Fuzzy C - Means based Automatic Reference Color Selection of an Image

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Abstract: Here we propose a fuzzy c-means automatic reference color selection of an image for the adaptive mathematical morphology (MM) method, and is specifically designed for color image segmentation applications. Because of the main advantages of being simple, in the past decade, it has contributed to the growing popularity of binary and gray-scale MM processing. However, the MM process typically neglects the details of reference color determination. Applying other ordering methods, which select only black as the reference color for sorting pixels, result in the problem in which the scope of the distance measurement is not optimal. The proposed Fuzzy c-means algorithm is used for determining the ideal reference color for MM and color image segmentation application and can be used for cluster based color segmentation. Due to this segmentation rate will be comparatively higher.

Index Terms—Adaptive mathematical morphology; Color image segmentation; Kernel density estimation; Reference color selection; Region growing; Region merging.

I. INTRODUCTION

Image segmentation is a necessary first process in image analysis and computer vision by correctly classifying the pixels of an image in decision-oriented applications. The essential goal of image segmentation is to partition an image into uniform and homogeneous attribute regions based on some likeness measure. Due to the variety and complexity of images, image segmentation is still a very challenging research topic. Various techniques have been introduced for object segmentation and feature extraction. Basically, segmentation approaches for images are based on the discontinuity and similarity of image intensity values. Discontinuity is an approach which partitions an image based on abrupt changes. According to the predefined criteria, the similarity approach is based on partitioning an image into similar regions. Researchers have proposed a variety of techniques to tackle the challenging problem of image segmentation. In general, the image segmentation can be divided into four different categories i.e., thresholding, edge detection, region extraction, and clustering. Image segmentation is one important process in image analysis and computer vision and is a valuable tool that can be applied in fields of image processing, health care, remote sensing, and traffic image detection. Given the lack of prior knowledge of the ground truth, unsupervised learning techniques like clustering have been largely adopted. Fuzzy clustering has been widely studied and successfully applied in image segmentation. In situations such as limited spatial resolution, poor contrast, overlapping intensities, and noise and intensity in homogeneities, fuzzy clustering can retain much more information than the hard clustering technique. Most fuzzy clustering algorithms have originated from fuzzy c-means (FCM) and have been successfully applied in image segmentation. However, the cluster prototype of the FCM method is hyper spherical or hyper ellipsoidal. FCM may not provide the accurate partition in situations where data consists of arbitrary shapes. Therefore, a Fuzzy C-Regression Model (FCRM) using spatial information has been proposed whose prototype is hyper planar and can be either linear or nonlinear allowing for better cluster partitioning. Thus, this paper implements FCRM and applies the algorithm to color segmentation using Berkeley’s segmentation database. The results show that FCRM obtains more accurate results compared to other fuzzy clustering algorithms.

A. Marginal ordering (M-ordering):

The M-ordering method, as shown in Fig. 1(a), ranks each component of channels individually, and ignores any interrelationship between channels. In an example of the M-ordering morphological erosion process, a ring-like junction with false colors emerges between the inside circle and the geometric shape, as shown in Fig. 2(b). This frequently results in the appearance of a false color, meaning that this new color is absent in the original image. This type of method is thus evidently inefficient and infeasible for use.
Zhao [17] proposed a modified M-ordering method, which considered each feature of a channel for sorting their sequential order to avoid the generation of a false color.

