# Brain Image Segmentation Based on Firefly Algorithm Combined with K-means Clustering

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**Abstract:** During the past few decades digital images have become an important part of numerous scientific fields. Digital images used in medicine enabled tremendous progress in the diagnostics, treatment determination process as well as in monitoring patient recovery. Detection of brain tumors represents one of the active research fields and an algorithm for brain image segmentation was developed with an aim to emphasize four different primary brain tumors: glioma, metastatic adenocarcinoma, metastatic bronchogenic carcinoma and sarcoma from PET, MRI and SPECT images. The proposed image segmentation method is based on the firefly algorithm whose solutions are improved by the k-means clustering algorithm when Otsu's criterion was used as the fitness function. The proposed combined algorithm was tested on commonly used images from Harvard Whole Brain Atlas and the results were compared to other method from literature. The method proposed in this paper achieved better segmentation considering standard segmentation quality metrics such as normalized root square mean error, peak signal to noise and structural similarity index metric.

**Keywords:** Medical digital images, Brain tumor detection, Image segmentation, Clustering, K-means, Optimization, Swarm intelligence, Firefly algorithm.

## 1. Introduction

Digital images have become part of numerous scientific fields. Due to very powerful processing methods, they have been used in different application and various approaches to digital image analysis were proposed in the last few decades.

Digital image processing methods can improve the image analysis and they can be used for detecting different features that are not necessarily visible to the human eye, thus facilitating a great progress in various fields. Besides improvements in the analysis, the process itself is usually much faster compared to the manual analysis by an expert.

Scientific fields that are using digital images are numerous: security, agriculture, astronomy, etc. Medicine represents one of the examples that has been benefiting from advances in digital imaging. In medicine, due to the human's body complexity, digital images from different sources have been used. Besides digital images that capture visible light, there are numerous other sources that are used for generating a digital image. Some of the well-known sources and devices used for obtaining medical digital images include X-ray, CT scanner, magnetic resonance (MRI), PET scanner, ultrasound and others. Different sources are used in order to capture images of different body parts, different tissues and different abnormalities).

In this article a method for brain images segmentation as a step in detecting brain tumors which detected in MRI, PET or SPECT images was proposed. In general, tumors can be categorized into two categories: cancerous and benign tumors. A cancerous tumor can be primary or secondary where primary are the ones that are developed inside the brain while the secondary tumor was developed in a different organs and from there spread to the brain. Different brain tumors have different characteristics and can be targeted for segmentation in order to detect boundaries as precise as possible.

A brain tumor in medical images from different sources can be detected by using different image segmentation methods. Image segmentation is a task where the image should be partitioned

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into multiple disjoint segments where elements in one segment are similar, but different from elements in other segments based on some criteria like intensity level, texture features, frequency components, etc. The goal of segmentation, when brain tumor detection is considered, is to clearly differentiate anomaly, i.e. tumor, from the rest of the image.

For image segmentation, various techniques were proposed. Some of the most used methods include thresholding, histogram based methods, clustering based techniques, region growing methods, edge detection, etc. In this paper we propose a method for medical image segmentation based on the clustering algorithm.

Clustering represents an unsupervised machine learning technique that separates data into disjoint clusters where data inside one cluster should be similar according to some metric, while different from data from other clusters. Clustering methods try to determine patterns in the given dataset so the further information can be extracted. Nowadays there are various clustering methods including hierarchical clustering, clustering methods based on the distribution, DBSCAN, k-means, k-median, and many more. One of the most used clustering algorithm, due to its simplicity, is k-means algorithm that represents an iterative process of a search for the centroids, i.e. cluster centers (Khalaf et al., 2018). Elements of each cluster are determined by their distance to centroids. The closest centroid represents the cluster where the instance belongs. The distance can be defined in numerous ways, usually as Euclidian distance. Each iteration contains two steps, assignments of clusters to instances and centroid update. The new centroids are set to the mean of data inside each cluster.

K-means algorithm is a simple clustering method but with one drawback. Determination of the optimal centroids represents NP-hard optimization problem and the quality of the final solution is determined by the initial position of the centroids. Most common initialization is random initialization, while in some application initial centroids can be determined by using different strategies.

