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QUANTUM INSPIRED ROUGH FUZZY C-MEANS CLUSTERING FOR LIVER TUMOR SEGMENTATION

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Abstract. *The combination of quantum logic and soft computing can make a breakthrough in computation methods. Rough fuzzy c-means clustering and quantum logic when combined together could achieve powerful computations. Over segmentation is one of the drawbacks when using fuzzy c-means and rough fuzzy c-means (RFCM) clustering which limits its applications in medical image segmentation. Motivated by quantum signal processing, this paper proposes a quantum inspired rough fuzzy c-means (QIRFCM) which defines the rough fuzzy c-means algorithm in a quantum form using quantum adaptive factor that uses the quantum power to define the probability of existence of an element within a cluster. The QIRFCM algorithm is applied on a dataset of infected livers with hepatocellular carcinoma (HCC) for accurate tumor segmentation. The obtained results show that the proposed QIRFCM can segment the tumor area in an effective way that overcomes over segmentation problem while using conventional rough fuzzy c-means. Moreover, the proposed QIRFCM gives higher peak signal-to-noise ratio and lower mean square error compared to the rough fuzzy c-means (RFCM).*
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1. **Introduction.** Clustering is one of the most widely used techniques for data partitioning into meaningful groups that hold similar information. Clustering algorithms usually use artificial intelligent techniques with the goal of imitating the human ability in organizing useful groups of information that can be used for further purposes [1]. The groups or clusters that results from applying a clustering algorithm on a dataset should fulfill a special condition that the internal similarity of data in one cluster should be maximized and the similarity between the data of different clusters is minimized [2,4,5]. Clustering algorithms are divided into two main types. The first is *hierarchical algorithms* that group the data with the sequence of partitions from singleton clusters to a cluster including all individual or the reverse. The second is *partitional algorithms* which aim dividing N data points into C number of clusters. Partitional clustering algorithms have been broadly received by the specialists because of the straight time unpredictability and low computational necessities [3].

A quantum computer is a machine that utilizes quantum mechanical marvels to consider computing tasks quicker than conventional computers. The intersection between the theoretical modern physics and theoretical computing is known as quantum computing. In the past few years, quantum computing played a main and important role in many

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real-life applications. Many joint researches arise to highlight the advantages of joining the quantum theory with other theories from mathematics, psychology, decision theory, artificial intelligence, probability, logic and experimental physics. Most of the joint researches focused on the theoretical and the quantum likeness approaches [7]. Despite of the researchers' hard effort for trying to build quantum computers, quantum computers are still just theories and there is no well defined quantum computer yet. Recently, several researches tried to re-implement and define classical soft computing algorithms and theories in terms of quantum computing theories and definitions, which were known as quantum inspired approaches. In [2] they proposed an enhanced quantum inspired fuzzy c-means clustering technique that tried to overcome the defects of classical fuzzy c-means using quantum approach to solve the problem of choosing the initial centers of clusters and choosing the fuzzification parameter. The centers of clusters and the fuzzification parameter were expressed in an interesting way using quantum qubits. In [8-10] they proposed quantum inspired genetic algorithms to improve the performance of the conventional genetic algorithm. Also in [7] the author defined the rough set in a quantum inspired notation. In [11,12] the authors built a new definition of particle swarm optimization. In addition, the authors in [13] explained neural network in a quantum inspired way.

This paper introduces a Quantum Inspired Rough Fuzzy C-Means (QIRFCM) that is introduced to limit the over clustering results from using conventional rough fuzzy c-means. The proposed model combines the quantum hypothesis and the hypothesis of the rough fuzzy c-means. The inspiration driving the investigation of quantum rough fuzzy c-means is its comparability with mind thinking as performing effectively undertakings in complex condition with unverifiable properties of objects. The paper is organized as follows. Section 2 defines the problem statement and preliminaries. Section 3 presents the brief explanation of the proposed method. Moreover, Section 4 presents the results of presented work. The paper is concluded in Section 5.

