CHAPTER 5

SEGMENTATION ALGORITHM

Image segmentation is a prerequisite in many image processing systems, such as pattern recognition, image retrieval and small surveillance. The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze (Kumar and Srinivas, 2013). The aim is to separate different parts of the fruit surface, which is a very challenging task with the overwhelming number of colors and textures in an image. Thus, fruit image segmentation is a relevant research area.

Mango fruit image analysis requires a segmentation step to distinguish and isolate different regions of the image, in order to separate normal and defective regions. Segmentation is a key task in fruit image analysis and disease detection and this task assigns labels to pixels in 2-D images. The effect is that the image is split up into segments, otherwise called as regions or areas.

Classically, it is defined as the task of image processing that partitions an image into non-intersecting regions such that each region is homogeneous and the union of no two adjacent regions is homogeneous (Jain and Saxena, 2013). If the domain of the image is given by I, then the segmentation problem is to determine the sets $S_k \subset I$ whose union is the entire image I. Thus, the sets that make up segmentation must satisfy Equation (5.1)

$$I = \bigcup_{k=1}^{k} S_k \qquad (5.1)$$

where $S_k \cap S_j = \phi$ for $k \neq j$., and each S_k is connected. Ideally, a segmentation method finds those sets that correspond to distinct anatomical structures or region of interest in the image.

Existing solutions to segmentation can be grouped into six categories (Rao *et al*., 2012) as listed below:

- Point-based approaches
- Edge-based approaches
- Region growing approaches
- Classification-based approaches
- Clustering-based approaches
- Artificial Neural Networks-based approaches

While each of the above approaches has their own advantages and disadvantages, this research work focuses on using a clustering-based approach to segment the fruit image. The reason behind this is due to its advantage of not requiring user input and can perform clustering naturally, without any training data.

As mentioned in Chapter 3 (Section 3.2.3), Phase II enhances Fuzzy C Means clustering algorithm to identify the normal and defective areas of the mango fruit image. This chapter presents detailed description of the conventional Fuzzy C Means algorithm, followed by the enhanced algorithm used to segment the mango fruit.

5.1. FUZZY C-MEANS (FCM) CLUSTERING ALGORITHM

The FCM algorithm can be seen as the fuzzified version of the c-means algorithm. This method, developed by Dunn (1973) and modified by Bezdek (1981), is frequently used in pattern recognition. The conventional Fuzzy C Means (FCM) clustering algorithm works by assigning membership to each pixel corresponding to each cluster center on the basis of distance between the cluster center and the data point. When the pixel is near to a cluster center, it’s membership towards the cluster centre is considered to be correlated. Here, the summation of membership of each pixel should be equal to one. After each iteration, membership and cluster centers are updated. The FCM algorithm has several advantages as listed below.

1. Gives best result for overlapped data set and comparatively better then k-means algorithm.
2. Unlike k-means where data point must exclusively belong to one cluster center here a pixel is assigned membership to each cluster center as a result of which data point may belong to more than one cluster center.

These advantages make FCM a most frequently used clustering algorithm.

FCM is an iterative clustering method that produces an optimal 'c' partition by minimizing the weighted within group sum of squared error objective function J_{FCM}:

$$J_{FCM}(V, U, X) = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{m} d(x_j, v_i), 1m < +\infty \quad (5.2)$$

where $X = \{x_1, x_2, ..., x_n\}$ □R_p is the data set in the p-dimensional vector space, p is the number of data items, c is the number of clusters with $2 \le c \le n-1$. $V = \{v_1, v_2, . . . ,v_c\}$ is the c centers or prototypes of the clusters, v_i is the p-dimension center of the cluster i, and $d_2(x_j, v_i)$ is a distance measure between object x_j and cluster centre v_i. $U = \{\mu_{ij}\}$ represents a fuzzy partition matrix with $u_{ij} = u_i (x_j)$ is the degree of membership of x_j in the i^{th} cluster; x_j is the jth of p-dimensional measured data. The fuzzy partition matrix satisfies the following.

$$0<\sum_{j=1}^{n} \mu_{ij} < □i □ \{1, ... , C\} \quad (5.3)$$

$$\sum_{i=1}^{c} \mu_{ij} = 1, □i □ \{1, ... , n\} \quad (5.4)$$

The parameter m is a weighting exponent on each fuzzy membership and determines the amount of fuzziness of the resulting classification; it is a fixed number greater than one. The objective function JFCM can be minimized under the constraint of U. specifically, taking of JFCM with respect to u_{ij} and v_i and zeroing then respectively, tow necessary but not sufficient conditions for JFCM to be at its local extreme a will be as the following:

$$u_{ij} = \left|\sum_{k=1}^{c}\left(\frac{d(x_j,v_i}{d(x_j,v_k}\right)^{2/(m-1)}\right| - 1, 1 \le i \le c, 1 \le j \le n \quad (5.5)$$

$$v_i = \frac{\sum_{k=1}^{n}\mu_{ik}^{m}x_k}{\sum_{k=1}^{n}\mu_{a}^{m}}, 1 \le i \le c. \quad (5.6)$$

The steps in FCM clustering algorithm are given in Figure 5.1.

