Hybrid Bee Colony and Cuckoo Search based centroid initialization for fuzzy c-means clustering in bio-medical image segmentation

M.Vijayakumar, S.Velmurugan, V.Mohan, P.Shanmugapriya

Abstract*: In current years, the grouping has become well identified for numerous investigators due to several application fields like communication, wireless networking, and biomedical domain and so on. So, much different research has already been made by the investigators to progress an improved system for grouping. One of the familiar investigations is an optimization that has been efficiently applied for grouping. In this paper, propose a method of Hybrid Bee Colony and Cuckoo Search (HBCCS) based centroid initialization for fuzzy c-means clustering (FCM) in bio-medical image segmentation (HBCC-KFCM-BIM). For MRI brain tissue segmentation, KFCM is most preferable technique because of its performance. The major limitation of the conventional KFCM is random centroids initialization because it leads to rising the execution time to reach the best resolution. In order to accelerate the segmentation process, HBCCS is used to adjust the centroids of required clusters. The quantitative measures of results were compared using the metrics are the number of iterations and processing time. The number of iterations and processing of HBCC-KFCM-BIM method take minimum value while compared to conventional KFCM. The HBCC-KFCM-BIM method is very efficient and faster than conventional KFCM for brain tissue segmentation.

***Index Terms*: clustering, centroid initialization, Hybrid Bee Colony and Cuckoo Search (HBCCS), Kernel fuzzy C-means (KFCM), MRI brain tissue segmentation.**

I. INTRODUCTION

To recognize the mental disease, the division is the most troublesome thing as a result of the ordinary and anomalous structures in the cerebrum Tissues [1]. In this HBCC-KFCM-BIM framework, a gathering based division is considered. The gathering is a strategy of collection a rigid of empowered contraptions into a measure of gatherings in one of this way that practically identical devices are permitted to one gathering. The primary methodologies in the gathering are Crisp bunching (CC) [2], FCM set of standards, phantom grouping [3], progressive techniques forceful acing calculations [4], and circulation fundamentally based strategies contraption [5], and thickness based techniques [6], [7]. Uncommonly, Density-based absolutely spatial Clustering programming with commotion (DBSCRN) and requesting focuses are utilized to end up mindful of the bunching structure [8]. A segment of the CC approach is that the cutoff among bundles is completely described. Nevertheless, in other certifiable events, the purposes of restriction among gatherings can't be extraordinarily portrayed. Two or three styles may have a spot with more than one gathering. Inside the precedent class, FC approach offers a higher gathering sway [9-11].

FCM is an iterative algorithm [12]. FCM is good at resolving the ambiguities and uncertainties in the image [13]. However, FCM can't deal with the intensity inhomogeneity and more difficult to reduce the noise. The application of brain tumour recognition is introduced by using a modified FCM system. In that, a wide-ranging feature vector is used in segmentation that is accompanied by the kernel hints. The KFCM gadget is expanded which fuses the network phrases into its objective capacity [14]. The explanation behind FCM is to find bundle centroids and that breaking point the goal component. The KFCM is gotten from the new FCM reliant on the segment methodology. [15]. through applying bit implies, the KFCM contraption endeavours to manage this inconvenience by mapping records with nonlinear capacity extraction [16]. Metaheuristic systems are conveyed for gathering way. In Metaheuristic based absolutely grouping limit of the investigations is focused inside the squared mix-ups and that they have utilized a couple of metaheuristic procedures, for example, Genetic calculation GA [17], PSO [18], bacterial rummaging streamlining [19] mimicked strengthening [20], fake honey bee province [21] and Firefly framework (FS) [22]. In this paper, to defeat the KFCM centroid arbitrary introduction issue the HBCC-KFCM-BIM strategy is presented. The HBCC-KFCM-BIM procedure improves the division execution. The presentation parameters are dice coefficient, Jaccard co-productive and exactness.

This paper is created as pursues. Area II studies a few latest papers on cerebrum tumour location related methodologies. In section III, HBCC-KFCM-BIM technique. Section IV shows the relative trial result for the existing and proposed methodology. The conclusion is defined in Section V.

II. RELATED WORK

Numerous researches are recommended by scientists in brain tumour detection. On this state of affairs, the brief assessment of a couple of fundamental commitments to the present literary works as advertised.

