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# Segmenting Medical Images using Computational Intelligence Technique

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The techniques of Computational Intelligence (CI) has become very important in the area of medical image analysis. In particular the concept of Fuzzy has become very important in the application of medical image segmentation. This is due to the large role of uncertainty and imprecision in the medical images. Although the traditional Fuzzy c-means (FCM) algorithm functions well on segmenting most noise free images, it fails to segment image corrupted by outliers, noise and other imaging artifacts. FCM leads to its non robust results mainly due to (1) Not utilizing the spatial information in the image. (2) use of Euclidean distance. To overcome first problem Spatial FCM (SFCM) is used by considering the spatial information which inturn gives the better result. However, Spatial FCM (SFCM) algorithm is not suitable for revealing non-Euclidean structure of the input data and fails to solve second problem. Thus, to overcome both problems, in this paper we propose a new CI technique called Robust Spatial Kernel FCM (RSKFCM) method. It considers the spatial information and uses the Gaussian kernel function to calculate the distance between the center of the cluster and the data point. Extensive experimentation are carried out on the standard dataset like Brain images, Lungs and Liver images. Experimental result reveals that the proposed RSK-FCM algorithm outperforms the traditional FCM algorithm with the use of various cluster validity functions.

**Keywords :** Computational Intelligence, Medical Images, Segmentation, Spatial Fuzzy C-means.

## 1. INTRODUCTION

Image segmentation is one of the most important processes in modern computer vision. It involves subdividing an image into its constituents parts or objects in the image *i.e.*, set of pixels. The pixels in the same region are similar according to some homogeneity criteria such as intensity, texture or color so as to locate and identify boundaries in an image. Image segmentation is widely used in many applications such as object recognition, geographical imaging, robot vision and medical imaging. Medical imaging is the technique to create an internal image of the human body for clinical or medical purpose. Image segmentation can be classified into three categories: Threshold Technique, Region-Based Image Segmentation, and Edge-Based Image Segmentation. Threshold technique [1] is very simplest segmentation method, where the image is segmented based on the pixel information such as intensity and color. Main drawback of this technique is that it does not involve the spatial information of the images. So it will bring about noise, blurred edges, or outlier in the images. In edge based [2] methods the image is segmented based on abrupt changes in intensity (such as edge, line).This method fails when the given image is blurry or too complex to identify a given border. In Region based methods [3][4] the image is segmented based on the regions that are similar according to a set of predefined criteria (intensity levels, similar texture, homogeneity or sharpness). The main drawback of the region based method is computationally expensive. However, the techniques based on pixel attributes leads to inaccuracy with segmentation because medical images have poor contrast, limited spatial resolution, non uniform intensity variation and noise. Recently, many researchers developed the medical image segmentation methods using Fuzzy clustering techniques.

only 3 components available). We implemented and simulated all the algorithms with Matlab$^R$ R2013a.

To evaluate the performance of the RSKFCM, we used 3 type of images they are 1)normal images obtained from dataset, 2)5% Gaussian noise added to normal images, and 3)Salt and Pepper noise added to normal images. A quantitative evaluation using several cluster validity function is presented in Table 1 to 3. It is necessary to show the assessment of segmented MRI output images are best subjective measure to determine the efficiency of the method. We used four cluster validity functions, the performance of clustering is better if the partition coefficient $V_{pc}$ is maximal and/or the partition entropy value $V_{pe}$ is minimal, the Fukuyama-Sugeno function $V_{fs}$ and the Xie-Beni function $V_{xb}$ are minimal. Table 1 compares the performance of FCM, KFCM, SKFCM, SFCM and our proposed RSKFCM in terms of the above cluster validity functions for Brain images. Table 2 compares the performance of FCM, KFCM, SKFCM, SFCM and our proposed RSKFCM in terms of the above cluster validity functions for Lung images. Table 3 compares the performance of FCM, KFCM, SKFCM, SFCM and our proposed RSKFCM in terms of the above cluster validity functions for Liver images.

The results for three type of images and various numbers of clusters indicates that our proposed RSKFCM outperforms the FCM, SFCM and previous SKFCM method for all the implementation in terms of cluster validity functions. Extensive experiments with several brain images demonstrate the superiority of the proposed RSKFCM algorithm.