Swarm intelligence algorithms, a class of nature inspired algorithms, were successfully applied to various optimization problems in the past decades. Some of the first swarm intelligence algorithms are particle swarm optimization and ant colony optimization while later numerous other algorithms with various exploration and exploitation techniques were proposed and applied to different continuous optimization problems (Li et al., 2018; Tuba, Tuba & Beko 2016); combinatorial optimization problems (Jothi, 2016; Alihodzic et al. 2019), multiobjective optimization problems (Yang, 2013; Strumberger et al., 2018), etc. They were used for hard optimization problems in medical image processing applications for image registration (Tuba, Tuba & Dolicanin, 2017), bleeding detection (Tuba, Tuba & Jovanovic, 2017), detecting different anomalies (Lahmiri, 2017; Tuba et al. 2017; Jothi, 2016), compression (Tuba et al., 2019), etc.

In this paper we consider a problem of brain medical image segmentation and an algorithm based on a combined k-means algorithm with swarm intelligence algorithm, firefly algorithm was proposed. Brain image segmentation is done with a goal of detecting different anomalies such as glioma, metastatic adenocarcinoma, metastatic bronchogenic carcinoma and sarcoma.

The rest of this paper is organized in the following way. A brief review of the clustering based segmentation algorithms is given in Section 2. In Section 3, k-means algorithm used for image segmentation is described. Firefly algorithm adjusted for the considered problem is described in Section 4. The proposed method was tested on several standard brain images from Harvard Whole Brain Atlas and the results were compared to other methods from literature. The results and their analysis are presented in Section 5. Conclusion and future research plans are given in Section 6.

## 2. Related Work

Numerous clustering based image segmentation methods were presented in the last few years. One of the common choices of clustering algorithm is the k-means clustering algorithm.

Ozturk, Hancer & Karaboga (2015) proposed an image segmentation method based on an improved k-means algorithm by artificial bee colony optimization. The proposed method included a novel fitness function that used both, inter and intra-class variance as well as the quantization error that describes the general quality of a clustering algorithm. The proposed method was compared with common fitness functions and other state-of-the-art segmentation methods. Based on the Davies–Bouldin Index and the XB Index, that is used to determine the quality of segmentation, the proposed artificial bee colony algorithm was finding better clusters.

Another method for medical image segmentation with particle swarm optimization hybridized by fuzzy k-means and kernelized fuzzy k-means algorithm was proposed by Venkatesan & Parthiban (2017). The proposed method was tested on brain MRI images and the average intracluster distance, computation time and Davies-Bouldin Index were used as quality measures. It has been shown that the proposed hybridized methods had faster convergence and were less sensitive to the noise in comparison with other existing methods.

Parasar & Rathod (2017) proposed particle swarm optimization (PSO) combined with k-means algorithm for fetus ultrasound images segmentation. Their method was compared to the seeded region growing method optimized by PSO, fuzzy C-means and watershed and it outperformed them when ultrasound images with and without noise were used.

The optimal centroids for fuzzy clustering were determined by the adaptive chemical reaction optimization algorithm in Asanambigai & Sasikala (2018). The proposed segmentation method was used for medical images and the goal was to detect abnormal regions in brain, liver, abdomen and eye images.

Liu & Qiao (2015) proposed differential evolution hybridized by particle swarm optimization for image segmentation that used fuzzy k-means algorithm. The proposed method was used for segmentation images in HIS color space. Based on the obtained results, it is capable of segmentation with the minimal within class distance for both, noisy and images without noise.

Aljawawdeh, Imraiziq & Aljawawdeh (2017) researched melanoma detection in skin images and they proposed a model for segmentation and classification of melanoma. The proposed method used the genetic algorithm and particle swarm optimization to improve segmentation obtained by the k-means clustering algorithm. Features for classification were extracted from segmented images while for classification neural networks were used. Classification accuracy achieved by enhanced k-means algorithm was the highest.

