J Electr Eng Technol.2017; 12(5): 1798-1804
http://doi.org/10.5370/JEET.2017.12.5.1798

ISSN(Print) 1975-0102
ISSN(Online) 2093-7423

A Study on the Gustafson-Kessel Clustering Algorithm in Power System Fault Identification

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Abstract – This paper presents an approach of the Gustafson-Kessel (GK) clustering algorithm's performance in fault identification on power transmission lines. The clustering algorithm is incorporated in a scheme that uses hybrid intelligent technique to combine artificial neural network and a fuzzy inference system, known as adaptive neuro-fuzzy inference system (ANFIS). The scheme is used to identify the type of fault that occurs on a power transmission line, either single line to ground, double line, double line to ground or three phase. The scheme is also capable an analyzing the fault location without information on line parameters. The range of error estimation is within 0.10 to 0.85 relative to five values of fault resistances. This paper also presents the performance of the GK clustering algorithm compared to fuzzy clustering means (FCM), which is particularly implemented in structuring a data. Results show that the GK algorithm may be implemented in fault identification on power system transmission and performs better than FCM.

Keywords: Gustafson-Kessel clustering algorithm, Fuzzy clustering means, Power transmission line, Adaptive neuro-fuzzy inference system

1. Introduction

Deterministic conventional approaches have several disadvantages that require handling by an expert operator such as low accuracy and complex mathematical calculation. Most techniques for identifying fault location depend on the parameters of transmission lines. This requirement limits the performance of conventional approaches.

Artificial intelligence (AI) is an alternative technique to overcome such problems that require a parameter-free algorithm [1]. In AI technique research, pattern recognition is a main aspect that requires data processing, data reduction, prediction and modeling. Each type of fault that occurs in the transmission line system has distinctive characteristics that lead to a proper pattern recognition scheme. Pattern recognition aims to consign the respective objects into one of several class numbers.

Methods in prediction can help in estimating fault type and fault distance. Fuzzy c-means technique has been considered [2] for the data under study. These data must be in the form of feature vectors. The total of clusters must be identified to attain the membership values of feature vectors. Following a previous investigation, [3] has elaborated on the use of classification technique as a numerical process description. However investigation on fuzzy clustering algorithms in power transmission lines is limited. Fuzzy clustering means (FCM) and Gustafson Kessel (GK) are kernel-based clustering methods that applied as well known standards [4].

This study examines the implementation of GK algorithm in the fault analysis of power transmission lines. The algorithm scheme is used to identify the type of fault that occurs on a power transmission line either single line to ground, double line, double line to ground or three phase. This scheme justify the type of fault and estimate the fault location without line information of the power transmission line. GK algorithm can be regarded as a special general algorithm with enhanced performance and is well suited for overcoming the problem of overfitting. Furthermore, a comparison between GK and FCM also is presented. In this study, GK algorithm is incorporated in a scheme that uses a hybrid intelligent technique to combine an artificial neural network and a fuzzy inference system, known as adaptive neuro-fuzzy inference system (ANFIS).

ANFIS has been used in fault detection and fault classification in power system for the last two decades [5]. Recently, researchers have focused on the capability of ANFIS to estimate fault location in transmission lines and distribution networks [5-8]. ANFIS contains five-layer feedforward neural network. Layer-1 is known as fuzzifications which explain the membership grades for every set of input. Layer-2 is represented by output nodes which are the main strength of the rule obtained from the membership grades. Layer-3 is the normalized layer.

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Received: May 18, 2016; Accepted: June 26, 2017

Layer-4 and 5 are the nodes output and single output respectively. The properties of ANFIS are similar to those of the Takagi Sugeno-type (TS) of the zero-th order.

This paper is organized as follows: Section II reviews a few fuzzy clustering algorithms. Section III evaluates the relation between the GK and FCM algorithms. Section IV presents the experimental studies and details the implementation of GK with ANFIS. Section V discusses the obtained results. Finally, Section VI presents the conclusions.

2. Fuzzy Clustering Algorithms

A cluster can be represented with or without a well-defined boundary. Clusters with well-defined boundaries are called crisp cluster. For the cluster without a well-defined boundary, it is called fuzzy clusters [4]. The fundamental of fuzzy clustering is to assess the clusters and determine to what degree the objects belong to the clusters [9]. Fuzzy clustering is defined as a partition-based clustering scheme that is advantageous when no clear and definite groups in the data set exist. Every individual data object belongs to not one one cluster, but to all the clusters with varying degrees of membership.