**Fig1.** color morphological processing. (a) Marginal ordering, (b) vectorized ordering.

### B. Reduced ordering (R-ordering):
The R-ordering approach is the most general ranking method and is based on the dimension reduction algorithm for mapping high-dimensional data onto low-dimensional data. The rank comparison is subsequently used for measuring the ordering relationship. The most popular methods using the R-ordering approach are distance mapping and principle component analysis. The authors in [18] introduced a vector median filter and a basic vector directional filter based on two R-ordering methods, and applied them to a color image. These filters enabled the system to reduce noise and maintain valid color information. The authors in [19] proposed a hyper spectral image processing application based on supervised R-ordering. The advantage of the R-ordering approach is the ability to perform a morphological operation in reduced dimensions, which lowers the computational complexity. Nevertheless, this dimension reduction leads to color information loss, and generates ambiguous conditions during the rank comparison process. For example, the two color pixels $p$ and $q$ are in a hue–saturation–intensity (HSI) color space. To compute the distances from the color pixels to the reference color, comprises and respectively; thus, we obtained . As shown in Fig. 3, we may encounter ambiguous conditions when the order judgment is applied for these two color pixels, consequently reducing the confidence of order ranking and increasing the probability of an improper color assignment.

### C. Conditional ordering (C-ordering):
The C-ordering method, also known as lexicographic ordering, is based on a specific condition for comparing the component of a feature vector, which sets priorities between changes, and compares the order of each component in a stepwise manner. This approach enables the system to entirely avoid ambiguous conditions that are generated by the sequential comparison error. However, this ordering method requires the comparison of each channel, resulting in relatively high computational complexity. Fig. 4 shows an example of lexicographic ordering, where each color vector of the structural elements is sorted according to the values. For the mechanism, the comparative order of the subjects is as follows: 1) Identify the values of the red component; 2) when the values of the red component are equal, compare the values of the green component; and 3) when the values of the green component are equal, compare the values of the blue component. Aptoula and Lefèvre [20] reported the merits and disadvantages of this type of method, and applied it in the morphological processing of color image noise reduction and color texture classification, and obtained satisfactory results.

**Fig 2.** R-Ordering

### D. Partial ordering (P-ordering):
The P-ordering approach [21] is a clustering-based scheme for which a vector partitioning approach is used. By using the information of the clusters, this approach allows the system to conduct ordering according to the weight of the vector and its extremeness. Evans [22] proposed a novel ranking method based on the P-ordering scheme, which ranked each pair of vectors in groups of a higher or lower order. It is efficient for simply reducing vector-ranking complexity. This type of methodology basically compares the rank relationship of each pair of vectors, and is thus called "pairwise vector ordering."

**II. Fuzzy C-MEANS**

**Fuzzy C-Means Clustering:**
Fuzzy clustering has been widely studied and successfully applied in image segmentation. In situations such as limited spatial resolution, poor contrast, overlapping intensities, noise, and intensity in homogeneities, fuzzy clustering can retain much more information than the hard clustering technique. Among the fuzzy clustering methods, fuzzy c-means (FCM) is one of the most popular methods. FCM classifies an image into different clusters using an iterative method. The image is represented in various feature spaces, and FCM groups similar data points that are dependent on
the distance of the pixels to the centroids in the feature domain.

Clustering, a major area of study in the scope of unsupervised learning, deals with recognizing meaningful groups of similar items. Under the influence of fuzzy logic, fuzzy clustering assigns each point with a degree of belonging to clusters, instead of belonging to exactly one cluster. In fuzzy event modeling, pixel colors in a dermoscopy image can be viewed as probability space where the pixels with some colors can belong partially to the background class and/or the skin lesion. The main advantage of this method is that, it does not require a priori knowledge about number of objects in the image.

Clustering is a process that can classify the objects or patterns into a predefined number of clusters such that the objects within a cluster have similar properties. In general, clustering methods can be divided into hierarchical and partitional approaches. Hierarchical algorithms produce a nested series of partitions while partitional algorithms produce only one partition. Due to the fact that construction of a dendrogram is computationally expensive, partitional algorithms have gained more attention in image segmentation. Partitional algorithms include two main clustering strategies the hard clustering scheme and the fuzzy clustering scheme. The conventional hard clustering methods classify each object to only one cluster. As a consequence, the results are crisp. On the other hand, fuzzy clustering allows the objects to belong to two or more clusters with varying degrees of membership. Fuzzy clustering plays a significant role in various problems such as feature analysis, systems identification, and classification due to the ability of handling impreciseness, uncertainty, and vagueness for real-world problems.

