A RECOGNITION APPROACH OF RADAR BLIPS BASED ON IMPROVED FUZZY C MEANS

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Abstract
This research proposes a Fuzzy C Means-based approach to identify moving vessels from a plethora of blips captured by radar. Initially, the graphical characteristics of radar blips in sequential radar frames, such as speed, course, and size, are quantified and selected as pieces of evidence in a Fuzzy C Means-based (FCM-based) model, which is used for identifying the authenticity of a blip being a real moving vessel. With the help of the FCM, it is feasible to build up an artificial intelligence to classify and identify the authenticities of radar blips, calculate the possibility of some blip being a real vessel based on the three pieces of evidence mentioned above. To archive the goals above, the chief problem of building a successful FCM framework is to find an appropriate way to offer a classification coefficient C and a fuzzy coefficient m. Since the C in classification is finite, this research proposes a method to obtain C by assessing the Euclidean distance of expected results. As the m is related to the discreteness of the evidence and results, this coefficient can be evaluated by Shannon Entropy and gain. In the field testing, the improved FCM was capable of classifying the radar blips accurately, lowering the working strength of ship operators, and improving the safety. A real case study has been conducted to validate the effectiveness and accuracy of the proposed approach.
Keywords: Marine Radar; Fuzzy C Means; Shannon Entropy; Fuzzy Inference.

1. INTRODUCTION

A Vessel Traffic Service (VTS) centre is the core part of a maritime safety system in a port. This research aims to propose an approach to build artificial intelligence for VTS systems using Fuzzy C Means. With this approach, much manual work of identifying radar blips in a VTS centre can be assisted or even replaced by this Artificial Intelligence, enhancing the service ability of VTS without increasing any operators. With the help of this research, the enhanced (intelligent) VTS system will be capable of providing refine, personalised service to any individual vessel in monitoring, improving the safety and efficiency.

For decades, the shipping industry has put much effort to improve vessels, navigation devices and remote service systems, pursuing higher returns, lower emissions, and fewer accidents [1]. Therefore, the majority of ships are well-equipped with navigational devices, such as Automatic Identification System (AIS) terminals, Inmarsat satellite transmitters, radar and GPS. Meanwhile, to avoid the collisions and grounding in harbours and in-land rivers, many government departments (harbour or port authorities) have established VTS centres, which are similar to air traffic control for aircraft. Typical VTS systems use radar, closed-circuit television (CCTV), VHF radiotelephony and AIS to keep track of vessel movements and provide navigational messages to vessels in a limited geographical area [2]. In fact, VTS centres are also the information exchanging centres between ships and shores. Presently, the key responsibilities of a VTS centre also include traffic flow control and offering situation awareness for ship operators. However, the development of VTS has stuck in a bottleneck; the service level cannot be improved even though many powerful sensors and communication tools have been invented. The chief problem is that there is huge uncertainty in radar sensors. Hence, all the target recognition, information fusion and situation awareness relies on manual works and the experience of operators. In fact, it is very difficult to train a qualified VTS operator, as this work requires much experience and knowledge [3] Because of the limited manpower in a VTS centre, it is impossible to investigate or serve vessels manually one by one. Therefore, the personalised and refine service for these vessel cannot be implemented.

Being aware of these problems, marine researchers suggested that all the information on-board and on-land should be exchanged seamlessly. In 2005, researchers in UK proposed a new concept, namely E-navigation, which is defined as "the harmonized collection, integration, exchange, presentation and analysis of marine information on board and ashore by electronic means to enhance berth to berth navigation and related services for safety and security at sea and protection of the marine environment."[4] Nowadays, E-navigation has been widely accepted. As the ship-shore data exchanging centres, VTS systems have to take many responsibilities in the framework of E-navigation; not only the safety guarantee, but also the route scheduling and optimisation for any individual vessel. However, it is impossible to serve any individual vessel by manual work. Referring to the applications of consumer electronics, such as SIRI (In an iPhone or an iPad) and Google maps, this problem can be addressed by historical data analysis and Artificial Intelligence. Thus, much manual work of a VTS system can also be accomplished by Artificial Intelligence using appropriate methodologies and sufficient historical data. The main challenge is that there are many uncertainties in maritime service. In particular, all the modern VTS centres possess a sophisticated database which stores much information of vessels and abundant historical records. In other words, the only thing lacking is the applicable methodologies which are capable of making reasonable inference under uncertainties.

