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The Hough transform in the classification process of inland ships

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Abstract

This article presents an analysis of the possibilities of using image processing methods for feature extraction that allows kNN classification based on a ship's image delivered from an on-water video surveillance system. The subject of the analysis is the Hough transform which enables the detection of straight lines in an image. The recognized straight lines and the information about them serve as features in the classification process. Above all, this approach allows ships to be recognized, which can then be characterized by a specific representation and shape. Recreational units that are often seen on inland waters were classified correctly using this method. Each analyzed camera image was previously prepared – brought to the form where the ship was visible from the side and the background removed (they were monochromatic – white). The results obtained in this work will allow for the development of the final ship classification method based on camera images. This method is a significant part of the emerging system prototype, which is implemented as part of the Automatic Ship Recognition and Identification (SHREC) project.

Introduction

Image processing and identification is one of the main subjects of artificial intelligence methods, which more and more often intrude into our lives. Visual recognition or decision-making is being taken over by machines, computers, tools and algorithms that do it for us. This happens to not only facilitate and automate a certain process, but also eliminates the human error that often occurs. The analyses that have been described in this article focus on the methods of image processing and identification for the purpose of automatic recognition of vessels. This research is a part of a larger project SHREC, financed by the Polish LIDER NCBiR program (Wawrzyniak & Stateczny, 2018). The idea for the project was initiated by the fact that the marine and inland services signaled the need to automatically recognize objects that move on the water. Of course, there are already existing systems that deal with this issue, but unfortunately they have some limitations, primarily associated with methods that are used for identification purposes – for example, the AIS (Automatic Identification System) – not all units are obliged to be equipped with AIS transponders. Another approach to identification is the ability to detect vessels using satellite images (Wang et al., 2014; Bobkowska, 2016; Kanjir, Greidanus & Oštir, 2018), but in this case there is a problem with almost real-time detection and the detection of small vessels. Therefore, a system based on video stream analysis (near-distance acquisition) has potential. The SHREC project was set up to develop a tool that will identify all kinds of vessels (especially leisure craft) based on the image from a digital camera. Most ship traffic monitoring systems have cameras, unfortunately the handling and analysis of the stream is done by hand. Many of these systems also store information about the ships that can serve as a reference in case of the need for identification. One such system is a part of the River Information Services of Lower Oder (Cohen et al., 2015). This system allows for the safety of inland waterway transport to be increased.

The development of a classification algorithm based on ship images is a task that will allow the process of the identification of vessels to be automated. As part of this task, many image processing methods were tested; one of them is the standard Hough transform, which allows straight lines in the image to be selected. It is widely used in computer vision, e.g. for the detection of line markings on motorways (Ali, Radzi & Saad, 2017) or the detection of buildings from high resolution satellite images (Turker & Koc-San, 2015). However, the Hough transform is not only used to detect straight lines; a modified method can be used to detect other shapes – for example, circles for particle analysis (Meng et al., 2018) or tree detection (Koc-San et al., 2018) and parabolas.

Work on the development of this algorithm was carried out in two ways. The assumptions described in this article were one of the paths and were designed to analyze the possibility of classification by simple, standard methods (here the focus was on the kNN method). Independently, research is being conducted on the use of deep learning for this purpose. Artificial neural networks are very often used in image classification (Rawat & Wang, 2017). They are used, among others, in the aforementioned problem of recognizing ships from satellite images.

During the literature review concerning the problem of the classification of vessels based on video data from standard ground monitoring cameras, three types of work were found. In the subject of the monitoring of vessels, scientists presented the problem of ship detection (Shao et al., 2019). Moving a step further, the problem of the detection and analysis of the text on a ship ((the call sign, IMO or registration)) can be marked (Ferreira et al., 2017), and publications have directly presented the problem of recognizing the type of ship; CNN (Convolutional Neural Network) is applicable in this case. A paper in the literature (Akiyama et al., 2018) described the classification results at F1 level of 70% for 5 classes. A paper in the literature (Zhang et al., 2015) described the CNN and Gnostic Fields tests; another example was also published (Solmaz et al., 2018). In this paper the authors propose a classification model based on a multi-task learning framework.

Method and data

Hough transform

For the Hough transform, a straight line representation is used:

$$\rho = x \cos \theta + y \sin \theta \tag{1}$$

where: the variable ρ is the distance from the origin of the coordinate system (in the case of image analysis in the Matlab program from the upper left corner) to the straight line at a right angle (in the case of image analysis, the unit of distance will be the pixel); the variable θ is the angle between the positive axis x and the vector perpendicular to a line passing through the origin of the coordinate system. This angle is measured clockwise and is in the range: $-90° \leq \theta \leq 90°$).