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Li, Haiyang et al. [23] presented a framework for MIS, called Dynamic PSO and K-implies bunching framework (DPSOK). Dynamic PSO (DPSO) and K-suggests bundling system was the base of the DPSOK structure. They made DPSOK a conventional streamlined figuring by overhauling the preparing technique of that one inertness weightiness and knowledge factors Research results displayed that DPSOK computation can gainfully improve the K-infers system's overall request limit. DPSOK estimation passed on better results in improving picture division quality and capability appeared differently in relation to standard PSO K-infers structure.

Ronghua Shang et al. [24] introduced a superior FCM framework duplicate bit three-dimensional FCM (CKS-FCM). A safe clone machine was utilized to streamline the underlying bunch offices, which allows the combination overall debut. The spatial insights are included inside the target highlight and CKS-FCM utilized a non-Euclidean separation fundamentally dependent on bit highlight to refresh the Euclidean separation. The primary restriction of the framework is Low division exactness and Low heartiness.

Elazab et al. [25] have a present division of mind tissues from MRI utilizing versatile regularized bit based absolutely FCM. That gadget wound up ordered into 3 stages which incorporate typical channel, centre channel out, and thought up the weighted picture. The system's organization the heterogeneity of monochromic inside of the system and adventure this degree for adjoining applicable material and update the regular Euclidean detachment through Gaussian extended foundation part limits. The crucial favours are acclimated to the adjacent setting, logically productive power that jam photograph information, the opportunity of collection parameters, and lessened computational expenses, yet the boss unsteady territory is lower entropy.

Li Liu et al. [26] proposed a novel extreme dataset type strategy subject to Neighbor looking and FCM (NSKFCM) structures to cut down the impact of parameters vulnerabilities with dataset request. Some redesigned strategies, together with a neighbor looking, controlling gathering structure and adaptable partition bit trademark, are used to decide the issues of different bundles, the steadfastness, and consistency of sort, independently. Numerical tests, at last, demonstrate the reachability and healthiness of the proposed method. The NSKFCM structure puts aside all the more taking care of exertion to segment the photos.

Y.T. Chen et al. [27] have proposed Independent part investigation based kernel-zed fluffy by utilizing MIS. They have talked about the division execution of six strategies (k-implies, FCM, KFCM, ICFCM, KWFLICM, and ICKFCM) for the mimicked MRI pictures in silent case, clamour case, and genuine therapeutic pictures. The fundamental disadvantage of the framework is less precise.

III. HBCC-KFCM-BIM METHOD

Picture division assumes a significant job in some continuous applications, for example, Medical handling, picture coding, object recognition, PC vision and Image assessment. In this paper, HBCC-KFCM-BIM algorithm is introduced for MRI brain tissue segmentation, which is presented in Fig. 1.