2. **Problem Statement and Preliminaries.** Rough Fuzzy C-Means (RFCM) is a hybrid model between fuzzy c-means and rough sets as explained and proposed by [1]. Given a set of data $X = \{x_1, x_2, \ldots, x_N\}$ and the main goal is to classify the given data into clusters $C = \{c_1, c_2, \ldots, c_k\}$, the main goal of rough fuzzy c-means is to minimize the objective function

$$obj_{RFCM} = \begin{cases} w * A_1 + w' * B_1 & \text{if } \underline{A}(C_i) \neq \emptyset,\ B(C_i) \neq \emptyset \\ A_1 = \displaystyle\sum_{i=1}^{k} \sum_{x_j \in \underline{A}(C_i)} {\mu_{ij}}^m ||x_j - c_i||^2 & \text{if } \underline{A}(C_i) \neq \emptyset,\ B(C_i) = \emptyset \\ B_1 = \displaystyle\sum_{i=1}^{k} \sum_{x_j \in B(C_i)} {\mu_{ij}}^m ||x_j - c_i||^2 & \text{if } \underline{A}(C_i) = \emptyset,\ B(C_i) \neq \emptyset \end{cases} \tag{1}$$

where the w and w' ($w' = 1 - w$) are the parameters that correspond to the relative importance of the lower and boundary regions. In addition μ_{ij} is the membership of an object in a cluster C. In RFCM each cluster C has three main components, the first is the cluster centroid c_i, the second is a crisp lower approximation $\underline{A}(C_i)$, and the third is a fuzzy boundary $B(C_i)$. According to rough set theory, if an object x_j belongs to the lower approximation set of cluster C_i, then x_j does not belong to any other lower approximation of another cluster C_k. In addition, x_j does not belong to the boundary set of the same cluster C_i which will mean that the object x_j will belong definitely to cluster C_i and will be assigned a membership $\mu_{ij} = 1$. On the other hand, if an object x_j belongs to the boundary approximation set $B(C_i)$, then the object will possibly belong to the cluster C_i as well as the possibility to belong to another cluster C_k. In such case, the object that will belong to the boundary set $B(C_i)$ will be assigned a membership μ_{ij} that takes a value in the interval $[0, 1]$ and should satisfy the following

$$\sum_{i=1}^{c} \mu_{ij} = 1 \tag{2}$$

As a summary, the RFCM will divide the data into two classes: lower approximation set and boundary set. Only the objects that will belong to the boundary set will be fuzzified. The centers of the clusters in RFCM will be updated using the following equation

$$c_i = \begin{cases} w * D_1 + w' * F_1 & \text{if } \underline{A}(C_i) \neq \emptyset,\ B(C_i) \neq \emptyset \\ D_1 = \dfrac{1}{|\underline{A}(C_i)|} \displaystyle\sum_{x_j \in \underline{A}(C_i)} x_j & \text{if } \underline{A}(C_i) \neq \emptyset,\ B(C_i) = \emptyset \\ B_1 = \dfrac{\sum_{x_j \in B(C_i)} {\mu_{ij}}^m x_j}{\sum_{x_j \in B(C_i)} {\mu_{ij}}^m} & \text{if } \underline{A}(C_i) = \emptyset,\ B(C_i) \neq \emptyset \end{cases} \tag{3}$$

where D_1 represents the updated center, lower approximation and boundary sets will have a great influence in the update process. In addition, the objects that lie in the lower approximation set will belong definitely to the cluster C_i and the membership of the object to the cluster will be updated to the value 1 and will be assigned a higher weight w while those of boundary set will be assigned a lower weight value w' and will take the value $0 < w' < w < 1$ and the membership will not be changed.

A quantum definition of lower and boundary approximation rough sets was introduced in [7]; quantum relation that maps objects of a data set X partitioned into a set of quantum equivalence classes is given by:

$$[X]R_q = \{x \in X | x_1 R_q x_2\} \tag{4}$$

where X is the data set and R_q is the quantum relation. Utilizing such a comparability relation R_q, any element that is a subset of data set X can be approximated as boundary and lower approximation. By the concept of quantum classes, with respect to R_q the boundary approximation of X will be given as:

$$B(X) = \{x \in [X]R_q \cap X \neq \emptyset\} \tag{5}$$

and with respect to R_q the lower approximation of X will be given as

$$\underline{A}(X) = \{x \in [X]R_q \cap B = \emptyset\} \tag{6}$$

The objective function, membership and the updating equation of the clusters' center are introduced by an inspired quantum technique in [15]. The quantum rotation gate that was used to express the pixel belonging to the cluster or not was given as $\begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix}$. And the probability of the pixel belonging to a cluster was defined as:

