

SEGMENTATION OF SOFT TISSUE SARCOMA IN MR IMAGES USING SWARM INTELLIGENCE BASED CLUSTERING TECHNIQUES

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Abstract: This paper presents soft tissue sarcoma segmentation in MR images using hard-clustering techniques with Swarm Intelligence (SI). Swarm Intelligence based clustering techniques are popular and widely used in segmentation of brain MRI. In this work, the noise in MRI is reduced using median filter and intensity in homogeneities are corrected in the preprocessing steps. In the subsequent steps the MR images are segmented using hard-clustering technique using Swarm Intelligence algorithms. Qualitative and quantitative performances are analyzed by applying clustering for segmentation of MR images using five SI algorithms such as Particle Swarm Optimizer, Artificial Bee Colony, Fire-Fly algorithm, Glowworm Swarm Optimizer with Generalized Opposition Based Learning, Fireworks algorithm with Adaptive Transfer Function.

1. Introduction

Soft tissue sarcomas (STS) are malignant tumors that originate in tissues like muscle, fat, nerves, fibrous tissues or blood vessels. Segmentation of soft tissue sarcomas in MR images is a very important medical image analysis task for diagnostic, treatment and follow-up the disease.

There are some interesting contributions to the segmentation of sarcoma. J. Juntu et al. [3] applied machine learning methods to classify benign and malignant soft-tissue tumors using texture features that are extracted from T1-weighted MRI images. H. Farhidzadeh et al. [4] proposed Otsu method for segmentation of soft tissue sarcoma. H. Farhidzadeh et al. [5] proposed Fuzzy c-means based segmentation method for soft tissue sarcoma. H. Farhidzadeh et al. [6] predicted metastatic and necrotic soft tissue sarcomas using texture feature analysis. M. Vallieres et al. [7] proposed a model for the prediction of lung metastases in soft-tissue sarcomas using FDG-PET and MRI texture features. J.O. Glass and W. E. Reddick [8] proposed a segmentation method for osteo-sarcoma

using multilayer back propagation neural network and Kohonen self-organizing map (SOM). W. L. Monsky et al. [9] used an iterated watershed method for volumetric quantification of tumor necrosis in soft tissue sarcoma.

Nature-inspired strategies such as artificial neural network and swarm intelligence (SI) are now playing a crucial role in the development of intelligent decision making systems for solving the medical image analysis problems [11]. The objective of this paper is to make a comprehensive study of the performance of five SI based clustering techniques in the segmentation of soft tissue sarcomas in MR images. The five SI algorithms are Particle Swarm Optimizer (PSO), Artificial Bee Colony (ABC), Fire-fly algorithm (FFA), Glowworm Swarm Optimizer with generalized opposition based learning (GOBL-GSO) and Fireworks algorithm with adaptive transfer function (FWA-ATF).

2. Materials and Methods

2.1 MRI Dataset

The MRI datasets [20-22] of two patients are used in this study. The MR images are collected from "The Cancer Imaging Archive" [22]. Each dataset in this study contains ten MR images. This dataset contains FDG-PET/C, T1-weighted, T2-weighted with fat-suppression MRI data with histologically proven soft-tissue sarcomas (STSs) of the extremities. In this study, T2-weighted with fat-suppression MRI data of two patients are used.

2.2 Noise Reduction

Segmentation of soft tissue sarcomas face difficulties due to the presence of noise across the MR images. The noises are removed from MR images using median filter with neighborhood size 3x3 [10]. Because the median filter is widely used de-noising method to

reduce noise in the MR image and it preserves the edges of the MR image [10].

2.3 Intensity Inhomogeneity Correction

The intensity non-uniformity or the bias field usually refers to the intensity variations of the same tissue over the image due to the radio-frequency non uniformity, static field inhomogeneity etc. in the imaging instrumentation, or the patient movement. A 10x10 Max filter based inhomogeneity correction method [16] is used to correct intensity in-homogeneities in the denoised images.