This research aims to propose an approach to build artificial intelligence, which is capable of identifying radar blips. The paper is organised as follows. Section 2 reviews the relevant research of radar and target classifications. Section 3 proposes an improved FCM-based approach. Section 4 uses a field testing to prove the effectiveness of the proposed approach. The paper is concluded in Section 5.

2. LITERATURE REVIEW

Many researchers have realized the limitation of marine radar, especially in the applications of VTS. Bin [5] puts the AIS and radar into comparing, and gives the conclusion that, AIS and radar are both important in collision avoidance, and the limitation of radar can be fixed by AIS information, but the radar is a real time tool, and it is more reliable, so making radar more intelligent would improve the safety significantly. Ma [6-9] had proved that, due to the limitation in design, the AIS signal is easily lost in inland rivers. By now, there are many ways to model the experience and knowledge above. It is obvious that the objective is to figure out which radar targets are real vessels, noise and a channel structures. Hence, the artificial intelligence above iis a typical classification problem. There are many ways to archive the objective, Bayesian Networks, fuzzy and so on. Liang [10] proposes a way to classify the driver cognitive distraction with Bayesian Networks. Danneshfar [12] uses the rough set to identify the owner ship of the car. Among varieties of math tools, FCM, Fuzzy C-Means, is considered to be a mature classification tool, and has been widely used in many areas, especially in the image processing and recognition. But the standard FCM has some limitations, so most of the researchers would apply the FCM in modified form. Daneshfar [12] applies two steps fuzzy clustering to finish the traffic flow control. J. Wang [13] uses an improved FCM to classify the MRI, Magnetic Resonance Imaging, images, and proves the accuracy. A. Ghosh[15] performs how the FCM running in the local image processing and pattern recognition. Chatzis[16] developed a new FCM based on Markov Random Chain to improve image characteristics extraction. Besides the application in the world of graphics, the FCM is also applied in the control engineering. Santosh[14] demonstrate the excellent effect of the FCM machinery noise feature extraction. All the references above infer that, the FCM is a kind of efficient and universal tool in classification and modeling the knowledge and experience, especially in the area of graphics, and it is extensible enough to accept any form of improvement. The major defect of FCM is that, the classification is usually established, and there is no description about the significance and discreteness of the different information or evidences. Many researchers focus on the improvement on the FCM itself, Yang [17] propose a comprehensive way to find the best classification number and fuzzy coefficient by the distribution analysis of the data set. The significance and discreteness are usually described by the Shannon Entropy, such as the decision tree algorithm ID3, C4.5. Tai-Yu [18] uses cross Shannon Entropy to state the confusion and discreteness. To improve the standard FCM, making the evaluation on the source information possible, the Shannon Entropy is an appropriate way. In summary, this research aims to propose an improved FCM-based approach to help operators to identify vessels in RADAR BLIPS.

3. A PROPOSED APPROACH

3.1 Step 1: Qualification of the Characteristics of Blips

Manual work is able to distinguish objects by inter-frame differences and graphic identities, including displacement, course, size, colour, width, length. Therefore, under such framework, all the characteristics above could be introduced to make the inference. To simplify the model, in this paper, three pieces of evidence are selected. They are displacement, motion course, and blip shape, which are represented in Figure 3. Referring to the manual work and ARPA function designed requirement IEC 62388, supervisors are generally able to identify the targets in 30 seconds, or 10 continuous frames. Therefore, the displacement and direction characteristics are extracted based on 10 frames analysis in following research.

Generally, the moving vessels are more likely to sail with a steady speed and steerable course. On contrary, the noise objects are more likely to drift around in small area. Hence, the displacement and motion course could be qualified as shown in the below of Figure 3. In this diagram, the displacement equals to how many units (pixels) the blip has moved, and the direction is the included angle between the true north and lineation of centers in 10 frames. It is noted that, the uncertainty has been implicated into the direction, and there is no assumption has been made.