Anter, Hassenian & Oliva (2019) proposed crow search optimization algorithm combined with fuzzy k-means clustering for segmentation of maize fields images. The proposed method was tested on images of different complexity, scene perspective and taken by various cameras. It has been proven that the crow search optimization improved the quality of the solutions obtained by the k-means algorithm and that was successful for crop rows detection.

## 3. K-means Algorithm for Image Segmentation

K-means algorithm is defined in the following way. Assume that the set $S$ contains $N$ instances that should be clustered into $K$ clusters, $S=\{X_1, X_2, ..., X_N\}$. Clusters are determined by their centroids $c_i$ where $i=1, 2, ..., K$. Initial centroids are randomly chosen. Iterative process begins after the initialization. In each iteration instances are assigned to the cluster with the closest centroid. As mentioned before, the distance can be defined in different ways, but in this paper, since the k-means algorithm is used for image segmentation, the distance between two instances is theirs difference in intensity levels. After defining clusters, centroids are updated. This is the second step in each iteration. Based on the instances that are assigned to one cluster, the centroid is calculated as follows:

$$c_i = \frac{1}{|S_i|} \sum_{X_j \in S_i} X_j \tag{1}$$

where $|S_i|$ is the total number of instances that are in cluster $i$ and $i=1, 2, ..., K$.

The k-means algorithm finishes when stopping criteria is reached which can be maximal number of iterations, when centroids have not been moved more that constant $\xi$ or the instances stay in the same cluster in two consecutive iterations.

Basic k-means algorithm is defined as an optimization problem where the goal is to minimize the sum of squared Euclidean distance between instances inside each cluster and their centroids. The fitness function is defined as follows:

$$fit = \sum_{i=1}^{K} \sum_{X_j \in S_i} d(c_i, X_j) \qquad (2)$$

where *d(a, b)* denotes squared Euclidean distance between *a* and *b*.

In the case of clustering based image segmentation technique, data (or instances) that should be divided into disjoint clusters are pixels. If the k-means algorithm is used as a clustering algorithm than the distances between pixels should be defined. The distance can be defined either based on the spatial information or on the intensity level of pixels. Region growing segmentation methods are often combined with clustering algorithms where the distance is defined as a combination of the position of the pixel and its intensity level (Agrawal et al., 2019; Li et al., 2018). In this paper, the distance is defined only on pixel's intensity level which means that the distance between two pixels is defined as the difference between their intensity levels.

## 4. Firefly Algorithm

Firefly algorithm (FA) represents a nature inspired algorithm and it is one of the swarm intelligence algorithms. The firefly algorithm is based on the attraction behavior of fireflies and it was proposed in 2010 by Yang (Yang, 2010). Since 2010, the FA algorithm has been successfully used in various application for tackling different optimization problems. The FA was adjusted for constrained (Yang, 2013), multi-objective (Yang, 2013) and discrete optimization problems (Sayadi, Hafezalkotob & Naini, 2013). Over the years, numerous improved and modified versions of the FA were proposed (Fister et al., 2013a; Fister et al., 2013; Verma, Aggarwal & Patodi, 2016). Also, the FA algorithm has been applied to numerous hard optimization problems such as image segmentation (Rajinikanth & Couceiro, 2015), support vector machine optimization (Tuba, Mrkela & Tuba, 2016), wireless sensor networks (Tuba, Tuba & Beko, 2016; Tuba, Tuba & Beko, 2017), etc.

As in any swarm intelligence algorithm, in the FA new solutions are generated through iterations based on the previous solutions and their quality. The convergence is ensured by the equations for creating new solutions that were inspired by the attraction behavior of fireflies in nature. The solutions with worse fitness function values are moved toward the solutions that have better fitness function values. If the FA is used for solving a minimization optimization problem, then the solutions with lower fitness function values will be considered as better. The quality (intensity) of the solution $\boldsymbol{x}$ is defined as:

$$I(x) = \begin{cases} \dfrac{1}{f(x)}, & if \quad f(x) > 0, \\ 1 + |f(x)|, & otherwise, \end{cases} \qquad (3)$$

where $\boldsymbol{x}$ represents one solution which is *d*-dimensional vector and function $f(\boldsymbol{x})$ is fitness function value at the point $\boldsymbol{x}$.

