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## A Recognition Approach of Radar Blips Based on Improved Fuzzy C Means

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### ABSTRACT

Maritime radar is the kernel sensor for tracking vessels in Vessel Traffic Service system, it is important for Maritime Situation Awareness. However, the images collected by the maritime radar are inundated with excessive noise blips, which bring variety of troubles in extraction of ship targets from the images. This paper proposes a radar target recognition method based on fuzzy C-means. First, the attributes of the blips in the sequential radar images, such as speed, direction and size, are quantified as three pieces of evidence to determine whether a radar blip is a moving vessel. Then, an artificial intelligence was built based on FCM. According to the three pieces of evidence, the possibility of a blip being a real vessel is computed with FCM. The main difficulty in building the FCM framework is to find an appropriate way to provide the classification coefficient  $C$  and the fuzzy coefficient  $m$ . Since the  $C$  in classification is finite, this study proposes a method to obtain  $C$  by assessing the Euclidean distance of the expected result. Since  $m$  is related to the discreteness of evidence and results, the coefficient can be assessed by Shannon entropy and gain. Field experiments suggest that the improved FCM is capable of classifying the radar blips accurately, and reducing the operational strength of the ship operators and improving the safety.

**Keywords:** marine radar, fuzzy C means, Shannon entropy, fuzzy inference

### 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,

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#### State of the literature

- The marine radar provides real time scenario on vessel traffic flow, it is the kernel sensor for maritime situation awareness. However, the limitation of radar is there are huge uncertainties on the authenticity of the radar blips.
- It is a typical classification issue for identifying the radar blips to be vessels, or floating garbage, or noise.
- FCM is one of the mature classification tool, but the best classification number and fuzzy coefficient needs to be discussed.

#### Contribution of this paper to the literature

- The maritime operators are able to identify the radar blips.
- An artificial intelligence was built to simulate the process of manually identifying radar blips.
- The best classification number and fuzzy coefficient of FCM are discussed.

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 (IALA Recommendation E-148, 2015). 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 inland 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. 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 images. 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 (IALA Guideline No. 1103, 2013). 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 vessels 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.” (IALA Guideline 1114, 2015) 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.

## LITERATURES REVIEWING

The limitations of marine radar have being concerned by many researchers, especially in the applications of maritime administration. Bin et al. (2006) gave a comparison study for AIS and maritime radar, and concluded that the radar is more reliable than AIS because the information received from radar is more timely. Therefore, if the radar is more intelligent, the navigation safeties of vessels are more guaranteed. Indeed, the AIS information can be introduced and integrated with the radar information, to make the VTS center more reliable on vessel tracking. However, the AIS information is not reliable. Through field experiments and simulation experiments, Ma et al. (2012; 2013) had proved that the AIS messages are easily lost in transmission in inland rivers. And Liu et al. (2014) indicated that there are errors in the sequential AIS information. It is primarily that the blips in sequential radar images should be recognized, namely which blips represent the real vessels, and which blips represent noise and floating garbage. Hence, the artificial intelligence above is a typical classification problem. There are many algorithms are suitable for solving this problem, such as Bayesian Networks, decision tree, fuzzy and so on. Seixas et al. (2014) proposed a Bayesian network based model for supporting diagnosis of neurodegenerative diseases. Farid et al. (2014) improved the decision tree model by introducing two independent hybrid mining algorithms, and the improved decision tree can deal with the noises in datasets. Among varieties of mathematical tools, FCM is considered to be mature classification tool, and it is very popular in the image processing and recognition. But the standard FCM has some limitations, so in most of the cases the FCM is applied in modified form. Zheng et al. (2015) introduced a new generalized hierarchical FCM into image segmentation, which is more robust to image noises. Su et al. (2014) present a FCM based approach to classify the partial discharge (PD) events in Gas Insulated Load Break Switches (GILBS). Liu et al. (2016) used the modified FCM Clustering algorithm to identify the new fluid in carbonate reservoir. Ghosh et al. (2011) performed how the FCM running in the local image processing and pattern recognition. Besides the application in the world of graphics, the FCM is also applied in the control engineering. Santosh et al. (2012) 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 modelling 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 et al. (2009) 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 et al. (2013) 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.