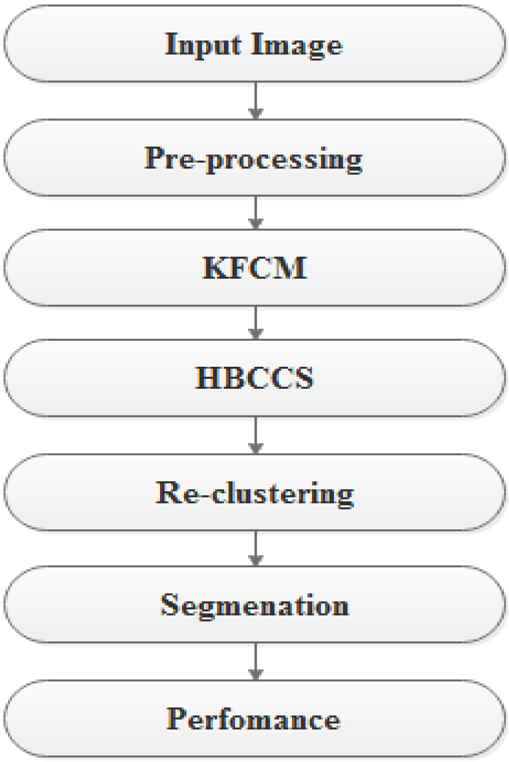


Figure.1.HBCC-KFCM-BIM Flow diagram

The expectation of HBCC-KFCM-BIM approach is to find the group focuses that limit a divergence capacity of FCM. By utilizing iteratively refreshing the bunch focuses and the enrollment grade for every record point, FCM iteratively activities the group offices to the "correct" place inside records set. Anyway, it's never again suitable to locate the best arrangement in the surest time. The working of the FCM depends on the underlying centroids so the determination of the centroids is the most significant thing in the FCM. For this reason, in this paper, the HBCC-KFCM-BIM strategy is a programmed centroid determination dependent on HBCC for FCM. The proposed strategy incorporates two segments, the HBCC bunching segment and the FCM grouping segment. In the underlying stage, the HBCC bunching module is executed for a brief period for programmed grouping, framing round or near circular shape information bunches. The outcome from the HBCC bunching module is utilized as the underlying seed of the FCM module. The improved portions are Contour by Geometric dynamic shape system (GACF). Here, the wellness worth determined and the best wellness worth is fixed as centroid esteem. By utilizing the wellness esteem, the KFCM division is handled lastly, the presentation is determined.

A. FCM Algorithm

FCM system is segregating the dataset $\{x_k\}_{k=1}^{N}$ into c the number of groups depending on the accompanying target work Eq. (1).

$$J_m = \sum_{i=1}^{c}\sum_{k=1}^{N} u_{ik}^{p} \left\| x_k - v_i \right\|^2$$
(1)

here p demonstrates the genuine amount, which means the amount managing of the fluffiness of the resultant gathering, u_{ik}^{p} is the membership of the data point x_k belongs to the group i and is the x_k pixel of the picture which satisfying $\sum_{i=1}^{c} u_{ik} = 1$ and v_i is the centroid of the cluster. From the above equation 1, where c is the overall amount of groups and N indicates the quantity of information focuses. The FCM makes the isolating by iteratively invigorating the cooperation regards and the gathering centres. The cooperation estimation of each datum point to every centrum in the like manner decided after every time reviving of centres that should be conceivable by the Eq. (2).

$$u_{ik} = \frac{1}{\sum_{j=1}^{c} \left(\frac{\left\| x_k - v_i \right\|^2}{\left\| x_k - v_j \right\|^2} \right)^{\frac{1}{p-1}}} \quad (2)$$

The group centrums are refreshed dependent on the separation among the information point to the bunch centrum which is finished the following Eq. (3).

$$v_k = \frac{\sum_{k=1}^{N} x_k U_{ik}^{p}}{\sum_{k=1}^{N} u_{ik}^{p}} \quad v_i = \frac{\sum_{j=1}^{N} u_{ij}^{m} x_j}{\sum_{j=1}^{N} u_{ij}^{m}} \quad (3)$$

The objective limit plays out the arithmetic to check the adulterated aggregate of results among the gathering centrums and information instant in the fleecy bundles. FCM gives among division results to the photos, which does not have any bustle. Regardless, the FCM fails to describe the noisy information in perspective on the peculiarities of the component data, which prompts assigning the cooperation regards to end up off-base. This is the rule clarification behind less than ideal division appears during the planning of a boisterous picture using the FCM.

B. KFCM

To overcome the standard FCM difficulty's, the KFCM computation is introduced. With the help of a non-linear aligning limit (MF), the KFCM changes over the information in the picture plane into front line dimensional component space. The baffling and non-linear detachable issue in the data plane can be altered over with the course of the charting limit to straightly distinguishable later on space. By formerly, the FCM can play out its activities with the induced characteristic space. The detached limit of the KFCM is portrayed in Eq (4).

$$\begin{aligned} J_m &= \sum_{i=1}^{c} \sum_{k=1}^{N} u_{ik}^{p} \left\| \varphi(x_k) - \varphi(v_i) \right\|^2 \\ &= 2 \sum_{i=1}^{c} \sum_{k=1}^{N} u_{ik}^{p} \left(1 - k\left(x_k - v_i\right)\right) \end{aligned} \quad (4)$$

Here φ is the MF. Here the Gaussian Kernel Function (GKF) for non-direct Charting of the picture level into the straight high dimensional element Planetary. The GKF is displayed in the accompanying beneath condition (5).