2.4 Segmentation using SI based Clustering Algorithm

2.4.1 SI based Clustering Algorithm

SI based clustering technique is now one of the most popular hybrid clustering techniques used for segmentation of MR images. The SI algorithms such as PSO [13], ABC [14], FFA [15], GOBL-GSO [16], FWA-ATF [17] are widely used in clustering techniques and they perform better than well-known K-means algorithm [12]. All these algorithms use three objective functions for better clustering and they are discussed in the next section.

2.4.2 Objective Functions

In this present work, all the existing SI based clustering algorithms used three objective functions to get better quality of clustering solutions. The first objective function is the maximum intra-cluster distance which has to be minimized. It is defined as follows:

$$f_1 = d_{\max}(X, \vec{m}) = \max_{\forall k \in K} \left\{ \sum_{\forall \vec{x} \in C_k} \frac{d(\vec{x}, \vec{m}_k)}{|C_k|} \right\}$$

Where $|C_k|$ is the number of pixels belonging to the cluster C_k . The second objective function f_2 is the minimum inter-class separation which is to be maximized and it is defined as follows:

$$f_2 = \min_{\substack{i \neq j \\ i, j \in K}} d(\vec{m}_i, \vec{m}_j)$$

The third objective function f_3 is the quantization error which has to be minimized and it is defined by the following equation:

$$f_3 = \frac{1}{K} \sum_{k=1}^K \sum_{\forall \vec{x} \in C_k} \frac{d(\vec{m}_k, \vec{m}_j)}{|C_k|}$$

Finally, all the objective functions above are transformed into one objective function (F) that has to

be minimized and it is defined by the following equation:

$$F = w_1 \cdot f_1 + w_2 \cdot (x_{\max} - f_2) + w_3 \cdot f_3$$

Where $w_i \in (0,1)$ is the weight value and $\sum_{i=1}^3 w_i = 1$. The second objective function f_2 is converted into minimization problem by subtracting it from the highest pixel intensity $X_{\max}$ of the MR images.

2.5 Performance Evaluation

In this work, Davis-Bouldin (DB) index [18] has been used to evaluate the performance of segmentation methods quantitatively. DB-Index is a well-known and widely used cluster validity index. DB-Index is a function of the ratio of the sum of intra-cluster scatter to inter-cluster separation. The i^{th} intra-cluster scatter is defined as follows:

$$S_{i,q} = \left[\frac{1}{N_i} \sum_{\forall \vec{x} \in C_k} |\vec{x} - \vec{m}_i|^q \right]^{\frac{1}{q}}$$

Inter-cluster distance between i^{th} and j^{th} cluster is defined as follows:

$$D_{ij} = \left[\sum_{p=1}^d |m_{i,p} - m_{j,p}|^t \right]^{\frac{1}{t}}$$

Where $\vec{m}_i$ is the centre of i^{th} cluster, $q, t \geq 1$, q, t are integer, $N_i = |C_i|$ is the number of data points in the i^{th} Cluster C_i . q and t are set to 2 in this present work. $R_{i,qt}$ is calculated as follows:

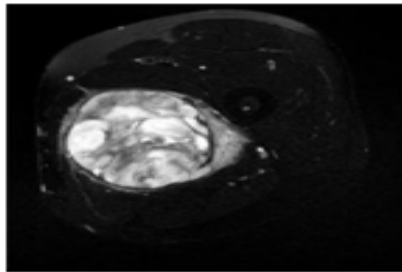
$$R_{i,qt} = \max_{\substack{j \in K \\ j \neq i}} \left\{ \frac{S_{i,q} + S_{j,q}}{D_{ij}} \right\}$$

Finally, DB-Index is measured as follows:

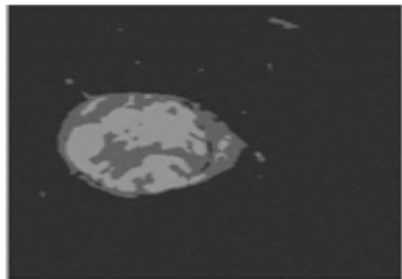
3. Results and Discussion

The classical K-means, PSO, ABC, FFA, GOBL-GSO and FWA-ATF based clustering techniques are applied on ten MR slices of each patient. The clustering techniques are applied to segment the MR images into three classes: (i) enhanced or active regions, (ii) non-enhanced or non-active sub regions and (iii) region includes other tissues and background. The qualitative results are given in Fig.1 (b)-(g) in terms of segmented image of one original image (Fig.1 (a)). In the segmented images, highest intensity indicates enhanced or active region of the sarcomas whereas medium level intensity indicates non-enhanced or non-active regions