## A PROPOSED APPROACH

### Step 1: Qualification of the Attributes of Blips

After years of observation, the maritime administrators are able to distinguish the blips in radar image by inter-frame differences and graphic identities, such as displacement, direction, size, et al. Therefore, under the FCM framework, the attributes of blips can be introduced to make the inference. In this paper, three pieces of evidence are selected. They are displacement, direction, and blip shape (i.e., size), which are represented in **Figure 1**. Referring to the maritime administrators' work and ARPA function designed requirement IEC 62388, supervisors are generally able to recognize the blips in 30 seconds, or 10 continuous frames of radar images. Therefore, the displacement and direction attributes are extracted based on 10 frames of radar images analysis in following research.

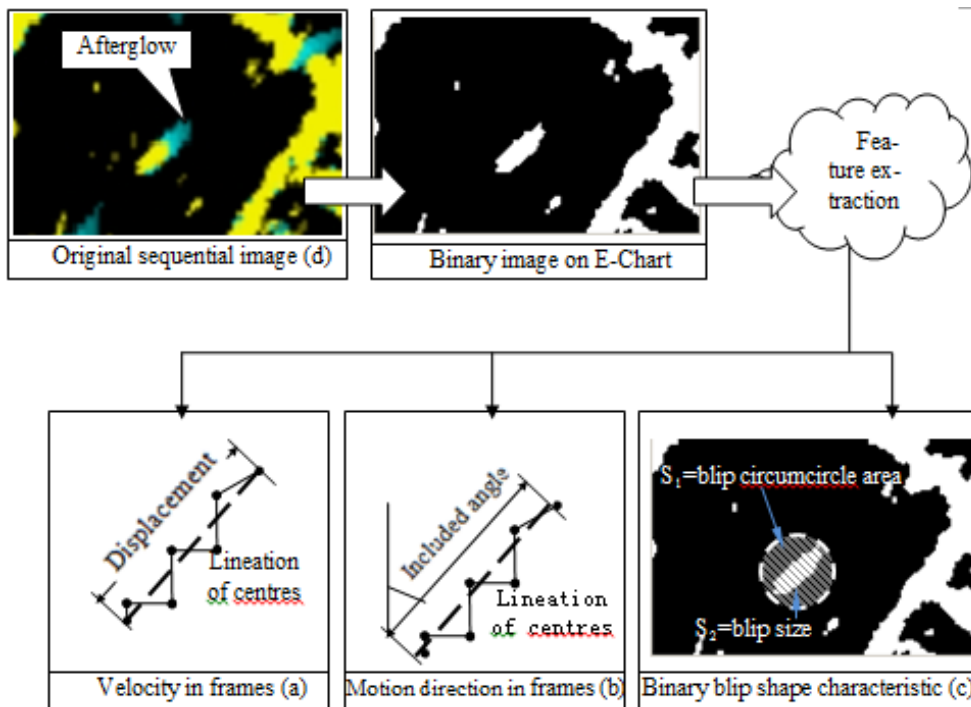


Figure 1. Blip attributes in frames of radar

In order to save fuel and abide by the navigational rules, ship pilots are tending to manoeuvre the vessels with steady speed and follow a fixed route. On contrary, the noise or floating garbage are more likely to float down or drift around in a small area. Hence, the displacement and direction could be qualified as shown in the below of Figure 1. 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 centres in 10 frames of radar images. It is worthy to note 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 ngraph 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  $S_1/S_2$  in right below of Figure 1.

### Step 2: Improved Fuzzy C Means-based Classification

After the qualifications of the attributes of blips, Fuzzy clustering is introduced to classify these blips. The FCM is proposed by (James C. Bezdek, Robert Ehrlich, William Full, 1984), 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.

$$\varphi_i = \prod_{j=1}^m g_{ij}(\mu_{ij}, \sigma_{ij}) \quad y = f(\sum_{i=1}^n w_i \varphi_i) \quad (1)$$

$$g_{ij} = e^{-1/2(\frac{x_j - \mu_{ij}}{\sigma_{ij}})^2} \quad f(x) = \frac{1}{1 + e^{-x}} \quad (2)$$

