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Advanced FCM Algorithm for Segmentation

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Abstract— ***An advanced FCM Algorithm is introduced to segment the image which is affected by noise, outliers or any other artifacts. In order to segment those images this algorithm is introduced. By using this algorithm both noise can be removed and the segmentation can be made efficiently. The trade-off weighted fuzzy factor and kernel distance measure are both used in the introduced algorithm and both are parameters free. By using the fuzzy factor, the damping extent of the neighbouring pixels can be estimated accurately. The experimental results also show that the algorithm is effective and efficient and it is independent of the type of the noises.***

Index Terms— ***Fuzzy clustering , gray-level constraint, image segmentation, kernel metric, spatial constraint.***

I. INTRODUCTION

Image segmentation is commonly used key techniques in image representation of the digital images. The task of image segmentation is to divide an image into a number of non-overlapping regions, which have same characteristics such as gray level, colour, tone, texture, etc. A lot of clustering based methods have been proposed for image segmentation [1]–[5]. Among the clustering methods, one of the most popular methods for image segmentation is fuzzy clustering, which can retain more image information than hard clustering in some cases.

Fuzzy c-means (FCM) algorithm is one of the most widely used fuzzy clustering algorithms in image segmentation. FCM algorithm was first introduced by Dunn [6] and later extended by Bezdek [7]. Although the conventional FCM algorithm works well on most noise-free images, it fails to segment images corrupted by noise, outliers and other imaging artifacts. Its non-robust results are mainly because of ignoring spatial contextual information in image and the use of non-robust Euclidean distance.

To deal with the first problem, many improved FCM algorithms have been proposed by incorporating local spatial information into original FCM objective function [8]–[12].Ahmed et al. [8] proposed FCM_S, which modified the objective function of FCM by introducing the spatial neighbourhood term. One drawback of FCM_S is that the spatial neighborhood term is computed in each iteration step, which is very time-consuming. To reduce the computational complexity of FCM_S, Chen and Zhang [9] proposed two variants,FCM_S1 and FCM_S2, which replace the neighborhood term of FCM_S by introducing the extra mean-filtered image and median-filtered image, respectively.

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The mean-filtered image and median-filtered image can be computed in advance, so the computational costs can be reduced. To speed up the image segmentation process, Szilagyi et al.

[10] proposed the enhanced FCM (EnFCM), which form a linearly-weighted sum image from both the local neighbourhood average gray level of each pixel and the original image, and then clustering is performed on the basis of the gray level histogram of summed image. Thus, the computational time of EnFCM is very small. Cai et al. [11] proposed the fast generalized FCM (FGFCM) algorithm. This method introduces a local similarity measure that combines both spatial and gray level information to form a non-linearly weighted sum image. Clustering is performed on the basis of the gray level histogram of the summed image.

Thus, its computational time, similar to EnFCM, is also very small. However, these algorithms do not directly apply on the original image. They need some parameters a (or λ) to control the trade-off between robustness to noise and effectiveness of preserving the details. The selection of these parameters is not an easy task, and has to be made by experience or by using the trial-and-error method.

To overcome the above mentioned problems, Stelios et al. [1] presents a novel robust fuzzy local information c-means clustering algorithm (FLICM), which is free of any parameter selection, as well as promoting the image segmentation performance. In FLICM, a novel fuzzy factor is defined to replace the parameter a used in above algorithms and its variants. More recently, we [12] proposed a variant of FLICM algorithm (RFLICM), which adopts the local coefficient of variation to replace the spatial distance as a local similarity measure. Furthermore, it presents a more robust result. Although RFLICM algorithm can exploit more local context information to estimate the relationship of pixels in neighbors since the local coefficient of variation, it is still unreasonable to ignore the influence of spatial constraint on the relationship between central pixel and pixels in neighbors.

Hence, in this study, one of our motivations is to design a trade-off weighted fuzzy factor for adaptively controlling the local spatial relationship. This factor depends on space distance of all neighbor pixels and their gray level difference simultaneously. In order to further improve the performance of FLICM in restraining noise, another novelty in this study is introducing the kernel distance measure to its objective function. In recent years, kernelmethods have received an enormous amountof attention in machine learning community.

