INITIALIZATION METHODS FOR CONVENTIONAL FUZZY C-MEANS AND ITS APPLICATION TOWARDS COLOUR IMAGE SEGMENTATION

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INITIALIZATION METHODS FOR CONVENTIONAL FUZZY C-MEANS AND ITS APPLICATION TOWARDS COLOUR IMAGE SEGMENTATION

by

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LIST OF ABBREVIATIONS

ACO	Ant Colony Optimization
AJNDH	Agglomerated Just Noticeable Difference Histogram
AMS	Anisotropic Mean Shift
AMSFCM	Anisotropic Mean Shift based Fuzzy C-Means
AS	Ant System
CQ	Colour Quantization
FCM	Fuzzy C-Means
FFCM	Fast Fuzzy C-Means
HA	Hierarchical Approach
HCM	Hard C-Means
HF	Hydro-Fluoride
HSI	Hue-Saturation-Intensity
HSL	Hue-Saturation-Lightness
HSV	Hue-Saturation-Value
HT	Histogram Thresholding
JND	Just Noticeable Difference
L_pNFCM	L_p Norm Fuzzy C-Means
MS	Mean Shift
RCFCM	Rival Checked Fuzzy C-Means
SFCM	Suppressed Fuzzy C-Means

KAEDAH-KAEDAH PEMEMULAAN BAGI PURATA-C FUZI KONVENSIONAL DAN APLIKASINYA UNTUK PERSEGMENAN IMEJ WARNA

ABSTRAK

Purata-C Fuzi (*Fuzzy C-Means (FCM)*) konvensional adalah satu algoritma persegmenan yang digunakan dengan meluas kerana ia berupaya untuk menjana penyelesaian yang memuaskan bagi mengatasi masalah pengelompokan. Namun, *FCM* konvensional sangat sensitif terhadap pememulaan awal seperti penentuan bilangan kelompok dan pusat kelompok awal yang optimum. Oleh itu, tiga kaedah pememulaan baharu yang dinamakan Kaedah Hirarki (*Hierarchical Approach (HA)*), Pengkuantum Warna (*Colour Quantization (CQ)*) dan Ambangan Histogram (*Histogram Thresholding (HT)*) telah dicadangkan untuk mendapatkan pememulaan awal bagi *FCM* konvensional secara automatik. Sebelum pembinaan tiga kaedah pememulaan baharu, satu algoritma yang dinamakan Analisis Histogram Pencarian Puncak (*Peak Finding Histogram Analysis (PFHA)*) dicadangkan untuk mencari mod dalam histogram and seterusnya lembah di antara dua puncak yang bersebelahan. Kemudian, algoritma PFHA digunakan untuk membahagi imej warna kepada kawasan-kawasan yang sekata sebelum algoritma penggabungan dilakukan untuk kaedah pememulaan HA, CQ dan HT dengan cara-cara yang berbeza. Daripada keputusan yang diperolehi, ketiga-tiga kaedah pememulaan yang dicadangkan adalah lebih baik daripada kaedah-kaedah pememulaan konvensional dengan berkeupayaan mengurangkan kesilapan dalam klasifikasi dan menghasilkan kawasan yang lebih sekata pada keputusan persegmenan.

INITIALIZATION METHODS FOR CONVENTIONAL FUZZY C-MEANS AND ITS APPLICATION TOWARDS COLOUR IMAGE SEGMENTATION

ABSTRACT

Due to its capability in providing a particularly promising solution to clustering problems, the conventional Fuzzy C-Mean (FCM) algorithm is widely used as a segmentation method. However, it is very sensitive to the initialization conditions of number of clusters and initial cluster centres. Thus, three initialization schemes for the conventional FCM algorithm namely the Hierarchical Approach (HA), the Colour Quantization (CQ) and the Histogram Thresholding (HT) are proposed to automatically obtain the initialization conditions for the conventional FCM algorithm. Prior to the development of the initialization schemes, the Peak Finding Histogram Analysis (PFHA) algorithm is proposed to locate the modes and then the valleys between any two adjecent modes in the histogram. Then, the PFHA algorithm is applied to split the colour image into multiple homogeneous regions before employing the merging algorithm for the HA, the CQ and the HT initialization schemes in different ways. The experimental results show that the proposed initialization schemes outperform other conventional initialization schemes by reducing the classification errors and producing more homogeneous regions in the segmentation results.

CHAPTER 1

INTRODUCTION

1.1 Research Background

Classically, image segmentation is defined as the partitioning of an image into non-overlapped, consistent regions which are homogeneous with respect to some characteristics (Hassanien *et al*., 2009; Pal and Pal, 1993). It serves as a critical and essential component of image analysis and pattern recognition system because it determines the quality of the final result of analysis (Cheng *et al*., 2001). Thus, it has been widely applied in many image analysis and pattern recognition applications such as object recognition (Bhanu and Jing, 2000; Jin *et al*., 2008; Yang *et al*., 2008), optical character recognition (Chen and Chang, 2005; Leimer, 1962), face recognition (Kim *et al*., 2006), fingerprint recognition (Cui *et al*., 2008; Hiew *et al*., 2006), medical image processing (Hance *et al*., 1996; Umbaugh *et al*., 1993), industrial automation (Leitch and Gallanti, 1992) and content based image retrieval (Kumar and Thomas, 2008).