The movement toward better solutions also depends on the distance between two solutions. Attractions between the solutions are directly proportional to their qualities. The attractiveness of the solution $\boldsymbol{x}$ is defined by the following equation (Yang, 2010):

$$\beta(r) = \frac{\beta_0}{1 + \gamma \cdot r^2} \qquad (4)$$

where $\beta_0$ represents the attractiveness at the distance *r=0* while $\gamma$ is a constant and it is one of the algorithm's parameters.

New solutions based on the previous ones are generated by the following equation (Yang, 2010):

$$x_i^{t+1} = x_i^t + \beta e^{\gamma \cdot r_{ij}^2}(x_j^t - x_i^t) + \alpha^t \varepsilon_i^t \qquad (5)$$

where $\alpha$ is a constant, algorithm's parameter that is used for solution diversification, $\varepsilon_i^t$ represents a vector of values either from a Gaussian or from a uniform distribution in iteration *t*, $r_{ij}^2$ represents the distance between solutions *i* and *j*. The distance between solutions is determined by Cartesian distance (Yang, 2010).

The FA convergence speed is determined by the choice of the parameter $\gamma$. It has been empirically established in Yang (2010) that the best results are achieved for $\gamma$ between 0.01 and 100.

### 4.1 Combined Firefly Algorithm with k-Means

In this paper, the FA was used for finding optimal centroids. Since the result of the k-means algorithm depends on the initial solution but it has good convergence, we used firefly algorithm for searching a solution but the obtained solutions were improved in each generation by one iteration of the k-means algorithm.

Fitness function for the firefly algorithm that was used in this paper is Otsu's criterion that is used for finding the optimal threshold values based on the image histogram. Otsu's method was frequently used for image segmentation (Shao et al. 2019; Wang & Cao, 2019). Quality of the clustering or segmentation is determined by the overall inter-cluster distance. The goal is to maximize that distance which is equivalent to the minimization of the intra-class distance. If *h(i)* represents the number of pixels with the intensity *i* in the *L*-level grayscale image, then the Otsu's criterion is defined by the following equation:

$$f(t) = \sum_{i=0}^{K} w_i \sigma_i^2, \tag{6}$$

where

$$N = \sum_{i=0}^{L-1} h(i), \tag{7}$$

$$p(i) = \frac{h(i)}{N}, \qquad 0 \le i \le L-1, \tag{8}$$

and

$$w_i = \sum_{j=t_i}^{t_{i+1}-1} p(i) \tag{9}$$

$$u_i = \sum_{j=t_i}^{t_{i+1}} j \cdot \frac{p(i)}{w_i}, \tag{10}$$

$$\sigma_i = \sum_{j=t_i}^{t_{i+1}-1} (i - w_i)^2 \frac{p(i)}{w_i}. \tag{11}$$

In the previous equations, it was considered that $t_0$ is 0 and $t_L$ is L-1.

In order to use Otsu's criterion as a fitness function, it is necessary to find threshold values that correspond to the cluster centers obtained by the combined k-means clustering algorithm with the FA. After assigning instances into the corresponding clusters, threshold values are determined by the highest pixel intensity level inside each cluster. Obtained values are sorted and used to calculate the Otsu's criterion whose values represent the quality measure of the solution obtained by the combined FA and k-means algorithm.

The proposed method for image segmentation is presented in Algorithm 1.

**Algorithm 1.** Pseudo-code for the proposed KM-FA algorithm

```
Initialization
Randomly initialize n solutions.
For each solution, determine threshold values, sort
them and calculate fitness function values.
Calculate the quality of each solution by Eq. (3)
repeat
  for i=1:n
    for j=1:n
      if (Ij>Ii)
        Move solution xi towards solution xj by using Eq. (5)
        Update a solution by one iteration of the k-means algorithm.
        Determine threshold values, sort them and calculate fitness function values.
      end if
      Calculate attractiveness for solutions xi and xj.
    end for
  end for
  Rank solutions and set the best one as cluster
until Maximal iteration number is reached.
```

### 4.2 Performance Evaluation

The quality of the images segmented by the proposed k-means FA method was measured by the same metrics used in Nanda et al. (2018). We used normalized root mean square error (NRMSE), peak signal to noise ratio (PSNR) and structural similarity index measure (SSIM).

