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Local Fuzzy Clustering for Accurate and Noise-Robust Multi-modal Medical Image Segmentation

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Abstract:
Multi-modal Medical Image segmentation could be especially for the purpose of object identification and recognition with medical images for the life saving purpose. For more accurate segmentation without image smoothing an anisotropic neighborhood, based on phase congruency features, is introduced. The increased time consumption is addressed by the kernel metric and the Local fuzzy Clustering is applied for improved accuracy. In order to achieve good performance in object classification problems, it is necessary to combine information from various image features by, two-step approach: at first, the kernel metric is applied into both the similarity measure and the membership function to compensate for the effect of noise. Second, adaptive weightage is determined by optimizing the kernel-target alignment score and then the combined kernel is used to improve the segmentation accuracy without image smoothing. The segmentation results, for both synthetic and real images, demonstrate method efficiently preserves the homogeneity of the regions and is more robust to noise than traditional method.
Keywords— Phase congruency, anisotropic neighborhood, kernel matrix, local fuzzy clustering.

I. INTRODUCTION

Image segmentation plays a key role in image analysis and is often the first processing step in many image applications. The main goal of the image segmentation is to homogeneous region with similar attributes such as intensity, depth, color, texture etc...Since manual segmentation is time consuming and very often subjective and prone to errors. Automated and accurate segmentation is needed. To date various segmentation techniques have become develop and roughly, they can be grouped in to five main categories: thresholding, edge-based methods, region based methods, neural networks and clustering. Since unsupervised fuzzy clustering is one of the most commonly used methods and has been successfully applied in the fields such as astronomy, geology, medical and molecular imaging.

The main characteristic of fuzzy segmentation method is to allow pixels to belong to multiple classes with certain degrees, which is very useful for applications. Limited spatial resolution noises are present. Among fuzzy clustering method the fuzzy c-mean (FCM) algorithm [1], is the most popular one. Conventional FCM algorithm [2], classify pixel in the future space without considering their spatial distribution in the image. It is highly sensitive to noise and other imaging artifact. The most common approach is to modify the FCM objective function are a similar measure directly by including special information. Spatial information and the membership function [3], of each cluster is altered from the clustered distribution in the neighborhood is considered. This scheme greatly reduced the effect of noise and biases of the algorithm to the homogeneous clustering.

In this local spatial and grey level information is the novel fuzzy way. Fuzzy local (both spatial and grey level) similarity measure aiming to guarantee noise insensitiveness and image detail prevention. FCM objective function by including a spatial penalty on the membership function is modified. The penalty leads to the interactive algorithm [4-6] which is similar to original FCM and allows estimating special smoothing membership function. The geometric condition is used to determine by taking the account of local neighborhood and each pixel [7]. The edge concurrency detector is used to identify the different feature types found in image [8]. Denoising image using a filter the image is segmented and minimizing the error global Thresholding [9].

An improved FCM based algorithm used for accurate and noise robust image segmentation [10]. The spatial information of local image features is integrated into both the similarity measure and the membership function to compensate for the effect of noise in the first stage. Next for more accurate segmentation without image smoothing an anisotropic neighborhood, based on phase congruency features, is introduced.

In proposed work Kernel fuzzy matrix framework solve the problem of image segmentation by multi resolution segmentation may enter with local optional procedure. The fuzzy clustering FCM assign each data point to all different clusters with some degree of membership. The iterative unsupervised Fuzzy –Means algorithm is the most widely used clustering algorithm for image segmentation. A modified FCM which incorporate the special information with the membership function for clustering. An adaptive weightage averaging FCM in which spatially influence of the neighboring pixel on the centroid pixel.

II. METHODS

Kernel metric:

The kernel or null space (also null space) of a matrix A is the set of all vectors x for which Ax = 0. The kernel of a matrix with n columns is a linear subspace of n-dimensional Euclidean space. The dimension of the null space of A is called the nullity of A.If viewed as a linear transformation, the null space of a matrix is precisely the kernel of the mapping (i.e. the set of vectors that map to zero). For this reason, the kernel of a linear transformation between abstract vector spaces is sometimes referred to as the null space of the transformation. The kernel of
a m × n matrix Where 0 denotes with m components. Ax = 0 is equivalent to a homogeneous system of linear equations, From this view point, the null space of A is the same as the solution set to the homogeneous system.

Kernel metric adaptive weightage:

In classical kernel regression approach, and provide some intuition behind it. After that, including the blurring effect, we derive a regularized kernel regression method for the blurring application.

A. Review

Defining the blurry function as Z(X) = (g*u)(X), we rewrite the data model

$$Y_i = z(X_i) + \epsilon_i, \quad i = 1,\dots, P, \; X_i = [x_{1i}, x_{2i}]^T \qquad (1)$$

As such, the kernel regression framework provides a rich mechanism for computing point-wise estimates of the regression function with minimal assumptions about global signal or noise models.