As compared to gray scale images, colour images contain much richer set of information. In colour images, the additional information provided by the colour attributes can help to yield better segmentation results because the use of varying colours allows the region of interest to be distinguishable from the background and non-subject regions (Gauch and Hsia, 1992; Li and Li, 2003; Marinai *et al*., 2004). As a result, there has been numerous works done in colour image segmentation. Basically, colour image segmentation approaches can be broadly classified into several categories (Cheng *et al*., 2001) as shown in Figure 1.1.

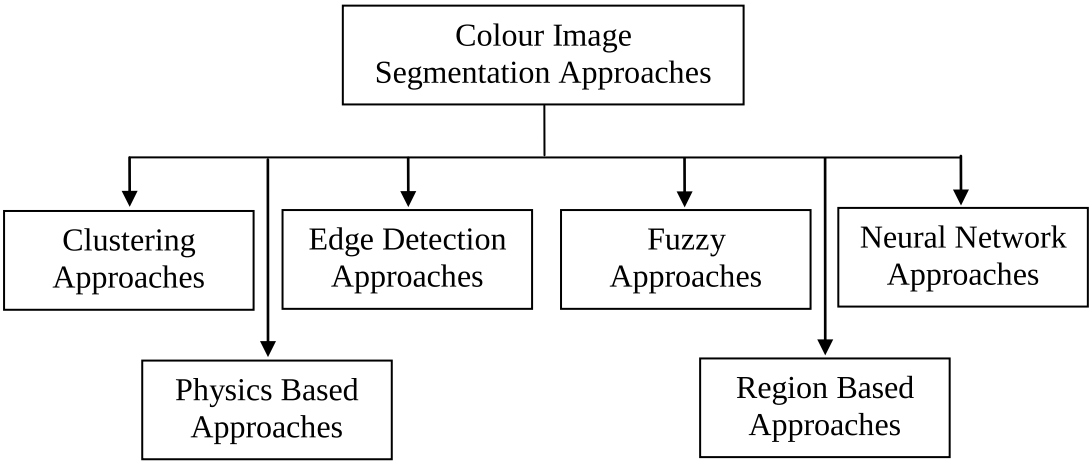


Figure 1.1 Categories for colour image segmentation approaches

Due to their straightforwardness for classification and the ease of implementation, the clustering approaches are widely used in colour image segmentation. Most clustering approaches are non-parametric and lead to satisfactory results (Aghbari and Ruba, 2006). In general, the clustering approaches can be mainly divided into two types namely the distance based clustering and the density estimation clustering (Aghbari and Ruba, 2006) as shown in Figure 1.2.

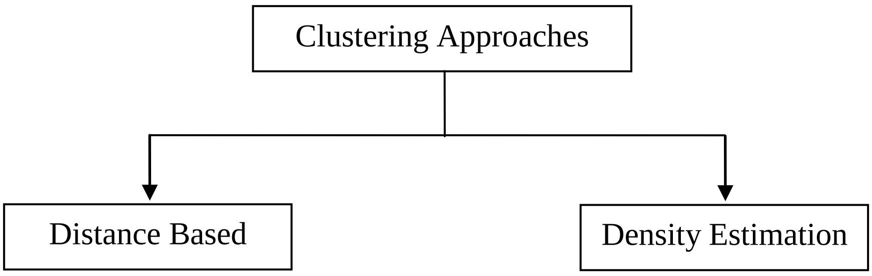


Figure 1.2 Types of clustering approaches

The distance based clustering assigns the pixels of an image based on the distance between their colour attributes without considering the global distribution of that feature. On the other hand, the density estimation clustering examines the feature space as a density function and selects the dense feature spaces as peaks of clusters. Although the distance based clustering is well known to be greatly affected by the noise in the image, it is still widely used due to the simplicity in implementation (Rui *et al.*, 1999). It can be further classified into crisp clustering and fuzzy clustering as shown in Figure 1.3.