$$|\alpha|^2 = \cos\left(med_{x_i \in \Omega}(\mu_{ij})\right)^2 \tag{7}$$

where Ω is 5×5 median filter of the quantum inspired factor, and μ_{ij} is the fuzzy membership of pixel x_i in the jth cluster. Bigger $|\alpha|^2$ implies the more probable pixel has a place with the current cluster j. The quantum-motivated fuzziness factor controls the power to commotion and nature of picture division results. The new quantum inspired adaptive evolution formula is given as follows:

$$\lambda_{ij} = \exp\left(\cos\left(med_{x_i \in \Omega}(\mu_{ij})\right)^2 \left(\frac{1}{n} \sum_{m \in N_i} \mu_{mj}\right)\right)^2 \tag{8}$$

where N_i is the 5×5 local window of the center pixel x_i and n is the number of neighboring pixels falling inside N_i of the center pixel x_i. The objective function to assign labels to each pixel:

$$obj = \sum_{i=1}^{N} \sum_{j=1}^{K} {\mu_{ij}}^m \lambda_{ij} ||x_i + \hat{x} - c_j||^2 \tag{9}$$

where μ_{ij} is the membership function, m is the weight of fuzziness which is almost taken by 2 [15], $\hat{x}$ is image pixel after adopting median filter with a 3×3 window, and c_j is the cluster center which will be updated by the following equation:

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\lambda_{ij}||x_i+\hat{x}-c_j||^2}{\lambda_{ik}||x_i+\hat{x}-c_k||^2} \right)^{\frac{1}{m-1}}} \tag{10}$$

$$c_j = \frac{\sum_{i=1}^{N} {\mu_{ij}}^m \lambda_{ij} (x_i + \hat{x})}{\sum_{i=1}^{N} {\mu_{ij}}^m \lambda_{ij}} \tag{11}$$

3. **Proposed QIRFCM (Quantum Inspired Rough Fuzzy C-Means).** In this section we proposed a new method QIRFCM which is a quantum inspired rough fuzzy c-means method. The motivation behind this proposed paper is the work done by [7,14,15]. The idea around the proposed quantum inspired rough fuzzy c-means method is mainly depending on the optimization of the quantum objective function obj_{QIRFCM} (Equation (12)).

$$obj_{QIRFCM} = \begin{cases} w * A_1 + w' * B_1 & \text{if } \underline{A}(C_i) \neq \emptyset,\ B(C_i) \neq \emptyset \\ A_1 = \sum_{i=1}^{k} \sum_{x_j \in \underline{A}(C_i)} {\mu_{ij}}^m \lambda_{ij} ||x_j + \hat{x} - c_i||^2 & \text{if } \underline{A}(C_i) \neq \emptyset,\ B(C_i) = \emptyset \\ B_1 = \sum_{i=1}^{k} \sum_{x_j \in B(C_i)} {\mu_{ij}}^m \lambda_{ij} ||x_j + \hat{x} - c_i||^2 & \text{if } \underline{A}(C_i) = \emptyset,\ B(C_i) \neq \emptyset \end{cases} \tag{12}$$

where w and $w' = 1 - w$ denotes the importance of lower and boundary approximation sets, $\underline{A}(C_i)$ is the quantum lower approximation set of the cluster C_i as is defined by Equation (6) and $B(C_i)$ is the quantum boundary (upper) approximation set of cluster C_i and is defined by Equation (5). μ_{ij} is the membership function of the quantum fuzzy c-means (Equation (10)) and m is the fuzzification degree which in most cases takes the value 2 [15]. λ_{ij} is the quantum-motivated fuzziness factor which controls the power to commotion and nature of picture division results. The quantum inspired adaptive evolution formula is given as in (Equation (8)), and $\hat{x}$ is the image pixel after adopting median filter with a 3×3 window.