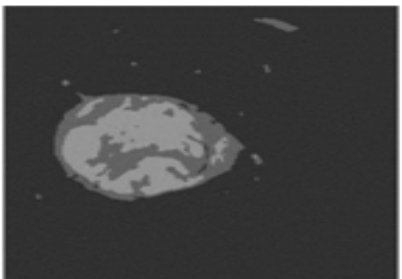
of the sarcomas. From Fig.1 (b)-(g), it is visually observed that ABC, GOBL-GSO and FWA-ATF based clustering techniques perform better segmentation than other algorithms



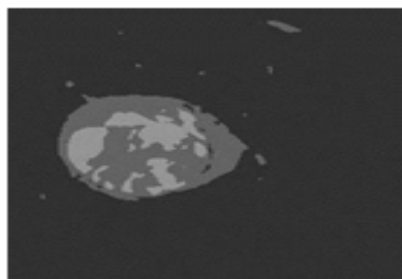
(a) Original MR Slice



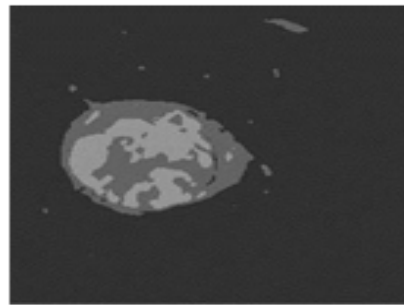
(b) Segmented using K-means



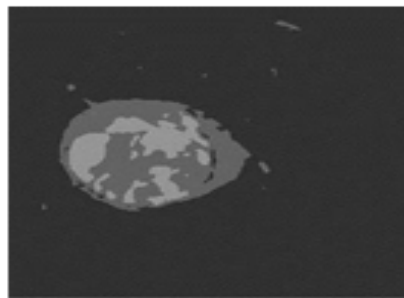
(c) Segmented using PSO



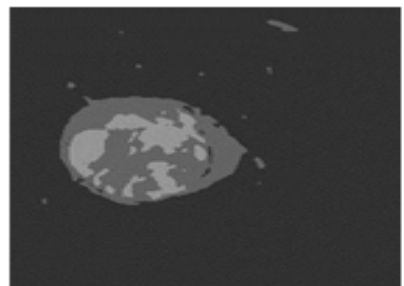
(d) Segmented using ABC



(e) Segmented using FFA



(f) Segmented using GOBL-GSO



(g) Segmented using FWA-ATF

Figure 1. Original MR slice and its segmented image using different methods.

The experiments with each of the K-means, PSO, ABC, FFA, GOBL-GSO, FWA-ATF methods are repeated for 51 times for each of the MR slices of both patients. The means and standard deviations of DB-Index values over 51 independent runs for each MR slice of the first and second patient are given in Table 1 and Table 2 respectively.

From the results in Table, it is observed that the K-means method performs better than SI based clustering methods for only two out of ten slices. Among the SI algorithms, ABC performs better

clustering than others and K-means for four out of ten slices.

From the results in Table 2, it is observed that the K-means method performs better than SI based clustering methods for only three out of ten slices. Among the SI algorithms, ABC performs better clustering than others.

As ABC algorithm performs better than K-means and other SI algorithms for most of the MR slices of both patients, a pair wise comparative study of ABC with other algorithms has been carried out using Wilcoxon signed rank test[19]. The results of the aforementioned statistical test are given in Table 3 and 4 for the first and second patient respectively.

From the results in Table 3, it is observed that ABC algorithm statistically performs better than K-means algorithm with significance level (α) = 0.05. There are no statistically significant differences in the performances of ABC as well as other SI algorithms. From the results in Table 4, it is observed that ABC algorithm statistically performs better than PSO algorithm with significance level (α) = 0.05. There are no statistically significant differences in the performances of ABC and other SI algorithms as well as K-means algorithm for the second patient.