After obtaining the final solution, i.e. the threshold values, segmentation was done by setting pixels from one segment (cluster) to the lower bound of the segment. Since the quality measures used for performance evaluation use pixel intensity difference between the original and segmented image, choice of the segment representative is important.

NRMSE is calculated by the following equation:

$$NRMSE = \sqrt{\frac{\sum_{i=1}^{N}\sum_{j=1}^{M}(x(i,j)-x'(i,j))^2}{\sum_{i=1}^{N}\sum_{j=1}^{M}x(i,j)^2}}, \qquad (12)$$

where the image of *N*x*M* while *x(i,j)* and *x'(i,j)* are intensities of pixels at position *(i,j)* of the original and segmented image, respectively. The smaller values for NRSME are better, where for two identical images NRSME is 0.

PSNR is measured in dB and it is calculated in the following way:

$$PSNR = 10\log_{10}(\frac{L^2}{MSE}) \qquad (13)$$

where *L* is the maximal intensity value and MSE is the mean square error:

$$MSE = \frac{1}{N\cdot M}\sum_{i=1}^{N}\sum_{j=1}^{M}(x(i,j)-x'(i,j))^2. \qquad (14)$$

Better values for PSNR are higher values, since they are achieved if the MSE is smaller which means that the two images have less differences.

Structural similarity index measure describes the similarity between two images, in our case between the original and segmented image. SSIM takes values between -1 and 1 where two identical images have SSIM value 1 while two images with no structural similarity have SSIM equal to 0. It is calculated as:

$$SSIM = \frac{(2\mu_n\mu_m + d_1)(2\sigma_{nm} + d_2)}{(\mu_n^2 + \mu_m^2 + d_1)(\sigma_n^2 + \sigma_m^2 + d_2)}, \qquad (15)$$

where $\mu_n$ and $\mu_m$ represent the mean values of the original image *m* and segmented image *n*, $\sigma_{nm}$ is the covariance of *m* and *n* while $\sigma_n^2$ and $\sigma_m^2$ are variances of the images *m* and *n*, respectively. Variables $d_1$ and $d_2$ are used for stabilizing division and if L represents the maximal intensity value than:

$$d_1 = (0.01\cdot L)^2,$$
$$d_2 = (0.03\cdot L)^2. \qquad (16)$$

## 5. Simulation Results

The proposed algorithm was tested on the platform Intel ® Core™ i5-9700K CPU at 4GHz, 8GB RAM, Windows 10 Professional OS. The proposed algorithm was implemented using Matlab R2016a.

Parameters of the firefly algorithm were determined empirically and their values are presented in Table 1. Population size and the maximal number of iterations were set same as in Nanda et al. (2018) so that fair comparison can be performed.

**Table 1.** Initial parameters for the firefly algorithm

| | |
|---|---|
| Randomization parameter $\alpha$ | 0.5 |
| Attractiveness at *r*=0, $\beta_0$ | 0.2 |
| Absorption coefficient $\gamma$ | 1.0 |
| Population size | 20 |
| Maximal number of iterations | 100 |

Quality of our proposed method was compared with the method proposed by Nanda et al. (2018). Nanda et al. (2018) proposed a method for brain tumor detection based on k-means galactic swarm optimization (GSO) based clustering algorithm. One initial solution of the GSO algorithm was the solution obtained by the k-means algorithm. Fitness function used in this paper, Otsu's criterion, was also used in Nanda et al. (2018). In order to fairly compare the results, we used the same images as in Nanda et al. (2018). The used images were obtained from Harvard Whole Brain Atlas (Johanson & Becker, 1995). Images that were used are fdg-PET, titc-SPECT and MRI images. Glioma was present in fdg-PET and titc-SPECT images, while MRI images contain metastatic adenocarcinoma, metastatic bronchogenic carcinoma and sarcoma. All images are 8-bit grey scale images of a size 256x256. The number of segments is chosen in a way to emphasize tumors and enable easier detection in the further analysis. Based on the characteristic of each of the considered tumors and images the number of clusters can be determined empirically and in this paper we used standard values that were also used by Nanda et al. (2018).