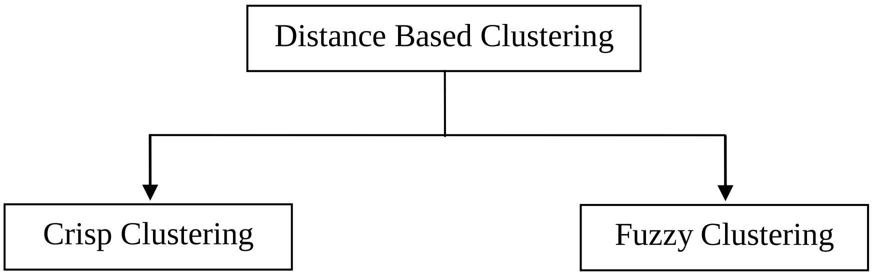


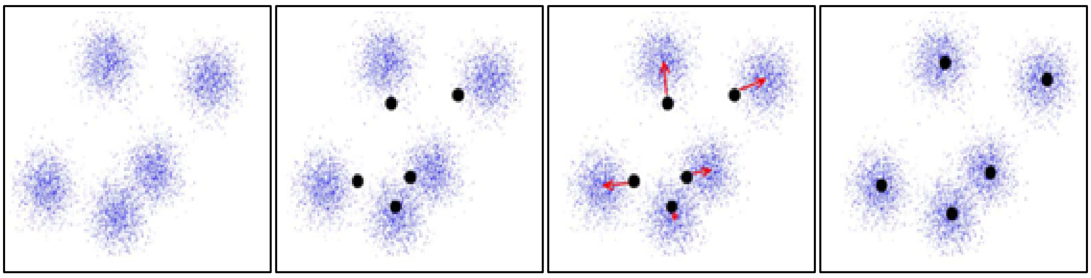
Figure 1.3 Types of distance based clustering

The crisp clustering assigns the pixels of an image to their own clusters based on the salient features. In this context, the salient features refer to features that do not carry the same information leading to redundancy among the homogeneous clusters (Iyer *et al.*, 2000). However, the distance between their colour attributes is not a good salient feature because boundaries separating a homogeneous cluster from another are highly indistinguishable for any images due to the image acquisition process (Bezdek *et al.*, 1999).

On the other hand, the fuzzy clustering assigns the pixels of an image to all clusters with varying partial membership. Compared to the crisp clustering, the fuzzy clustering is capable of reducing the uncertainty of pixels belonging to one cluster. As a result, the fuzzy clustering is less prone to fall into the local optima than the crisp clustering (Wang *et al.*, 2005). In addition, the fuzzy clustering has been also proven to be able to provide a particularly promising solution to the clustering problems (Jain and Dubes, 1988). Of all the fuzzy clustering, the conventional Fuzzy C-Means algorithm is the most widely used for image segmentation (Cai *et al.*, 2007).

1.2 Overview of Conventional Fuzzy C-Means Algorithm

Fuzzy C-Means algorithm (FCM) was introduced by Ruspini (1970) and then improved by Dune (1973) and Bezdek (1981). It is a segmentation algorithm that is based on the idea of finding cluster centres by iteratively adjusting their position and evaluation of an objective function and its success chiefly attributes to the introduction of fuzziness for the belongingness of each image pixels. The iterative optimization of the conventional FCM algorithm is essentially a local searching method, which is used to minimize the distance among the image pixels in corresponding clusters and to maximize the distance between cluster centres. The general effect of the conventional FCM algorithm is illustrated in Figure 1.4.



(a) (b) (c) (d)

Figure 1.4 Illustration of conventional FCM algorithm (a) Available clusters (b) Random centres (c) Converging (d) Final settlement

The conventional FCM algorithm allows more flexibility by introducing the possibility of partial memberships to clusters. The membership is proportional to the probability that a pixel belongs to a specific cluster where the probability is only dependent on the distance between the image pixel and each independent cluster centre. By iteratively adjusting their cluster centres, the objective function can reach the global minimum when pixels nearby the centre of corresponding clusters are assigned higher membership values, while lower membership values are assigned to pixels far from the centre (Chuang *et al*., 2006).

1.3 Problem Statements

The conventional FCM algorithm has long been a popular image segmentation algorithm for its clustering validity and simplicity of implementation (Karmakar and Dooley, 2002; Yamany *et al*., 1999; Yang *et al*., 2002). However, it is very sensitive to the initialization conditions of number of clusters and initial cluster centres (Kim *et al*., 2004). The initialization conditions of number of clusters and initial cluster centres have their unneglectable impacts on the segmentation quality.

The number of clusters imposes significant impact on the segment area of colour images and hence the clustering result depends largely on this initialization. Usually, a laborious process of determining the optimal number of clusters is needed for the conventional FCM algorithm and the determination is carried out based on prior knowledge. In the conventional FCM algorithm, different selection of the initial cluster centres can potentially lead to different local optimal or different partition. Thus, the initial cluster centres affect the classification accuracy of the conventional FCM algorithm. Usually, the precise initial cluster centres are not always known in advance. This is particularly the case for colour images due to its complexity and diversity.

1.4 Objectives and Scopes

To overcome the sensitiveness of the conventional FCM algorithm to the initialization conditions in colour image segmentation, the main objective of this research is to propose initialization schemes for the conventional FCM algorithm based on the basic of histogram analysis. As a result, a peak finding algorithm is also proposed to obtain the modes, which are dominating peaks, in the histogram in this study before developing these initialization schemes. In general, the objectives of this study are specifically designed to fulfil the following criteria:

1. To develop a peak finding algorithm to detect the modes in the histogram
2. To design initialization schemes that are capable to automatically determine the optimal number of clusters and obtain the precise initial cluster centres in colour images for the conventional FCM algorithm

In the histogram analysis, the histogram of an image can be separated into a number of modes, each corresponds to one region and there is a threshold value corresponding to the valley between two adjacent modes. The valley between two adjacent modes can be used as the boundary for the segmentation. As a result, a peak finding algorithm is proposed to obtain the modes in the histogram in this study with the aim to design initialization schemes to the conventional FCM algorithm.