Intuitively, according to the images, moving vessel's graph is more slender than noise's. This is because that the imagery delay is a typical function in radar system, which would make moving blip having afterglows. Therefore, the slenderness of the blip could be considered as a graph identity, which could be computed as the quotient of blip's size and blip circumcircle area, or S1/S2 in right below of Figure 1.

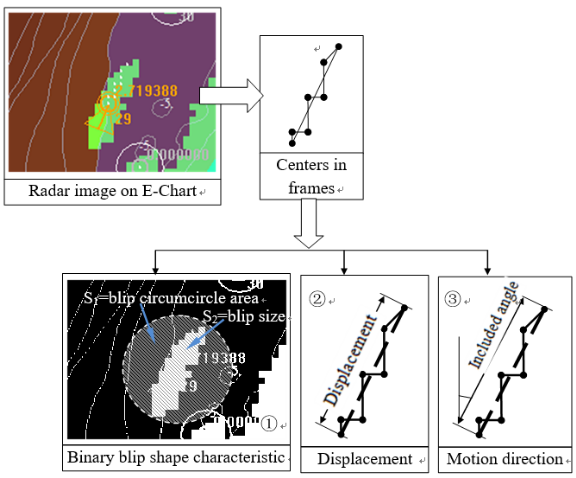

Fig. 1. Blip Characteristics in Frames of Radar

3.2 Step 2: Improved Fuzzy C Means-Based Classification

After the qualifications of the characteristics of blips, Fuzzy clustering is introduced to classify these blips. Fuzzy clustering is a branch of fuzzy mathematics, and the FCM is the most flexible one, and has been widely used in medical science, economics, control engineering, biology. The FCM is proposed by Bezdek [19], derived from standard HCM, hard C mean, which is the traditional classification method. It assigns a class membership to a data point, depending on the similarity of the data point to a particular class relative to all other classes. The standard FCM objective function of partitioning an image into C clusters is

$$J_m(\mu, v) = \sum_{i=1}^{c}\sum_{j=1}^{c}\mu_{ij}^{m} d^2 \quad \text{Subject to} \quad \sum_{i=1}^{c}\mu_{ij} = 1 \tag{1}$$

Where $X = (x_1, x_2, \dots, x_j, \dots, x_n)$ is a data matrix with the size of $p \times n$, p represents the dimension of each x_j "feature" vector, and n represents the number of feature vectors. The feature vector X in radar targets classification means the belief degree, so $p = 1$ μ_{ij} is the membership of the j_{th} data in the i_{th} cluster c_i, m presents the index of fuzziness, in most researches, the m equals to 2, and v_i is the fuzzy cluster centroid of the i_{th} cluster. Using the Euclidean norm, the distance metric d measure the similarity the similarity between a feature vector x_j and a cluster centroid v_i in the feature space, i.e.:

$$d^2(x_j, v_i) = \|x_j - v_i\|^2 \tag{2}$$

The objective function is minimized when data points close to the centroid of their clusters are assigned high membership values, and low membership values are assigned to data points far from the centroid. Letting the first derivatives of J_m with respect to μ and ν equal to zero yields the two necessary conditions for minimizing J_m as follows:

$$\mu_{ij} = \left(\sum_{k=1}^{c} \left(\frac{d(x_j, v_i)}{d(x_j, v_k)} \right)^{2/(m-1)} \right)^{-1} \tag{3}$$

And

$$v_i = \frac{\sum_{j=1}^{n}\mu_{ij}^{m} x_j}{\sum_{j=1}^{n}\mu_{ij}^{m}} \tag{4}$$

The FCM algorithm proceeds by iterating the two necessary conditions until a solution is reached. Each data point will be associated with a membership value for each class after FCM clustering. By assigning the data point to the class with the highest membership value, a segmentation of the data could be obtained.

