CHAPTER 8

Conclusion

In this thesis, we proposed the texture feature extraction method by incorporating fuzzy clustering into Gray Levels Co-occurrence Matrix (GLCM) called Fuzzy Co-Occurrence Matrix (FCOM). 14 properties were computed from each FCOM, e.g., contrast, correlation, energy, and homogeneity. We evaluated our feature sets on the gray levels texture data sets namely Brodatz, Kylberg, UIUC, and UMD. The best validation set classification results on these data sets were 100% with $C = 4$ and $d = 2$, 100% with $C = 4$ and $d = 1$, 100% with $C = 32$ and $d = 5$, 100% with $C = 4$ and $d = 1$, respectively. We compared our results with the feature extracted from GLCM. The best validation set classification results on the same data set were 100% with $N_g = 32$ and $d = 1$, 99.55% with $N_g = 8$ and $d = 4$, 92.00% with $N_g = 16$ and $d = 5$, 99.00% with $N_g = 32$ and $d = 5$, respectively. Next, we introduced the breast abnormalities detection system without any pre-processing and ROI selection. We evaluated our system on the mini-MIAS public data set. The best blind test set detection results for architectural distortion (ARCH), speculated masses (SPIC), calcification (CALC), and well-defined /circumscribed masses (CIRC) were 100% with 9.46 false positives per image (FPI), 90% with 13.72 FPI, 100% with 13.39 FPI, and 81.25% with 18 FPI, respectively. We also compared the results with the feature set extracted from GLCM. The best detection results for ARCH, SPIC, CALC, and CIRC were 100% with 9.46 FPI, 70% with 4.45 FPI, 89.47% with 10.81 FPI, and 68.75% with 6.78 FPI, respectively. Furthermore, we presented the synthetic aperture radar automatic target recognition using our FCOM texture features. We evaluated the system on MSTAR public release data set. The best blind test set recognition result was 97.94% from the fusion of twenty best FCOM with RBF network models whereas the best fusion result of FCOM with MSVM was 95.37% correct classification. The feature set from GLCM was generated as a comparison. The results from FCOM were better than those from GLCM in all cases.

Finally, we introduced two color texture feature extraction algorithms. The FCOM was computed from each color channel whereas the FCLCOM was computed from all color channel. We also created feature sets from GLCM and CLCM for comparison. We selected five color data sets, namely Outex, USPTex, Biomass, MondailMarmi, and NewBarkTex to evaluate the classification results. The best validation set recognition results on these data sets were 97.06% from GLCM, 97.03% from FCOM, 100% from all methods, 100% from all methods, and 97.55% from FCOM feature sets, respectively. In this case, we set d = 1, and Ng or C as 4, 8, and 16 levels. We used MSVM with one-against-all strategy as classifier. The kernel in this study was RBF.

From the experimental results, the proposed FCOM texture feature extraction method provided a better result than the original GLCM in most cases. This method can be used in image analysis with a wide variety of images. In addition, this proposed FCOM has brightness invariance property as mentioned in section 4.3. However, the three factors, i.e., C, d, and θ are important consideration for determining the FCOM. In our studied, we set d ranging from 1, 2, 3, 5, and 10. Using small distance value for the fine texture pattern and large distance value for the coarse texture pattern would yield the higher classification rates. From the previous chapter, it has been concluded that overall classification accuracies with d = 1, 2, 3, 5, and 10 are acceptable since these distances are appropriate for all texture patterns. Distance value equals to the size of texture element improves classification. For the orientation factor, every pixel has eight neighboring pixels. There are eight orientations as shown in figure 2.1. However, the FCOM obtained from θ = 0°, 45°, 90°, and 135° is similar to those obtained from θ = 180°, 225°, 270°, and 315°, respectively. Feature extracted from four orientations provides textural information than those extracted from only one orientation. The last factor is a number of clusters. The dimension of a FCOM is determined by the number of clusters. Number of clusters is an important factor in FCOM computation. More clusters would mean more accurate extracted textural properties. Moreover, some membership values for each pixel might be small. The FCOM value in this case might be similar for some elements. The experiment results showed that a number of clusters less than or equal to eight is acceptable to capture textural information in all cases. In addition, stochastic texture pattern should be experimented in detail since this texture appears in the natural images. Recognizing the stochastic texture pattern is very difficult since shape and orientation of texture primitive are varieties occurring.

However, there are some problems for FCOM texture feature extraction. The first disadvantage is a large dimensional texture feature extracted from FCOM. The dimensional texture feature is depending on the number of cluster. Another problem is how to select the appropriate parameters *d* and θ to compute the FCOM.

For further works, one possible improvement to the proposed method in the texture feature extraction is to reduce the feature dimension. The first way is computed the texture properties using vectorization. Another way is using feature selection method to reduce the correlated features. Moreover, an automatic selection algorithm to determine the suitable parameters *C*, *d*, and θ which gives the best performance and reduces the computational time in search space is required.

There are three possible improvements for the FCOM textural descriptor. The first improvement is to remove the small membership values in each membership plane. This method might help reducing the noise. Removing these values might provide FCOM planes differently for each texture pattern. The second improvement is including a rotation invariant into FCOM such as circular FCOM instead of regular FCOM. This method might help in improving the irregular texture pattern recognition. The irregular texture pattern is randomly texture primitive replacement [6] since shape and orientation of texture primitive cannot predict. The last improvement is including a scaling invariance into FCOM such as Gaussian pyramid and wavelet transform. This method will be able to help recognition the scaling texture as well.

Moreover, we suggest that a suitable clustering method should be selected for each data set, e.g., centroid-based clustering, distribution-based clustering and density-based clustering. The centroid-based clustering is optimization cluster centers. The data is assigned to the nearest centroid. This method is not including shape and orientation of the data set. The distribution-based clustering model is related to statistics. The data is assigned to the most likely to the same distribution. This clustering method produces complex models for clusters to capture correlation and dependence between attributes. In density-based clustering, clusters are defined as areas of higher density than the remainder of the data set. A cluster consists of all density-connected objects including all objects that are within these objects' range. Select the appropriate clustering method might help improved the classification rate. In addition, there are more distance measure in clustering method, e.g., spheroid and ellipsoid. Changing distance function may create difference membership values. The FCOM planes may be difference. Selecting the suitable distance measure for clustering method might be improve the color texture classification accuracy.

In recent years, deep learning [69] models are frequently setting state-of-the-art in many research fields including texture analysis, e.g., Convolutional Neural Networks (CNN) [70], one type of multilayer neural network. CNN model is trained using back propagation similar to an original neural network. Since FCOM might be considered as a higher-dimensional feature set in some cases, it is possible to classify FCOM using any deep learning algorithm or it might be possible to embed FCOM into deep learning algorithm similar to CNN algorithm.