In Table 2 the results presented by Nanda et al. (2018) along with the results obtained by our proposed k-means firefly algorithm (KM-FA) are presented. Best results are printed in bold.

**Table 2.** A comparison between the KM-FA method proposed by the authors of this paper and approaches from Nanda et al. (2018)

| Image | Algorithm | NRMSE | PSNR | SSIM |
|---|---|---|---|---|
| Glioma(fdg)PET (No. of cluster = 3) | K-Means | 0.6937 | 16.3426 | 0.5500 |
| | GSO | 0.6807 | 16.4458 | 0.5676 |
| | RGA | 0.6840 | 16.4580 | 0.5598 |
| | KM-GSO | 0.6782 | 16.4779 | 0.5676 |
| | KM-FA | **0.4617** | **19.8192** | **0.6469** |
| Glioma(titc)SPECT (No. of cluster = 4) | K-Means | 0.3990 | 18.0223 | 0.6813 |
| | GSO | 0.3576 | 18.3697 | 0.6918 |
| | RGA | 0.3782 | 18.0892 | 0.6910 |
| | KM-GSO | 0.3537 | 18.4652 | 0.6950 |
| | KM-FA | **0.3164** | **19.4321** | **0.7068** |
| Metastatic Adenocarcinoma (No. of cluster = 8) | K-Means | 0.2425 | 24.4619 | 0.8085 |
| | GSO | 0.3650 | 20.6039 | 0.7502 |
| | RGA | 0.3360 | 21.3050 | 0.8080 |
| | KM-GSO | 0.2410 | 24.4834 | 0.8164 |
| | KM-FA | **0.1559** | **27.9912** | **0.8541** |
| Metastatic bronchogenic carcinoma (No. of cluster = 4) | K-Means | 0.3834 | 18.8560 | 0.6717 |
| | GSO | 0.3869 | 18.9737 | 0.6996 |
| | RGA | 0.3860 | 18.8488 | 0.6780 |
| | KM-GSO | 0.3388 | 20.1285 | 0.7146 |
| | KM-FA | **0.2939** | **21.3631** | **0.7535** |
| Sarcoma (No. of cluster = 3) | K-Means | 0.5967 | 15.5893 | 0.6142 |
| | GSO | 0.5787 | 15.8206 | 0.6226 |
| | RGA | 0.5780 | 15.8233 | 0.6180 |
| | KM-GSO | 0.5863 | 15.7074 | 0.6220 |
| | KM-FA | **0.4325** | **18.3508** | **0.6766** |

Based on the results presented in Table 2, it can be concluded that our proposed KA-FA method achieved better results compared to the method proposed by Nanda et al. (2018) and all other methods used for comparison, i.e. the original GSO, real coded genetic algorithm (RGA) and basic k-means algorithm. Nanda et al. (2018) proposed KM-GSO method that achieved better results for all test images except for detection sarcoma where real coded genetic algorithm found better values for NRSME and PSNR while SSIM was the best when the original GSO was used.

Compared to the method proposed by Nanda et al. (2018), KM-GSO, our proposed algorithm achieved the best improvement for glioma in ftg-PET image. For glioma in ftg-PET image, KM-GSO, the method proposed by Nanda et al. (2018), obtained NRMSE 0.6782 while the proposed KM-FA reduced the error to 0.4617. The best PSNR value in Nanda et al. (2018) was 16.4779 obtained by the KM-GSO while our KM-FA method achieved 19.8192. The SSIM obtained by KM-GSO was 0.5676 and our proposed combined method, KM-FA, obtained SSIM equal to 0.6469. On the other hand, the smallest improvement was achieved for segmentation of the SPETC glioma image when 4 clusters were determined. The NRMSE was 3.164 which is slightly better than 0.3537 that was obtained by segmentation by KM-GSO. Improvements in PSNR was from 18.4652 to 19.4321 while SSIM obtained by KM-GSO was 0.6950 and SSIM by our proposed KM-FA was 0.7068.

