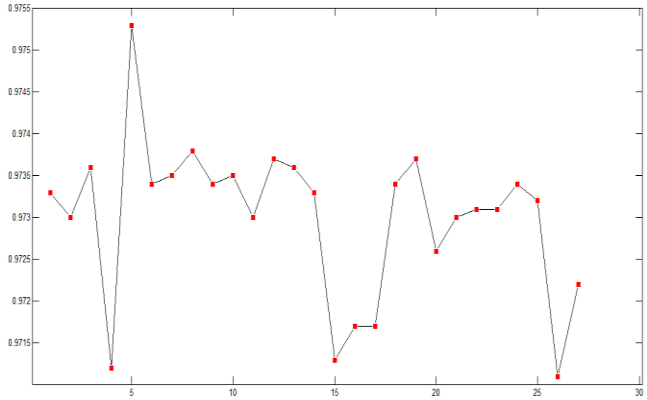

Fig. 12 Homogeneity graph of images in database

The y-axis in Fig. 12 represents the total homogeneity of image (4) and the x-axis represents the number Horizontal and vertical bands. From the graph in Fig. 12, the optimized reconstructed image is of three vertical bands and six horizontal bands.

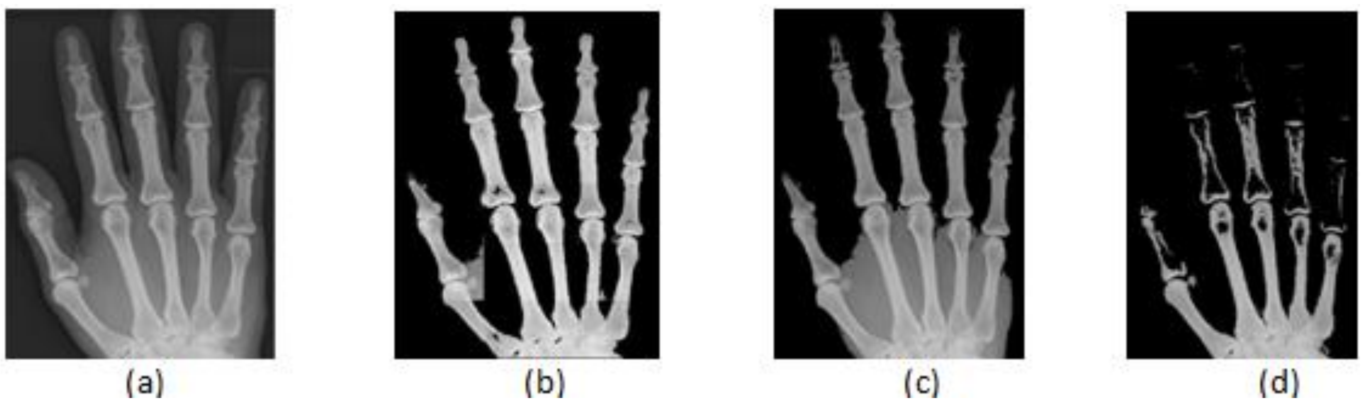

Fig. 13 (a)Input digital radiograph of hand (b) ACR k-means optimized segmented image (c) Global k-mean segmented image, k=2(d) global k-mean segmented image, k=3

IV. Discussion

The result obtained has shown the algorithm proposed has improved the segmentation result compared to conventional k-means clustering. However the result obtained is not globally optimized. There are regions where segmentation outcome is not satisfying, some cancellous bone area which has similar intensity with soft-tissue area has become zero value, and some soft tissue regions which suppose to become zero value still remain same intensity value due to a few facts:

(a) There is only one feature of GLCM implemented as texture analysis to demonstrate the algorithm designed.
(b) The GLCM implemented use four levels of gray level to compute due to computational speed constrained.
(c) The result only tested on limited number of V and T.

Recommendations:

(a) To improve the results obtained using multiple features rather than single feature, feature selection can be accomplished by discriminant analysis like fisher linear discriminant analysis and maximum likelihood discriminant rule.
(b) To improve the results obtained using an optimum number of gray levels rather than fixing it as four in terms of computational speed and performance.
(c) To improve the results obtained by designing algorithm to find optimum number of V and T.

V. Conclusion

The GLCM based adaptive crossed reconstructed (ACR) k-mean clustering segmentation method proposed has improved the hand bone segmentation result and is proved to be more effective than using conventional k-means clustering methods, and proved to have low number of threshold value used during the process and no preprocessing is needed.

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VI. Biographies

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