$$K(x, y) = \exp\left(-d(x, y)^2 / \sigma^2\right) \quad (5)$$

The GKF is presented in the below equation (6)

$$\begin{aligned} J_m &= \sum_{i=1}^{c} \sum_{k=1}^{N} u_{ik}^{p} \left\| \varphi(x_k) - \varphi(v_i) \right\|^2 \\ &= 2 \sum_{i=1}^{c} \sum_{k=1}^{N} u_{ik}^{p} \left(1 - K\left(x_k, v_i\right)\right) \end{aligned} \quad (6)$$

Where the membership function (MF) and the informing the centroid is calculated by the following Eq 5 and 6.

$$u_{ik} = \frac{\left(1 - K\left(x_k, v_i\right)\right)^{-1/(p-1)}}{\sum_{i=1}^{c} \left(1 - K\left(x_j, c_i\right)\right)^{-1/(p-1)}} \quad (7)$$

$$v_i = \frac{\sum_{k=1}^{n} u_{ik}^{p} K\left(x_k - v_i\right) x_k}{\sum_{k=1}^{n} u_{ik}^{p} K\left(x_k, v_i\right)} \quad (8)$$

C. Hybrid Bee Colony and Cuckoo Search (HBCCS)

HBCCS is seen as a champion among the greatest current metaheuristic just as Swarm Intelligent estimations (SI) like GA, PSO, ACO, and DE. A metaheuristic can have described as an iterative age process that escorts a subroutine heuristic by uniting shrewdly changed plans to research and abuse the request space to find perfect courses of action. It depends on reproducing and duty flight rummaging conduct of the cuckoo flying creatures [28]. The working of the HBCCS appears in the Fig.2.

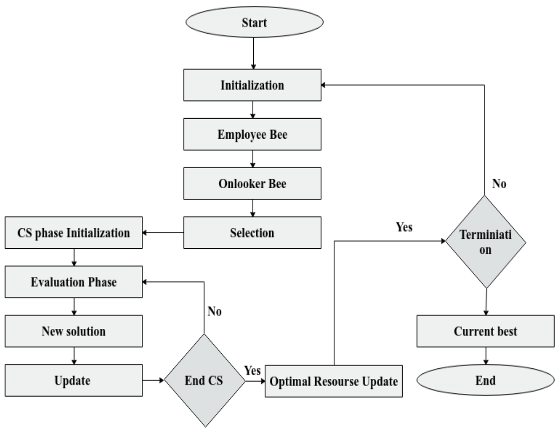


Figure.2. HBCCS Algorithms working.

IV. RESULTS AND DISCUSSIONS

The HBCC-KFCM-BIM framework was performed with the assistance of T1-WCEMRI database. The HBCC-KFCM-BIM was investigated with the assistance of MATLAB trigger programming adaptation 2018b. The whole work is finished by utilizing I3 framework with 2 GB RAM. The greatest measure of cycles 2 is utilized in HBCC grouping. This emphasis is adequate to yield the ideal centroids for this HBCC-KFCM-BIM technique. Both quantitative and subjective approvals were utilized for the presentation assessment. The exhibition of the HBCC-KFCM-BIM strategy was looked at regarding dice coefficient, Jaccard co-proficient and precision.

A. Performance measure

In segmentation, validation is obtained by matching the segmented result to the ground truth image. Which is shown in the Eq. (11).

$$Dicecoefficient = \frac{2tp}{(2tp+fp+fn)} \quad (11)$$

In the Jaccard coefficient, the TP values segmented ground-truth tumour labels and the machine-generated tumour labels. Which is denoted in the Eq (12)

$$Jaccardcoefficient = \frac{tp}{fp+fn+tp} \quad (12)$$

Accuracy:

The degree of conformance among a measurement of an observable quantity and a recognized standard or specification that indicates the true value of the quantity presented in equation (13).

$$\text{Accuracy} = \frac{tp+tn}{tp+fp+tn+fn} \quad (13)$$

B. T1-WCEMRI dataset description and results validation

In this HBCC-KFCM-BIM system is analysis, T1-WCEMRI database is assessed for associating the dice, Jaccard coefficient and accuracy performance of FCM and GA-KFCM and the HBCC-KFCM-BIM which is shown in table 1. The T1-WCEMRI dataset contains 3064 images with three classes of brain images: meningioma, glioma and pituitary tumour. The performance evaluated example images are shown in table.1.

