Deep Convolutional Neural Network Based Unmanned Surface Vehicle Maneuvering

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***Abstract*—The level of automated unmanned surface vehicle is always dependent on human interactions. An automated collision avoidance approach is proposed which is based on the visual system in order to improve it. Deep convolutional neural network (CNN) is a popular deep neural network for pattern recognition. Three types of encounter scenes are created and recorded which are used as the CNN training samples. The maneuver operations of these samples are conforming to the COLREGs rules. The CNN can predict the maneuvering operation according to the input scene as crewman after the training of CNN, and the central control system can take measures to avoid collision. Different simulations are taken to testify the validity of this approach.**

Keywords*—*deep learning; convolutional neural network; pattern recognition; unmanned surface vehicel; collision avoidance;

I. INTRODUCTION (*HEADING 1*)

The USV [1] has developed quickly due to the civilian application, commercial usage and military maritime mission requirement. Although the USV is called "Unmanned", it is always reliant on human interactions. The navigation equipment's developments, such as the cameras application, Automatic Radar Plotting Aid (ARPA) equipment and Automatic Identification System (AIS) have greater suppuration than ever before for USV[2]. ARPA can obtain the nearby obstacles' information, such as the bearing and range etc. AIS is special which can provide kinds of information about the ship, such as the structural information of the ship, position data, course and speed data. The main challenge for the automatic Navigation, Guidance and Control (NGC) of USV is a problem of obstacle recognition and collision avoidance process to minimize the dependency of ship maneuvering on operator intervention. Normally, vessel maneuvering is always dependent on the crewman's vision in the narrow channel or a busy harbor. Vision information is very important for a vessel navigating in the unknown environment [3, 4]. However, the intelligent application of vision system is limited which is reliant on machine learning technology.

Due to the proposition of deep learning[5], machine vision has got tremendous progress. CNN is a special neural network which is designed to make use the 2D structure and neighborhood characteristics. LeNet is the first successful applied CNN which named as the author's name Yann LeCun [6]. CNN has the inherent deep property, but the application of deep CNN is limited. The computing power and the data deficiency is the main problem. After the proposition of deep learning at 2006, the deep neural networks become popular. The deep CNN has a wide application such as the image recognition and speech recognition [7]. In this paper, a deep CNN is adopted to learn the maneuvering charactertics of the USV and realize the automatic operation of USV based on the visual system. By the training of the deep CNN, the USV can learn to steer vessel through the sample data and then it can navigate autonomously.

II. CNN AND VESSEL COLLISION AVOIDANCE

A. CNN

The CNN is a unique deep artificial neural network making use of the 2D structural information of the images. CNN takes advantage of the neighborhood characteristics and uses the weight sharing technique to reduce the parameter numbers of the network [8]. CNN always includes some typical layers, such as convolutional layer, optional pooling layer, optional normalization layer, optional dropout layer and fully connected layer. The convolutional layer makes use of a convolution kernel to convolute the input image, and creates a smaller feature map after activation. The pooling layer is a dimension reduction operation, such as the common used max pooling operation and average pooling operation etc. The batch normalization layer is always used to adjust the data distribution [9]; and the dropout strategy is adopted to overcome the overfit problem[10]. The fully connected layer is the final one.

The convolutional layer can be described as following,

$$x_j^l = f(\sum x_i^{l-1} * k_{ij}^l + b_j^l) \tag{1}$$

l is the layer number. k is the convolutional kernel and x is the input image. In deep neural network, the output information of the previous layer is the input of the current layer. b is a bias value. f is an active function, such as the sigmoid or relu function.

There is always a down sampling layer as equation (2),

$$x_j^l = f(\sum \beta_j^l down(x_i^{l-1}) + b_j^l) \tag{2}$$

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down() is the down sampling function, and β is the adjustment parameter.

After the operations, there will be some feature maps the same as the convolutional kernels. Some feature maps are combined and create a new image. In order to select an optimal combination, a parameter α is used to adjust the contribution of feature map in the combination.

$$x_j^l = f(\sum_{i=1}^{N} \alpha_{ij}(x_i^{l-1} * k_{ij}^l) + b_j^l) \tag{3}$$

$$\sum_i \alpha_{ij} = 1 \text{ and } 0 \le \alpha_{ij} \le 1 \tag{4}$$

$$\alpha_{ij} = \frac{\exp(c_{ij})}{\sum_k \exp(c_{kj})} \tag{5}$$

α can be computation according to the softmax.

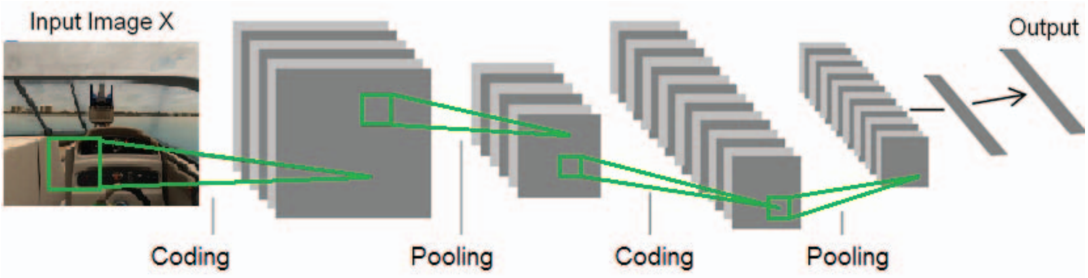

Fig. 1. The CNN structure

B. *Collision avoidance regulation*

The COLREGs is a criterion of vessel navigation on the sea [11]. The COLREGs describe the collision avoidance operation and duty in different encounter situations such as crossing, head-on and overtaking as figure 2 showing. The COLREGs provide safe guideline for crewman. Therefore, we can make use of the CNN to learn the maneuvering experience of crewman, and the automatic collision avoidance will be with respect to the COLREGs. If two vessels constitute an encounter situation, the own ship and target ship have the responsibility of taking appropriate strategy to avoid collision. According to the COLREGs, the stand-on vessel should maintain it current navigational status, while the given-way vessel has responsibility to avoid collision according to the COLREGs. But, if the given-way ship doesn't take any helpful strategy to avoid collision, then the stand-on ship should adopt a suitable operation to avoid collision.