Its main ideais to transform complex nonlinear problems in original lowdimensional feature space to the problems easily solved in the transformed space. Typical examples are support vector machines (SVM) [13], [14] kernel principle component analysis (KPCA) [15] and kernel perceptron algorithm [16].

Particularly, the clustering algorithms based on the kernel methods have been shown to be robust to the outliers or noises of the dataset [17]. So, the clustering algorithms based on kernel methods have been applied to many fields of image segmentation [18]–[21].

Because of this advantage, Zhang et al. [21] introduced a new kernel-induced distance measure for the original data space into the objective function of FCM (KFCM) to replace the conventional measures.Meanwhile, a penalty term takes into account the influence the neighboring pixels on the central pixel. It is shown to be more robust to noise and the outlier in image segmentation than the algorithms without the kernel substitution.

However, as mentioned above, this penalty term must be computed in each iteration step, which is very time-consuming. Therefore, Chen et al. [9] also proposed two variants of KFCM, which replace this term using the mean filtered (KFCM_S1) or median-filtered (KFCM_S2) image to reduce the computational cost. In general, the Gaussian RBF (GRBF) kernel [9] is adopted in the kernel function for its facility. But the parameter σ in GRBF has a great influence on the performance of the algorithm. Therefore, we use a fast bandwidth selection rule, which can adaptively compute the parameter σ.

The rest of this paper is organized as follows. In the next section, the main ideas of the proposed approach and our motivation will be introduced. Section III will describe the proposed algorithm in details. In Section IV, experimental results on synthetic images, medical images and natural images will be described. Conclusions will be drawn in section V.

II. MOTIVATION

Let us consider an image be composed of N points, each point i ∈ _ having a given value (gray-level) xi. Let us suppose that this image has to be segmented into c (c ≥ 2) classes. In the FCM approach, the segmentation process of a gray-level image can be defined as the minimization of an energy function.

FLICM [1] introduces a novel fuzzy factor as a fuzzy local similarity measure in its objective function, which is aimed at guaranteeing noise insensitiveness and image detail preservation. Its objective function for partitioning a dataset (in the gray-level space) into c clusters is defined in terms of

$$J_m=\sum_{i=1}^{N}\sum_{k=1}^{c}\left[u_{ki}^{m}\|x_i-v_k\|+G_{ki}\right] \quad (1)$$

where ||•|| denotes the Euclidean norm, $\{v_k\}$ c_k=1 stands for the centers or prototypes of the clusters. The parameter m is a weighting exponent on each fuzzy membership and determines the amount of fuzziness of the resulting classification. This fuzzification factor m in the proposed algorithm and the above algorithms plays the same role as FCM which has been Here, we set m = 2 for the following

$$U€\{u_{ki} \in [0,1] \ \sum_{k=1}^{c} u_{ki}=1, \forall i \text{ and } 0<\sum_{k=1}^{c} u_{ki}<N \quad (2)$$

while the fuzzy factor Gki is defined mathematically as follow

$$G_{ki} = (1 - u_{kj})^{m} \|x_j - v_k\| \quad (3)$$

The objective function can get the minimum by updating the membership $\{u_{ki}\}$ and the cluster center $\{v_k c_k\}$ =1 and When the algorithm has converged (max V (b) – V (b+1) <ε, where V = [v1, v2, ...V_c] are the vectors of the cluster prototypes).

A de-fuzzification process takes place in order to convert the fuzzy partition matrix U to a crisp partition. In a general way, the maximum membership in the procedure method is adopted. This procedure assigns the pixel i to the class C_K with the highest membership.

$$C_k = arg\{max\{u_{ki}\}\} \quad (4)$$

It is used to convert the fuzzy image to the crisp segmented image by the KWFLICM algorithm. In Section IV, experimental results on synthetic images, medical images and natural images will be described. Conclusions will be drawn in section V.