Introduced in 1981, FCM is known as a datacustering technique [2]. FCM algorithm provides a method of clustering that enables a data item to belong to two or more clusters. This method is frequently used in pattern recognition applications where the degree at which every point is owned by a cluster is recognized by a membership grade. It is an improved technique compared to previous approaches [10]. FCM can manage the data points that have some multidimensional space into a definite number of diverse clusters. To assure the membership function for every cluster, an appropriate matrix named U which has factors of numbers between 0 and 1, should be constructed. The next step is building the membership's degree between the data and the centers of clusters. However, this method is sensistive to the choice of distance metric. In [11], the author has claimed that FCM can show improvement when all clusters are *spheroids* with the same size or when all clusters are finely separated. The improvement is based on the minimization of the following objective function:

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \left\| x_i - c_j \right\|^2, 1 \leq m < \infty$$

where m is any real number larger than 1, u_{ij} is the degree of membership of x_i in the cluster j, x_i is the i^{th} of the d-dimensional measured data, c_j is the dimension center of the cluster, N is the total data and ||*|| is any norm expressing the similarity between any measured data and the center. Partitioning is executed based on the iterative optimization of the objective function shown above. The following function is used to update the membership u_{ij} and the cluster centers c_j . k is the iteration steps that will discontinue if a termination criterion between 0 and 1, where:

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

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m . x_i}{\sum_{i=1}^{N} u_{ij}^m}$$

The algorithm was executed using the improved covariance estimation proposed by [16]. When the amount of training samples is lower than the amount of clusters, overfitting can be reduced by including a scaled unity matrix to the computed covariance matrix [12]. A few advantages of clustering algorithms are as follows:

1. They gives the best results for overlapped data sets and are comparatively better than k-means algorithm.
2. Unlike k-means, where data points must belong exclusively belong to one cluster center the data points in clustering algorithms are assigned membership to each cluster center. Thus, the data points may belong to more than one cluster center.

Most of the drawbacks of FCM Algorithm are due to the restriction that the sum of the membership values of a data point xi in all the clusters must be equal to 1 [2]. This restiction tends to give high membership values for the outlier points and thus the algorithm encounters difficulty in handling outlier points [2]. The membership of a data points in a cluster depends directly on the membership values of other cluster centers, a condition that may lead to undesirable results [2]. FCM also faces problems in handling high- dimensional data sets and a large number of prototypes. Also FCM is sensitive to initialization and is easily trapped in local optima [2]. Thus, the resulting clusters cannot be directly used to form membership functions.

3. Relation Between GK and FCM

FCM and GK assemble the data points located in an n-dimensional space into a certain number of clusters [17]. Normally, the unknowns in the analysis of an FCM cluster are the positions of the c cluster centers in the n-dimensional space and the membership values of every sample. Partial memberships which implemented in the fuzzy concept allows for most data points to be cluster s of a cluster, and also possible to be partial members of another cluster. The FCM algorithm applied a Euclidian norm to figure out the distance of a sample from a cluster center. determine Furthermore, it to identifythe spherical clusters of approximately the same dimension of the data sets.

To implement the data affectedusing the FCM algorithm, Briggs logarithm is applied to cluster analysis and reduce the skewness (a measurable degree of asymmetry on a distribution) of the data histogram [18].

The center position and membership information were able to identify in the GK algorithm. The covariance of each cluster is influenced by the stretching one or several axes of the n-dimensional space. Thus, a good performance of the FCM algorithm requires data normalization based on linear transformations.

The GK algorithm [12] is a great clustering technique that has been implemented in numoeusumbers of research field [13, 14]. In [4, 12], the authors proposed a GK algorithm that applied the well-known Mahalanob is distance as the metric in FCM. When GK algorithm applied for subspace clustering such that each of the dimensions has possibly different weights associated with different clusters. GK algorithm is better than Euclidean distance based algorithms because it considers the data shape. In [15], the authors proposed a new formulation, based on Euclidean-distance-based algorithm. The benefit of this formulation is that the distance metric is adapted locally to cluster shape by estimating the cluster covariance matrix [14]. The FCM-GK algorithm is created through the iterative optimization of an objective functional of the c-means type:

$$J_m(U,V,\{A_i\}) = \sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^m d_{ikA_i}^2$$

