Combing rough set and RBF neural network for large-scale ship recognition in optical satellite images

LU Chunyan, ZOU Huanxin, SUN Hao and ZHOU Shilin
College of Electronic Science and Engineering, National University of Defense Technology, Changsha, China.

Email: luchunyanld@163.com

Abstract. Large scale ship recognition in optical remote sensing images is of great importance for many military applications. It aims to recognize the category information of the detected ships for effective maritime surveillance. The contributions of the paper can be summarized as follows: Firstly, based on the rough set theory, the common discernibility degree is used to compute the significance weight of each candidate feature and select valid recognition features automatically; Secondly, RBF neural network is constructed based on the selected recognition features. Experiments on recorded optical satellite images show the proposed method is effective and can get better classification rates at a higher speed than the state of the art methods.

1. Introduction
Large scale ship recognition in optical remote sensing images is of great importance for many military applications. It aims to recognize the category information of the detected ships for effective maritime surveillance. A lot of different approaches have been proposed in the literature. Yet the problem is far from being completely resolved.

Essentially, there exist two components in typical recognition algorithms, feature extraction and machine classification. Lots of feature extraction schemes have been proposed and they have been proved to be effective for different scenarios[1-4]. However, practitioners still face the difficult problem of feature selection. Besides, for the classification step, nearest neighbor(NN) and support vector machine (SVM) classifier are often adopted. Yet operators often face the dilemma that they have little knowledge on weights distribution of features. BP-neural network can find out the relationship between input and output via studying and training the sample data without depending on experience knowledge and rules to problems. However the BP neural network costs a long time in training, and is easy to convergence to a local value.

To solve the problems above, this paper presents a new novel and robust ship recognition algorithm based on rough set theory and RBF neural network. Firstly, based on the rough set theory[5], the common discernibility degree is used to compute the significance weight of each candidate feature and select valid recognition features automatically; Secondly, RBF neural network is constructed based on the selected features.

2. Feature extraction and selection
Feature extraction is an important step in ship recognition. In large scale optical remote sensing images, different ships have different sizes and shapes, the feature extracted in this paper includes the

sizes and shapes. The size feature includes: length F_1, width F_2, the ratio of length and width F_3, area F_4, girth F_5, the shape is described by area ratio code (ARC)[6] $\{F_6, F_7, F_8, F_9, F_{10}, F_{11}, F_{12}, F_{13}, F_{14}, F_{15}, F_{16}, F_{17}\}$, shape complicated degree F_{18}^O, eccentricity F_{19}^O, principal axis length F_{20}^O.

2.1. Feature extraction

In the definition of ARC[6], Ship chips are rotate to horizon surround its principal axis firstly, and then get the circum-rectangles and divide it to N parts, the area of the $i-th$ part is S_i ,finally, code this part is as follows:

$$C_i = floor\left(\frac{S_i}{\max\limits_{1\le i\le N}(S_i)} \times 10\right) \tag{1}$$

The ARC is defined as:

$$C = [C_1, C_2, \cdots, C_N] \tag{2}$$

For example, figure 1 showed a ship chip from an optical remote sensing image with a resolution of 1 meter. As defined above, if we set $N=6$, the ARC of the ship chip is $C=[7,8,10,10,8,6]$.

Figure 1. Example of area ratio code.

If we set $N=12$, the ARC can be expressed as $\{F_6, F_7, F_8, F_9, F_{10}, F_{11}, F_{12}, F_{13}, F_{14}, F_{15}, F_{16}, F_{17}\}$.

2.2. Feature selection based on rough set theory

Information systems can be denoted as a $S=(U,R,V,f)$,where $U=\{x_1, x_2, \cdots x_{|U|}\}$ is a not empty limited domain, $R=C\bigcup U$ is a not empty limited attribute set, C and Y are conditioned attribute set and decision attribute set respectively; $V=\bigcup\limits_{r_j\in R} V_j$ is the attribute value set, it denotes the vary range of attribute value $r_j \in R$; $f: U\times R \to V$ is an information function, if it sacrifices $\forall r_j \in R, f(x,r_j)\in V_j$,it can endues each attributive characteristic an information value. if $C\bigcup Y = R, C\bigcap Y = \phi$, $S=(U,C,Y)$ is the decision table; if $\exists r_j \in R$ make V_j contains an empty value, the decision table S is deficiency.