Fuzzy C-Means Algorithm (FCM):
Fuzzy C-Means (FCM) clustering algorithm is one of the most popular fuzzy clustering algorithms. FCM is based on minimization of the objective function $F_m(u, c)$:

$$F_m(u, c) = \sum_{j=1}^{n} \sum_{k=1}^{c} u_{jk}^m \| x_j - c_k \|^2$$

FCM computes the membership $u_{ij}$ and the cluster centers $c_j$ by:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left( \frac{\| x_j - c_k \|^2}{\| x_j - c_j \|^2} \right)^{\frac{m}{2}}}$$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m x_i}{\sum_{i=1}^{N} u_{ij}^m}$$

where $m$, the fuzzification factor which is a weighting exponent on each fuzzy membership, is any real number greater than 1, $u_{ij}$ is the degree of membership of $x_i$ in the cluster $j$, $c_j$ is the $j$th of $d$-dimensional measured data, $d$ is the dimension center of the cluster, $d^2(x_j, c_j)$ is a distance measure between object $x_j$ and cluster center $c_j$, and $\| \cdot \|$ is any norm expressing the similarity between any measured data and the center.

The FCM Algorithm involves the following steps:

1. Set values for $c$ and $m$
2. Initial membership matrix $U^0 = [u_{ij}]$, which is $U^0$ ((i = number of members, $|j|$ = number of clusters))
3. At $k$-step: calculate the centroids for each cluster through equation (2) if $k \neq 0$. (If $k=0$, initial centroids location by random)
4. For each member, calculate membership degree by equation (1) and store the information in $U^{(k)}$
5. If the difference between $U^{(k)}$ and $U^{(k+1)}$ less than a certain threshold, then STOP; otherwise, return to step.

The FCM clustering is obtained by minimizing an objective function shown in equation:

$$A = \sum_{i=1}^{n} \sum_{k=1}^{c} u_{ik}^m (p_i - v_k)^2$$

Where:
- $A$ is the objective function.
- $n$ is the number of pixels in the image $E$.
- $c$ is the number of clusters.
- $\mu$ is the fuzzy membership value.
- $m$ is a fuzziness factor (a value > 1).
- $p_i$ is the $i$th pixel in $E$.
- $v_k$ is the centroid of the $k$th cluster.
- $|p_i - v_k|$ is the Euclidean distance between $p_i$ and $v_k$ defined by equation:

$$|p_i - v_k| = \sqrt{\sum_{i=1}^{n} (p_i - v_k)^2}$$

The calculation of the centroid of the $k$th cluster is achieved using equation:

$$v_k = \frac{\sum_{i=1}^{n} u_{ik}^m p_i / \sum_{i=1}^{n} u_{ik}^m}{\sum_{i=1}^{n} u_{ik}^m}$$

The fuzzy membership is calculated using the original equation.

Image Segmentation Based Fuzzy C-Means Algorithm:
The FCM algorithm try to minimizes the objective function with related to membership functions and the centroids. The FCM algorithm assigns input pixels to the fuzzy clusters without labeling. Unlike hard clustering techniques like k-means clustering technique which enforce input pixels to belong absolutely to one class, the FCM permits input pixels
to belong to the multiple clusters with variable degrees of the membership value. Hence, Because of flexibility, The FCM is a soft segmentation algorithm which recently has been utilized for images segmentation applications.

The steps of FCM algorithm are as follows:
1. Initialize the number of clusters c.
2. Select an inner product metric Euclidean norm and the weighting metric (fuzziness).
3. Initialize the cluster prototype.
4. Then calculate the partition matrix.
5. Update the fuzzy cluster centers

Structure of FCM Algorithm:

A clustering method that involves in minimizing some objective function belongs to the groups objective function algorithms. When the algorithm is able to minimize an error function, it is often called C-Means being c the number of classes or clusters, and if the used classes are using the fuzzy technique or simply fuzzy, then it is known to be FCM. The FCM approach uses a fuzzy membership which assigns a degree of membership for every class. The importance of degree of membership in fuzzy clustering is similar to the pixel probability in a mixture. The benefit of FCM is the formation of new clusters from the data points that have close membership values to existing classes. Basically, there are three basic operators in FCM method: the fuzzy membership function, partition matrix and the objective function.