To overcome the difficulty in determining the optimal number of clusters, three initialization schemes are proposed to automatically obtain the optimal number of clusters in colour images for the conventional FCM algorithm. Thus, laborious process of determining the optimal number of clusters can be prevented and the determination does not need any prior knowledge. In addition, to reduce erroneous classification and poor final cluster centres from occurring, the initialization schemes are proposed to automatically obtain the precise initial cluster centres in colour images for the conventional FCM algorithm.

To examine the performance of the proposed initialization schemes for the conventional FCM algorithm toward colour image segmentation, natural colour images and clinker microscopic colour images are adopted for evaluation. In this study, the natural colour images are taken from public segmentation database and the clinker microscopic colour images are obtained from the School of Material and Mineral Resources Engineering, Universiti Sains Malaysia.

1.5 Thesis Outline

In general, this thesis consists of 5 chapters. Chapter 1 briefly presents the introduction about the project to be done. In this chapter, the research background, the overview of conventional FCM algorithm, the problem statements of the research, and the objectives and scopes of the research are included.

In Chapter 2, several relevant modifications to the conventional FCM algorithm toward colour image segmentation will be given as they have been proven to be able to speed up the conventional FCM algorithm, to improve the conventional FCM performance with respect to noise or imaging artefact, or both. However, these modifications are still very sensitive to the initialization conditions. To overcome the sensitiveness of the conventional FCM algorithm to the initialization conditions, initialization schemes for the conventional FCM algorithm have been proposed in the scientific literature. This study is particularly interested in the initialization schemes that can obtain the initialization conditions automatically. Hence, the workings of these initialization schemes will be provided in detail in this chapter.

In Chapter 3, the methodology of the proposed initialization schemes for the conventional FCM algorithm will be provided. In this chapter, 3 initialization schemes are proposed, which all are capable to produce the initialization conditions automatically. The detail regarding the steps of the implementation for these proposed initialization schemes will be explained in detail in Chapter 3. The details on the concept and type of the qualitative and quantitative analyses to be employed for the colour image segmentation will be also provided in this chapter as they can be used to provide a comparison for the segmentation results.

In Chapter 4, the effectiveness of the proposed peak finding algorithm will be first evaluated before providing the implementation illustration for the proposed initialization schemes. The objective of the evaluation on the peak finding algorithm is to see the capability of the proposed algorithm in locating the modes in the histogram. The remaining of this chapter will provide and discuss the segmentation results qualitatively and quantitatively in order to compare the performance of the initialization schemes on obtaining the initialization conditions for the conventional FCM algorithm toward colour image segmentation.

In this thesis, Chapter 5 is functioning to conclude and summarize the entire project. Suggestions for the future works will also be included in this final chapter.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Many studies have been reported on the superior performance of the conventional FCM algorithm on image segmentation dealing with the uncertainties (Bensaid *et al*., 1996; Cheng *et al*., 1998; Lim and Lee, 1990; Ozdemir and Akarun, 2002; Tolias and Panas, 1998). Although the conventional FCM algorithm yields good segmentation results on noise-free images, it fails to segment images corrupted by noise or imaging artefact since it does not consider any spatial information in the images (Isa *et al*., 2009). In addition, it is also computational intensive due to the iterative nature of the algorithm and a large number of feature vectors is often involved in the calculations (Cheng *et al*., 1998). Furthermore, it is also very sensitive to the initialization conditions of number of clusters and initial cluster centres.

In view of the drawbacks of the conventional FCM algorithm, several modifications to the conventional FCM algorithm toward colour image segmentation have been proposed to speed up the clustering algorithm, to improve the clustering performance with respect to noise or imaging artefact, or both. Their success mainly attributes to the modifications on the membership, the objective function or the general procedure of the conventional FCM algorithm. But, they are still sensitive to the initialization conditions. As a result, several initialization schemes for the conventional FCM algorithm have been proposed to overcome the sensitiveness of the conventional FCM algorithm to the initialization conditions.

In this chapter, the underlying principle of the conventional FCM algorithm will be presented in detail in Section 2.2. Several relevant modifications to the conventional FCM algorithm toward colour image segmentation will be discussed in brief in Section 2.3. In Section 2.4, conventional initialization schemes for the conventional FCM algorithm will be explored in detail. These initialization schemes are selected due to their superior performances on colour image segmentation. Thus, the working of these initialization schemes will be examined. Finally, Section 2.5 will conclude the work on Chapter 2.