A. Trade-Off Weighted Fuzzy Factor

In FLICM [1], with the application of the fuzzy factor $G_{ki}$the corresponding membership values of the non-noisy pixels, as well as the noisy pixels that falling into the local window will converge to a similar value, and thereby balance the membership values of the pixels that located in the window.

Thus, FLICM becomes more robust to outliers. As shown in Eq. (3), it can be seen that the factor G_{ki} is formulated without setting any artificial parameter that controls the trade-off between image noise and the image details. What's more, the influence of pixels within the local window in G_{ki} is exerted flexibly by using their spatial Euclidean distance from the central pixel.

A90	22	13
32	20	35
28	B120	27

Fig. 1a 3 x 3 window with noisy central pixel

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It is not conformity with the discrepancy between the pixels in the neighborhood. In [12], we proposed a variant of the factor by utilizing the local coefficient of variation to replace the spatial distance for overcoming above shortcomings and contribute to use more local context information.

A90	22	13
32	20	35
28	B120	27

Fig. 1b 3 x 3 Damping extent of the neighbours

The fuzzy factor can reflect the damping extent of the neighbors with the spatial distance from the central pixel. Such as the noisy pixels A and B in Fig. 1, the gray level difference between A and central pixel is less than pixel B, shown in Fig. 1 (a).

But the damping extent of them is opposite. While the central pixel is noisy pixel, this situation as Fig. 1(b) shown, it fails to analyze the impact of each neighboring pixel.

Visually, fuzzy factor makes the relationship between neighboring pixels and the central pixel is relatively accordance with the gray level difference between them.

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But it is still unreasonable to ignore the effect of spatial distance constraint on the relationship between central pixel and pixels in the neighborhood when the size of window is enlarged.

KWFLICM Algorithm is used in segmenting the image. In KWFLICM, the objective function is defined as Jm while the reformulated fuzzy factor is written as follow G'ki. The two updating formulas for minimizing Jm used. When the algorithm has converged, a defuzzification process takes place to convert the fuzzy image to the crisp segmented image.

The objective function can get the minimum by updating the membership $\{u_{ki}\}$ and the cluster center $\{v_k c_k\}$ =1 and When the algorithm has converged (max V (b) – V (b+1) <ε, where V = [v1, v2, ...V_c] are the vectors of the cluster prototypes).nsity in homogeneities and noise.

The trade- off weighted fuzzy factor and the kernel distance measure are both free of the empirically adjusted parameters which can be incorporated into other fuzzy c-means algorithms easily. In this module, we propose an unsupervised FCM algorithm based on the kernel metric for segmentation of images that have been corrupted.

In addition, the damping extent of the neighbors cannot be accurately calculated, as the same gray-level distribution and different spatial constraint. Hence, in this paper, we define a new trade-off weighted fuzzy factor to adaptively control the local neighbor relationship. This factor depends on space distance of all neighbor pixels and their gray level discrepancy simultaneously. In Section III.B, we will present this tradeoff weighted fuzzy factor in details.

B. Non- Euclidean Distance

It can be seen that the measure used in the objective function of FLICM is still the Euclidean metric as in FCM. Although this metrical method is computationally simple, the use of Euclidean distance can lead to non-robust results on segmentation of image corrupted by noise, outliers, and other imaging artifacts. Therefore, some researchers adopted so-called robust distance measures, such as L p norms (0 < p < 1) [22], [23] to replace the L2 norm in the FCM objective function to reduce the effect of outliers on clustering results.