While the particular form of z (·) may remain unspecified for now, we can rely on a generic local expansion of the function about a sampling point X_i. Specifically, if X is near the sample at X_i, we have

Furthermore, β_0 is z(X), which is the pixel value of interest, and the vectors β_1 and β_2 are

$$\beta_1 = \left[\frac{\partial z(X)}{\partial x_1} \; \frac{\partial z(X)}{\partial x_2}\right]^T \qquad (2)$$

$$\beta_2 = \left[\frac{\partial^2 z(X)}{2\,\partial x_1^2} \; \frac{\partial^2 z(X)}{2x_1 2x_2} \; \frac{\partial^2 z(X)}{2\,\partial x_2^2}\right]^T \qquad (3)$$

A formulation of the fitting problem capturing this idea is to solve the following optimization problem. For example, it is desirable to use kernels with larger footprints in the smooth areas of the image to reduce the noise effects, while relatively smaller foot-prints are desirable in the edge and texture areas.

$$\min_{\{B_N\}_{n=0}^{N}} \sum_{i=1}^{P} \left| yi - \beta_0 - \beta_1^T(X_i - X) - \beta_2^T \operatorname{vech}\{X_i - X\}(X_i - X)^T\} - \dots \right|^q K_{Hi}(X_i - X) \quad \dots\dots(7)$$

With

$$K_{Hi}(X_i - X) = \frac{1}{\det(H_i)} K(H_i^{-1}(X_i - X)) \qquad (4)$$

More details about the optimization problem above can be found and, choice of the kernel functions sum up so far, the optimization problem, which we term “classic” kernel regression, eventually provides a point-wise estimator of the regression function. Regardless of the choice of the kernel function K and the regression order N, the estimator always yields a weighted linear combination of nearby samples, that is

$$\hat{z}(X) = \hat{\beta}_0 = \sum_{i=1}^{P} W_i\,(K, N, X_i - X) y_i, \quad \sum_{i=1}^{P} W_i\,(\cdot) = 1 \qquad (5)$$

$$\hat{z}(X) = \frac{\sum_{i=1}^{P} K_{Hi}(X_i - X) y_i}{\sum_{i=1}^{P} K_{Hi}(X_i - X)} \qquad (6)$$

On the other hand, for N=2, the shape of the equivalent kernel is transformed and the weight values in the tail area are negative due to the higher order polynomial in the Taylor series. In general, lower order approximates, such as NWE, result in smoother images (large bias and small variance) as there are fewer degrees of freedom. On the other hand, over- fitting happens in regressions using higher orders of approximation, resulting in small bias and large estimation variance smaller values for h (the global smoothing parameter) result in small bias and consequently large variance in estimates.

The firestones, supervised learning algorithms, take as an input a setoff labeled examples, $(x_1, y_1),\dots, (x_n, y_n)$ where x_i are in some input x and y_1 are typically in R and they produce as an output, a function f : x → R which (hopefully)is able to predict the label y of new examples x of new examples. The second ones work on unlabeled examples (x_i only) and try to describe the structure of the data. Kernel methods have been applied to several signal processing and communications problems. Some of them are direct application of the standard SVM algorithm for detection or estimation and others incorporate prior knowledge into the learning process, either using virtual training samples or by constructing a relevant kernel for the given problem. The applications include speech and audio processing(speech recognition, speaker identification, extraction of audio features, audio signal segmentation),image processing (face detection and recognition, image coding)and communications (channel equalization on-stationary channel models multi-user detection signal classification).This list is not exhaustive but shows the diversity of problems that can be treated by the techniques presented in previous sections.

To choose an optimal weight to deal with unbalanced classification problems, an adaptive weighting procedure, which adaptively updates the weights by utilizing the classification information, including the within group error rates estimated class proportions .Before the adaptive procedure, first show an interesting property of the choice of weights. Define the equivalent weight set on Rk to a given weight vector as follows:

The weight vector {wj, j = 1… k} belongs to the equivalent weight set. If there are multiple elements in Wπ, one can find a different weight vector in Wπ to get the same Bayes rule as that of {1/, j = 1… k} and it may have different finite sample behaviors. Thus, an adaptive procedure may find better weights than (1/, 1/ …). The following example further illustrates the equivalent weight set of {1/ , j = 1… k}. Example: Let d = 1, x = [0, 1] and k = 3, with π1 =0.45, π2 = 0.45, and π3 = 0.1. Then class 3 is the minority.