The model of FCM above infers that, it is very refined and convenient to be implemented in diversity platforms. Besides that, the FCM is able to carry out the classification in high dimensional space, and provide membership and the centres to any class, which is the foundation to do further optimization. However, to any independent classification example, the core problem is the appropriate number of classification C, and fuzzy coefficient m. There are three different way to optimize the C.

3.2.1 The Assessment on Fuzzy Degree In Subset

Based on the intuitive inference, the best classification would lead to a minimum fuzzy degree result in subset. On the basis of this, the founding father of FCM, Bezdek [20] proposed a practical method to find the best classification number C, basing on new parameter, fuzzy partition entropy. In the subsequent research, the fuzzy partition entropy is proved to be not rational enough, but some researchers are still focusing on it, wishing to find a way to amend it [21].

3.2.2 The Distribution Of the Data In Geometric Space

It is obvious that, the better classification of data in geometric space, the data class would be more compact, and the centres between different classes would be more separated. To describe the characteristics above, the subset compact parameter and separated parameter are introduced. Gath and Geva [22] invent the concept of fuzzy volume, density, and the function about the effectiveness according to the subset structures. The distribution optimization method is the most coincident way to intuitive thinking, there are plenty of works are basing on it.

3.2.3 Statistical Information

Some researchers believed that, the best classification would provide the best statistical information. Beni and Liu [23] propose an effectiveness function and non-bias classification algorithm based on the maxim entropy. Roberts [24] invent an different effectiveness function, derived from the maxim relevance and scalar space filtering. Rui-Ping [25] modified the FCM by calculating all the maxim information Shannon Entropy.

The first way, assessment on fuzzy degree in subset is considered to be easy to implement, and it leads to very low calculate amount, but the relevance between the source information and result fuzzy degree is widely believed farfetched. The second way, the effeteness of classification is closely related to the subset data distribution in geometric space is widely accepted, but the expressions are usually complicated and leads to huge calculate amount. The third way, statistical information take effect relies on the precondition that the distribution of data must be consistent to the statistical hypothesis.

Different from that about the classification number C, the discussion about the fuzzy parameter m is much rarer. The m is also called smooth factor, which determine the sharing level between different fuzzy classes, apparently, the parameter would take great influence on the result of classification.

When m equals 1, FCM degenerates to HCM;

When m equals 2, FCM is the standard form, which is also the built-in FCM function m value in MATLAB.

When m equals infinitely great, the fuzziness of classification FCM increases to maxim.

Bezdek [26] suggest that the m should be set in the area 1.1≤m≤5, and prove that 2 is the appropriate value which shows the best consistency with the physical laws, and even if choosing another value, the m should be greater than n/(n-2). Chan [27] found that the best value of m in the Hanzi recognition is between 1.25 and 1.75. Pal [28] proves that the m should be set between 1.5 and 2.5 which performed the best effeteness in experiment, and the 2 might be a suitable default value. By now, in most of the FCM math software, the m is set to 2.

In the latest research, Yang [17] proposes an optimization method to get a best classification number C and fuzzy parameter m in two-dimension geometry space by calculating the distribution; he believes that best C would leads to a maxim distance sum among class centres, and the minimum distance sum among class members.

In summary, in the FCM application, researchers are still trying to search a better solution to find appropriate C and m, and there are no acknowledged methods. In following discussion, radar specialized FCM is presented.

The appropriate classification number C in the radar targets depends on actual targets distribution. Generally, radar blips contain five types, normal vessels, banks, buoys, channel structures and noise, but most of the time, less than five. So the possible value of the classification number C is very limited, when the C is larger than five, the classification is meaningless.

As mentioned before, there are three different way to find the best classification, and the most pregnant way is based on the distribution of the data in geometric space, which the defect is the giant computation amount. In the very condition of targets, the defect is inconspicuous, as there are only few possible value for the classification number C. The main idea of this method is that the best classification should lead to largest compactness inside the sub data set, and the biggest separability among sub data sets. Referring to the definition the compactness, the sum of each distance in the vectors inside the subset is common in the former research. Meanwhile, there is two individual ways to describe the separability, which are the edge distance and centre distance. In the FCM model, the centres would be evaluated in the processing, so the centre distance way might be more convenient. Talking to the vectors distance, many conceptions are in discussion, such as the Euclidean distance, Mahalanobis distance. In consideration of the ARPA data itself, the data randomness is difficult to be presented in specific way, so the traditional Euclidean distance might be more reasonable.