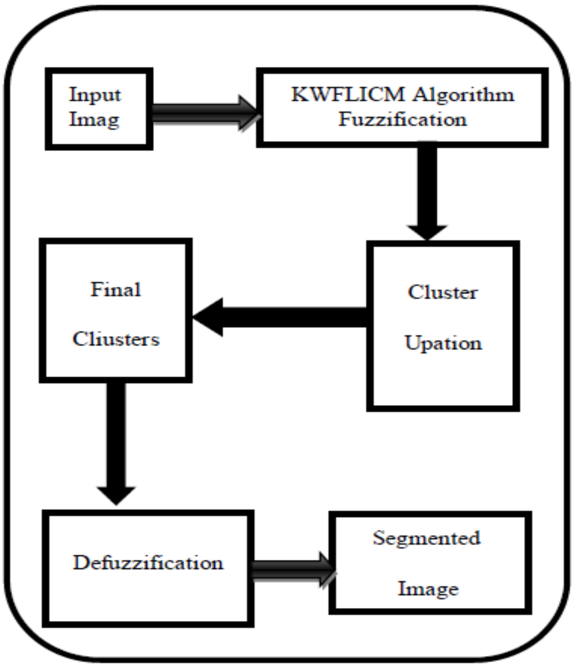

Fig 2 Architecture Design

On the other hand, there is a trend in recent machine learning work to construct a nonlinear version of a linear algorithm using the 'kernel method', which aims at transforming the complex nonlinear problems in original low-dimensional feature space to the problems which can be easily solved in the transformed space.

And this method can also be used in clustering, as shown in support vector clustering [14] and kernel (fuzzy) c-means algorithms [9].A kernel in the feature space can be represented as the following function K

$$K(x, y) = \{ Ø(x), Ø(y) \} \tag{5}$$

where Ø(•) refers to an implicit nonlinear map,(Ø(x),Ø(y)) denotes the inner product operation.There are many kernel functions in literature .

There are many kernel functions in literature [24]. Different kernels will induce different measure for the original space. Gaussian Radial basis function (GRBF) kernel is a commonly used method. Note, that the parameter σ in Gaussian RBF has a very important effect on performance of the algorithms.

However, the selection of an appropriate band-width value for a kernel-based clustering algorithm could be very troublesome since all the data points are unlabeled and their true classes are unknown.

III. METHODOLOGY

Motivated by the above descriptions, we improve FLICM by introducing a trade-off weighted fuzzy factor and kernel method. The details of the proposed algorithm, termed as the KWFLICM for short, will be described in this section.

Initially the objective function is given as follows

$$J_m = \sum_{i=1}^{N} \sum_{k=1}^{c} [u_{ki}^m \| x_i - v_k \| + G_{ki} \tag{6}$$

The formulated fuzzy factor is written as follows

$$J_m = (1 - u_{kj})^m \| x_j - v_k \| G_{ki} \sum_{j \in N_i} \frac{1}{d_{ij+1}} \tag{7}$$

where Ni stands for the set of neighbours in a window around x_i is the trade-off weighted fuzzy factor of jth in a local window around x_i and w_{ij} represents on Euclidean distance measure based on kernel method, (1 $-u_{ki}$)m is a penalty which can accelerate the iterative convergence to some extent. $\{v_k c_k\}$=1. It is the centers or prototypes of the clusters and the array $\{u_{ki}\}$ represents a membership matrix which also must satisfy the equation. The two updating formulas for minimizing J_m, with respect to u_{ki} and v_k is obtained are used in the algorithm.

Step 1: Set the number c of the cluster prototypes, fuzzification parameter m, window size N_i and the Stopping condition ε.

Step 2: Initialize randomly the fuzzy cluster prototypes.

Step 3: Set the loop counter b = 0.

Step 4: Calculate the trade-off weighted fuzzy factor w_{ij} and the modified distance measurement D_{ik}

Step 5: Update the partition matrx.

Step 6: Update the cluster prototypes.

Step 7: If max $|V_{new} - V_{old}|$ < ε then stop, otherwise, set b = b+ 1 and go to step 4.

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When the algorithm has converged, a defuzzification process takes place to convert the fuzzy image to the crisp segmented image.

B. Trade off Weighted Fuzzy Factor

The noise resistance property of the proposed KWFLICM mainly relies on the fuzzy factor The adaptive trade-off weighted fuzzy factor depends on the local spatial constraint and local gray-level constraint. For each pixel xi with coordinate the spatial constraint reflects the damping extent of the neighbors with the spatial distance from the central pixel and defined as where the i th pixel is the center of the local window Ni and the j th pixel represents the set of the neighbors falling into the window around the i th pixel, di j is the spatial Euclidean distance between the j th pixel in neighbors and the central pixel.