## 6. CONCLUSIONS

In this paper, we segment medical images using Computational Intelligence technique. We proposed a Robust Spatial Kernel Fuzzy c-means(RSKFCM) algorithm for segmentation. This method has been applied to the segmentation of MRI brain images, Lung and Liver datasets. We compared our experimental result with FCM based methods to demonstrate superiority of our algorithm. Four cluster validity functions are applied to segmentation result to evaluate the performance of the proposed method. From the quantitative evaluation and the visual inspection, we can conclude that RSKFCM algorithm yields superior segmentation result than other FCM based methods.

Table 2
Performance Comparison of FCM, KFCM, SKFCM, SFCM and RSKFCM for Lung Images

| | Normal Image | 5% Gaussian Noise Image | Salt and Pepper Noise Image |
|---|---|---|---|
| $V_{pc}$ | | | |
| FCM | 0.910 | 0.886 | 0.903 |
| KFCM | 0.900 | 0.876 | 0.893 |
| SKFCM | 0.935 | 0.912 | 0.938 |
| SFCM | 0.951 | 0.939 | 0.958 |
| **RSKFCM** | **0.963** | **0.954** | **0.961** |
| $V_{pe}$ | | | |
| FCM | 0.177 | 0.219 | 0.189 |
| KFCM | 0.198 | 0.241 | 0.211 |
| SKFCM | 0.092 | 0.112 | 0.102 |
| SFCM | 0.069 | 0.082 | 0.082 |
| **RSKFCM** | **0.065** | **0.080** | **0.069** |
| $V_{xb}$[X10$^{-3}$] | | | |
| FCM | 32.69 | 47.35 | 35.16 |
| KFCM | 31.61 | 48.92 | 35.67 |
| SKFCM | 31.05 | 48.25 | 34.06 |
| SFCM | 30.58 | 46.50 | 34.82 |
| **RSKFCM** | **30.07** | **43.25** | **31.66** |
| $V_{fs}$[-1X10$^6$] | | | |
| FCM | 253.68 | 198.59 | 240.77 |
| KFCM | 251.27 | 196.26 | 238.51 |
| SKFCM | 253.78 | 200.85 | 241.17 |
| SFCM | 264.11 | 209.35 | 251.70 |
| **RSKFCM** | **267.56** | **210.16** | **253.66** |

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Table 1: Performance Comparison of FCM, KFCM, SKFCM, SFCM and RSKFCM for Brain Images

