Ships Angular Position Detection Using Computer Vision Techniques and Artificial Neural Networks

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Abstract—This paper presents a system for detecting angular position of warships, using features extraction techniques from acquired digital imaging and artificial neural networks. The used ships images are graphically generated by three-dimensional solid modeling software. Different groups of features are considered. They are obtained from modelled ships at different angles and zooms. Tests using neural networks were applied to three distinct characteristics groups: geometric, invariant moments and the *Hu* moments. The main is achieving a recognition algorithm for identification of the ship angular direction regardless of their distance from the viewer. The methodology produced good results concerning the target spatial position information. In next future this will be applied in real infrared images of Brazilian navy ships.

Keywords- Neural Networks, Computer Vision, Recognition, Infrared Images.

I. INTRODUCTION

Nowadays, the recognition of targets systems by infrared images is very useful for military and commercial applications [1][9]. The efficiency of these systems is sensitive to many circumstances that can affect image capture, as weather change and noise. Indeed, it is a passive system and safer for EPM (electronic protection measures). In war tactics, it's possible to lose the target tracking when ships are intercepted by false shadows that are moving to a different direction. Therefore, knowing the angular position of the ships (Fig. 1), it's possible to predict his movement and avoid the loss of tracking.

In the presented paper, to analyze and to extract the features, it's used a set of images of ships with various length and angular position, obtained through three-dimensional ships models. The ships were built using the computational solid modeling software SolidWorks®. Here, we consider only the steps of feature extraction and angular recognition. In the decision phase of the research different back-propagation neural networks topologies were considered [10], which uses three different groups of image characteristics like geometric feature, invariant moments and the *Hu* moments as input data.

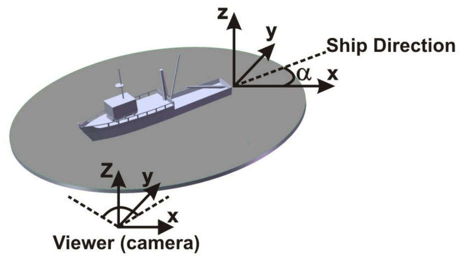

Figure 1. Angular direction of the ship in relation to the viewer coordinate system (referential).

II. COMPUTER VISION SYSTEM

There are several steps in a generic computer vision (CV) system. In the pre-processing step, CV techniques are related to image restoration, enhancement and segmentation stages to recover information contained in the image or make an improvement in image quality. Techniques for pre-processing infrared images, commonly used in military applications, are presented by Neves 2005 [9] and Carvalho 2008 [2]. They pointed out the importance of the choice of adequate techniques for recognizing objects in infrared images. Using inadequate pre-processing it may add or delete information in the image, which can cause incorrect results in the feature extraction stage.

The difficulty to detecting the angular position in naval applications it due the similarity shapes for different angular positions of the ship. The recognition of ships by invariants moments, presented by Alves in 2001, and the recognition of aircraft using wavelet invariants moment, presented by Feng in 2008 [4], worked with object images projections which do not modify the angular position of the studied object and the acquired viewed image, as well. Alves (2001) used decision trees in the identification and recognition of ships [1].

A. Features Extraction – Brief Review

The images used consist in two dimensional representations of three dimensional objects in perspective projection. Therefore, it is proposed to evaluate different groups of feature sets, extracted from these two-dimensional representations, which, once identified the ships, may be useful in obtaining their angular direction in the three dimension space. Thus, we can mention different features that can be extracted from objects detected in gray scale images. In this paper, we used some dimensional and inertial characteristics, and the Hu set of invariant moments. Inertial features are based on the theory of inertial moments. The invariant moments with respect to rotation and translation, are related to geometric moments, which are based on the concepts of inertia of rigid bodies [8].

It is important to observe that these features are sensitive to the acquisition process. Specially of two aspect: The dimensions of the objects in relation to its distance from the camera; The angle between the reference axial system of the camera, angle θ, and the direction of the ship movement (α). Figure 1 depicts this.