Figure 2 shows a fuzzy-neuron specially intended for classification problems. The n-inputs of the neuron are rules of a fuzzy controller. Let  $x = (x_1, x_2, \dots, x_m)$  be the input set to the classifier. The in-put  $x_j$  in the rule  $i$ , is assigned a membership function  $q_{ij}(x_j)$ . Typical membership functions are triangular, trapezoidal and gaussian. Gaussian membership functions have been selected here, where  $\mu_{ij}$  is the mean value, and  $\sigma_{ij}$ , the standard deviation,

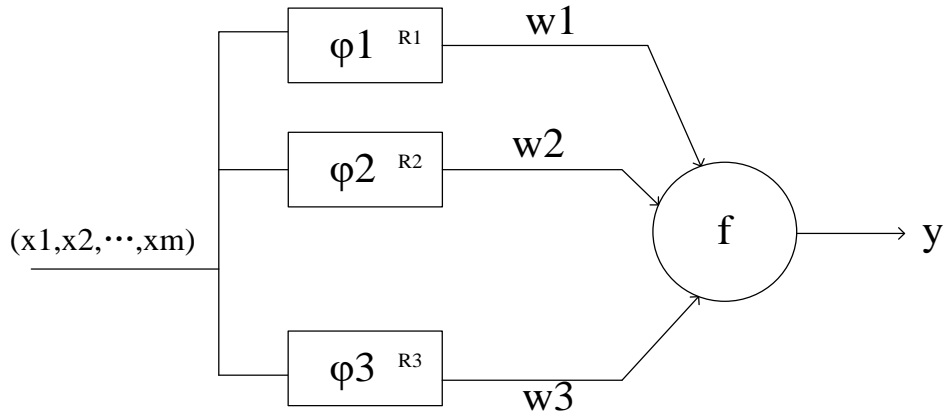


Figure 2. Fuzzy neuron-based classifier

$$g_{ij}(x_j) = e^{-\frac{1}{2}(\frac{x_j - u_{ij}}{\sigma_{ij}})^2} \tag{3}$$

The sentence connective and in rule i.

Rule i: if  $x_i$  is  $A_{i1}$  and ... and  $x_m$  is  $A_{im}$  (4) is implemented by means of the product

$$\varphi_i = \prod_{j=1}^m g_{ij}(x_j) \tag{4}$$

Finally, the neuron output is obtained by means of a weighted sum of its inputs, and a sigmoidal function.

$$y = f\left(\sum_{i=1}^n \omega_i \varphi_i\right) = \frac{1}{1 + e^{-\sum_{i=1}^n \omega_i \varphi_i}} \tag{5}$$

This fuzzy-neuron is a universal approximator in the  $m$ -dimensional space. Then, arbitrarily shaped regions can be classified using this fuzzy-neuron.

The system in Figure 1 will be applied to classify from the Monte-Carlo simulations. The system parameters ( $p_{ij}$ ,  $u_{ij}$  and  $w_i$ ) can be tuned in an automatic way, by means of the back-propagation learning method

Step 1, choose an input-output pair  $(x, y^d)$  to be learnt.  $x$  is the input vector and  $y^d$  the desired output.

Step 2, compute the output  $y$ , corresponding to the input vector  $x$  (forward process).

Step 3, Update parameters according to the following equations (backward process):

$$\Delta w_i = \eta_\omega [y^d - y] \frac{\partial y}{\partial \omega_i} \tag{6}$$

$$\Delta \mu_{ij} = \eta_\mu [y^d - y] \frac{\partial y}{\partial \mu_{ij}} \tag{7}$$

$$\Delta \sigma_{ij} = \eta_\sigma [y^d - y] \frac{\partial y}{\partial \sigma_{ij}} \tag{8}$$

Step 4, return to step 2 until

$$\text{Error} = \frac{1}{2} \sum_{\text{learning points}} (y^d - y)^2 < \epsilon \tag{9}$$

or until a predefined number of iterations is exceeded.

The derivatives  $\partial y / \partial \omega_i$ ,  $\partial y / \partial \mu_{ij}$ ,  $\partial y / \partial \sigma_{ij}$  can be obtained using the chain rule.  $\eta_\omega$ ,  $\eta_\mu$  and  $\eta_\sigma$  are learning rate parameters.