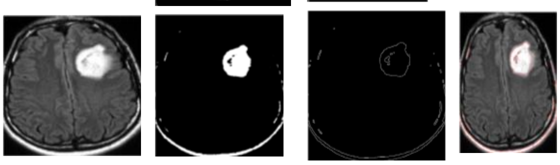
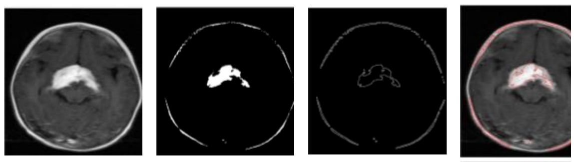
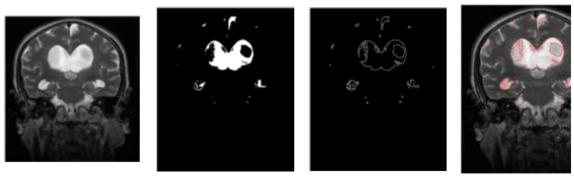
Sl. No	Input image	KFCM segmented image	HBCC optimized image	GACF image
1				
2				
3				
4				

Table 2. Dice and Jaccard coefficient comparison of IWO-KFCM and the HBCC-KFCM-BIM

Class	Technique	DSE	JSI	Acc
Meningioma	IWO-KFCM	0.26158	0.1625	94.1253
	HBCC-KFCM-BIM	**0.4075**	**0.3041**	**96.4890**
Glioma	IWO-KFCM	0.4765	0.2511	93.7741
	HBCC-KFCM-BIM	**0.92380**	**0.88347**	**96.9931**
Pituitary	IWO-KFCM	0.5847	0.3570	97.0235
	HBCC-KFCM-BIM	**0.7258**	**0.6010**	**98.8912**

From table 2. The analysis shows that the HBCC-KFCM-BIM technique provides much better results. The average of the HBCC-KFCM-BIM technique is Dice coefficient is 0.6857 and average of Jaccard coefficient is 0.5962. IWO-KFCM delivers 0. 0.5658 Of dice coefficient. Similarly, the average Jaccard coefficient of the IWO-KFCM techniques is 0.3444. The average accuracy of the IWO-KFCM is 96.1383, and the HBCC-KFCM-BIM technique provides 97.4577 accuracy which is much better compared to other existing systems.

C. Comparative analysis

Table.2 and Fig.2. Presents a similar investigation of prevailing work and the HBCC-KFCM-BIM system execution. H. Ali, M. Elmogy, *et al.* [38] has introduced a new BIM system, which was created on morphological operation with FCM clustering. Initially, a wavelet multi-resolution was developed in order to maintain spatial context among the pixels. Then, the morphological pyramid was utilized to increase the sharpness of brain images. Finally, segmentation was carried-out using grouping FCM. The trial result demonstrates that the created system accomplished 96% of grouping exactness. In order to validate the HBCC-KFCM-BIM method accuracy. A novel centroid acquaintance strategy reliant on HBCC with start the FCM gathering to piece the MRI of head channels.

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Table 3. Proportional analysis of HBCC-KFCM-BIM and existing methodologies

Reference s	Database	methodology	AC (%)
H. Ali, M. Elmogy, *et al.* [29]	Brain Web (DS1), BRATS (DS2)	Morphological pyramid with FCM clustering technique	96
Proposed	**T1-WCEMRI**	HBCC-KFCM-BIM	**97.4577**

V. CONCLUSION

Brain tumour discovery is one of the greatest investigation tasks in computer-aided health intensive care system. The impartial of the experiment is to progress a correct segmentation approach to segmenting the healthy and tumour region of the brain using T1-WCEMRI database. HBCC-KFCM-BIM work is a novel centroid acquaintance system subject to HBCC with start the FCM gathering to piece the MRI of head channels. The results show that the HBCC-KFCM-BIM initialization along with 21 iterations is sufficient to yield the optimal results. The experimental results show that the HBCC-KFCM-BIM method gives better results and is more robust against conventions FCM. This is helpful to animate the mind demonstrative framework relying upon the cerebrum tissue division process.

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