Recognizing the formations of CVBG based on shape context using electronic reconnaissance data

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To recognize the formation of the carrier battle group (CVBG) from passive electronic reconnaissance and location data, a shape context-based method is proposed. The proposed method treats the location data as a graph model, and a graph matching method is used for formation recognition. The shape context and background context for each unit in CVBG is calculated and used for multi-viewpoint shape feature, which is rotation invariance and distinctive. The experimental results show that the proposed method can recognize the formation with a higher accuracy and locate the ship with electromagnetic silence.

Introduction: The formation of the carrier battle group (CVBG) varies with the task types and environment of battlefield and plays an important role in modern battles. Recognizing the formation of enemy fleets can help commanders to discover their purpose and weakness, eventually seize the opportunity to win a battle. Passive electronic reconnaissance (PER) technology can locate each unit of a CVBG using satellite-borne or airborne radar to receive electromagnetic signal transmitted by the fleet. It was widely used for war ship detection because of its wide detection range and difficulty to be found by the enemy. However, most of the current researches [1–2] focused on analysing individual unit of a CVBG, and the location of each unit in the fleet was not involved, which made it hard to recognize the formation of a CVBG. Context-based recognition methods [3–4] treat the formation recognition as shape matching problem, and the location information is encoded by shape context.

A CVBG can be treated as a sparse target group, which can be characterized by a set of scattered points. But the traditional context-based methods were designed for continuous object, which cannot get enough feature from a CVBG for recognition, and the symmetry of CVBG formation makes it worse. Another difficulty is that the formation of a CVBG cannot be described by a fixed shape, because relative position between ships and the number of ships is not fixed. When some unit in the fleet is electromagnetic silence or more ship join in temporary, the fleet is electromagnetic silence or more ship join in temporary, the number of units obtained by the PER system will change and which need the recognition method to be robust to the variation of units number.

Proposed method: This paper proposes a novel CVBG formation recognition method, which uses the location result from passive electronic reconnaissance to build a graph model and treats the recognition problem as graph matching. In order to obtain enough features for matching, the shape context and the background context of each unit were combined to get a shape feature for each unit in the fleet, and the number of units obtained by the PER system will change and which need the recognition method to be robust to the variation of units number.

![Flow chart for the proposed method](image1)

![Coordinate space divided: schematic diagrams for (a) shape context calculation and (b) CGS divide](image2)

All edges congregating on Xi is denoted by Ei, and its complementary set is \( E_i\). The shape context uses a histogram to capture the distribution of the remaining units relative to the reference unit, thus one can obtain the globally discriminative characterization of the CVBG.

Shape context: For a given ship located on \( X_i \), its shape context can be calculated as follows.

A polar coordinate \( \rho - \theta \) is built, with \( X_i \) be origin and velocity reversal be the reference direction, which is rotation invariance when the angle between the fleet and the radar platform changes. As shown in Figure 2(a), the coordinate space of \( \rho - \theta \) is divided into \( N_\rho \times N_\theta \) bins, each is represented by \( \pi_{\rho,\theta}(X)\). The number of ships in each bin is obtained by averaging \( X \) over each bin

\[
h_{\rho,\theta}(X_i) = \int \pi_{\rho,\theta}(X) h(X)dX
\]

which was used to form the descriptor \( F_C = [h_{\rho,\theta}(X_i)] \) and the fleet shape context \( F_C = [F_1^C, F_2^C, \ldots, F_M^C] \).

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Background context: For a given ship located on \( X_i \), its background context is calculated as follows. A right-handed rectangular coordinate system \( x-y \)-axis obtained, with the centre of the fleet without the reference point \( X_i \) be the origin and the velocity reversal be the \( x \)-axis coordinate axis. In order to get a distinctive descriptor of the background context, each edge in \( E_i \) is represented by its middle point position in \( x-y \)-axis and the gradient of the edge. Therefore, each edge is encoded in a three-dimensional (3D) space, which is called coordination-gradient space (CGS) in [5], with one dimension be the gradient direction and the others be the coordinates of the middle point. To calculate the distribution of \( E_i \), the 3D space is divided into \( N_\mu \times N_\nu \times N_\theta \) bins, which is shown in Figure 2. Then, a histogram \( F_\mu^B \) is exploited to present the number of edges located in each bin. Unlike [5], a local coordinate system is built on each reference point where \( E_i \) is represented. And the velocity reversal obtained by passive electronic reconnaissance is encoded in this local coordinate system.