In the n-dimension space, the m vectors could be presented as,

$$X = \{x_1, x_2, \dots, x_m\} \tag{5}$$

The compactness of the data set is,

$$K_{compactness} = \sum_{j=1}^{m} \sum_{i=1}^{n} [\sum_{k=i}^{n} (x_{ij} - x_{kj})^2]^{\frac{1}{2}} \tag{6}$$

The FCM is capable to provide the subset centres automatically， the centres set of s subsets in n-dimension space is $O = \{o_1, o_2, \dots, o_s\}$

The separability of the whole data classification is,

$$K_{separability} = \sum_{j=1}^{s} \sum_{i=1}^{n} [\sum_{k=i}^{s} (o_{ij} - o_{kj})^2]^{\frac{1}{2}} \tag{7}$$

So the objective function is,

$$\min F = \frac{K_{compactness}}{K_{separability}} \tag{8}$$

With constraint function s = {2, 3, 4, 5, 6}.

In the former research, there is no acknowledged and reasonable math deduction for calculating a suitable fuzzy parameter m in FCM, which is widely believed to be relevance to the application circumvent. In general, the best value of m should be based on the uncertainty of the source information. According to the definition of the FCM framework, along with the growing of the parameter m, the ability of noise points disposing getting stronger, but it is much harder to make the classification result convergent. The noise points are the kind of data which are quite difficult to be assigned to any class. So, the best parameter m should make the FCM convergent; meanwhile, make sure to assign the noise points into classes as reasonable as possible.

Luckily, the characteristics of the data set with noise points are measurable, that more noise points would cause the inconsistency of the classification result. The inconsistency of the data set can be assessed by the Shannon Entropy, which is an efficient tool in computing the uncertainty and randomness. In the decision tree algorithm ID3 and C4.5, the Shannon Entropy is a parameter to describe the complexity and deviation of the information, including the source and result. By comparing the difference of the Shannon Entropy between result and source information, it is also possible to evaluate the contribution and consistency of specific source information, called, gain.

The definition of the Shannon Entropy is below,

There is a data set D = {d1,d2,...,dn}, the Entropy is defined as,

$$\mathrm{H}(D) = \sum_{i=1}^{n} \frac{d_i}{sum} \log_2 \frac{d_i}{sum} \tag{9}$$

If the Entropy of the result is H(C), then the gain is presented as,

$$\mathrm{gain}(D) = \mathrm{H}(C) - \mathrm{H}(D) \tag{10}$$

The proper classification should be consistent with the artificial expectation, which is based on the source information subjective judgment. All these means, there is a nature connection between source and result. When the Entropies are quite irrelevant, the classification result could be considered to be farfetched. The relationship above could be a clue to do the optimization on the fuzzy parameter m. Meanwhile, the gain is another clue to present the contribution of very source information, the smallest gain absolute value stands for the largest consistency with the result.

Hence, the evaluation of the best m is presented as below. In the limited source information, choose the tendentious one or a few, exhaust all the possible m, select the one which leads the smallest sum of the gains. Due to the continuity of the m, and the parity and monotony is hard to evaluate, the rigorous exhaustion seems impossible. So the model is simplified as below.

The objective function is min $F = gain(D)$ (11)

Constraint condition $m = \{m \mid 1.0 \leq m \leq 3.0\}$.

To reduce the computation amount, the step is set to 0.1.

So the constraint condition is transformed to,

m = {1.0, 1.1, 1.2, 1.3, 1.4, 1.5, 1.6, 1.7, 1.8, 1.9, 2.0, 2.1, 2.2, 2.3, 2.4, 2.5, 2.6, 2.7, 2.8, 2.9, 3.0}.