The class-conditional probability density functions gj(x) and the conditional class probability functions pj(x) are given as follows By some simple calculation, the Bayes decision rule under the classic criteria becomes Adaptive weighting algorithm1:

Step 1: (Initialization) fit a classifier using a certain classification procedure on the training dataset using the weight vector {, j = 1… k} = {1, 1… 1} with the corresponding within group error rates for the training dataset {, j = 1… k}

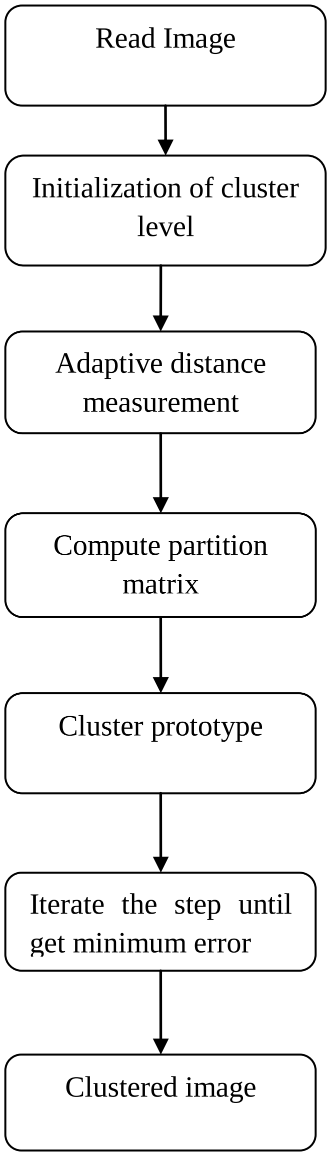

Fig1: System Architecture

For iteration s = 2…, with given $\{e_j^{(s-1)}, j = 1, \dots, k\}$ and $\{w_j^{(s-1)}, j = 1, \dots, k\}$ from iteration s – 1,

Step2: (weight update) Set $w_j^{(s)} = w_j^{(s-1)} W(e_j^{(s-1)}, \hat{\pi}_j, j =$ 1….k, and standardize the weights so they sum up to one. Then fit a weighted classifier with corresponding within group error rates for the training dataset $\{e_j^{(s)}$, j = 1… k}

Step 3 :(Stopping rule) Stop the iteration if

$$\sum_j (e_j^{(s)} - e_j^{(s-1)}) \leq \varepsilon$$

for some prespecified ε > 0 reaches the prespecified maximum number of iterations. Otherwise, lets = s + 1 and go to Step 2.

Here the updating rule W ($\hat{e}_j\hat{\pi}_j$) is critical to use W ($\hat{e}_j\hat{\pi}_j$) = ($1/\hat{\pi}_j$) max ($\hat{e}_j, \partial$), a modified version of that forte one-step fixed weight in, where $\partial \in (0, 1)$ is a filter parameter, which lower bounds the within group error. $\delta = 0.1$ in the numerical studies. The use of δ is to prevent potential significance decrease of the weight for class *j* when $\hat{}ej$ becomes very small or equals to 0. Otherwise, a small weight on the minority class may lead to bad performance on that class again in the next step and result in a dead loop.

As a remark, we note that for the adaptive procedure, modify the weights by a small amount depending on the within group errors($\hat{e}_1, \hat{e}_2, \ldots\ldots \hat{e}_k$). To decide whether the iteration, compare the current within group errors to those in the previous iteration. In the case that misclassification costs are unequal a mentioned ($\hat{e}_1, \hat{e}_2, \ldots\ldots \hat{e}_k$) by their generalization using the unequal cost information,

$$\{\sum_{j=1}^{k} C_{1j}\, m_{1j}/n_1, \sum_{j=1}^{k} C_{2j}\, m_{2j}/n_2, \ldots, \sum_{j=1}^{k} C_{kj}\, m_{kj}/n_k\}$$

Where m_{1j} denotes the number of misclassifications from class i to class j for $i \neq j$ and $m_{ii} = 0$ for i = 1, …., k.

III. EXPERIMENTAL RESULT

Experimental results for three different types of images: (1) synthetic image with four-class pattern, (2) phantom Magnetic Resonance Images (MRI) of the human brain real images.

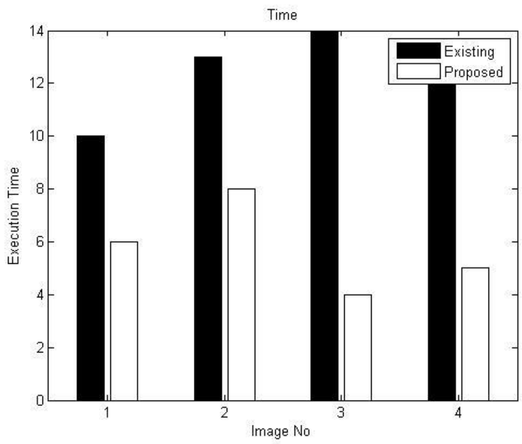

Fig 2: Comparison of existing and proposed system

The qualitative comparison results between the proposed noise-robust FCM method and other related approaches are shown for a synthetic image and for the brain MRI with 9% noise. In the first example, the synthetic image is corrupted with the zero mean Gaussian noise where Signal to Noise Ratio (SNR) between the original and noisy image is 14 dB. For the synthetic image the goal was to accurately segment three homogeneous regions and preserve a line (in total four clusters). For MRI image, the goal was to segment the brain into three classes: white matter, greymatter and cerebrospinal fluid (CSF) (which can be identified as white, light grey and dark grey tissue class in the "ground truth" image. The results show that the standard FCM method has the worst performance and high sensitivity to image noise.