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. 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 et al. (2013) 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 (S.R. Kannan, S. Ramathilagam, P.C. Chung, 2012) are still focusing on it, wishing to find a way to amend it.

#### (1) 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 attributes above, the subset compact parameter and separated parameter are introduced. Gath and Geva (Abonyi, J., 2002) 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.

#### (2) Statistical Information

Some researchers believed that, the best classification would provide the best statistical information. Roberts et al. (2001) invent a different effectiveness function, derived from the maxim relevance and scalar space filtering. Rui-Ping et al. (1995) 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, the FCM degenerates to HCM;

When  $m$  equals 2, the 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 (1981) suggest that the  $m$  should be set in the area  $1.1 \leq m \leq 5$ , 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 et al. (1983) found that the best value of  $m$  in the Hanzi recognition is between 1.25 and 1.75. Pal et al. (1995) 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 et al (2009) 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,

$$X = \{x_1, x_2, \dots, x_m\} \tag{10}$$

The compactness of the data set is,

$$K_{compactness} = \sum_{j=1}^m \sum_{i=1}^n \left[ \sum_{k=i}^n (x_{ij} - x_{kj})^2 \right]^{\frac{1}{2}} \tag{11}$$

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,

$$K_{separability} = \sum_{j=1}^s \sum_{i=1}^n \left[ \sum_{k=i}^s (o_{ij} - o_{kj})^2 \right]^{\frac{1}{2}} \tag{12}$$

So, the objective function is,

$$\min F = \frac{K_{compactness}}{K_{separability}} \tag{13}$$

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 attributes 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  $D = \{d_1, d_2, \dots, d_n\}$ , the Entropy is defined as,

$$H(D) = \sum_{i=1}^n \frac{d_i}{sum} \log_2 \frac{d_i}{sum} \quad (14)$$

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

$$gain(D) = H(C) - H(D) \quad (15)$$

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

$$\min F = gain(D) \quad (16)$$

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

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

So, the constraint condition is transformed to,

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

## A CASE STUDY

### The experimental Platform

To validate the approach proposed in Section 3, an experiment was conducted at Wuzhou, Guangxin, China. In particular, the test radar is FAR2127s, which is widely used in the coastal surveillance. The experiment lasted from 09:00 to 10:55 on the 21th May 2016. In total, 271 targets were captured, including 159 vessels and 112 stationary targets or noises. In the experiment, all the targets were verified manually. It is noted that many observations or blips were indeed from the same target since the radar scanned the area once per 2.4 seconds. In total, 30,367 individual observations (blips) have been captured. In these observations (blips), 22,955 observations are from moving vessels and 7,412 observations are from noises or stationary targets. In the following research, all the stationary and noise targets are treated as noise samples for simplicity.

Meanwhile, an AIS receiver was placed in the same area, which received 1,200,000 AIS messages from 15th March to 25th April 2016. Particularly, all the AIS messages are obtained from the same area as that of the blip recognition. These records will be used for training the coefficients of collision potential fields as described in Section 3.2.

A software program is developed and shown in [Figure 3](#). As shown in this figure, radar images have already been overlapped on the e-chart of this waterway. Three typical verified objects were notified in [Figure 3](#).