2.2 Conventional Fuzzy C-Means Algorithm

The conventional FCM algorithm is an unsupervised classification technique, thus there is no need for prior knowledge about the pixels set. It is a segmentation algorithm that is based on clustering similar pixels in an iterative way where the cluster centres are adjusted during the iteration (Bezdek, 1980). It attempts to partition the pixels into a collection of F fuzzy clusters. Based on the minimization of the objective function, the conventional FCM algorithm yields extremely good segmentation results. Typically, the objective function of the conventional FCM algorithm is defined as

$$W = \sum_{j=1}^{F}\sum_{i=1}^{N}\mu_{ij}{}^{m}\left\|x_i - c_j\right\|^2 \tag{2.1}$$

where N is the number of image pixels, μ_{ij} is the membership of pixel x_i to the *j-th* cluster identified by its centre c_j, and m is a constant that defines the fuzziness of the resulting partition. $\| x_i - c_j \|$ denotes the Euclidean distance between x_i and c_j. The parameter m controls the fuzziness of the membership. The value of m is manually determined by the user. In general, most users choose m in the range [1.5, 2.5], with m = 2.0 an overwhelming favourite (Bezdek, 1999; Kim *et al.*, 2004). The membership of pixel x_i to the *j-th* cluster identified by its centre c_j is defined as

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{F}\left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right)^{\frac{2}{m-1}}} \tag{2.2}$$

where μ_{ij} indicates the strength of the association between x_i and c_j and has the value in the range [0, 1]. In the conventional FCM algorithm, the cluster centres are iteratively updated by the following equation:

$$c_j = \frac{\sum_{i=1}^{N} \mu_{ij}^{\ m} x_i}{\sum_{i=1}^{N} \mu_{ij}^{\ m}} \tag{2.3}$$

The general procedure of the conventional FCM algorithm can be described as follows:

i. Initialize the number of fuzzy centres, F and the cluster centres value. Set the iteration time $q = 0$.

ii. Calculate the membership of pixel x_i to the *j-th* cluster identified by its centre c_j according to Equation 2.2. Notice that if $\| x_i - c_j \| = 0$, then $\mu_{ij} = 1$ and set others membership of this pixel to 0.

iii. Calculate the objective function, $W^{(q)}$ according to Equation 2.1.

iv. Update $q = q + 1$. Then, calculate the new cluster centres according to Equation 2.3.

v. Repeat Steps *ii* to *iv* if $\| W^{(q)} - W^{(q-1)} \| \geq \varepsilon$. Otherwise, stop iteration.

(Note: ε is a constant and its value is manually determined by the user. In general, most users choose ε in the range [0.01, 0.0001])

2.3 Modifications to Conventional Fuzzy C-Means Algorithm

Although a number of modifications to the conventional FCM algorithm have been introduced in the literature, only some of them are applicable to colour image segmentation. For colour image segmentation, these modifications to the conventional FCM algorithm, as shown in Figure 2.1, target at algorithmic speedup, improvement of clustering performance with respect to noise or imaging artefact, or both.

The Rival Checked FCM algorithm, the Suppressed FCM algorithm and the Fast FCM algorithm target at the algorithmic speedup while the L_p Norm FCM algorithm aims on the improvement of clustering performance with respect to noise or imaging artefact. On the other hand, the Anisotropic Mean Shift Based FCM algorithm targets at both the algorithmic speedup and the improvement of clustering performance with respect to noise or imaging artefact. These modifications to the conventional FCM algorithm are applicable to colour image segmentation and will be discussed briefly in the following sections.

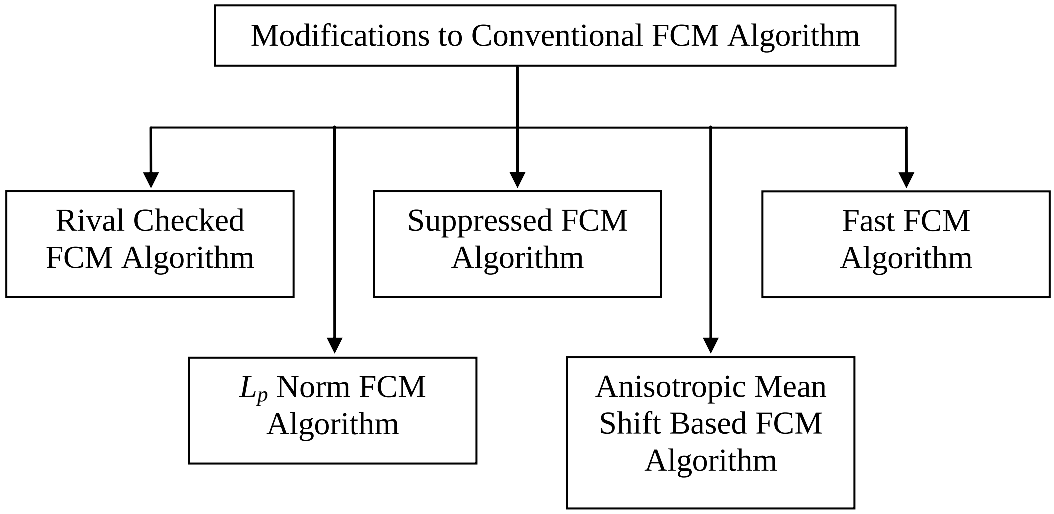


Figure 2.1 Modifications to conventional FCM algorithm towards colour image segmentation