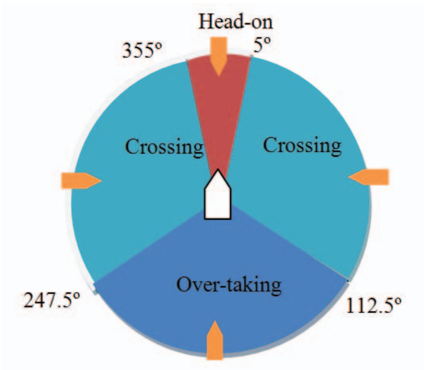

Fig. 2. Encounter situations

There are two kinds of collision avoidance categories, course changing and speed changing. However, on traditional navigational systems, the course changing strategy is alsways adopted. The speed changing is only adopted in critical situation. Therefore, the CNN is adopted to study the course changing experience of the crewman according to optical visual information.

III. Simulation

Some simulated scenes are created testify the effectiveness of the method. However, we don't have enough vision data coming of USV for this paper's method. Due to the short of the USV maneuvering vision data, the European Ship Simulator game is used to create the visual data and record by the Fraps software. The forward visual data is recorded manually. Several standard encounter situations are created to simulate the encounter situation.

Figure 9 is the encounter situation of crossing. As shown in Figure 3, the vessel is crossing to the right side of the USV which will cause a collision unless an appropriate maneuvering operation is adopted. The USV is operated to starboard to avoid this risk as figure 3(b). The USV is overtaking the target vessel in Figure 4, and the USV has a full responsibility of avoiding collision according to the COLREGs. The USV takes a starboard operation to avoid the collision which is with respect to the COLREGs, as illustrated in Figure 4(b). The USV overtakes the target vessel successfully and avoids collision.

(a) Initial situation

(b) After collision avoidance
Fig. 3. Crossing situation

(a) Initial situation

(b) After collision avoidance
Fig. 4. Overtaking situation

Although many chaff interferent exist in the samples, such as the window frame, the ship mast or the part of ship etc., the CNN can study the maneuvering ability effectively. The CNN training is realized on a DELL T7910 workstation with a Tesla K40 GPU. Some specific training process are shown in figure 5 and figure 6, figure 5 shows the training process and figure 6 shows the training accuracy.

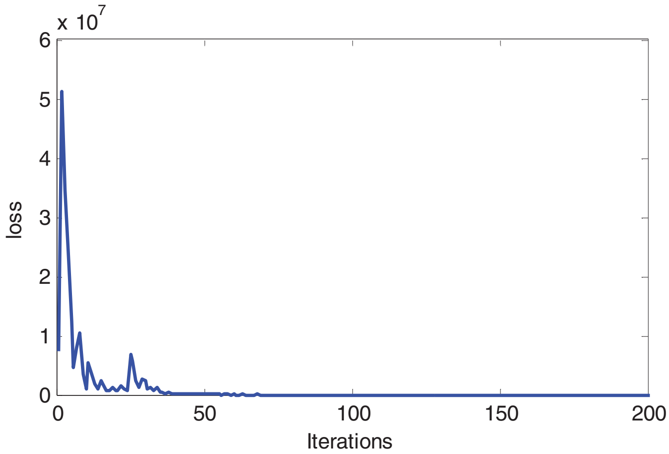

Fig. 5 Training process diagram

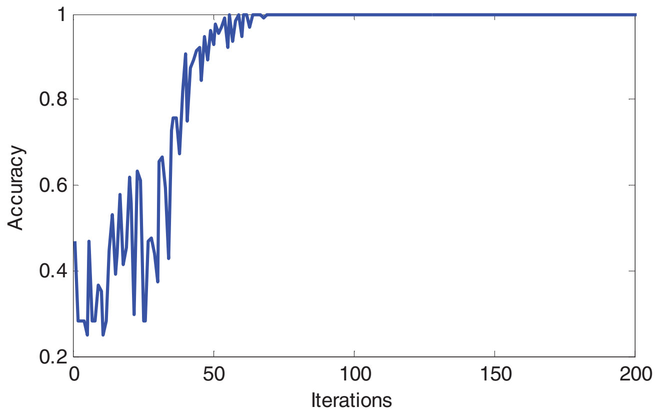

Fig. 6 The accuracy diagram

After the training of CNN, the maneuver operations can be predicted according to the encounter visual data. For example, figure 7 shows the prediction of maneuvering operation at overtaking encounter situation. The NGC system can steer the USV According to prediction result.

Fig. 7. The prediction of maneuver

IV. CONCLUSIONS

USV has a great requirement, such as military requirement, civilian application and commercial usage. In order to enhance the USV automated level, the vision system based collision avoidance method is proposed. The deep CNN is adopted to study the maneuver experience of crewman by visual information. The European Ship Simulator is adopted to simulate the USV to create enough encounter scenes data. And also, the operation of USV is with respect to the COLREGs to make sure the CNN learning the COLREGs. After training of CNN, it can predict the maneuver operation which indicates the validity of this proposed method. This method would reduce the human interactions in the navigation of USV and promote the automation level.

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