III. ALGORITHM IMPLEMENTATION

1. Image enhancement techniques:
Image enhancement improves the quality of images for human perception by removing noise, reducing blurring, increasing contrast and providing more detail. This section will provide some of the techniques used in image enhancement.

2. Histogram processing:
Histogram processing is used in image enhancement and can be useful in image compression and segmentation processing. A histogram simply plots the frequency at which each grey-level occurs from 0 (black) to 255 (white). Scanned or captured images may have a limited range of colours, or are lacking contrast (details). Enhancing the image by histogram processing can allow for improved detail, but can also aid other machine vision operations, such as segmentation. Thus, histogram processing should be the initial step in preprocessing. Histogram equalization and histogram specification (matching) are two methods widely used to modify the histogram of an image to produce a much better image.

3. Noise removal:
The advancements in technology produced image acquisition devices with better improvements. While modern technology has made it possible to reduce the noise levels associated with various electro-optical devices to almost negligible levels, there are still some noise sources which cannot be eliminated. Images acquired through modern sensors may be contaminated by a variety of noise sources. By noise we refer to stochastic variations as opposed to deterministic distortions, such as shading or lack of focus. There are different types of noise that are related to the electronic capturing devices or the light source used such types of noise are photon, thermal, On-Chip electronic and quantization. Most of the noise may be eliminated by the capturing sensors or the CCD cameras. Document analysis systems benefit from the reduction of noise in the preprocessing stage this can provide a substantial improvement in the reliability and robustness of the feature extraction and recognition stages of the OCR system. A common manifestation of noise in binary images takes the form of isolated pixels, salt-and-pepper noise or speckle noise, thus; the processing of removing this type of noise is called filling, where each isolated pixel salt and pepper
“island” is filled in by the surrounding “sea” (O’Gorman, et al., 2008). In greylevel images or median filters and low-pass filters such as average or Gaussian blur filters proved to eliminate isolated pixel noise. Gaussian blur and average filters are a better choice to provide smooth texture to the image. On the other hand, periodic noise which manifests itself as impulse-like bursts which often are visible in the Fourier spectrum can be filtered using notch filtering.

**Color Space Conversion:**

Color space also known as the color model (or color system), is an abstract mathematical model which simply describes the range of colors as tuples of numbers, typically as 3 or 4 values or color components (e.g. RGB). YCbCr is Digital. MPEG compression, which is used in DVDs, digital TV and Video CDs, is coded in YCbCr, and digital camcorders (MiniDV, DV, Digital Betacam, etc.) output YCbCr over a digital link such as FireWire or SDI. The ITU-R BT.601 standard for digital video defines both YCbCr and RGB color spaces.

**Kernel Density Estimation (KDE):**

In statistics, kernel density estimation (KDE) is a non-parametric way to estimate the probability density function of a random variable. Kernel density estimation is a fundamental data smoothing problem where inferences about the population are made, based on a finite data sample. The kernel is the essential center of a computer operating system, the core that provides basic services for all other parts of the operating system. A synonym is nucleus. A kernel can be contrasted with a shell, the outermost part of an operating system that interacts with user commands.

**Density Estimation:**

In probability and statistics, density estimation is the construction of an estimate, based on observed data, of an unobservable underlying probability density function.

**Pixel Bin Position:**

Pixel Binning Image sensors, which are in essence transducers, convert photons into electrical signals. As the photons fall onto the surface of the image sensors, electrons accumulate in each pixel. Once the exposure is finished, the charges are transferred to the output and digitized. Most image sensors have the ability to combine multiple pixel charges with one single large pixel, which represents all the individual pixels contributing to the charge. This is referred to as binning. No-binning or 1x1 binning means the individual pixels are retained. With 2 x2 binning, four adjacent pixels are binned into one larger pixel and read out. With this option, the light sensitivity is increased four times from the four-pixel contribution; however, the image resolution is reduced by half. The diagram in Fig. 1 illustrates the pixel-binning process for no-binning, 2 x2 binning, and 3 x3 binning.