2.3.1 Rival Checked Fuzzy C-Means Algorithm

The Rival Checked FCM (RCFCM) algorithm was proposed on the basis of competitive learning (Wei and Xie, 2000). The main idea of the RCFCM algorithm is to magnify the largest membership, to suppress the second largest membership and to keep others membership invariable. In the RCFCM algorithm, the largest membership of pixel x_i to the *j-th* cluster is magnified as shown in the following equation:

$$\mu_{ip}^{new} = \mu_{ip}^{old} + (1-\alpha)\mu_{iq}^{old} \tag{2.4}$$

while the second largest membership of pixel x_i to the *j-th* cluster is suppressed as shown in the following equation:

$$\mu_{iq}{}^{new} = \alpha \mu_{iq}{}^{old} \tag{2.5}$$

where α is the control parameter and has the value in the range [0, 1]. The value of α greatly affects the algorithmic speedup. If the selection of α is not suitable, this may lead to even slower algorithmic speedup in the RCFCM algorithm as the second largest membership after being suppressed disturbs the rank of the membership of pixel x_i to the *j-th* cluster. The rank of the membership of pixel x_i to the *j-th* cluster can be preserved only if the second largest membership after suppressed remains as the second largest membership in the rank. Hence, the selection of α is very crucial in the RCFCM algorithm.

2.3.2 Suppressed Fuzzy C-Means Algorithm

In view of the drawbacks of the RCFCM algorithm, the Suppressed FCM (SFCM) algorithm was introduced (Fan *et al*., 2003). By rewarding the largest membership and suppressing the others memberships, the SFCM algorithm does not disturb the rank of the membership of pixel x_i to the *j-th* cluster and hence successfully avoids the defect of the RCFCM algorithm. In the SFCM algorithm, the largest membership of pixel x_i to the *j-th* cluster is rewarded as shown in the following equation:

$$\mu_{ip}{}^{new} = 1 - \alpha + \alpha \mu_{ip}{}^{old} \tag{2.6}$$

while the others memberships of pixel x_i to the *j-th* cluster are suppressed as shown in the following equation:

$$\mu_{ij}^{new} = \alpha \mu_{ij}^{old}, j \neq p \tag{2.7}$$

where α is the control parameter and has the value in the range [0, 1] as in the RCFCM algorithm. Interestingly, the SFCM algorithm becomes the conventional Hard C-Means algorithm (HCM) if $\alpha = 0$. On the other hand, the SFCM algorithm takes on the form of conventional FCM algorithm if $\alpha = 1$. Therefore, the SFCM algorithm holds a balanced point between the conventional HCM algorithm and the conventional FCM algorithm. The SFCM algorithm can compromise the advantages of the HCM's fast algorithmic speedup and the FCM's good partition performance if the selection of α is reasonable. Hence, the determination of α will dominate the algorithmic speedup.

2.3.3 Fast Fuzzy C-Means Algorithm

The conventional FCM algorithm is computational intensive since it works on large number of individual image pixels. To combat the computational intensive facing by the conventional FCM algorithm, the Fast FCM (FFCM) algorithm was proposed (Bhoyar and Omprakash, 2010). Instead of working on large number of individual image pixels, the FFCM algorithm works on histogram bins as data elements. The number of histogram bins is always much less than the number of individual image pixels and hence the FFCM algorithm can overcome the computational intensive facing by the conventional FCM algorithm. In the FFCM algorithm, the objective function and the membership of pixel x_i to the *j-th* cluster are defined respectively as

$$W = \sum_{j=1}^{F} \sum_{i=1}^{n} \mu_{ij}{}^{m} \left\| v_i - c_j \right\|^2 \tag{2.8}$$

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{F} \left(\frac{\left\| v_i - c_j \right\|}{\left\| v_i - c_k \right\|} \right)^{\frac{2}{m-1}}} \tag{2.9}$$

and the cluster centres are defined as

$$c_j = \frac{\sum_{i=1}^{n} \mu_{ij}{}^{m} v_i}{\sum_{i=1}^{n} \mu_{ij}{}^{m}} \tag{2.10}$$

where n is the number of histogram bins and v_i is the *i-th* colour attribute in the histogram. In the FFCM algorithm, the cluster centres are iteratively updated until the minimization of the objective function is achieved.

2.3.4 L_p Norm Fuzzy C-Means Algorithm

It is well known that the conventional FCM algorithm is greatly affected by noise or imaging artefact. This is due to the fact that $\| x_i - c_j \|^2$ can place considerable weight on noise or imaging artefact. Thus, the cluster prototype is being pulled away from the main distribution of the cluster. As a result, the quality of the computed cluster centres can be degraded in the presence of noise or imaging artefact (Hathaway and Bezdek, 1994; Kersten, 1997). To reduce the effect of noise or imaging artefact on the computed cluster centres, the L_p Norm FCM (L_pNFCM) algorithm was introduced (Hathaway *et al*., 2000). Typical, the distance between x_i and c_j in the L_pNFCM algorithm is defined as

$$d_{ij} = \left\| x_i - c_j \right\|^p, p > 0 \tag{2.11}$$

The choice of p has considerable effect on the influence of noise or imaging artefact. For p = 2, the L_pNFCM algorithm takes on the form of the conventional FCM algorithm. Based on the experimental results, the L_pNFCM algorithm can increase the robustness to noise or imaging artefact for p = 1. Thus, in the L_pNFCM algorithm, the objective function and the membership of pixel x_i to the *j-th* cluster are defined respectively as

$$W = \sum_{j=1}^{F} \sum_{i=1}^{N} \mu_{ij}{}^{m} \left\| x_i - c_j \right\| \tag{2.12}$$

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{F} \left(\frac{\left\| x_i - c_j \right\|}{\left\| x_i - c_k \right\|} \right)^{\frac{1}{m-1}}} \tag{2.13}$$

Thus, the L_pNFCM algorithm has been proven to be capable of providing better performance in the presence of noise or imaging artefact compared to the conventional FCM algorithm.