In the decision table S ,the discernibility of $P \subseteq R$ is:

$$DIS(P) = \{(x,y)\in U\times U \,|\, \exists r\in P, f(x,r)\ne f(y,r), f(x,r)\ne *, f(y,r)\ne *\} \tag{3}$$

If the max set of the common discernibility object of x is: $D_p(x)=\{y\in U \,|\, (x,y)\in DIS(P)\}$,thus the discernibility degree of P is : $|DIS(P)| = \sum\limits_{i=1}^{|U|} D_p(x_i)$ where $|DIS(P)|$ denoted the discernibility of P, its value $DIS(P)$ is the significance weight of ordinal elements pairs.

The common discernibility of P and Q is:

$$DIS(Q;P) = DIS(Q)\bigcap DIS(P) \tag{4}$$

The relative common discernibility degree is:

$$|DIS(Q;P)| = |DIS(Q)|\bigcap|DIS(P)| \tag{5}$$

Where $DIS(Q;P)$ denotes the set of the ordinal elements pairs in P and Q that can division U ; $|DIS(Q;P)|$ is the quantity of ordinal elements pairs of $DIS(Q;P)$, it measured the common discernibility between P and Q.

Scatter the abstracted characteristics of ships and construct the characteristic decision table:

$$S=(U,C,Y)=\begin{array}{c|c} & \begin{array}{ccc|c} C_1 & & C_n & Y \end{array} \\ \begin{array}{c} X_1 \\ \vdots \\ X_N \end{array} & \left(\begin{array}{ccc|c} F_{11} & \cdots & F_{1n} & y_1 \\ \vdots & & \vdots & \vdots \\ F_{N1} & \cdots & F_{Nn} & y_N \end{array}\right) \end{array} \tag{6}$$

Where $U=\{X_1,X_2,\cdots,X_N\}$ is the sample set, $X_i=(F_{i1},F_{i2},\cdots,F_{iN})$ denotes the eigenvector of the $i-th$ target; $C=\{C_1,C_2,\cdots,C_n\}$ is the candidate feature set, $C_i=(F_{1i},F_{2i},\cdots,F_{Ni})^T$ is the $i-th$ candidate feature; $Y=\{y_1,y_2,\cdots,y_N\}$ is the relative ship decision set; F_{ij} denotes the $j-th$ feature of the $i-th$ sample; N,n are the sample quantity and dimension of the feature vector respectively. The steps of feature choosing can be summarized as followed:

(a) Define feature sets Q and T ,let $Q=\phi,T=C$,compute the $|DIS(Q;T)|$;

(b) The feature essential function is $SGF(C_k,Q,T)=|DIS(T;(Q\cup\{C_k\}))|-|DIS(T;Q)|$, and the foremost feature C_k in $C-Q$ is $SGF(C_k,Q,T)=\max_{C_i\in T} SGF(C_i,Q,T)$;

(c) If $|DIS(T;Q)|=|DIS(T;C)|$, jumped to step(d),otherwise jump to step(b);

(d) The final $Q=\{C_1,C_2,\cdots C_L,\}$ is the selected feature set, so the reduced sample set is:

$$X=\begin{array}{c|c} & \begin{array}{ccc|c} C_1 & & C_L & D \end{array} \\ \begin{array}{c} X_1 \\ \vdots \\ X_N \end{array} & \left(\begin{array}{ccc|c} F_{11} & \cdots & F_{1L} & d_1 \\ \vdots & & \vdots & \vdots \\ F_{N1} & \cdots & F_{NL} & d_N \end{array}\right) \end{array} \tag{7}$$

Where X_i is the reduced feature vector of the $i-th$ target, L is its feature dimension.

3. Ship recognition based on RBF neural network

The classifier is designed based on RBF neural network, RBF neural network is not only has a simply structure and learning rapidity, but also has the same classify equivalence with bayes classifier. The configuration of RBF neural network is showed in figure 2.

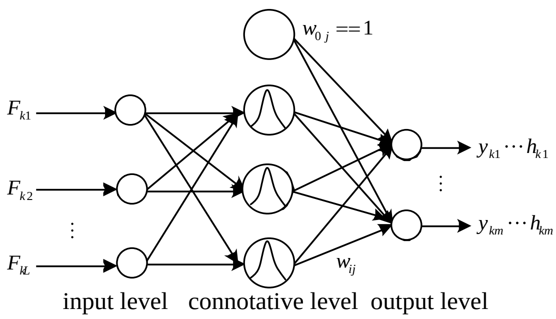

Figure 2. Configuration of RBF neural network.

As showed in figure 2, RBF neural network is constituted of input level, connotative level, output level, its core idea is to construct the connotative level space via regarding the RBF function as the radicle, then the low- dimension pattern is then converted to the high-dimension pattern which make the impartibility in the low- dimension space partibility in the high-dimension space.