. The 3 × 3 window, in Fig. 1(a), extracted from the noise image is an example of this situation, and Fig. 1(c) depicts its damping extent of the neighbors with the spatial distance. The 3 × 3 window, in Fig. 1(a), extracted from the noise image is an example of this situation,

and Fig. 1(c) depicts its damping extent of the neighbors with the spatial distance, five iterations the algorithm converges. In such case, the gray level values of the noisy pixels are different from the other pixels within the window, while the fuzzy factor balances their membership values.

Thus, all pixels within the window belong to one cluster. Therefore, the combination of the spatial and the gray level constraints incorporated in the factor suppress the influence of the noisy pixels. Moreover, the factor is automatically determined rather than artificially set, even in the absence of any prior noise knowledge. Hence, the algorithm becomes more robust to the outliers.

C. Non- Euclidean Distance based on Kernel Metric

The objective function in KWFLICM is

$$J_m=\sum_{i=1}^{N}\sum_{k=1}^{c}\left[u_{ki}^{m}\|x_i-v_k\|+G_{ki}\right] \quad (8)$$

Where Ø(•) refers to an implicit nonlinear map,(Ø(x),Ø(y)) denotes the inner product operation.There are many kernel functions in literature The distance variance of the data points represents the degree of aggregation around the clusters. The small value of variance means the clusters are compact and well separated around cluster centers. That is, if the data set with distinguishable clusters, the membership should present separate.

However, if the data set with fuzzy or undistinguished clusters, the value of variance is large. The membership should present well fuzzy distribution for all data points. This could contribute to suppressing the influence of the outliers. Fig. 4 shows different membership curves for different parameter σ in the case of two clusters. The range of the value for the tested artificial data set x is 0 to 3, with two cluster center. One center is 0, and the other center is 2. The distribution of these data points, as shown in Fig. 4, is undistinguished.

It is just like the two compact clusters corrupted by the noisy point. Therefore, the value of distance variance for this data distribution is relatively large. So, the distance variance of them is relatively a little large. The membership should present fuzzy distribution. As we can see from these curves, when σ = 0.05, the membership curve presents that the belonging of some data points are ambiguous since the membership values of them are close to 0.5. When σ = 20, the membership curve well fits the concentrative distribution of the data set. The belonging of these data points is distinct. Therefore, the result reveals that the distance variance of the data points, estimates the kernel parameter σ.

$$D_{ik}^2 = 1 - K(x_i, v_k) \quad (9)$$

Then, the distance metric based on kernel method can be transformed as

$$D_{ik}^2 = 1 - \exp(-\| x_i - v_k \| \quad (10)$$

From the above descriptions, we can see that the tradeoff weighted fuzzy factor and the kernel distance measure are both free of the empirically adjusted parameters which can be incorporated into other fuzzy c-means algorithms easily.

IV. EXPERIMENTAL STUDY

In this section, we describe the experimental results on three synthetic images, four medical images and three natural images with different types of noises. In addition, we test and compare the efficiency and the robustness of the proposed method (KWFLICM) with spectral graph grouping using Nystrom method (NNcut) [25] and its predecessors, FLICM [1], RFLICM [12] and WFLICM (only introduce the trade-off weighted fuzzy factor into FLICM algorithm, here termed as WFLICM for short). The effectiveness of the tradeoff weighted fuzzy factor can be validated by comparisons between FLICM and WFLICM.

And the effectiveness of the kernel metric can be validated by comparisons between WFLICM and KWFLICM.

A. Results on Natural Images

The kernel method has been recently applied to unsupervised clustering. An FCM algorithm based on the kernel metric the segmentation of images that have been corrupted by intensity in homogeneities and noise.