4. A CASE STUDY

The Experimental Platform

To validate the proposed methodology, three experiments have been conducted at the same location, which is depicted on the left-hand side of Figure 2.

The objective of the first experiment is to obtain sufficient verified vessel samples, which can be used to find the probabilistic relationships between the True state of an object and its attribute values, as described in Section 3.2. It is difficult to investigate the speed, course and position of a vessel by direct or physical inspection in the field. However, it is much easier to obtain such information from AIS. Since only a real vessel possesses an AIS terminal, all AIS messages must be from real vessels. To collect sufficient real vessel samples, an AIS receiver was placed, which received 13,087,776 valid AIS messages from 17:11:45 2014-04-12 to 11:31:01 2014-06-07 in the above location. As mentioned, the AIS messages contain all the dynamic and static information of the vessels.

The other two experiments are used to gather verified radar blips. The testing radar is FURUNO FAR 2127S, and is installed on a wharf boat, which is marked as a cylinder on the left-hand side of Figure 3. The circle scan area is also represented as a shadow region in this figure, and the radius of the area is 1.5 nautical miles (2.748 km).

One radar experiment was conducted from 10:31:00 2014-06-07 to 12:30:59 2014-06-07 and it captured 66,507 records or observations of radar blips, which were from 120 individual targets. In that period, the waterway shown in Figure 2 was temporarily prohibited for safety reasons. Therefore, all the targets captured by radar during this time period are definitely false. These verified false targets will be used to model probabilistic relationships between the False state of an object and the attribute values of the object.

Another radar experiment was also conducted from 13:35 2013-11-10 to 16:65 2013-11-10. 55 targets were captured and verified, including 22 vessels and 33 false targets or noises. In this testing, all of the targets were double checked with a telescope in a distance of 5 km, including 1,808 individual records of radar blips. It is worth noting that a target can be located and verified only if it approaches a known buoy. Therefore, the number of verified samples is limited. These samples are used to validate the proposed methodology.

Eventually, all these samples or records of blips were quantified with the method mentioned in Section 3.1.

Fig. 2. Radar Platforms

As shown in Figure 3, a software program has been developed to analyse these quantified records, and it is based on MATLAB 2013b and Visual Studio C++ 6.0. In this software program, an blip target is presented as a green circle; the line from the centre represents the course; the length indicates the speed; the number on the right-bottom is its serial number; and the floating number on the right-top is the probability of the object being a real moving vessel predicted using the proposed methodology.

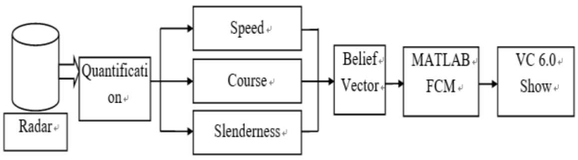

Fig. 3. Working Flow

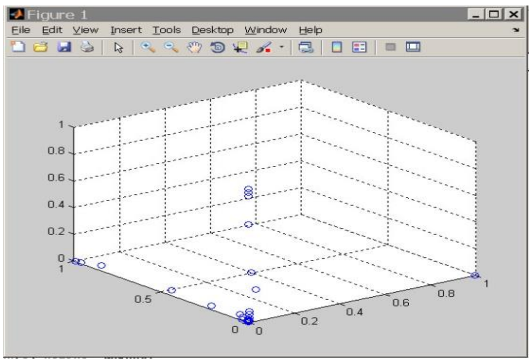

Fig. 4. Matlab Fcm

Step 1: Radar Blips

Before applying the new FCM, all the source information should be modelled in the unique and uniform framework. Referring to the manual processing of judging targets, apparently, speed over ground, vector over ground, and position might be the most effective evidences, and they are also representing some kind of belief degree. Hence, the framework is similar to any other fuzzy decision problems, which is based on the believe degree, and all the parameters should be mapped into believe space.