**1-Level KDE:**

This is possibly one of the most widely used and most simple method to adjust an image. It’s so simple and effective that you will want to use it on all your pictures from now on, so keep an eye on this, and have fun. This is meant to be a brief, practical introduction to the discrete wavelet transform (DWT). Therefore, this document is not meant to be comprehensive, but does include a discussion on the following topics:

1. Qualitative discussion on the DWT decomposition of a signal;
2. Procedure for computing the forward and inverse DWT;
3. The 2D DWT.

**DWT Decomposition:**

In Fourier analysis, the Discrete Fourier Transform (DFT) decompose a signal into sinusoidal basis functions of different frequencies. No information is lost in this transformation; in other words, we can completely recover the original signal from its DFT (FFT) representation. In wavelet analysis, the Discrete Wavelet Transform (DWT) decomposes a signal into a set of mutually orthogonal wavelet basis functions. These functions differ from sinusoidal basis functions in that they are spatially localized – that is, nonzero over only part of the total signal length. Furthermore, wavelet functions are dilated, translated and scaled versions of a common function \( \phi \) known as the mother wavelet. As is the case in Fourier analysis, the DWT is invertible, so that the original signal can be completely recovered from its DWT representation. Unlike the DFT, the DWT, in fact, refers not just to a single transform, but rather a set of transforms, each with a different set of wavelet basis functions. Two of the most common are the Haar wavelets and the Daubechies set of wavelets. For example, Figures 1 and 2 illustrate the complete set of 64 Haar and Daubechies-4 wavelet functions (for signals of length 64), respectively. Here, we will not delve into the
details of how these were derived; however, it is important to note the following important properties:

1. Wavelet functions are spatially localized;
2. Wavelet functions are dilated, translated and scaled versions of a common mother wavelet; Each set of wavelet functions forms an orthogonal set of basis functions.

**DWT in one dimension:**

In this section, we describe the algorithm for computing the one-dimensional DWT and its inverse.

**i) Forward DWT:**
The (one-dimensional) DWT operates on a real-valued vector \( x \) of length \( 2n \), \( n \in \{2, 3, \ldots\} \), and results in a transformed vector \( w \) of equal length. The first two steps of the DWT for a vector of length 16. First, the vector \( x \) is filtered with some discrete-time, low-pass filter (LPF) \( h \) of given length (in the Figures, we use length four for illustration purposes) at intervals of two, and the resulting values are stored in the first eight elements of \( w \). Second, the vector \( x \) is filtered with some discrete-time, high-pass filter (HPF) \( g \) of given length (again, for illustration purposes, we use a filter of length four) at intervals of two, and the resulting high-pass values are stored in the last eight elements of \( w \).

**ii) Inverse DWT:**
To understand the procedure for computing the one-dimensional inverse DWT, consider Fig.5, where we illustrate the inverse DWT for a one-level DWT of length 16 (assuming filters of length four). Note that the two filters are now \( h^{-1} \) and \( g^{-1} \) where, and \( g^{-1} \) is determined from \( h^{-1} \). To understand how to compute the one-dimensional inverse DWT for multi-level DWTs, consider Figure 4. First, to compute \( w_2 \) from \( w_3 \), the procedure in Figure 5 is applied only to values \( L_3 \) and \( H_3 \). Second, to compute \( w_1 \) from \( w_2 \), the procedure in Figure 5 is applied to values \( L_2 \) and \( H_2 \). Finally, to compute \( x \) from \( w_1 \), the procedure in Figure 5 is applied to all of \( w_1 \) – namely, \( L_1 \) and \( H_1 \).