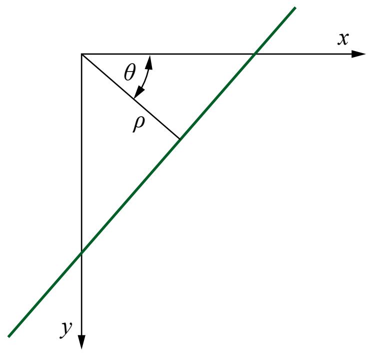

Figure 1. Representation of a straight line in the Hough space

Figure 1 is a graphical representation of the Hough transform.

Detection of straight lines

The analyses conducted for the purposes of the research were made using Matlab Mathworks software. The process of detecting straight lines assumed:

- Extraction of the edge of the input image – the use of the Prewitt edge filter was arbitrarily assumed (Shrivakshan & Chandrasekar, 2012). With the filtration process, a binary image with recognized edges was obtained.
- Conducting a standard Hough Transform, the result of which is a matrix (SHT) of the parameter area, where the rows and columns correspond respectively to the values of ρ and θ.

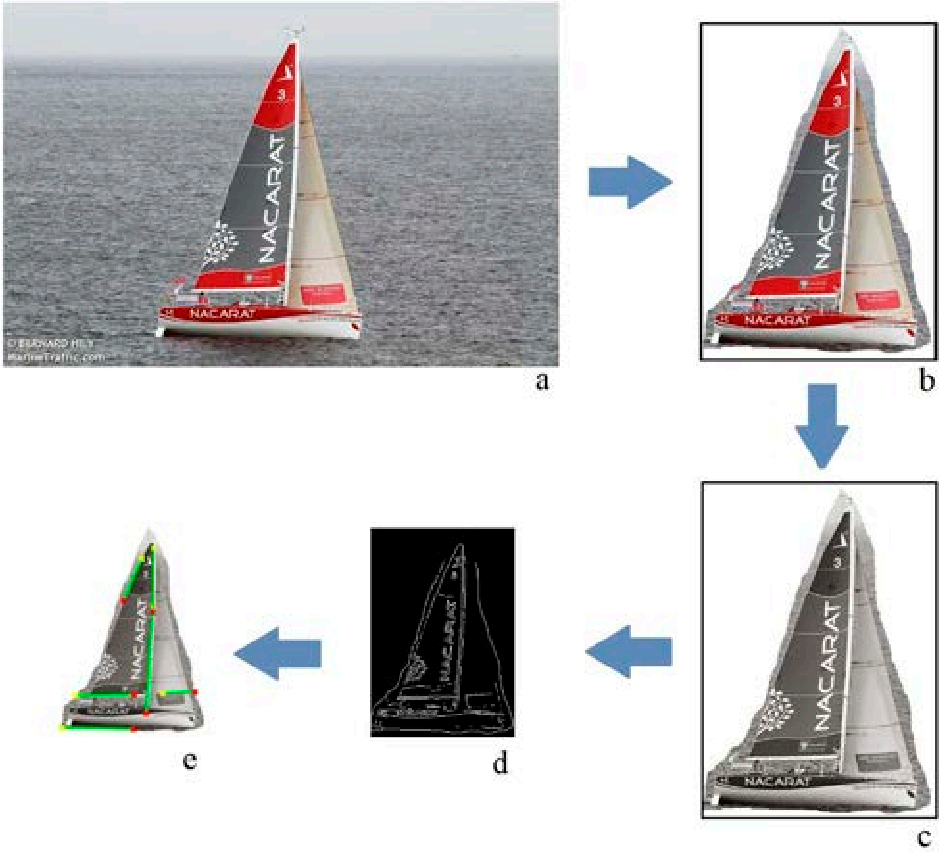

Figure 2. Images of the processing stages and the detection of straight lines, a) initial image, b) image cropped manually –background removed, c) grayscale image after Gauss filtration, d) image after edge filtration e) image b with straight lines applied

The values of the elements in the SHT matrix represent accumulative cells, which are initially zero and then, for the points that do not belong to the background, the value of ρ is calculated and rounded to the nearest assumed value of the SHT matrix. The values of the matrix's elements are then increased. As a last resort, the value of Q in the SHT matrix (where Q is the element of the SHT matrix for row r – corresponding/assigned to the specific value of θ and the column c – corresponding/assigned value ρ) denotes the point lying on the line. The peaks in the SHT matrix are the representation of the line in the input image.

- Detection of straight lines

The various stages of image processing and final detection are illustrated in Figure 2. Figures 2b and 2c are images of the result of pre-processing.