2.3.5 Anisotropic Mean Shift based Fuzzy C-Means Algorithm

Mean Shift (MS) algorithm has been proven to be capable of estimating the local density gradients of similar pixels. The gradient estimate is iteratively performed so that all pixels can find similar pixels in the image (Comaniciu and Meer, 2002). Unfortunately, the temporal coherence will be reduced in the presence of noise or imaging artefact as the MS algorithm uses radially symmetric kernel. The reduced coherence may not be properly detected by radially symmetric kernel and thus the Anisotropic Mean Shift (AMS) algorithm was proposed. The AMS algorithm is intended to modulate the kernel during the procedure of the MS algorithm and its objective is to keep reducing the Mahalanobis distance so as to group similar pixels as much as possible although in the presence of noise or imaging artefact (Wang *et al*., 2004).

To reduce the effect of noise or imaging artefact on the conventional FCM algorithm, the Anisotropic Mean Shift based FCM (AMSFCM) algorithm was proposed by incorporating the AMS algorithm within the conventional FCM algorithm (Zhou *et al*., 2009). The success of the AMSFCM algorithm is due to the fact that the anisotropic kernel allows the algorithm to dynamically update the state parameters and achieve fast convolution by the anisotropic kernel function. Thus, the AMSFCM algorithm can also help to overcome the computational intensive facing by the conventional FCM algorithm.

2.4 Initialization Schemes to Conventional Fuzzy C-Means Algorithm

Several modifications to the conventional FCM algorithm have been proven to be capable of increasing the algorithmic speedup, the improvement of clustering performance with respect to noise or imaging artefact, or both as shown in Table 2.1. But they are still very sensitive to the initialization conditions of number of clusters and initial cluster centres.

Table 2.1 Targets of modifications to conventional FCM algorithm

	Algorithmic Speedup	Improvement of Clustering Performance with respect to Noise or Imaging Artefact
RCFCM	√	×
SFCM	√	×
FFCM	√	×
L_pFCM	×	√
AMSFCM	√	√

(Note: √ represents YES while × represents NO)

As a result, several initialization schemes for the conventional FCM algorithm have been proposed to overcome the sensitiveness of the conventional FCM algorithm to the initialization conditions. There are three most popular initialization schemes as reported by Bezdek (1999), which can be described as follow:

1. Using F image pixels randomly selected from the image

2. Using the first F distinct image pixels in the image

3. Using F image pixels uniformly distributed across the image

Among these initialization schemes, using F image pixels randomly selected from the image has been proven to be the best initialization scheme because it ensures the conventional FCM algorithm to converge (Khan and Ahmad, 2004). This initialization scheme is well known as randomly initialization. However, the optimal number of clusters must be given by the users in this initialization scheme.

In view of the difficulties in determining the optimal number of clusters, two conventional initialization schemes namely the Agglomerated Just Noticeable Difference Histogram (AJNDH) and the Ant Colony Optimization (ACO) has been proposed recently. They are the only two initialization schemes that have been proven to be capable of automatically determining the optimal number of clusters as well as obtaining the initial cluster centres in the colour images. As a result, the AJNDH and the ACO initialization schemes are selected to be discussed due to their superior capability to initialize the conventional FCM algorithm for colour image segmentation. Thus, the workings of these initialization schemes will be examined.

2.4.1 Agglomerated Just Noticeable Difference Histogram

In the Agglomerated Just Noticeable Difference Histogram (AJNDH) initialization scheme (Bhoyar and Omprakash, 2010), the Just Noticeable Difference (JND) histogram is constructed by forming a table of size $n \times 4$, where n indicates the number of histogram bins for the colour image, as shown in Table 2.2. Out of the four columns, first three columns are used to store the RGB value of a colour and the last column is used to store the frequency of that colour. In the JND histogram, the number of histogram bins represents the number of colours in the colour image.

Table 2.2 JND histogram structure

RGB value of colours			Frequency, F
R	G	B	
R_1	G_1	B_1	F_1
.	.	.	.
.	.	.	.
R_n	G_n	B_n	F_n

In the JND histogram, all colours are at least one JND away from each others as the human eye can only discriminate between two colours perceptually if they are at least one JND away from each others. In this context, one JND is defined as the smallest difference between two colours that human eye can detect perceptually. Thus, the number of colours is much less than the number of unique colours in the colour image. This drastic reduction in the number of unique colours in the colour image brings it to the range suitable for machine analysis in real time. But, the actual value of one JND in term of colour coordinates may not be constant over the RGB colour space due to non-linearity of the human vision and the non-uniformity of the RGB colour space (Chang *et al*., 2000).