In QIRFCM the centers of the clusters will be updated using the following equation:

$$c_i^{QIRFCM} = \begin{cases} w * D_1 + w' * F_1 & \text{if } \underline{A}(C_i) \neq \emptyset,\ B(C_i) \neq \emptyset \\ D_1 = \frac{1}{|\underline{A}(C_i)|} \sum_{x_j \in \underline{A}(C_i)} x_j + \hat{x} & \text{if } \underline{A}(C_i) \neq \emptyset,\ B(C_i) = \emptyset \\ B_1 = \frac{\sum_{x_j \in B(C_i)} {\mu_{ij}}^m \lambda_{ij} (x_j + \hat{x})}{\sum_{x_j \in B(C_i)} {\mu_{ij}}^m \lambda_{ij}} & \text{if } \underline{A}(C_i) = \emptyset,\ B(C_i) \neq \emptyset \end{cases} \tag{13}$$

The process will start by using the initial centers of clusters randomly. The following step will be calculating the matrices of memberships that will use initially the membership equation of normal FCM algorithm proposed in [4,6].

Let $\mu_i = (\mu_{i1}, \ldots, \mu_{ij}, \ldots, \mu_{in})$ be the memberships of all objects in a cluster C_i of center c_i. By using the properties of quantum the membership of an object in a cluster acts as

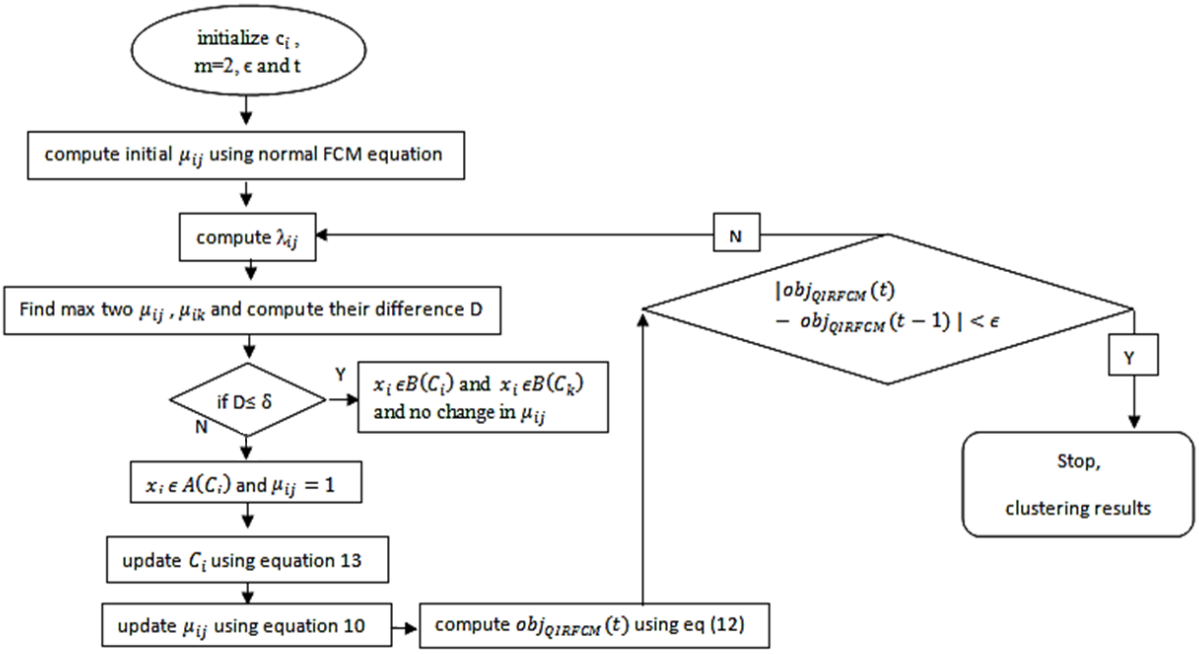


FIGURE 1. Flow chart of the proposed QIRFCM

projection, that is a signal that gives power to an object to be set to a cluster according to the following definition $\langle P_{C_1}x_j, x_j\rangle \leq \langle P_{C_2}x_j, x_j\rangle$, where $P_{C_1}x_j$ is the projection of object x_j to cluster C_1 while $P_{C_2}x_j$ is the projection of object x_j to cluster C_2 and the membership will be updated as in Equation (10). After computing the memberships of each cluster, the two highest memberships or projections of each object will be chosen and subtracted with each other to be compared to a measure δ. According to the comparison the object will be assigned to either a lower approximation set or a boundary (upper) approximation set using the definition of quantum rough sets in Equations (5) and (6), for every object that will be assigned to lower approximation set, the projection of the object to this cluster will be modified to 1 (which will certainly belong to the cluster with probability 1) otherwise the projection or membership will not change. After modifying the membership values the centers will be updating using the quantum center (Equation (13)). A flow chart of the proposed QIRFCM method is given in Figure 1 and the main steps of QIRFCM algorithm are explained as follows.