Computational complexities are given in Table 5 and Table 6 for the first and second patient respectively. PSO and FWA-ATF take lower computational time than other SI algorithms.

From the analysis of the above results, it is observed that all the SI based clustering algorithms perform better than K-means algorithm for the first patient. For the second patient, all the SI based clustering algorithms except PSO based clustering

algorithm performs statistically equivalent to K-means algorithm. PSO and FWA-ATF take the lower computational time for segmentation of the image than other SI algorithms. But, PSO performs poor in segmentation of the images of the second patient. Therefore, FWA-ATF based clustering algorithm is more effective and efficient in the segmentation of soft tissue sarcomas.

4. Conclusions

In this article, the Swarm Intelligence based clustering algorithms are applied in segmentation of soft tissue sarcomas in MR images. The SI-based clustering techniques statistically perform better than K-means algorithms in segmentation of MR images of the first patient dataset. There is no statistical difference in the performance of SI-based clustering techniques except PSO based clustering technique and K-means algorithm in segmentation of MR images of second patient dataset. Though the most of the SI based clustering algorithms provide good performance in segmentation of soft tissue sarcomas, some other healthy tissues are also segmented as sarcomas because they have the similar intensity levels to sarcomas in MR images. The experimental results has shown that the SI-based clustering techniques would be useful for assisting radiologists in the diagnosis of soft tissue sarcomas in MR images.

In this work, we have used only gray level feature for MR image segmentation. Spatial or texture information can be used as features for better segmentation of soft tissue sarcomas in MR images.

Table 1. Mean and standard deviation of DB-Index over 51 independent runs for each image of patient-1.

MRI#	K-means		PSO		ABC		FFA		GOBL-GSO		FWA-ATF	
	Means	Std	Means	Std	Means	Std	Means	Std	Means	Std	Means	Std
1	0.1039	0.0002	0.1010	0.0028	0.0974	0.0006	0.0986	0.0017	0.0975	0.0008	0.0978	0.0002
2	0.1121	0.0088	0.1066	0.0020	0.1068	0.0004	0.1070	0.0010	0.1070	0.0006	0.1068	0.0003
3	0.1028	0.0011	0.1081	0.0037	0.1088	0.0003	0.1098	0.0016	0.1099	0.0012	0.1095	0.0006
4	0.1075	0.0016	0.1046	0.0054	0.1047	0.0016	0.1027	0.0039	0.1036	0.0025	0.1041	0.0022
5	0.1089	0.0066	0.1051	0.0011	0.1045	0.0004	0.1051	0.0006	0.1049	0.0004	0.1047	0.0002
6	0.1291	0.0115	0.1057	0.0027	0.1072	0.0006	0.1069	0.0013	0.1070	0.0011	0.1072	0.0002
7	0.1091	0.0020	0.1133	0.0030	0.1137	0.0001	0.1130	0.0018	0.1137	0.0006	0.1135	0.0006
8	0.1043	0.0005	0.0987	0.0046	0.0955	0.0003	0.0967	0.0021	0.0961	0.0008	0.0958	0.0002
9	0.1311	0.0011	0.1101	0.0044	0.1091	0.0026	0.1082	0.0015	0.1084	0.0018	0.1079	0.0018
10	0.1080	0.0062	0.1016	0.0014	0.1012	0.0004	0.1015	0.0009	0.1012	0.0004	0.1012	0.0004

Table 2. Mean and standard deviation of DB-Index over 51 independent runs for each image of patient-2.