The distance norm d_{ikA_i} is shown in the above equation. The metric of every cluster is recognized by a local norm-inducing matrix Ai, to optimize the variables. This condition will allow the distance norm to adjust to the local topological arrangement of the data. GK minimization is achieved by using the alternating optimization (AO) method according to the well-known algorithm [16]. For l = 1; 2; _ _ _ s, where l denotes each step in the iteration process and s is the maximum number of iterations allowed (stop criteria). The following steps explain the implemented modified GK algorithm;

Step 1: Calculate cluster prototypes (means)

$$V_i^{(l)} = \frac{\sum_{k=1}^{N}(\mu_{ik}^{(l-1)})^m z_k}{\sum_{k=1}^{N}(\mu_{ik}^{(l-1)})^m}\,,\quad 1 \le i \le K \tag{1}$$

Step 2: Calculate the cluster covariance

$$F_i = \frac{\sum_{k=1}^{N}\left(\mu_{ik}^{(l-1)}\right)^m (z_k - V_i^{(l)})(z_k - V_i^{(l)})^T}{\sum_{k=1}^{N}\left(\mu_{ik}^{(l-1)}\right)^m}\,,\quad 1 \le i \le K \tag{2}$$

Include a scaled identity matrix:

$$F_i = (1-\gamma)F_i + \gamma \det(F_0)^{\frac{1}{n}} I\,, \tag{3}$$

Extract eigenvalues λ_{ij} and eigenvectorsϕ_{ij} from F_i.
Find$\lambda_{i\,max} = max_j \lambda_{ij}$and set:

$$\lambda_{ij} = \lambda_{i\,max} / \beta\ \forall j \text{ for which} \lambda_{i\,max} / \lambda_{i\,j} > \beta \tag{4}$$

Reconstruct F_i by

$$= [\phi_{i1} \dots \phi_{in}]\mathrm{diag}(\lambda_{i1}, \dots, \lambda_{in})[\phi_{i1} \dots \phi_{in}]^{-1}$$

Step 3: Calculate the distances

$$D_{ikA_i}^2 = (z_k - V_i^{(l)})^T \,[\rho_i \det(F_i)^{\frac{1}{n}} F_i^{-1}]\,(z_k - V_i^{(l)})\,,\quad 1 \le i \le K, 1 \le k \le N\,. \tag{5}$$

Step 4: Check the partition matrix

$$\text{for } 1 \le k \le N, \text{if } D_{ikA_i} > 0 \text{ for } 1 \le i \le K\,,$$
$$\mu_{ik}^{(l)} = \frac{1}{\sum_{j=1}^{K}(D_{ikA_i}/D_{jkA_i})^{2/(m-1)}} \quad \text{otherwise}$$
$$\mu_{ik}^{(l)} = 0 \text{ if} D_{ikA_i} > 0\,, \text{and } \mu_{ik}^{(l)} \in [0,1] \tag{6}$$

with $\sum_{i=1}^{K}\mu_{ik}^{(l)} = 1$ otherwise until $\|U^{(l)} - U^{(l-1)}\| < \epsilon$

4. Experimental Studies

This section is divided into two parts. In the first part, the application results of the GK algorithm in fault identification pertinent to classification and location are presented to identify the capability of this algorithm. In the second part, a comparison between the GK and FCM algorithms pertinent to membership function, time consumption, and accuracy is presented. Before fault identification is investigated, the first step is to identify whether the data are considered as faults or not faults. The characteristics of root mean square and fast fourier transform are applied for this purpose. After fault detection, the fault type and distance estimation will be analyzed. Wavelet transform is used to give information about the frequency components present in the signal in the form of detail coefficients (Cd) by applying digital wavelet transformation (DWT) [10]. The aim of this process is to achieve data reduction. Daubechies at level 6 is used to extract the wavelet coefficient. The next step is implementation to the ANFIS architecture. Fig. 1 shows the implementation of GK algorithm in the proposed ANFIS.