To obtain such features, it is considered a binary discrete image with N x M pixels (that is only two values of gray are used: black and white). Black pixels are considered belongings to the object and the white pixels to the background. Conci 2008 [3] presents the geometric moments of order ($p + q$), the centroid, the inertia central moments, the inertial moments, the eccentricity and the set of invariants geometric moment proposed by Hu (1961) [8]. Eq. 1 produces central moments that are usually considered to feature extraction of area, static moments, inertial moments and others.

$$\mu_{pq} = \sum_{k=1}^{n} B(i_k, j_k)(i_k - i_0)^p (j_k - j_0)^q B(i_k, j_k)$$

$$p,q = 0,1,2,\ldots \qquad (1)$$

Where n is the number of black pixels, $B(i,j)$ consists in a pixel that belongs to the object and, i_o and j_o are the centroid coordinates. Using the inertial moments $\mu_{1,1}$, $\mu_{2,0}$ and $\mu_{0,2}$, we can obtain the angle θ (Fig. 2) that identifies the orientation of the principal axes. Note that this angle is obtained by considering the theoretical two-dimensional image, angle θ, and not the angles that represents the spatial angular position of the ships (α), which is the objective of this work.

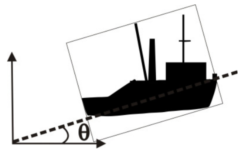

Figure 2. Orientation.

Another feature consists in the eccentricity that is obtained by the adjusted ellipse [3]. The eccentricity (E) is defined as the division between the size of the smallest and largest axis, characterizing how the object is spatially distributed between their axes. This measure can also be calculated based on the principal central moments [8] of the object $I'_{\min}(\theta)$ and $I'_{\max}(\theta)$. When it is obtained by the division of the inertial moments it is named E_1. In case it is achieved by the parameters lengths of the semi-axes major and minor of the ellipse it is named E_2.

Normalizing the central moments we can obtain the invariant moments to the scale, which is the base to obtain the set of *Hu* moments [8].

B. Recognition

Most of the problems in pattern recognition (classification) have two distinct phases. The first often called "training" (learning) from a database or existing samples previously selected for this phase. The second stage, known as "generalization", is performed to the data that were not used in training. The second phase allows the evaluation with a new data. Thus the data can be classified. Classification methods consist of techniques that distinguish objects of different classes. The classification techniques can be reported as: supervised and unsupervised.

The supervised classification is one in which a set of known objects belonging to different classes is analyzed, choosing the ideal parameters for the classes partition. These parameters define the discriminated function.

A supervised classification can be done by statistical distribution or free distribution. The first is based on models of the probability distribution. The second requires no prior knowledge of probability distribution functions, based on deduction and heuristic. Artificial neural networks is an example of grouping in free distribution that allows rapid progress to a final decision, which are used in this paper in recognition of the direction angle of the ships.

Artificial neural networks (ANN) are mathematical representations of a set of neurons, massively connected, based on biological neural networks model [7]. The architecture of a neural network can be defined by connecting neurons to each other, using synaptic weights.

In the task of pattern recognition (classification), the architecture of the neural network receives in its first layer, object attribute as input. During the training process, the ANN is modeled taking into account the classification result. Thus the weights are adjusted according to the recognition task. Once the ANN is well made, it is possible to present new object features (that were not used as training set) and then obtain its class.

III. METHODOLOGY

The goal of this paper is to extract general characteristics of ships and use them in the decision-making (process/stage) to obtain the direction angle of the ships. Figure 3 shows images obtained from different angles in perspective (from 0 to 360º with the viewer) and the ships at sea level, in the horizontal plane as showed in Figure 1.

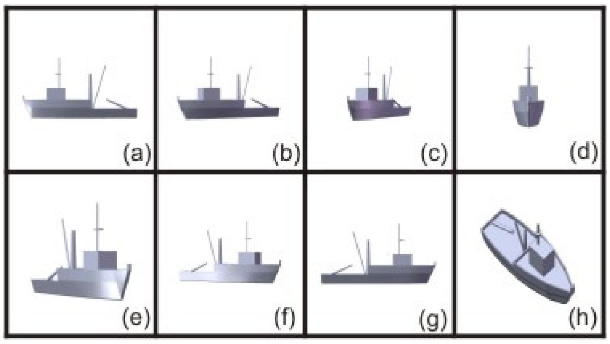

Figure 3. Angles of views of a synthetic ship in perspective (a to g: camera in the horizontal plane; h: plane camera with inclination).

In military applications, superior views or angles above the horizontal plane (Fig. 3.h) do not correspond to the reality of an image acquired by an usual system. Therefore here, the results were obtained considering three different angular positions (0º, 90º and 150º) of three types of ships (Buoy, Corvette and Frigate) presented in Figures 4.