Let the training sample set is $U=\{X_1,X_2,\cdots X_N\}$,each sample can be denoted as $X_k=(F_{k1},F_{k2},\cdots,F_{kn})(k=1,2,\cdots N)$,the selected feature set is $X_k=(F_{k1},F_{k2},\cdots,F_{kL})(k=1,2,\cdots N)$ which is the input of the training sample. Under the condition, the input level has L nerve cells, each nerve cell is denoted as i ,the output level has J nerve cells, each nerve cell is denoted as j ,the significance value of the synapsis between connotative level and output level is $w_{ij}(i=1,2,\cdots,I;j=1,2,\cdots,J)$ .To modulate the right of the network better, this paper set another nerve cell which has an invariable significance value of 1, the actual output of X_k is $Y_k=[y_{k1},y_{k2},\cdots y_{km}](k=1,2,\cdots N)$, the relative anticipant output is $H_k=[h_{k1},h_{k2},\cdots h_{km}](k=1,2,\cdots N)$. Thus, if a training sample X_k is input to the network, the actual output of the $j-th$ nerve cell is denoted as follows:

$$y_{kj}(X_k)=w_{0j}+\sum_{i=1}^{I}w_{ij}f(X_k,t_i) \tag{8}$$

The transfer function of the nerve cells in connotative level is denoted as gauss RBF:

$$f(X_k,t_i)=G(\|X_k-t_i\|)=\exp\left\{-\frac{1}{2\sigma_i^2}\|X_k-t_i\|^2\right\}=\exp\left\{-\frac{1}{2\sigma_i^2}\sum_{l=1}^{L}(F_{kl}-t_{il})^2\right\} \tag{9}$$

Where $t_i=[t_{i1},t_{i2},\cdots,t_{il},\cdots,t_{iL}],(i=1,2,\cdots,I)$ is the center of the gauss RBF, σ_i^2 is its variance.

As analyzed above, there are four parameters need to confirm, they are: the center of the gauss radial basic function, variance, the significance weight synapsis between connotative level and output level and the quantity of nerve cells in connotative level.

(a) The center of the gauss radial basic function t_i

The clustering center is confirmed by K-Means method. The traditional K-Means method calculate the comparability by the minimum Euclidean distance and then compare it with the settled threshold. This method relies on the choice of the threshold, if the threshold is not appropriate, the clustering result will be wrong. To solve the problem above, this paper utilize a new double thresholds method. in this method, The two settled thresholds are denoted as sd_1 and sd_2 respectively, where $sd_1<sd_2$. Let the distance between sample X_k and the $i-th$ clustering center is $sd(X_k,t_i)$,if $sd(X_k,t_i)<sd_1$ And the sample X_k belongs to class i , if $sd(X_k,t_i)>sd_2$ A new class is constructed, otherwise do nothing.

(b) Variance σ_i^2

σ_i^2 denotes the separate degree of each sample to the clustering center, it can be calculate as follows:

$$\sigma_i^2=\sum_{X_k\in A(t_i)}\left|(X_k-t_i)\right|^2\Big/(A(t_i)) \tag{10}$$

(c) The significance weight of synapsis between connotative level and output level w_{ij}

The significance weight of synapsis can be got via iterative formula as below:

$$w_{ij}(k+1)=w_{ij}(k)+\xi(Y_k-H_k)f(X_k,t_i) \tag{11}$$

The iterative process will not stop until difference between two near times is less than a settled ε .

$$\left|w_{ij}(k+1)-w_{ij}(k)\right|\le\varepsilon \tag{12}$$

(d) The quantity of nerve cells in connotative level

The quantity of nerve cells in connotative level reflects the mapping ability. The more the nerve cells are, the low the training false ratio is. But too many nerve cells may cause overfitting which will increase the test false ratio, if the nerve cells are not enough, the network will not have enough degree of freedom which will cause a high training false ratio. Besides, we increased an additional nerve cell to improve the veracity. If the class number of clustering result is I , the nerve cells number will be $I+1$.

The ships in optical imaging can be denoted as $S=\{s_1,s_2,\cdots s_{n_s}\}$,if ship s_i is put to RBF network ,then we can get the recognizing result:

$$P^{Os_i}=\{P_1^{Os_i},P_2^{Os_i},\cdots,P_{M_1}^{Os_i}\} \tag{13}$$

If s_i belongs to type k , then $P_k^{Os_i}=1$,otherwise $P_j^{Os_i}=0(j=1,2,\cdots M_1,j\neq k)$.The flowchart of the proposed ship target recognition algorithm is showed in figure 3.