Segmentation of the metastatic adenocarcinoma was the optimization problem of the highest dimension, i.e. 8 clusters needed to be determined. In this case our proposed KM-FA method obtained NRMSE, PSNR and SSIM were 0.1559, 27.9912 and 0.8541, respectively, while these quality measurements for the KM-GSO method by Nanda et al. (2018) were 0.2410, 24.4834 and 0.8164.

Since different numbers of clusters were used for segmentation, it can be concluded that our proposed KM-FA algorithm achieved good results for both, low and high dimensions of the considered problem. Based on the resulting images, besides numerical results, we can see that each considered tumor was successfully emphasized by the obtained segmentation.

The used images and segmented images obtained by our proposed method are presented in Figure 1.

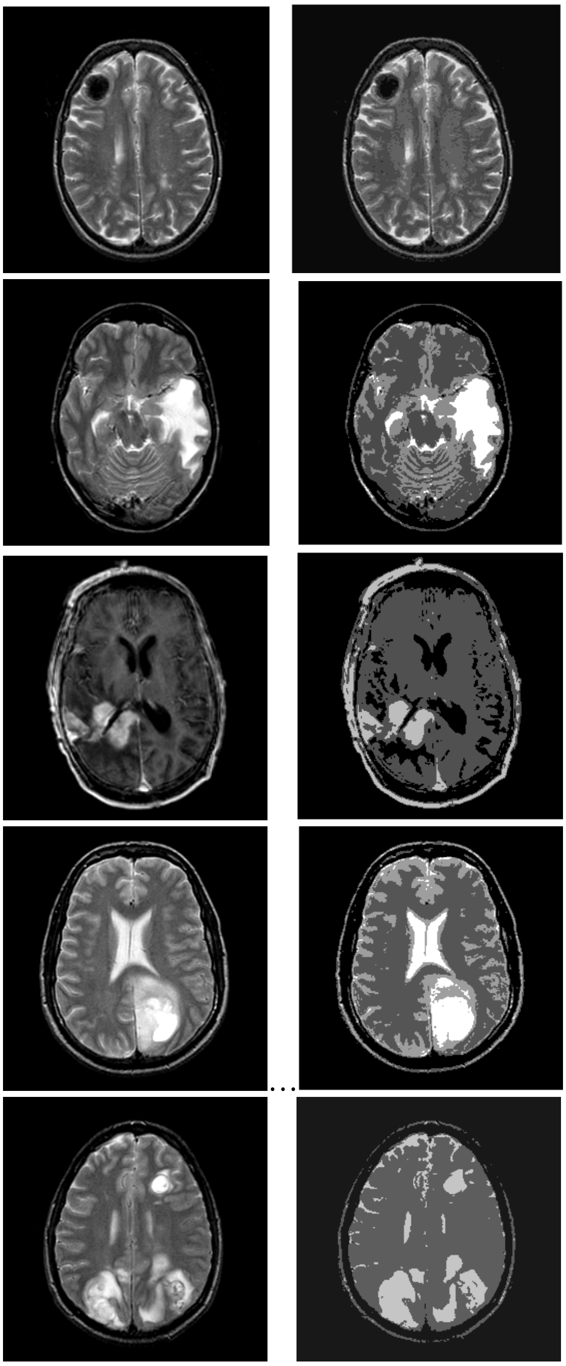

**Figure 1.** The original and resulting segmented images by the proposed combined KM-FA algorithm

## 6. Conclusion

Digital image processing algorithms for medical applications is highly researched area and the need for more accurate and faster algorithms is large. In this paper we proposed a method for brain image segmentation with the aim of detecting different primary tumors. Brain images are segmented by firefly algorithm combined by k-means clustering method in order to emphasize anomalies like glioma, metastatic adenocarcinoma, metastatic bronchogenic carcinoma and sarcoma. The proposed method was tested on standard benchmark images and it obtained better results compared to other state-of-the-art method from literature. Future work can include automatic determination of cluster numbers and adjustment of the fitness function, including spatial information in the segmentation process.

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