**iii) DWT in two dimensions:**
In this section, we describe the algorithm for computing the two-dimensional DWT through repeated application of the one-dimensional DWT. The two-dimensional DWT is of particular interest for image processing and computer vision applications, and is a relatively straightforward extension of the one-dimensional DWT discussed above.

**IV. EXPERIMENTAL RESULTS**

Thus, to achieve this, first we take the original image which is shown in Fig.6, and then do the preprocessing. In preprocessing, some image enhancement techniques to remove noise or correct the contrast in the image, second, thresholding to remove the background containing any scenes, watermarks and/or noise, third, page segmentation to separate graphics from text, fourth, character segmentation to separate characters from each other and, finally, morphological processing to enhance the characters in cases where thresholding and/or other preprocessing techniques eroded parts of the characters or added pixels to them.

In image processing filters are used to suppress either the high frequencies in the image, i.e. smoothing the image, or the low frequencies, i.e. enhancing or detecting edges in the image. An image can be filtered either in the frequency or in the spatial domain shown in Fig.8.

An adaptive background subtraction method based on kernel density estimation was presented. The background is modeled as a probabilistic model by kernel density estimation. To reduce the computational complexity and memory requirements, we modified the original kernel density estimation method and modified the updating method. This method automatically adapts to the environment as time progresses and it can reduce the complexity compared with original KDE approach method.
The image segmentation is proposed based on mean shift algorithm and normalized cuts algorithm. The normalized cuts algorithm gives good accuracy and better segmentation compared to all most of the existing methods. But it requires high computational power, also it takes huge time. The reason for this is it takes entire image as one matrix and computes.

By using mean shift algorithm on the original image to partition it into sub graphs we can create image matrices with lower dimensions. The proposed algorithm is applied mean shift algorithm to obtain sub graphs. The normalized cuts algorithm is applied on the sub graphs. The experimental results also show that the results obtained by the proposed algorithm are better than results obtained by individual algorithms of mean shift, normalized cuts.

An incorporating the advantages of the mean shift segmentation and the normalized cut (Ncut) partitioning methods, the proposed method preprocesses an image by using the mean shift algorithm an image by using the mean shift algorithm to form segmented regions, we use region nodes instead of these regions, then use the Ncut method for region nodes clustering. In many literatures, the Ncut method is applied directly to image pixels. This result shows the cluster performance for the experimental figure. In this result, the graph indicates performance analysis of different methods like morpho, morpoptimi, mathematical morphology, proposed method fuzzy c-means, with respect to noise level (variance).

This result shows the Gen Color Performance for the experimental figure. In this result, the graph indicates performance analysis of different methods like morpho, morpoptimi, mathematical morphology, proposed method fuzzy c-means with respect to noise level (variance).

This result shows the Opt Autoref Performance for the experimental figure. In this result, the graph indicates performance analysis of different methods like morpho, morpoptimi, mathematical morphology, proposed method fuzzy c-means with respect to noise level (variance).
V. CONCLUSION

Traditional FCM algorithm based pixel attributes lead to accuracy degradation. But in this THESIS, we have implemented an efficient approach for the segmentation of noisy images. The proposed approach made use of histogram based Fuzzy C-Means clustering with denoising & spatial probability for the segmentation of noisy images, which will give better segmentation accuracy. The incorporation of spatial probability into the objective function of FCM has improved segmentation accuracy. The denoising of noisy images before to segmentation has been found robust against various noise levels. The denoising of noisy images prior to segmentation with the aid of sparse 3D transform domain collaborative filtering strategy has further improved the robustness of the approach. The experimentation with synthetic and real images has demonstrated the efficiency and robustness of the proposed approach in segmenting noisy images. It was observed that as the numbers of clusters were increased there was a decline in segmentation accuracy values.

FCM method is very popular and been widely used in various application domains. So, FCM can be a dynamic method for the new challenging application areas. It can be concluded that FCM has been widely used in different Image analysis applications than the other application areas. It is suggested that, diverse applications like cognitive science, physiology etc.

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