Let $X = \{x_1, x_2, x_3 ..., x_n\}$ be the set of data points and $V = \{v_1, v_2, v_3 ..., v_c\}$ be the set of centers. 1) Randomly select 'c' cluster centers. 2) Calculate the fuzzy membership 3) Compute the fuzzy centers 4) Repeat Steps 2 & 3 until minimum J value is achieved.

Figure 5.1 : Conventional Fuzzy C-Means Algorithm

5.2. FUZZY POSSIBILISTIC C-MEANS (FPCM) ALGORITHM

As FCM algorithm is sensitive to initial states and gets stuck in local optima solutions, a Fuzzy Possibilistic C-Means (MFPCM) algorithm is used. The FPCM algorithm is efficient in solving the local optimal issue, but still requires user input for initial centroid selection. Although FCM is a very useful clustering method, its memberships do not always correspond well to the degree of belonging of the data, and may be inaccurate in a noisy environment, because the real data unavoidably involves some noises.

To improve this weakness of FCM and to produce memberships that have a good explanation for the degree of belonging for the data, the fuzzy c-partition to obtain a Possibilistic type of membership function and propose PCM for unsupervised clustering. The component generated by the PCM corresponds to a dense region in the data set; each cluster is independent of the other clusters in the PCM strategy. The objective function of the PCM can be formulated as follows:

$$J_{PCM}(V, U, X) = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{m} d(x_j, v_i) + \sum_{i=1}^{c} n_i \sum_{j=1}^{n} (1 - u_{ij})^{m} \quad (5.7)$$

where $n_i = \frac{\sum_{j=1}^{n} \mu_{ij}^{m} \|x_j - v_i\|^2}{\sum_{j=1}^{n} \mu_{ij}^{m}}$ is the scale parameter at the ith cluster, $u_{ij} = \frac{1}{1+\left(\frac{d^2(x_j, v_i)}{n_i}\right)^{\frac{1}{m-1}}}$ is the Possibilistic typicality value of training sample x_j belonging to the cluster I and m ∈ [1,∞) is a weighting factor called the Possibilistic parameter.

In PCM techniques, the clusters do not have a lot of mobility, since each data point is classified as only one cluster at a time rather than all the clusters simultaneously. Therefore, a suitable initialization is required for the algorithms to converge to nearly global minimum. FPCM can be defined as a clustering algorithm that combines the characteristics of both fuzzy and Possibilistic c-means, where memberships and typicalities are important for the correct feature of data substructure in clustering problem. Thus, an objective function in the FPCM depending on both memberships and typicalities can be shown as:

$$J_{FPCM}(U, T, V) = \sum_{i=1}^{c} \sum_{j=1}^{n} \left(u_{ij}^{m} + t^{n}\right) d(x_j, v_i) \quad (5.8)$$

With the following constraints:

$$\sum_{i=1}^{c} \mu_{ij} = 1, \forall j \in \{1, \ldots, n\} \quad (5.9)$$

$$\sum_{j=1}^{n} t_{ij} = 1, \forall i \in \{1, \ldots, c\} \quad (5.10)$$

A solution of the objective function is obtained via an iterative process where the degrees of membership and the cluster centers are update using the following equations.

$$u_{ij} = \left[\sum_{k=1}^{c}\left(\frac{d(x_j,v_i)}{d(x_j,v_k)}\right)^{2/(m-1)}\right]^{-1}, 1 \le i \le c,\ 1 \le j \le n \qquad (5.11)$$

$$t_{ij} = \left[\sum_{k=1}^{n}\left(\frac{d(x_j,v_i)}{d(x_j,v_k)}\right)^{2/(m-1)}\right]^{-1}, 1 \le i \le c,\ 1 \le j \le n \qquad (5.12)$$

$$v_i = \frac{\sum_{k=1}^{n}(u_{ik}^{m}+t_{ik}^{n})x_k}{\sum_{k=1}^{n}(u_{ik}^{m}+t_{ik}^{n})}, 1 \le i \le c \qquad (5.13)$$

PFCM produces memberships and possibilities simultaneously, along with the usual point prototypes or cluster centers for each cluster.