| | Normal image | | | | 5% Gaussian Noise image | | | | Salt and Pepper Noise image | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Number of clusters | | | | Number of clusters | | | | Number of clusters | | | |
| $V_{pc}$ | 2 | 3 | 4 | 5 | 2 | 3 | 4 | 5 | 2 | 3 | 4 | 5 |
| FCM | 0.928 | 0.862 | 0.856 | 0.838 | 0.913 | 0.849 | 0.813 | 0.788 | 0.920 | 0.847 | 0.821 | 0.798 |
| KFCM | 0.907 | 0.853 | 0.846 | 0.830 | 0.896 | 0.836 | 0.801 | 0.776 | 0.898 | 0.833 | 0.808 | 0.789 |
| SKFCM | 0.825 | 0.871 | 0.886 | 0.893 | 0.847 | 0.826 | 0.837 | 0.861 | 0.880 | 0.863 | 0.845 | 0.885 |
| SFCM | 0.972 | 0.929 | 0.932 | 0.918 | 0.964 | 0.925 | 0.907 | 0.888 | 0.969 | 0.924 | 0.917 | 0.896 |
| **RSKFCM** | **0.967** | **0.939** | **0.944** | **0.934** | **0.959** | **0.926** | **0.950** | **0.949** | **0.964** | **0.925** | **0.949** | **0.975** |
| $V_{pe}$ | | | | | | | | | | | | |
| FCM | 0.130 | 0.245 | 0.275 | 0.319 | 0.153 | 0.275 | 0.359 | 0.419 | 0.146 | 0.279 | 0.341 | 0.387 |
| KFCM | 0.165 | 0.266 | 0.299 | 0.339 | 0.182 | 0.302 | 0.387 | 0.447 | 0.182 | 0.309 | 0.371 | 0.413 |
| SKFCM | 0.290 | 0.266 | 0.250 | 0.180 | 0.202 | 0.279 | 0.283 | 0.248 | 0.299 | 0.284 | 0.278 | 0.214 |
| SFCM | 0.047 | 0.119 | 0.115 | 0.139 | 0.060 | 0.126 | 0.158 | 0.192 | 0.052 | 0.127 | 0.142 | 0.177 |
| **RSKFCM** | **0.057** | **0.091** | **0.114** | **0.111** | **0.069** | **0.126** | **0.085** | **0.107** | **0.062** | **0.129** | **0.042** | **0.064** |
| $V_{xb}$[X$10^{-3}$] | | | | | | | | | | | | |
| FCM | 26.00 | 72.00 | 50.94 | 55.76 | 32.39 | 73.68 | 83.53 | 91.20 | 30.04 | 82.18 | 66.60 | 64.44 |
| KFCM | 25.68 | 76.02 | 51.82 | 57.30 | 32.18 | 75.58 | 86.47 | 87.75 | 29.75 | 86.24 | 68.29 | 66.93 |
| SKFCM | 23.68 | 74.02 | 49.82 | 55.30 | 29.18 | 72.58 | 83.47 | 84.75 | 25.75 | 82.24 | 64.29 | 62.93 |
| SFCM | 27.80 | 75.60 | 52.25 | 54.26 | 34.75 | 73.95 | 77.74 | 88.91 | 32.19 | 85.80 | 68.77 | 74.31 |
| **RSKFCM** | **66.93** | **66.93** | **46.93** | **56.93** | **66.93** | **46.93** | **66.93** | **56.93** | **66.93** | **66.93** | **56.93** | **36.93** |
| $V_{fs}$[-1X$10^{6}$] | | | | | | | | | | | | |
| FCM | 296.12 | 305.86 | 317.67 | 318.06 | 203.36 | 218.62 | 221.43 | 218.01 | 252.41 | 262.36 | 268.86 | 269.28 |
| KFCM | 297.28 | 306.21 | 315.54 | 316.40 | 202.51 | 215.30 | 218.14 | 213.41 | 251.82 | 260.40 | 265.80 | 266.78 |
| SKFCM | 415.64 | 455.81 | 315.80 | 239.32 | 155.38 | 260.23 | 103.67 | 60.58 | 408.45 | 362.62 | 359.37 | 103.56 |
| SFCM | 304.50 | 316.42 | 334.14 | 334.54 | 211.78 | 232.03 | 239.06 | 239.76 | 261.59 | 276.57 | 290.64 | 288.94 |
| **RSKFCM** | **266.7** | **266.7** | **366.7** | **466.7** | **266.7** | **366.7** | **266.7** | **466.7** | **266.7** | **466.7** | **266.7** | **366.7** |

Table 3
Performance Comparison of FCM, KFCM, SKFCM, SFCM and RSKFCM for Liver Images

| | Normal Image | 5% Gaussian Noise Image | Salt and Pepper Noise Image |
|---|---|---|---|
| $V_{pc}$ | | | |
| FCM | 0.934 | 0.839 | 0.905 |
| KFCM | 0.934 | 0.833 | 0.902 |
| SKFCM | 0.953 | 0.857 | 0.935 |
| SFCM | 0.962 | 0.925 | 0.961 |
| **RSKFCM** | **0.974** | **0.936** | **0.973** |
| $V_{pe}$ | | | |
| FCM | 0.122 | 0.297 | 0.174 |
| KFCM | 0.126 | 0.304 | 0.181 |
| SKFCM | 0.115 | 0.231 | 0.117 |
| SFCM | 0.056 | 0.134 | 0.089 |
| **RSKFCM** | **0.045** | **0.112** | **0.068** |
| $V_{xb}$[X$10^{-3}$] | | | |
| FCM | 38.00 | 81.04 | 58.74 |
| KFCM | 35.65 | 82.58 | 59.93 |
| SKFCM | 36.86 | 79.23 | 60.78 |
| SFCM | 35.90 | 77.94 | 58.87 |
| **RSKFCM** | **31.00** | **74.69** | **55.83** |
| $V_{fs}$[-1X$10^{6}$] | | | |
| FCM | 127.79 | 73.96 | 115.11 |
| KFCM | 129.83 | 72.06 | 116.97 |
| SKFCM | 129.86 | 74.95 | 118.24 |
| SFCM | 130.58 | 78.72 | 120.18 |
| **RSKFCM** | **132.68** | **80.953** | **126.68** |


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