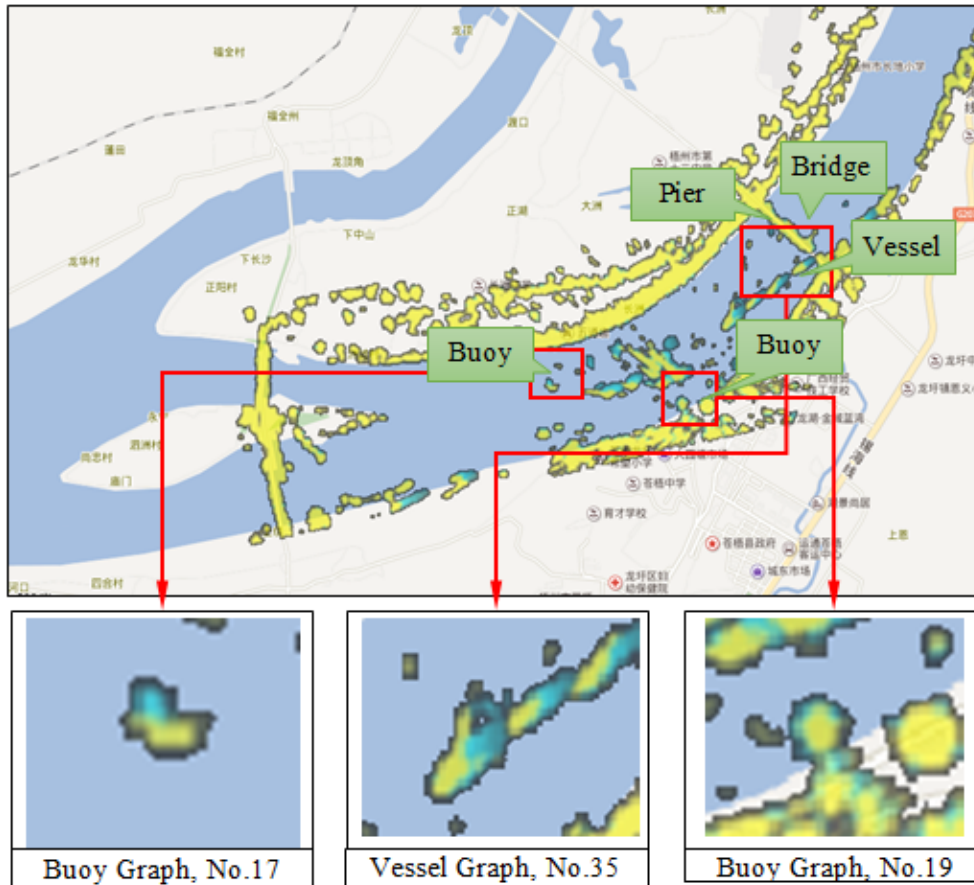


Figure 3. Radar platforms

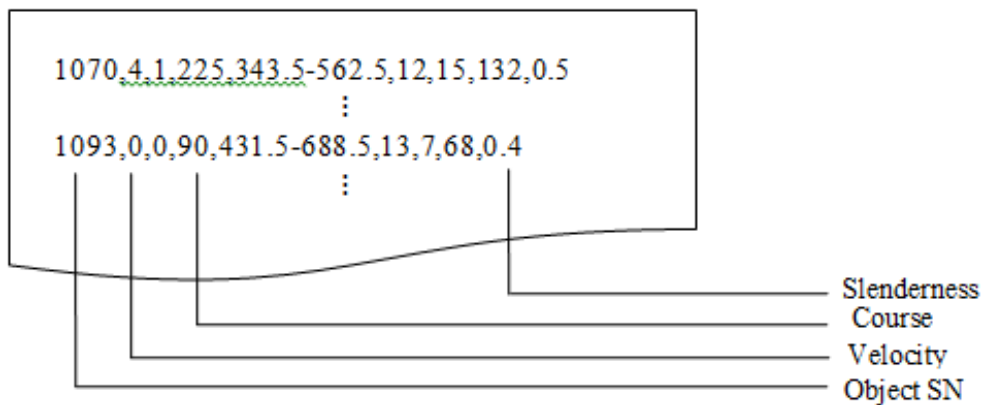


Figure 4. Text record definitions

They are buoys No.17, No.35, and a moving vessel No.19. Intuitively, the moving vessel objects are different from noises in terms of the attributes of the velocity, course, and graphic shape.

Using the methods proposed in Section 3.1, these attributes, velocity, vector and slenderness are quantified in the software program. All the blips in sequential images have been transformed to verified records that are presented in a text form with discrete values. A typical record is presented in Figure 4. The record contains several

fields, which are separated by commas and represent different types of discrete attribute values. In this way, the course (direction), velocity, and size are all stored in one record. Moreover, the verified vessel and noise records are saved separately.

### 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](#),

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.