Multi-viewpoint shape context: The shape context \( F_C \) and background context \( F_\mu^B \) are combined to get a shape feature for each unit in the fleet,
Table 1. Accuracy of CVBG formation recognition

|                | MVC [4]  | SC [3]  | Proposed method |
|----------------|----------|---------|-----------------|
| Proceeding formation | 100%     | 95%     | 100%            |
| Offensive formation | 100%     | 96%     | 100%            |
| Combat formation   | 94%      | 90%     | 96%             |

and the multi-view shape feature is obtained by aligning $F^C_i$ and $F^B_i$. The graph model feature of a CVBG is represented by multi-viewpoint shape feature $F = (F^C_1, F^C_2, ..., F^C_M)$, the column of which corresponding to the shape feature of a unit.

Feature matching: Let $F = \{F_i, F_2, ..., F_M\}$ and $H = \{H_1, H_2, ..., H_M\}$ be the multi-viewpoint shape feature of CVBG formation diagram and PER, with $M_1$ and $M_2$ be the number of units in them. The similarity between $F_i$ and $H_j$ can be defined by the cost function as

$$\mu(F_i, H_j) = (1 - \lambda)C^S(F_i, H_j) + \lambda C^C(F_i, H_j)$$

(2)

where $C^S(F_i, H_j) = \sqrt{\sum_{j=1}^{M_2} (F^C_i - H_j)^2}$ is the square loss, $C^C(F_i, H_j)$ is cosine loss, and $\lambda \in [0, 1]$ is a coefficient of balance.

The best candidate match for each unit of PER is found by identify its nearest neighbour from CVBG formation diagram. However, many units from PER will not have a correct match because the symmetry of the formation. So, the k nearest neighbour is conceded as candidate matching. The similarity of multi-viewpoint shape features between PER and CVBG formation diagram is calculated from the candidate matching as

$$\mu(F, H) = \min_{i=1}^{M_1} \mu(F_i, H_j)$$

(3)

where $M_i = \min(M_1, M_2)$. We set a constraint on Equation (3) that each $H_j$ can only have a best matching.

Experimental results: The experimental results of the proposed method in this paper, in [3] (SC) and [4] (MVC), are compared with the data generated according to [4]. Shape context (SC) proposed in [3] is a traditional shape matching method, and the one in [4] is the state-of-the-art method. The CVBG is composed of one aircraft carrier (CV), three cruisers (CG), four guided-missile destroyers (DD), and two frigates (FFG), totalling 10.

As shown in Figure 3, three kinds of CVBG formations are used, which are proceeding formation, offensive formation and combat formation. And 900 data are generated, 300 data for each kind of formation.

For the proposed method, the number of units of CVBG is $M = 10$, coordinate space of $\rho - \theta$ is divided into 2 $\times$ 12 bins and the CGS is divided into 6 $\times$ 4 $\times$ 4 bins. The recognition results are shown in Table 1.

As shown in Table 1, the recognition accuracy of the proposed method is 2% higher than MVC for the combat formation, and the same for the other formations.

In order to show the ability of the proposed method can recognize the formation of a fleet with different number of units, we randomly delete or and a DD (or CG, FFG) in the PER data. And the recognition result is shown in Table 2. In Table 2 DD+ means a DD was added to the PER data at a random location without change the formation of the fleet, and DD− means a DD was missing. From Table 2 we can see that the proposed method can recognize the formation accurately, even the number of units in the fleet is different. The inconsistent ship amount has less influence on the proceeding formation compared with the other two.

The exits of the CV are important for formation recognition, especially for the combat formation. If the CV is missing from the PER data due to the electromagnetic silence or other reasons, the recognition accuracy will drop down to 91%, 90.5% and 88% for the proceeding, offensive and combat formation, respectively.

Conclusions: This paper proposed a CVBG formation recognition method, which builds a graph model using PER data, and a shape feature which can encode both the shape and background context used for matching. The proposed method used local coordinates, which are built according to the heading directions of the fleet, to analyse the distribution of each unit in CVBG and make it invariant to the rotation between the PER data and the CVBG formation diagram. The experimental result shows that, compared with MVC method, the proposed method can get a higher recognition accuracy.

Acknowledgements: The authors thank the editor and reviewers for their valuable and constructive comments.

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