Variations in the symmetry of the silhouettes between the symmetrical angles to the frontal plane are not differentiated by the extracted features, except the object orientation angle, that allow the recognition of just images whose angular direction of the ships ranges from 0º to 180º. Therefore, for each ship, images from only three different angular views in perspective are chosen. Each generated images, on a given angular position was converted to gray scale and then converted into a binary image.

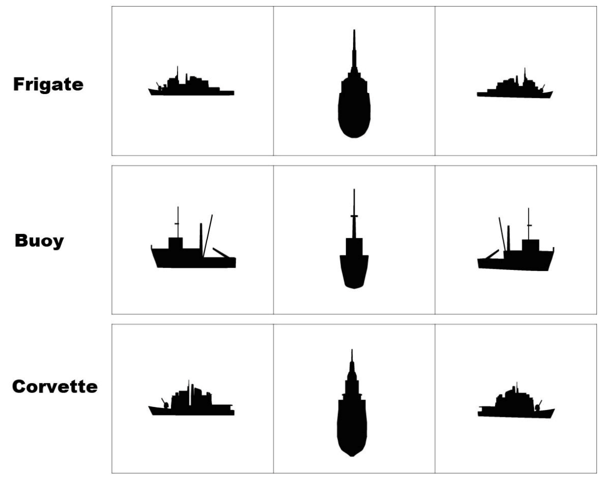

Figure 4. Examples of images after pre-processing preprocessing of the three views generated from a solid model.

For each ship, 25 scales are used for each angular position (0º, 90º and 150º). For each image, twenty two features are extracted from the three groups: Geometric Characteristics (GC), Inertial Moments (up to second order) (IM) and Hu invariant moments (HU). The algorithms to extract the characteristics have been developed in MATLAB ®. To obtain the results in terms of network models, and changes in the topologies, it is analyzed the number of correct answers regarding the architecture as shown in Figure 5, which uses only 1 neuron as output. For the hidden layers, the transfer functions (sigmoid and hyperbolic tangent) were evaluated.

The group called GC considers the following features: Area, L max (max length), Hmax (max height), perimeter, orientation angle and the eccentricities E, E1 and E2. The IM group refers to the features $\mu_{1,1}$, $\mu_{1,2}$, $\mu_{2,1}$, $\mu_{2,0}$, $\mu_{0,2}$, $\mu_{3,0}$ and $\mu_{0,3}$, obtained by Eq. 1, and the HU group refers to the first seven Hu invariant moments (Hu, 1961) [8].

TABLE I. THE USED NETWORK TOPOLOGIES

Network Topologies												
	Identifications											
	1	2	3	4	5	6	7	8	9	10	11	12
No.HL	1	1	1	1	2	2	2	2	2	2	2	2
No.FHL	2	5	10	20	2	5	2	5	10	10	20	20
No.SHL	-	-	-	-	2	2	5	5	5	10	10	20
HL = Hidden Layers FHL = node of the First Hidden Layers SHL = node of the Second Hidden Layers												

Once all characteristics for each group were obtained, it was possible to train and test different neural network topologies. Two topologies were tested: one and two hidden layers. These topologies were identified by 1 to 12 according to the different neurons quantities in the Hidden Layers (HL), Number of nodes in the First Hidden Layer (FHL) and Number of nodes in the Second Hidden Layer (SHL) as shown in Table 1 and Figure 5. From a total of 75 sets of characteristics by group, it was chosen 66 sets to train each network and nine remaining sets were used to test them.

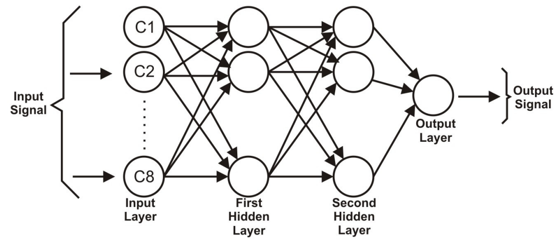

Figure 5. Network architecture.

IV. RESULTS

The extracted features were placed on tables for the various positions and scales (zooms). They are coded according to a standard maximally sparse, *i.e.* encoding 001 to 0° position, 010 for 90° and 100 to 150°. For each ship, three training and test sets considering the network topologies (Table 1) are created, one for each feature group, resulting in a total of nine sets of training and testing each ship.