Percentage of noise removal in Existing system	Percentage of noise in Proposed system
10	6
13	8
14	4
12	5

Table 1: Percentage of noise removal in Existing and Proposed System

The quantitative results are computed for the first two image types where the "ground truth" segmentation is available. In all experiments we use the weighting exponent n = 2s, the stop criterion and the parameters is equal to1.A better segmentation is obtained by using the neighborhood weighted similarity measure but this method is not enough efficient to deal with higher noise levels. The results of our new proposed method, without using phase congruency and anisotropic neighborhoods, indicate that this method is good for segmenting coarse homogeneous regions (good performance for very noisy images), but it is not efficient in segmenting line elements.

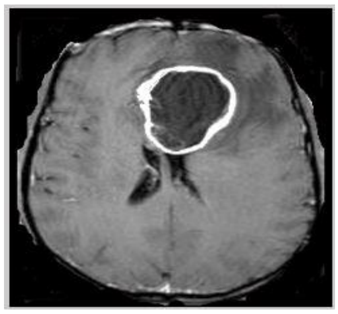

Fig 3: Input image with added noise

To improve the Standard FCM Algorithm and overcome the noise problem, integrate local neighbourhood information. For more accurate segmentation, use phase congruency isotropic or anisotropic neighborhood configuration. It is used to detect the noise in the image accurately. To define the neighborood configuration use the local phase, it is the normalization of 0 to 1.were 0 is closer to line and 1 is closer to step edge. The experimental result of the project has low accuracy due to weighted Fuzzy factor and it has high time consumption. By using the multi-modal method the image is segmented and kernel metrics and local fuzzy clustering is used for reducing time consumption for improving accuracy.

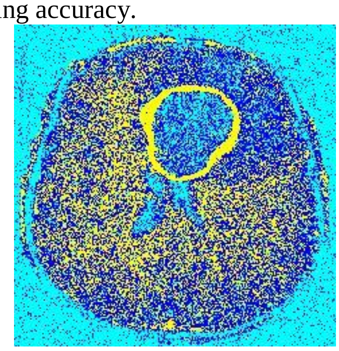

Fig 4: Fuzzy clustering

Segmentation coefficient as the similarity index pi = $(2|A_i \cap B_i|)/(|A_i|+|B_i|)$, where A_i and B_i denote the set of pixels labeled into the cluster by the "ground truth" and our method respectively, and $|A_i|$ denote the number of elements A_i..The experimental results indicate that our method has the highest accuracy in segmentation comparing with other methods

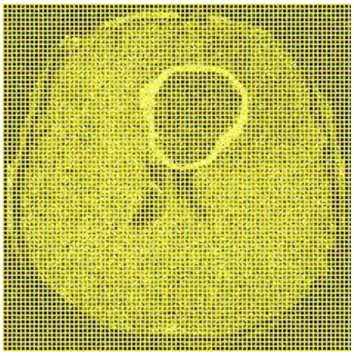

Fig 5: Block division method for accurate noise removal

The fuzzy clustering method is use cluster the image by using the centroid value. The values are been calculated by using the adaptive weightage value. By using the Adaptive weight Fuzzy clustering value 0 to 1.The image are been cluster and divided into block division. The image is splited into number of block by using the centroid value and compares the nearby value for effectively remove the noise in the image accurately segments edges and line elements.

IV. CONCLUSION

A novel FCM-based method for accurate and noise robust image segmentation .The method is integrates spatial contextual information of the neighbouring pixels into the FCM algorithm using phase congruency, Anisotropic neighborood and adaptive weights for membership calculation. The segments, edges, line and coarse homogeneous region at the same time calculated. Accurate image segmentation can be done by using muti-model image segmentation.

The method spatial feature extraction of neighbouring pixels in to the FCM algorithm using phase congruency, anisotropic neighborhoods and adaptive weightage for membership calculation. Adaptive weightage is determined by optimizing the kernel-target alignment score and then the combined kernel is used to improve the segmentation accuracy without image smoothing. The segmentation results, for both synthetic and real images, demonstrate that our method efficiently. In future work will focus on the extension of the existing algorithm to 3D data image segmentation.

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