The proposed scheme of the ANFIS-GK approach is independent between fault classification and location. Thus, the result of fault classification will not affect the result of fault location. An adaptive network is trained based on the analysis of the ANFIS-GK structure. The fuzzy inference system (FIS) model parameter optimization method, which is the hybrid method may be chosen. FIS adapts the membership function parameters and is able to

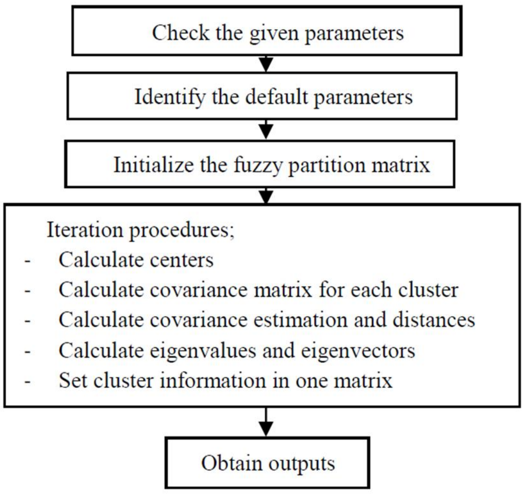

Fig. 1. Implementation of the GK algorithm

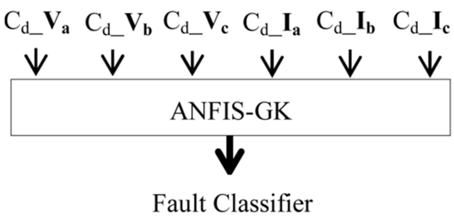

Fig. 2. ANFIS-GK fault classifier

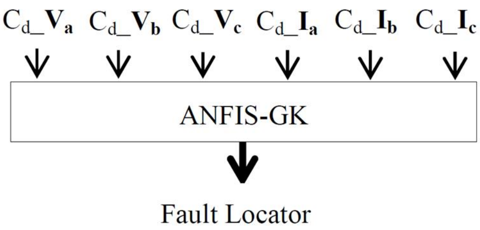

Fig. 3. ANFIS-GK fault locator

display the error. In fault classification scheme, the ANFIS-GK structure is performed with the structure in figure 2. It is based on the features of each type of fault.

In the fault location scheme, the structure of ANFIS-GK is performed with the structure in figure 3. This scheme is based on the features of each type of fault.

A test system is developed by using the ATP/ EMTP program. The purpose of this system is to obtain a large amount of data through the simulation. When the data obtained, these will be sent to the Matlab software for further analysis. The power system model is 100km of double circuit transmission line which delivers 15kV from both sides of the transmission line. A three phase fault simulator used to simulate faults at various positions on the transmission line. Fig. 4 shows the snapshot of the system in EMTP. The robustness of the double circuit/ parallel line is the most significant because faults commonly happen in this type of system voltage [19, 20]. Setting the parameters for generating training patterns are set as follows:

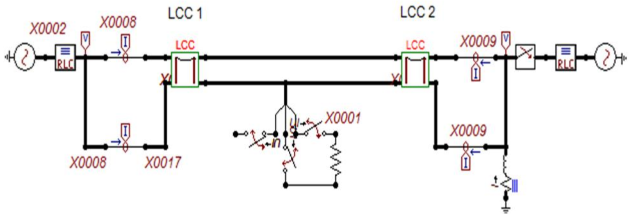

Fig. 4. Snapshot of the system in EMTP

Table 1. Parameters

Parameter	FCM	GK
Number of clusters, c	3	3
Fuzziness of clustering, m	2	2
Termination tolerance, ε	0.001	0.001

- Fault types consist of SLG, DL, DLG and three phase.
- Fault location on the transmission line were measured at every 2km from the sending end.
- The fault resistances; 0.5Ω, 5 Ω, 25 Ω, 100 Ω, 200 Ω.
- The loading conditions over the protected transmission line is assumed to be nearly constant.
- Frequency 50Hz.

In the second part, this study comparse of GK and FCM algorithm in terms of the performance in membership function, accuracy and time consumption. A total of 300 data pertinent to SLG, DLG and DL will be considered. The aim is to observe the performance of each algorithm. The membership function of x and y are to be extracted using FCM and GK algorithms. Table 1 shows the parameter used for simulation. The parameters are fixed by trial and error.

5. Results and Discussion

Part 1; The first step in the identification phase is fault classification. The inputs are six wavelet detail coefficients of the fault data; namely Cd_Va, Cd_Vb, Cd_Vc, Cd_Ia, Cd_Ib and Cd_Ic. The membership of each data point is calculated for each defined class. The data point may belong to more than one class with a certain degree of membership. The membership to one class is assigned based on the highest value of the membership value. Fig. 5 shows a snapshot of the fault classification using the proposed algorithm, which can classify the training data consisting of SLG fault; phase A to ground (AG), phase B to ground (BG) and phase C to ground (CG). A total 2350 data samples pass through the algorithm in scattered form. For each set, 70% of the total samples are used for training purposes, and 15% are used for validation and testing purposes.