MRI#	K-means		PSO		ABC		FFA		GOBL-GSO		FWA-ATF	
	Means	Std	Means	Std	Means	Std	Means	Std	Means	Std	Means	Std
1	0.0986	0.0003	0.0901	0.0014	0.0886	0.0002	0.0892	0.0009	0.0890	0.0007	0.0888	0.0003
2	0.0819	0.0000	0.0902	0.0081	0.0812	0.0001	0.0834	0.0038	0.0810	0.0008	0.0812	0.0002
3	0.0872	0.0001	0.0940	0.0034	0.0879	0.0004	0.0912	0.0037	0.0889	0.0019	0.0890	0.0018
4	0.1004	0.0002	0.1133	0.0083	0.1059	0.0002	0.1027	0.0051	0.1031	0.0051	0.1021	0.0034
5	0.1079	0.0202	0.0939	0.0036	0.0898	0.0002	0.0923	0.0012	0.0909	0.0008	0.0910	0.0011
6	0.1156	0.0008	0.0947	0.0031	0.0932	0.0008	0.0944	0.0025	0.0938	0.0015	0.0942	0.0015
7	0.0930	0.0002	0.0913	0.0036	0.0873	0.0001	0.0885	0.0017	0.0875	0.0003	0.0873	0.0001
8	0.0839	0.0000	0.0945	0.0094	0.0844	0.0003	0.0876	0.0055	0.0851	0.0025	0.0866	0.0043
9	0.0931	0.0000	0.1005	0.0063	0.0928	0.0002	0.0950	0.0039	0.0934	0.0011	0.0935	0.0012
10	0.0990	0.0002	0.1012	0.0072	0.0939	0.0000	0.0949	0.0011	0.0944	0.0006	0.0940	0.0004

Table 3. Wilcoxon Signed Ranks Test Statistics for the first patient. R^+ : sum of positive ranks, R^- : sum of negative ranks.

Sl. No.	Comparison	R^+	R^-	Z	p (2-tailed)
1	ABC vs K-means	47.00	8.00	-1.988	0.047
2	ABC vs PSO	34.50	20.50	-0.714	0.475
3	ABC vs FFA	31.50	23.50	-0.408	0.683
4	ABC vs GOBL-GSO	20.00	16.00	-0.281	0.779
5	ABC vs FWA-ATF	14.50	13.50	-0.085	0.933

Table 4. Wilcoxon Signed Ranks Test Statistics for the second patient. R^+ : sum of positive ranks, R^- : sum of negative ranks.

Sl. No.	Comparison	R^+	R^-	Z	p (2-tailed)
1	ABC vs K-means	43.50	11.50	-1.632	0.1027
2	ABC vs PSO	55.00	0.00	-2.805	0.005
3	ABC vs FFA	46.50	8.50	-1.940	0.052
4	ABC vs GOBL-GSO	43.50	11.50	-1.633	0.1025
5	ABC vs FWA-ATF	28.00	8.00	-1.400	0.161

Table 5. Mean computational complexities (in seconds) for the first patient.

K means	PSO	ABC	FFA	GOBL-GSO	FWA-ATF
4.36	23.97	250.49	2524.07	386.37	23.72
4.16	23.73	236.57	2443.26	380.88	23.61
4.35	23.96	230.38	2448.21	380.80	24.39
4.27	23.94	230.27	2439.62	380.42	24.37
4.06	23.91	229.19	2430.82	379.97	23.63
4.03	23.65	239.53	2421.06	384.56	23.51
4.65	23.99	231.34	2435.17	391.52	24.02
4.37	23.96	229.49	2435.70	379.69	23.63
4.04	23.93	233.24	2448.97	381.60	23.70
4.02	23.85	233.28	2444.13	379.66	23.69

Table 6. Mean computational complexities (in seconds) for the second patient.

K means	PSO	ABC	FFA	GOBL-GSO	FWA-ATF
3.84	23.76	235.42	1467.43	382.00	23.57
3.85	23.73	241.47	1452.66	382.60	23.42
3.87	23.77	239.30	1476.42	381.95	23.68
3.83	23.75	240.26	1464.41	385.84	23.85
3.83	23.75	238.06	1457.30	382.76	23.83
4.08	23.62	238.71	1445.53	381.66	23.70
3.90	23.74	237.48	1465.30	382.34	23.78
3.82	23.72	239.19	1448.40	383.68	23.87
3.87	23.78	239.07	2447.82	383.27	24.14
3.76	23.83	240.44	2441.73	384.57	24.15

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