To derive approximate value of one JND in term of colour coordinates, the RGB colour space is mapped on to a new colour space $J_r J_g J_b$ where J_r, J_g and J_b are three orthogonal axes which represent the JND on respective R, G and B axes. The value of J on each of the colour axes vary in the range [0, 24], [0, 28] and [0, 26] respectively for red, green and blue colours based on the physiological knowledge. From the physiological knowledge, the red cones in the human retina are least sensitive, the green cones are most sensitive and the blue cones are moderately sensitive (Bhurchandi *et al*., 2000). Thus, in the new colour space J_r J_g J_b, the red, green and blue axes have been quantized in 24 levels, 28 levels and 26 levels respectively. This new space is a perceptually uniform space and offers the advantages of the uniform spaces in image analysis.

Two types of JND are involved in the human vision system as stated in the research in physiology of human eye. One is the JND of the human eye referred to as JND_{eye} and the other is the JND of the human perception referred to as JND_h. It is found that the neural network in the human eye is more powerful and can distinguish more colours than those perceived by the human brain (Bhurchandi *et al*. 2000). The approximate relationship between these two types of JND is defined as

$$JND_h = 3 \times JND_{eye} \tag{2.14}$$

By calculating the Euclidean distance between any colours and its immediate JND neighbour in the new quantized space, the approximate value of one JND_{eye} in term of RGB colour coordinates can be obtained as

$$JND_{eye} = 17.09 \tag{2.15}$$

Hence, the approximate value of one JND_h in term of RGB colour coordinates can be obtained as

$$JND_h = 3 \times 17.09 = 51.27 \tag{2.16}$$

In the AJNDH initialization scheme, this approximate value of one JND_h in term of RGB colour coordinates is used to compute the JND histogram. The general procedure to compute the JND histogram can be described as follow:

i. Initialize the first entry in Table 2.2 by the first pixel colour in the image and the frequency of that entry is set to one. Set the histogram binning threshold, $\Theta_1 = JND_h = 51.27$.

ii. Read the next pixel colour in scan line order.

iii. Compare the new pixel colour with all the previous entries in Table 2.2 respectively and accommodate the pixel in the respective bin if it is found similar to any of them using Θ_1. Otherwise, increase the row index of Table 2.2, enter that pixel colour in it and set its frequency to one.

iv. Repeat Steps *ii* to *iii* for all the pixels in the image.

In the AJNDH initialization scheme, the agglomeration technique is further used to reduce the number of colours in the JND histogram by combining the smaller colour segments to the larger colour segments which are similar. To implement the agglomeration technique, an agglomeration threshold, Θ_2 which is slightly greater than Θ_1, is used. Typically, $\Theta_2 = 52.23$ works well in the AJNDH initialization scheme. The general procedure of the agglomeration technique can be described as follow:

i. Sort Table 2.2 in descending order of frequency.

ii. Compare the first colour with the next colour in Table 2.2. Merge the smaller colour segment to the larger colour segment if the frequency of the smaller colour segment is less than 0.1% of the total number of image pixels and found similar with Θ_2. Otherwise, go to Step *vi*.

iii. Update Table 2.2 by adding the frequency of the smaller colour segment to the larger colour segment.

iv. Remove the merged entry from Table 2.2.

v. Reduce the number of rows in Table 2.2 by one.

vi. Compare the first colour with every remaining colour in Table 2.2 and repeat *Steps ii* to *v* if the frequency of the smaller colour segment is less than 0.1% of the total number of image pixels and found similar with Θ_2.

vii. Repeat Steps *ii* to *vi* for every colour in Table 2.2 until Table 2.2 does not further reduce.

In the AJNDH initialization scheme, the number of colour segments having their frequency more than the average frequency of the colour segments in the completely agglomerated JND histogram is used as the optimal number of clusters to be created for the conventional FCM algorithm. In this initialization scheme, the initial membership for every image pixels to the initial cluster centres is provided to initialize the conventional FCM algorithm. The general procedure to perform colour image segmentation can be described as follow:

i. Find out the average frequency of colour segments in the completely agglomerated JND histogram.

ii. Obtain the initial cluster centres of the conventional FCM algorithm from the colour segments having their frequency more than the average frequency.

iii. Initialize the membership for every image pixels to the initial cluster centres by the following equation:

$$\mu_{ij} = \frac{1}{1 + \lambda \left\| x_i - c_j \right\|^2} \tag{2.17}$$

where λ is an arbitrary constant in the range [0, 1] and is used to control the dependence of the membership on the distance between pixel x_i and centre c_j.

iv. Set the iteration time $q = 0$ and initialize the objective function, $W^{(q)}$ according to Equation 2.1.

v. Repeat Steps *ii* to *iv* of the conventional FCM algorithm as shown in Section 2.2 if $\| W^{(q)} - W^{(q-1)} \| \geq \varepsilon$. Otherwise, stop iteration.

2.4.2 Ant Colony Optimization

In the Ant Colony Optimization (ACO) initialization scheme (Yu *et al.*, 2010), the improved Ant System (AS) is introduced based on the modifications to the conventional AS. Instead of the computation among all image pixels in the conventional AS, the improved AS transforms it into the computation between the image pixels and the cluster centres. Thus, the computational complexity of the