1) Assign initial centroids c_i, $i = 1, 2, \ldots, c$. The weight of fuzziness is set as $m = 2$, set threshold $\epsilon = 0.0001$ and the maximum amount of iterations is set as $t = 100$ and is initialized by $t = 1$.
2) Compute initially the membership function of the initial clusters using the following equation

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

3) Compute λ_{ij} as in Equation (8).
4) If μ_{ij} and μ_{ik} are the two highest memberships of pixel x_i and $(\mu_{ij} - \mu_{ik}) \leq \delta$, then $x_i \in B(C_i)$ and $x_i \in B(C_k)$. In addition, x_i is not part of any lower approximation set. Here $\delta = \frac{1}{n}\sum_{i=1}^{n}(\mu_{ij} - \mu_{ik})$, n is the total number of objects and μ_{ij} and μ_{ik} are the two highest memberships of pixel x_i.
5) If $(\mu_{ij} - \mu_{ik}) > \delta$, then $x_i \in \underline{A}(C_i)$.
6) The memberships of the pixels belong to the lower approximation set of the cluster will be modified to $\mu_{ij} = 1$ otherwise the pixel will belong to the boundary (upper)

approximation set and their memberships will remain the same and will not be modified.

7) The centers of clusters will be updated and modified using the updated memberships using Equation (13).
8) The steps from 3) to 8) will be repeated until
   a) The number of iterations reaches its maximum value $t = 100$, or
   b) The objective function fulfills the following condition $|obj_{QIRFCM}(t) - obj_{QIRFCM}(t-1)| < \epsilon$, or
   c) $|\mu_{ij}(t) - \mu_{ij}(t-1)| > \epsilon$.

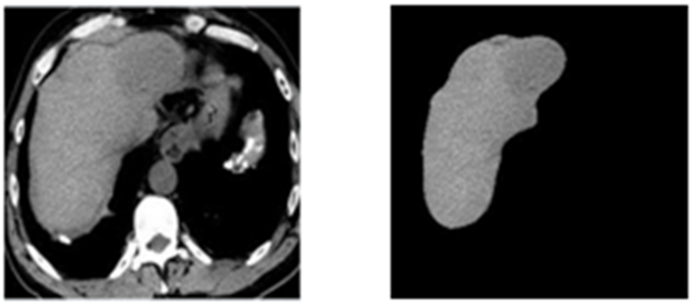
4. **Experimental Results of the Proposed Method.** In this section, we present the results when applying the proposed QIRFCM method on a data set that represents images of infected patients liver with hepatocellular carcinoma. The purpose of applying the QIRFCM method to the images is clustering the image into three clusters that represent three regions. The first, is the background region. The second, is the tumors region and the third, is the liver tissues region. In this paper we used a data set of 140 CT of 14 primary diagnosed HCC patients images. The images of the data set were taken from an online reference for infected liver imaging called liver imaging Atlas [16]. The format of all taken images is JPG and of size 256×256, where each image represents the extracted liver of one patient. The images were preprocessed to segment the liver from the whole 2D CT images using our previously introduced liver segmentation technique [14]. This proposed work was coded using MATLAB R2013b on hpProBook 4540s. The images were divided into 40 low contrast images, where the liver pixels and the tumor pixels have very likely intensities and 100 high contrast images, where there is a remarkable difference in intensities between the liver and the tumor.

The results of applying the proposed QIRFCM algorithm were compared to the results obtained when applying the RFCM algorithm proposed in [1]. The quality metrics of images approximation were calculated for the images of 14 patients.