The results were also verified using the Neural Network Start toolbox. Fig. 6 shows the analysis using the confusion matrix. The figure illustrates the performance of the fault classification pertinent to SLG. Class 1 is for AG, class 2

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Model Target

Fault is AGW
Percentage of above mentioned fault successfully classified: 32.5 %

Model Target

Fault is BGW
Percentage of above mentioned fault successfully classified: 34.3 %

Model Target

Fault is CGW
Percentage of above mentioned fault successfully classified: 34.0 %

Total percentage of classified:100.0 %
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Fig 5. Results of the classification phase

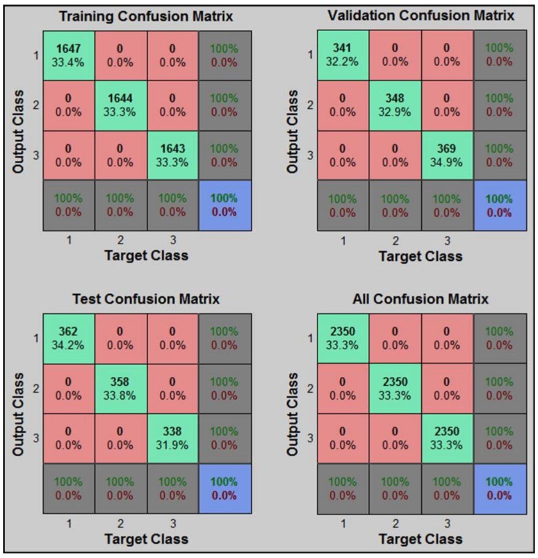

Fig. 6. Confusion matrix on fault classification

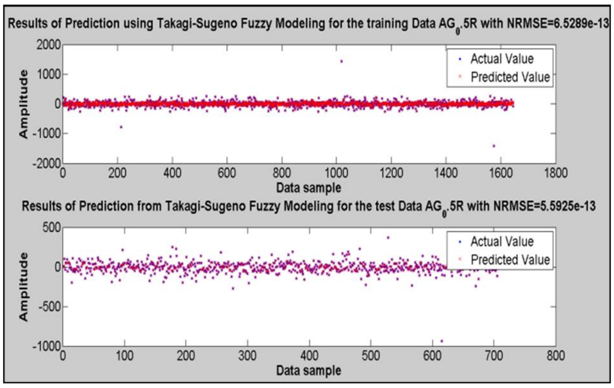

Fig. 7. Actual and predicted values

for BG, and class 3 is for CG. The green cell in the diagonal denotes the correct classified data in the expected class. The red cell represents the mis-classified data. It shows that the three types of faults were classified between the actual and the predicted. The blue cell represented the total percentage of performance. The second step in the

Table 2. Results of fault distance estimation

Fault Distance Estimation For Single Line to Ground					
Actual distance (km)	Estimation Error (Actual–Predicted)				
	R_F=0.5Ω	R_F = 5Ω	R_F = 25Ω	R_F = 100Ω	R_F = 200Ω
2.0	0.12	0.10	-0.096	-0.50	-0.53
10.0	-0.14	0.19	-0.16	-0.30	-0.26
20.0	0.29	0.26	-0.38	0.10	-0.22
30.0	-0.37	0.56	0.89	-0.15	-0.34
40.0	-0.27	-0.15	-0.55	0.10	0.25
50.0	0.12	0.19	-0.46	0.85	-0.13
60.0	0.13	0.29	-0.13	0.27	-0.32
70.0	-0.51	-0.26	0.12	0.11	-0.12
80.0	-0.14	-0.17	-0.12	0.59	0.32
90.0	0.54	0.13	0.79	0.28	0.12
100.0	-0.22	0.54	0.12	0.12	0.43

identification is fault location estimation. In this part, the same strategy is used. Our aim is to identify fault data pertinent to AG, BG and CG. These are the classes of fault data. The input is six wavelet coefficients.

The same strategy on membership value and clustering is used in the program. The distance of fault location is predicted based on the developed algorithm. Fig. 7 shows the results of the training and testing data sets for respective distance and fault resistance. Actual and predicted values denote the error in calculating estimated distance from the fault location. The plotting data of actual and predicted values are almost overlapping which shows that the results are closely accurate. Table 2 presents the results of fault distance estimation pertinent to the training phase.

