Clustering technique to determinate signal-to-noise ratio of *Rhizophora spp.* binderless and araldite resin particleboard as phantom material on computed tomography images

M W Marashdeh1*, A Abubaker2, K M Suwais3, M Alshipli3,4, A A Oglat3, A A Tajuddin3

1Department of Physics, College of Sciences, Al Imam Mohammad Ibn Saud Islamic University (IMSIU), P.O. Box 90950, Riyadh 11623, Saudi Arabia
2Faculty of Information Technology and Computing, Arab Open University (AOU), P.O. Box 84901, Riyadh 11681, Saudi Arabia.
3Department of Medical Physics and Radiation Science, School of Physics, Universiti Sains Malaysia, 11800 Minden, Penang, Malaysia.
4Department of Radiography, Princess Aisha Bint Al-Hussein College of Nursing & Health Sciences, Al-Hussein Bin Talal University, P.O. Box 20 Ma’an, Jordan.

Email: mwmarashdeh@gmail.com

Abstract. The signal-to-noise ratio (SNR) is an important measure of the quality of computed tomography (CT) images. In this study, a new clustering method is proposed to calculate the SNR ratio of CT image. Multi-Objective Simulated Annealing clustering is used for the comparison based on segmentation parameters such as SNR ratio. Two samples are used in this study as phantom materials, namely, *Rhizophora Spp.* binderless and araldite resin particleboard, with dimension of 20 cm x 20 cm. For each scanned datum, ImageJ software is utilised as the combination method to analyse CT images. Results shows that the automatic clustering algorithm improves the SNR results of the sample images. In addition, the SNR value of images using MOSA clustering is higher than that of normal CT images.

1. Introduction
Computed tomography scan (CT) is a cross-sectional medical imaging technology that uses the computer to scan the inner parts of the body. Diagnostic and classification of the disease by CT imaging depends on morphological parameters, such as tissue, tissue attenuation and size [1]. Therefore, to better understand and use any image, the performance of the imaging system must be determined in terms of image quality. The image quality of the system is usually described as the image noise in terms of signal-to-noise ratio (SNR). Phantoms are important tools for the quality assurance of diagnostic radiology and radiotherapy equipment. Previous studies assumed that *Rhizophora spp.* wood has properties comparable with those obtained from other standard phantom materials used for radiation dosimetry [2–4]. Marashdeh et al. [5] proposed that *Rhizophora spp.* wood be shredded into particles and compressed into binderless particleboards. Moreover, Marashdeh et al. [6] showed that the binderless particleboard
phantom can be used for dosimetric measurements in kilovoltage X-ray beam dosimetry. In addition, the epoxy resin is often used in phantom fabrication with a mixture of compounds. A series of phantom materials that are equivalent to tissue based on epoxy resin is modified to mimic biological tissues [7]. To understand the imaging system for both phantom materials, the clustering method was used.

Clustering is a data mining technique in the field of unsupervised datasets; this technique is used to explore and understand large collections of data [8]. The clustering technique distributes the dataset into clusters of similar features. The clustering has widespread applications in many fields, such as gene expression data [9][10], marketing [11][12] and image processing [13][14].

Image segmentation is one of the most important techniques in image processing [15]. Clustering an image is a good technique used for the segmentation of images. The goal of clustering in image segmentation is to subdivide an image into different regions of certain properties and extract the desired parts [16]. Clustering has different types: hierarchical clustering [17], fuzzy C-means clustering [18] and K-means clustering [19]. In this study, automatic clustering algorithm called Multi-Objective Particle Swarm Optimization with Simulated Annealing (MOPSOSA) [20] was used for noisy image segmentation to obtain clearer images. This technique was applied on Rhizophora Spp. binderless and araldite resin particleboards (ARRP) as two phantom materials.

2. Material and Methods

2.1 Samples preparation

Rhizophora spp. binderless particleboards were prepared in accordance with the method described by Marashdeh et al., [6]. Binderless particleboard samples with a particle size of < 50 μm were fabricated as described by Marashdeh et al. [21] at a moisture content of 5%–6%. The binderless particleboards had dimensions of 20 cm x 20 cm.

Epoxy resin (Araldite MY 6010) and hardener (Jeffamine D-230) ratio of 3:1 were thoroughly mixed by a hand mixer for 30 min to ensure good homogeneity. The mixture was decanted into a 20 cm x 20 cm plastic Teflon-coated mould. The mixture underwent curing for 48 h.