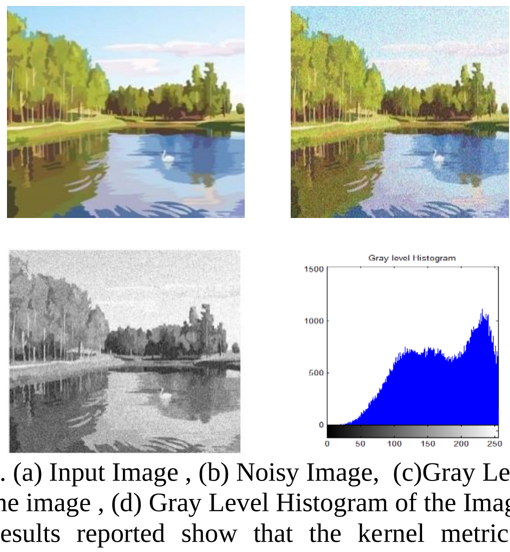

Fig 4. (a) Input Image , (b) Noisy Image, (c)Gray Level of the image , (d) Gray Level Histogram of the Image

The results reported show that the kernel metric is an effective approach to constructing a robust image clustering method. The results obtained from KWFLICM have smoother regions and much clearer image edge while removing almost added noise.

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The numerical results on the the natural images show that the algorithm is efficient. Visually, the smallest value E can be obtained using the proposed method. All the experiment results show that KWFLICM can remove the noise while preserving significant image details and obtain the good performance. Furthermore, it is relatively independent of the type of noises.

The Segmentation Accuracy (SA) is defined as the sum of the correctly classified pixels divided by the total number of the pixels.

$$SA=\sum_{i=1}^{c}\frac{A_{i}\cap C_{i}}{\sum_{j=1}^{c} C_{j}} \quad (11)$$

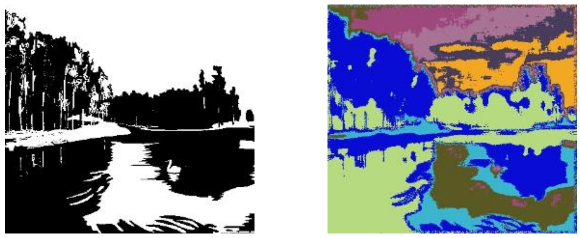

Fig 5 (a) Trade off weighted fuzzy factor , (b) Segmented Image

The segmentation results of the newly proposed algorithm is being compared with the existing algorithms.(a) NNcut ,(b) FLICM ,(c) RFLICM ,(d) WFLICM. The results of the proposed algorithm shows that the segmentation is more accurate.

Compared with its pre-existing algorithms it shows the good performance and the performance of the segmentation is improved better than the other algorithms.KWFLICM algorithm also removes almost all the added noise .

It also preserves all the details even after the segmentation is done by the proposed algorithm.Thus KWFLICM Agorithm shows the better parformance.

TABLE I

NOISE	NNcut	FLICM	RFLICM	WFLICM	KW-FLICM
Gaussian noise 15%	94.62	99.969	99.972	99.981	99.988
Gaussian noise 20%	91.69	99.945	99.951	99.945	99.982
Salt&Pepper noise 15%	99.25	99.518	99.561	99.652	99.996
Salt&Pepper noise 20%	99.01	99.426	99.499	99.536	99.994
Salt&Pepper noise 30%	99.61	99.145	99.182	99.188	99.988

Segmentation Accuracy(SA%) of Image with different noises

V. CONCLUSION

The kernel method has been recently applied to unsupervised clustering. In the propose method an unsupervised FCM algorithm based on the kernel metric for segmentation of images that have been corrupted by intensity in homogeneities and noise. The results show that the kernel metric is an effective approach to constructing a robust image clustering algorithm. Furthermore, the improved algorithm introduced a reformulated spatial constraint, with the trade-off weighted fuzzy factor as a local similarity measure to make a trade-off between image detail and noise.

Compared with its preexistences, it is able to incorporate the local information more exactly. In addition, the trade-off weighted fuzzy factor and the kernel distance measure are completely free of the empirically adjusted parameters determination, thereby allowing the automated applications. In our experiments, we test the proposed algorithm on natural images. The experiment results show that the proposed algorithm obviously improves the performance of image segmentation, as well as the robustness to the type of noises.

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