Part 2; The FCM and GK algorithms are conducted as mentioned in Section 5. Table 2 illustrates the comparison of performance for both algorithms. Figs. 8 and 9 clearly shows that the FCM algorithm takes longer time for computation than the GK algorithm.

Performance on completion time compared to the number of clusters

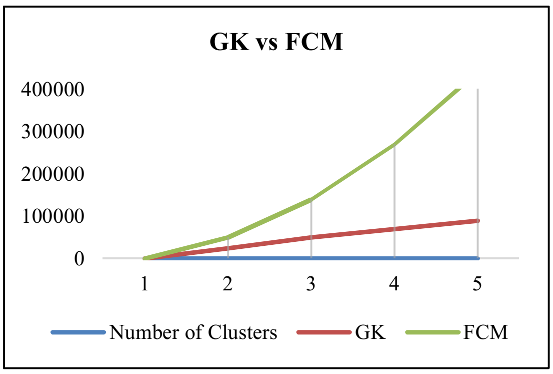

Fig. 8. GK versus FCM in terms of time completion with varying number of clusters

Performance on completion time taken

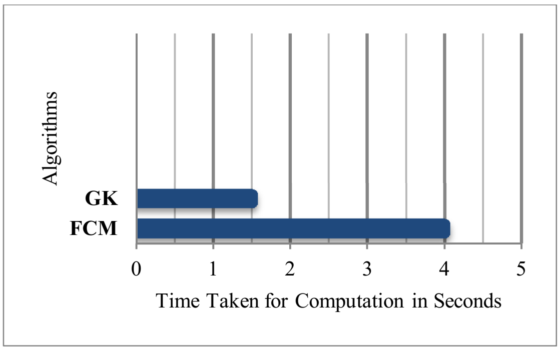

Fig. 9. Time of FCM versus GK in completing the clustering task

In the performance of clustering data (Figure 10), both FCM and GK perform well. Clustering can also be understood as a form of data compression, where a large number of samples are converted into a small number of representative clusters. The clustering function should work for data of any dimension. It returns cluster centers and the degrees to which the different data points belong to each cluster center. The data are centered around a certain point. A partition matrix indicates the degree to which each data point belongs to a particular cluster center, and a list contains the progression of cluster centers found during the run.

Note that the GK algorithm discovers clusters in low dimensional subspaces. Using the function of initialization, a random initial partition matrix will be returned for the use of the GK cluster function. The data points along with a pot of how the cluster centers migrated during the application of GK. An advantage of GK is that its smaller cluster has the capability to grab what belongs to the larger cluster because it does not take size into account. The simulation results reveal that GK clustering gives better performance for a nonlinear function compared to FCM.

Performance on clustering

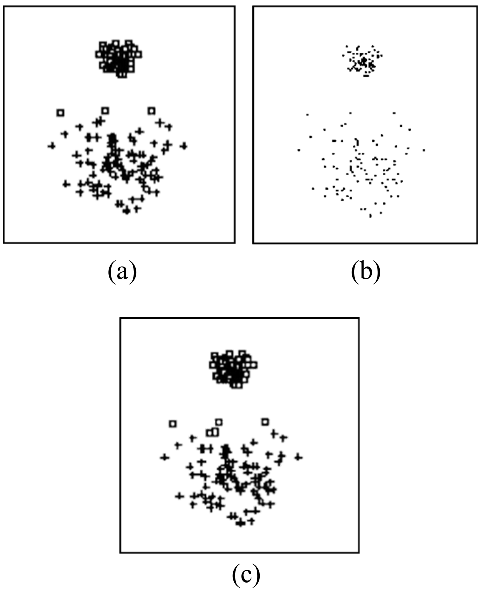

Fig. 10. (a) The original data in scattered form (b) FCM clustering (c) GK clustering

6. Conclusion

A new approach on Gustafson-Kessel (GK) algorithms in the fault identification on power transmission lines is presented. GK can overcome the clustering problem by using the characteristics and capabilities of distance matrices to prevent overfitting which is important in the pattern recognition aspect. The proposed method also has considerably reduced calculation time and is almost unaffected by fault resistance. The aspect of series impedance matrix per unit length is not considered in identifying the fault distance. The results of fault distance can be estimated regardless of the type of fault. In our future work, thel focus will be on adapting the proposed method in real applications where the actual fault data pertinent to the types and distances are unknown.

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