Assumptions and the concept of selecting features that allow for the classification of vessels

During the implementation of the components of the SHREC project, hundreds of photos of vessels were reviewed. Visual analysis of their appearance and shape allowed the authors to state that some types of units are characterized by a specific representation of straight lines in an image. Such units include, for example, a large motor yacht (many straight parallel lines) or a sailing boat (predominantly long vertical or almost vertical lines). Hence the idea of using simple information recognized in the image for classification purposes. As a list of features, the following was proposed:

- number of horizontal lines – for which $-45° \leq \theta \leq 45°$ – l_l_poz,
- number of vertical lines – for which $\theta > 60°$ or $\theta < -60°$ – l_l_pio,
- min. position of horizontal lines along the x axis pmlpoz_x,
- max. position of horizontal lines along the x axis pMlpoz_x,
- min. position of horizontal lines along the y axis pmlpoz_y,
- max. position of horizontal lines on the y axis pMlpoz_y,
- min. position of vertical lines along the x axis pmlpioz_x,
- max. position of vertical lines along the x axis pMlpioz_x,

- min. position of vertical lines along the *y* axis pMlpioz_y,
- max. position of vertical lines along the *y* axis pMlpioz_y,
- the sum of the lengths of the horizontal lines to the sum of the lengths of all lines st_dl_poz,
- the sum of the lengths of vertical lines to the sum of the lengths of all lines st_dl_pio.

Figure 3 shows some of the features in order to better understand the assumptions.

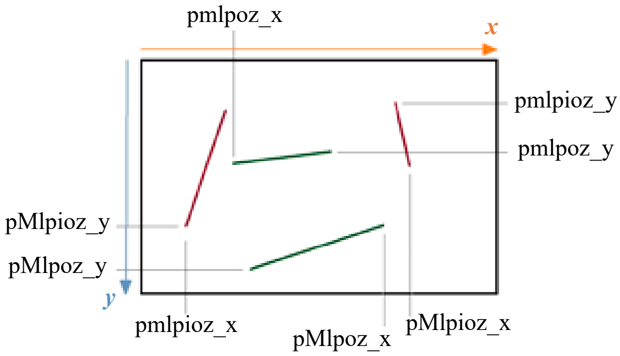

Figure 3. Representation of the features regarding the position of lines in an image

Due to the fact that the selected features have a value from various ranges, it was necessary to analyze and select the best approach to classification. Testing of two data normalization approaches was then assumed. However, it was also important to choose the normalization of the size of the images. Two approaches to testing have also been proposed. Detailed information is provided in Tables 1 and 2.

Table 2. Normalization of image size

Method	The method of normalizing the size of the images	Remarks
1	Change the size of each image to 200×300 pixels (height × width).	Double analysis (for data normalization approaches I and II)
2	Scale the whole image in such a way that the height value is equal to 300.	Double analysis (for data normalization approaches I and II)

Finally, the analysis of 4 options was carried out: I1, I2, II1 and II2. Each of these options assumed a suitable method of normalizing the size of the image and the data obtained for them (numerical values for features).

It should be mentioned that the preparation of the data for the classification task starts at the ship detection stage. The ship detection algorithm detects ships from the video stream and passes the result (a cropped bmp image (bitmap) with a corresponding detection mask) to the classification module of the SHREC system. It is important to initially remove the background, which is made easier by analyzing a stream rather than a single image. Preliminary results and conclusions of that process have been included in the literature (Hyla & Wawrzyniak, 2019; Wawrzyniak & Hyla, 2019). The results will be implemented during subsequent tests of the algorithm.

Table 1. Data normalization process

Method	The method of data normalization for the values of features
I	The division of features into 3 groups: A – l_l_poz, l_l_pio B – pmlpoz_x, pMlpoz_x, pmlpoz_y, pMlpoz_y, pmlpioz_x, pMlpioz_x, pmlpioz_y, pMlpioz_y C – st_dl_poz, st_dl_pio Classification for each group separately. Analysis of the accuracy of the classification and selection of the combining method of the partial classification results for the final classification of the vessel.
II	Normalization of values. Changing the values in each group to a value between [0, 1]. For the C group proposed above, there is no need for normalization due to the data being from the given range. For group A the assumptions were: – if the number of lines equal 0, the value 0 remains – if the number of lines is greater than 0 and less than 4, then the value is 0.5 – if the number of lines is greater than 3, then the value is 1. For group B, change the value to the ratio of a given value to the width or height of the image (depending on whether it applies to horizontal or vertical lines). Finally, all the features for classification are taken into account.

Data set

The data used in this article came from the database built for the needs of the project. The number of classes that were taken into account for the analysis were:

1 – a large motor yacht,
2 – a large sailing ship,
3 – a sailing yacht,
5 – a kayak,
6 – a container ship,
7 – a small boat/a motorboat,
8 – a barge,
9 – a pusher,
10 – a fishing vessel.

A set of training data was prepared, which consisted of 47 elements – photos of vessels. These photos were previously prepared (background removed and the image of the object was cropped – see Figure 2). For each class, the collection consisted of a minimum of 3 photos.