Each training table includes 22 feature sets for each angular position: 66 sets in total. Tested tables with three sets of features for each angular position that is nine feature sets for each ship are considered. The quantity of correct outputs is plotted in figures 6 to 8 for the three ships. These illustrate the results of the three sets of characteristics (GC, HU and IM), with a rate of 10% tolerance.

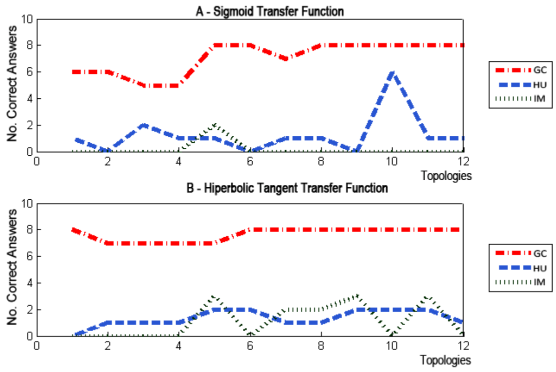

Figure 6. Result for the Buoy ship.

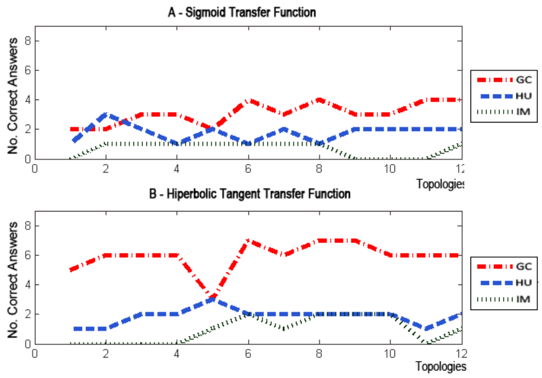

Figure 7. Result for the Corvette.

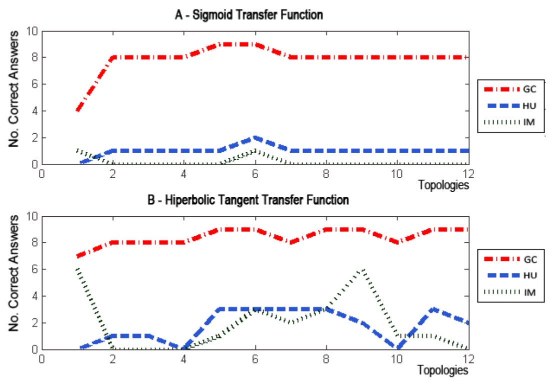

Figure 8. Result for the Frigate.

Results show that the group of geometric characteristics is better than inertial moments and *Hu* moments. Indeed it was observed that the inertial moments and Hu moments coefficients presented the lowest correlation values, considering the output targets. A possible reason to this fact is that Hu moments were developed to evaluate objects that don't change their 3D position. The IM group has worse results for the three ships. The HU group presents results with few variations in relation to different network topologies. It can also be noted that, although the results do not present a stable variation in relation to the number of neurons and the number of hidden layers for the presented topologies of networks architecture, we do not have sufficient information to define the best topology. In addition, network using hyperbolic tangent function works better for sigmoid function.

V. CONCLUSION

Based on the results from the architecture and network topologies presented, we conclude that the inertial moments and *Hu* moments are not suitable for detecting angular position of ships. Surely, it happens because these moments were developed to bidimensional pictures. This was not expected, since many authors usually use *Hu* moments to identify different kinds of objects for recognition in similar applications [1][4]. If the results consider the number of layers and neurons, we observe that the network scheme can affect the results. Therefore, the presented methodology confirms that both the choice of features sets as the choice of network topology to be used in determining the angular position of the ships moving is a factor to be considered to obtain good results.

Moreover, comparative analysis of the results obtained from the different groups of feature sets, indicates the geometric (GC) as the most suitable group to the purpose, among those presented, since it presents the most significant response when we compare the results independent of the changes in network topologies. We can say that the used approach to the automatic evaluation of the navigation angle of ships can be considered as a starting point for a future work on tracking of targets in infrared images. In this case, we can consider the use of other techniques for recognition and also the use of other network architectures and topologies. Thus, this paper opens new possibilities for improving the efficiency of one of the steps involved in designing a classifier based on infrared signatures of ships.

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