Taking speed over ground as an example, in the artificial processing, the different speed stands for different believe degree. For a vessel in sailing, 3km/h is rational, and some radar target is moving in this speed means that it is similar to a vessel. However, 30km/h is illogical, and some radar target is moving in this speed means that it is not likely a vessel. So, there is some way to model a function to describe how much the target like a vessel in specific speed, which is called belief function, or membership function. In fuzzy modelling, the membership function is quite a crucial problem, which would determine the effect.

Step 2: classification

The processing flow is shown in Figure 5,

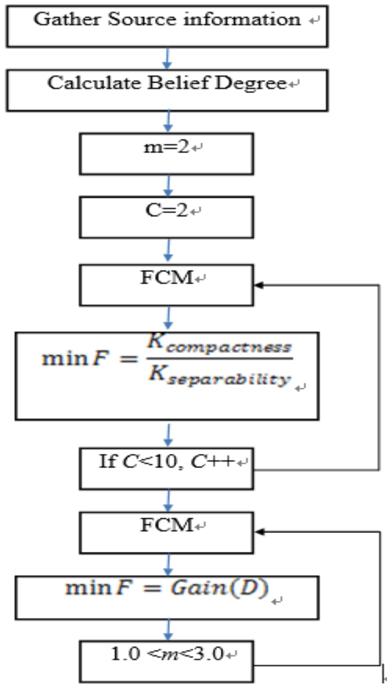

Fig. 5. The Flow Chart of the Proposed Improved Fcm-Based Approach

Basing on the belief membership function, assign the targets in three dimension space;

Set the fuzzy coefficient m to 2, do the exhaustion to classification number C from 2 to 6, choose the best C, which meets to the equation (6) to (8);

Alter the fuzzy coefficient m from 1.0 to 3.0; choose the best m, which leads a best entropy and gain.

Export the classification result with the parameters optimized above. In the sub sets, the one whose centre point contains largest membership to a vessel, and no member is less than 0.5 could be considered as the vessels set. When there is no such data set, we could infer that, there is no vessels set.

The analysis of the results

Use two different ways to process the data, which is gathered by the platform radar shown in Figure 2. It is easy to infer that, too many targets are shown in the processing, which are very difficult to be verified manually.

After 200 hundred times standard and improved FCM, the results are shown as follows. To simplify the processing, the classification number C is set from 3 to 6; fuzzy coefficient m is set from 1.5 to 2.5. Furthermore, in artificial judgment, due to the location is obviously the most important evidence, so the optimization objective of fuzzy coefficient m is set to find the min gain absolute value of the location. When applied the improved FCM, the result is shown in Form3. It is apparent that, the accuracy of identifying a verified vessel is raising, and sailing vessel belief degree for the targets increases to 92.2%, and the gain absolute value decreases, the maxim value drop to 0.14, and average value is 0.11. All this prove that, the improved FCM is more effective than the standard one, and the location evidence takes more influence to the result. Homoplastic ally, in the processing of the other vessels, the improved FCM shows satisfied performance, and the accuracy increased to 91.5%.

Unlike the sailing vessels which have distinguishing features, the noise targets are very difficult to be recognized, even for artificial judgment. The improved FCM also shows good performance, that the accuracy reached 81.5%. To channel buildings, the recognition accuracy reached 92.0% in improved FCM. All the result turns out that the improved FCM is efficient in the application of radar targets classification.

5. CONCLUSIONS

The field testing infer that the improved FCM, which is optimized in two parameters fuzzy classification number C by compactness and separability in Euclidean space and fuzzy coefficient number m by Shannon Entropy and gain, is very suitable in the application of blip classification, the result is highly consistent with the artificial judgments.

To a real moving vessel, the improved FCM could take 92.1% right recognition.

(2) To a noise, or bank, channel target, the improved FCM could take 83.3% right recognition.

In the future research, there are also some deficiencies needs to be ameliorated. Although a FCM framework is presented, some important source information has been ignored, especially for the continuity in different frames data. Furthermore, the weights of different evidences has not been discussed roundly, as the entropy and gain are not convictive enough two describe weight difference quantized, and there is no strict derivation in the processing. The FCM framework is not perfect enough to tolerate all the information indeed; some new theory should be introduced.

6. ACKNOWLEDGEMENTS

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