2.2 CT number measurements

The phantom was scanned using a DECT scanner (SOMATOM Definition AS, Siemens 2014, Germany) to investigate the CT number inside the Rhizophora spp. binderless particleboard and ARRP samples. Nine square zones over CT image were considered as regions of interest (ROI) for each sample. ImageJ was used to calculate the mean and standard deviation of the scanned images at ROI. The coefficient of variation (COV) of the SNR were computed using the following equations:

\[
SNR = \frac{\text{Mean}(ROI)}{\text{SD}(ROI)}
\]

\[
COV = \frac{\text{SD} \times 100}{\text{Mean}}
\]

2.3 Image segmentation

The CT images were segmented using automatic clustering algorithm MOPSOSA (figure 1). Matlab was used in coding the algorithm. The MOPSOSA algorithm is a hybrid K-means technique, multi-objective PSO, multi-objective SA, and sharing fitness.

The main strategy of MOPSOSA algorithm starts with the K-means technique [19], which is used to improve the selection of the initial particle position (swarm) because of its significance in the overall performance of the search process. The Multi-Objective Particle Swarm Optimization (MPSO) is implemented, where all particles in the swarm are launched through the search space by following the current optimum particles to search for the best solution. The MPSO simultaneously deals with three different cluster validity indices, namely, DB-index [22], Sym-index [23] and Conn-index [24]. During the search, the Multi-Objective Simulated Annealing (MOSA) was used if no change occurred in the
position of a particle, or if the particle moved to a bad position. The MOSA algorithm was merged to improve the performance of particles in the search process, as well as escape the stagnation and entrapment in local solutions. Through trade-off between the three different validity indices in the MOPSO algorithm, many Pareto optimal solutions were created. Therefore, the idea of sharing fitness [25] was incorporated to maintain diversity in the repository that contained optimal Pareto solutions. Optimal Pareto solutions are important for decision makers to choose from.

**Figure 1.** Flowchart of the MOPSOSA algorithm.
3. Results and discussion
Automatic clustering algorithm improved the SNR results of the sample images with different ratios based on variation in CT number of binderless particleboard and ARRP samples (figures 2 and 3).

![SNR of binderless particleboard before and after using MOPSOSA](image1)

**Figure 2.** SNR of binderless particleboard before and after using MOPSOSA

![SNR of Araldite Resin Particleboard before and after using MOPSOSA](image2)

**Figure 3.** SNR of Araldite Resin Particleboard before and after using MOPSOSA
The results show the difference in noise levels by comparing standard deviation (SD) values in binderless particleboard and AARP samples images. The ImageJ calculated the image noise in CT images by measuring the mean SD values at nine ROIs. The range of calculated SD values were 19.62–31.59 and 19.61–29.79 for binderless particleboard and AARP sample images, respectively, before MOPSOSA clustering. By contrast, the range of calculated SD values were 17.65–20.71 and 16.07–20.78 for binderless particleboard and AARP sample images, respectively, after using MOPSOSA clustering. The results showed no significant variation between SD values and a slight decrease in image noise level after using MOPSOSA clustering. The CT images did not include different materials (lesions) such that no significant difference was observed between the pixel values when using MOPSOSA. Thus, MOPSOSA clustering can be useful and effective for images containing different lesion areas.

Table 1 shows the results of the COV of the SNR results in the nine ROIs of binderless particleboard and ARRP sample were 8.18 and 8.98, respectively, after using MOPSOSA compared with 20.88 and 21.77 before clustering, respectively. In addition, ARRP sample showed slightly higher COV value compared with binderless particleboard sample. Therefore, the results indicated that binderless sample had a more homogenous profile density than the ARRP sample.

Table 1. Mean, Standard deviation, and COV of SNR for binderless particleboard and Araldite Resin Particleboard before and after using MOPSOSA

| Material                    | Mean Before | SD Before | COV Before | Mean After | SD After | COV After |
|-----------------------------|-------------|-----------|------------|------------|----------|-----------|
| binderless particleboard    | 6.11        | 7.63      | 1.28       | 0.62       | 20.88    | 8.18      |
| Araldite Resin Particleboard| 4.27        | 6.11      | 0.93       | 0.55       | 21.77    | 8.98      |

4. Conclusion
The automatic clustering algorithm improved the image quality. In addition, the binderless particleboard showed the least variation in CT number profile compared with ARRP samples. Thus, it has potential use as a tissue-equivalent phantom material in diagnostic imaging application.

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