Given an image 256×256 where the image represents a primary HCC infected image, the image is prepared to apply the proposed QIRFCM method. First, the image is preprocessed for infected liver extraction as explained in our previous work [14] as shown in Figure 2 where image (a) represents the original image and (b) represents the image after liver segmentation. The number of clusters is predefined as three clusters which are: background, liver pixels and tumor pixels. The two algorithms RFCM explained in [1] and the proposed QIRFCM are applied to the image each at a time for the purpose of tumor segmentation as explained in Figure 3 image after clustering. The image in Figure 3(a) represents the result when applying the RFCM algorithm on image of Figure 2(b) and Figure 3(b) represents the result when applying the QIRFCM algorithm on image in Figure 2(b). By measuring the peak signal-to-noise ratio (PSNR) and mean square error (MSE) of the two images in Figure 3 we observe that QIRFCM has higher PSNR and lower MSE, which means that QIRFCM has better classification results than RFCM.

A comparison between both the QIRFCM and the RFCM is achieved on the data set and the peak signal-to-noise ratio (PSNR) is calculated and presented for 14 different cases, as shown in Figure 4, which demonstrates that the resultant images from the QIRFCM have higher values than the images resultant from the RFCM. The mean square error (MSE) is also calculated as shown in Figure 5, which shows lower values in case of the proposed QIRFCM.

5. **Conclusions.** Tumor segmentation is a mandatory process in liver cancer diagnosis. The accuracy of the segmentation process helps in early, accurate, and non-invasive treatments. In this paper a new QIRFCM algorithm has been presented. This succeeded in accurate tumor segmentation compared to conventional clustering techniques. The



(a) Original image (b) Segmented liver

Figure 2. Image before clustering

(a) Image after RFCM (b) Image after QIRFCM

Figure 3. Image after clustering

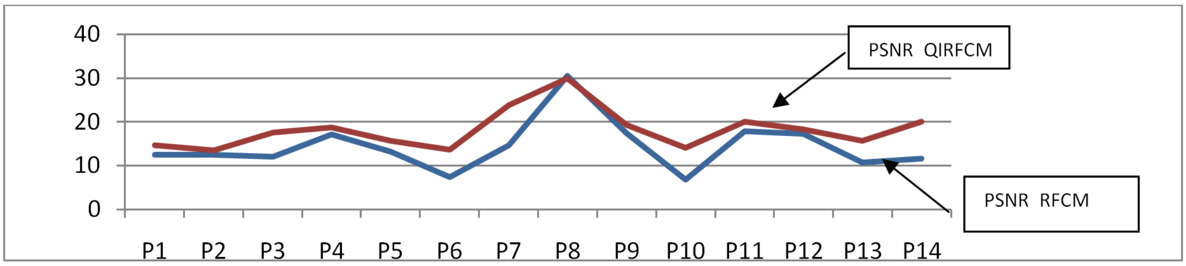


Figure 4. PSNR of the images

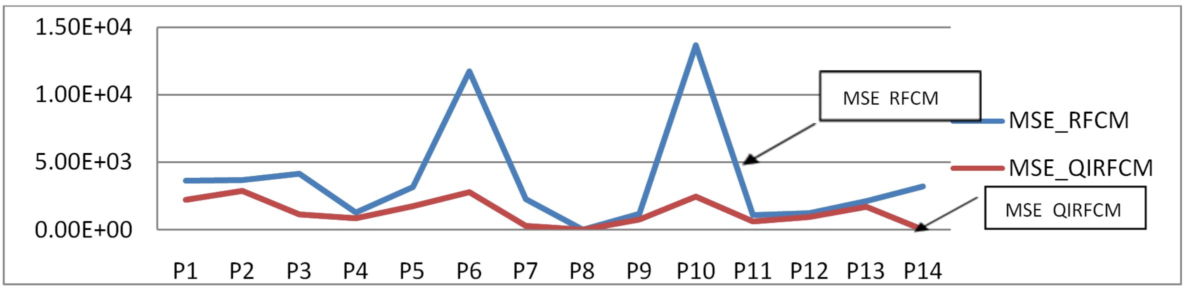


Figure 5. MSE of the images

proposed QIRFCM has given better performance compared to the conventional RFCM especially in case studies with poor intensities or high noise densities. The average PSNR increment has been improved from 6.774 to 14.1425 and the MSE has been reduced in an inversely proportional manner. The experimental results were accomplished on 140 CT images representing 14 primary diagnosed HCC patients. Further studies will be accomplished to detect accurate size of segmented tumor, detecting the safe area and accurate tumor classification.

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