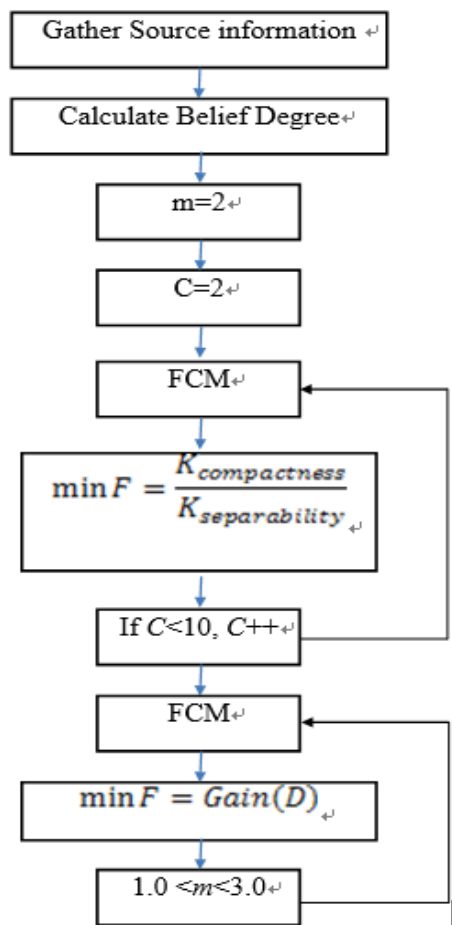
Export the classification result with the parameters optimized above. In the sub sets, the one whose centre point contains largest membership to a vessel, and no member is less than 0.5 could be considered as the vessels set. When there is no such data set, we could infer that, there is no vessels set.

### The Analysis of the Results

Use two different ways to process the data, which is gathered by the platform radar shown in [Figure 3](#). 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.



**Figure 5.** The flow chart of the proposed improved FCM-based approach

## DISCUSSIONS

For the huge uncertainty in radar sensors, all the target recognition, information fusion and situation awareness relies on manual works and the experience of operators. This research proposed an approach to build artificial intelligence for VTS systems using FCM, and the field experiments suggest that the accuracy is acceptable.

Many researchers proposed filtering algorithm, such as  $\alpha$ - $\beta$  filter,  $\alpha$ - $\beta$ - $\gamma$  filter, least square algorithm, extended Kalman filter, and particle filter (Yoo and Kim, 2003; He et al., 2015; De Feo et al., 1997). These algorithms are only practical in the open sea, because assumptions on the status of real moving vessels have to be made. However, the assumptions are not true in inland waterway. The experienced VTS operators can recognize the radar blips to be vessels, or floating garbage, or shore structures. This reminds us simulate the process of manually identifying radar blips to build an artificial intelligence. As the most mature classification algorithm, FCM are widely used in targets identification. The standard FCM has some limitations. Therefore, most of the researchers utilize the FCM algorithm in a modified form. Yang et al. (2009) propose a comprehensive way to find the best classification number and fuzzy coefficient by the distribution analysis of the data set. Tai-Yu et al. (2013) uses cross Shannon Entropy to state the confusion and discreteness. This suggests that to improve the standard FCM, making the evaluation on the source information possible, the Shannon Entropy is an appropriate way.

Field experiments are conducted in Wuzhou, Guangxin, China, the experimental results suggest that the accuracy of the improved FCM is acceptable. However, although we have introduced a lot of real data samples to

train the coefficient of FCM, the proposed FCM model is still not completely reliable. This may be caused by the reliability of the data samples.

## CONCLUSIONS

Maritime radar is the kernel sensor for maritime situation awareness, but it is not reliable because of the uncertainty of blips in radar images. This paper proposed a FCM based approach to recognize the blips in radar images. The conclusions are as follow.

(1) Referring to the experience of maritime administrators, the displacement, direction, and size are selected and quantified to three pieces of evidence. With the three pieces of evidence, it is possible to make inference on radar blips synthetically.

(2) In order to obtain the best parameters in FCM, the fuzzy classification number  $C$  was optimized by compactness and separability in Euclidean space, and the fuzzy coefficient number  $m$  was optimized by Shannon Entropy and gain.

(3) The improved FCM is feasible for radar blips classification. Field experimental results show that, the improved FCM is capable of identifying 92.1% of the moving vessels from the massive blips in radar images and 83.3% of the floating garbage and noise. Its accuracy is very close to experienced administrators.

The proposed methodology is useful for VTS centres. It can help the administrators to release the work load and improve marine safety.

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