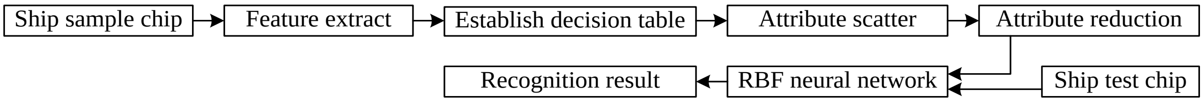

Figure 3. Flowchart of the proposed method.

4. Experiment results

To test performance of RS-RBF algorithm, we run experiments on real large-scale remote sensing images with a resolution of better than 4 meter. Firstly, we preprocess the images such as division of the land and sea and so on. Then we get potential ship targets based on connected operator[7]. Finally, the ship target chips can be get by means of graph partitioning active contous[8].We have 100 chip images including 5 kinds of ships, each kind has 20 chips, all of the images are offered by SPOT-5, IKONOS and so on. A demonstration of the ship chips in the database is given in figure 4.

(a) Aircraft carriers (b) Depot ships (c) Cruisers (d) Chasers (e) Frigates

Figure 4. Demonstration of the ship chips in the database.

Consider the ship kind as the interested domain U , ship types composed the decision set Y , that is to say the information system $S=(U,C,Y)$ is constructed. Firstly, we scatter the attribute parameter based on the transcendental information about ships. Then Rough Set is used to select features. The selected features and their weights are given in table 1.

Table 1. Selected features

Features	Weights	
	w_{C_k}	$\overline{w}_{C_k}$
F_1	23	0.0991
F_2	6	0.0258
F_6	50	0.2155
F_7	56	0.2413
F_{18}	55	0.2370
F_{20}	42	0.1810

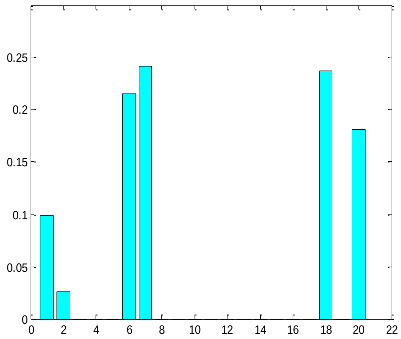

Figure 5. Feature essential weights

Figure 5 showed the selected features. As showed in table 1 and figure 5, we can see that the selected feature set is: $\{F_1, F_2, F_6, F_7, F_{18}, F_{20}\}$, length F_1, width F_2, the first and the second parameters of ARC F_6 and F_7, shape complicated degree F_{18}, principal axis length F_{20}, their feature essential weight is $\{23, 6, 50, 56, 55, 42\}$, and $\{0.0991, 0.0258, 0.2155, 0.2413, 0.2370, 0.1810\}$ is the unitary feature essential weight.

Input the selected features to RBF neural network classifier, we choose 25 chips as the training data, including 5 chips of aircraft carriers, 5 chips of depot ships, 5 chips of cruisers, 5 chips of chasers, 5 chips of frigates and the rest 75 chips are used for testing. The recognizing result of RBF network is showed in table 2.

Table 2. Ship recognition result

Algorithms	Right recognition ratio					Average recognition ratio	Time costs （s）
	Aircraft carrier	Depot ship	Cruiser	Chaser	Frigate		
KNN	15/15	13/15	6/15	8/15	8/15	66.8%	0.164759
SVM	15/15	14/15	7/15	8/15	7/15	68.0%	0.020822
RS-RBFNN	15/15	15/15	9/15	12/15	11/15	82.7%	2.448103

As showed in table 2, the proposed algorithm RS-RBFNN is better than KNN and SVM classifiers. Its average recognition ratio is higher than KNN algorithm and SVM algorithm 15.9% and 14.7% respectively. This is because KNN algorithm need to searching the whole data and divide different types by distance, ships have the nearest feature are considered as the same type. SVM algorithm is proposed based on statistical theory, it is suitable for non-linear and non-gauss problems. While it is proposed to two-class recognition problems and is not robust to multi-class recognition problems.

5. Conclusions

This paper combined Rough Set and RBF neural network together for large-scale ship recognition in optical satellite images. Firstly, Rough Set is utilized to feature extraction, the effective features to recognition is extracted; Secondly, introduced the detail steps to ship recognition based on RBF neural network. Experiments on recorded optical satellite images showed the proposed method is effective and can get better classification rates than the state of the art methods.

6. References

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