Two sets of test data were prepared. The first one consisted of 23 elements that represented 9 classes of vessels. Due to the results obtained during the analysis, a second set of test data was assumed, consisting of 40 elements. The images of the test sets were prepared identically to the image of the training set.

Classification method

The method of k Nearest Neighbors (kNN) was chosen as the classification method. Due to the fact that a number of objects represented particular classes in the training set (not less than 3 objects), the analysis of the nearest 3 neighbors was selected. The standard and commonly used distance was taken into account – the Euclidean distance.

Results

According to the initial assumptions, the features for the training set and the first test set were selected. The results are presented in Table 3, which contains data about the object class in the test set and recognized classes for four types of normalization. In the case of Normalization I1 and I2, the classification was a two-stage process. For a particular group (A, B, C) the kNN classification was made, and then the final classification was made – assignment to a given class if, in two cases, the same class was assigned. Otherwise, 0 was assigned – this meant no classification.

Table 3. Classification results for the first test set

Class	Normalization methods													
	I1					I2					II1		II2	
	RCG			RC	ERC	RCG			RC	ERC	RC	ERC	RC	ERC
	A	B	C			A	B	C						
10	2	1	10	0	F	1	1	1	1	F	1	F	9	F
10	1	2	10	0	F	7	2	1	0	F	2	F	5	F
1	8	8	10	8	F	6	1	1	1	T	8	F	9	F
1	1	1	10	1	T	1	6	1	1	T	1	T	6	F
1	2	1	10	0	F	5	6	1	0	F	1	T	1	T
2	1	2	10	0	F	1	2	1	1	F	2	T	1	F
2	1	1	10	1	F	3	3	3	3	F	1	F	3	F
2	5	3	2	0	F	3	10	3	3	F	3	F	3	F
3	1	2	10	0	F	3	3	3	3	**T**	2	F	3	**T**
3	2	3	2	2	F	3	3	3	3	**T**	3	**T**	3	**T**
3	3	10	3	3	**T**	3	3	3	3	**T**	3	**T**	3	**T**
3	3	3	3	3	**T**	3	3	3	3	**T**	3	**T**	3	**T**
3	2	3	3	3	**T**	3	3	3	3	**T**	3	**T**	3	**T**
3	3	3	3	3	**T**	3	3	3	3	**T**	3	**T**	3	**T**
3	2	3	3	3	**T**	3	3	3	3	**T**	3	**T**	3	**T**
3	1	2	10	0	F	3	2	3	3	**T**	2	F	10	F
3	1	2	10	0	F	3	3	3	3	**T**	2	F	3	**T**
6	1	2	10	0	F	6	1	6	6	T	2	F	5	F
7	1	8	10	0	F	7	7	9	7	T	8	F	1	F
7	1	1	10	1	F	7	7	7	7	T	1	F	8	F
8	1	7	10	0	F	8	6	5	0	F	7	F	5	F
9	1	1	10	1	F	9	7	1	0	F	1	F	1	F
9	1	8	10	0	F	9	1	9	9	T	7	F	7	F

RC – classified class
ERC – assessment of a classified class (T – true, F – False)
RC = 0 – no classified class
RCG – classified class for the group

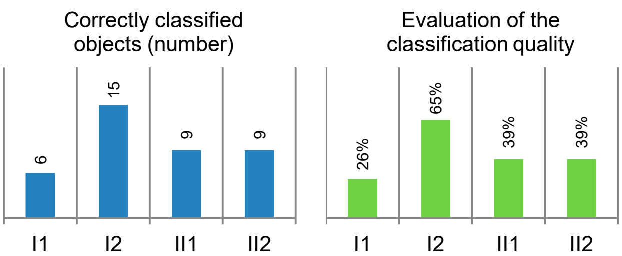

Figure 4. Classification assessment for the first test set

The results that were presented in Table 3 were then analyzed. Figures 4 and 5 illustrate the graphs presenting the analyses.

Figure 4 contains information about how many objects were correctly classified (the result is presented in the form of numerical and percentage values.) However, the obtained classification results are insufficient. It was noticed (Table 3) that in most cases sailboats were correctly classified. In addition, the incorrect classification of another object as a sailboat was also low; such analyses are presented in Figure 5. The number of sailboat objects in the first test set was 9. The analyses show that normalization approaches I1 and II1 should be rejected, due to their low accuracy. These were the options that assumed the normalization of the image size – for all the analyzed objects the image was scaled to a set size (200×300 pixels). Only normalization approaches I2 and II2 were considered for further analysis. The reason for this was the relatively high accuracy of the classification of sailboats (in the case of I2 – 9 out of 9, for II2 – 8 out of 9 and the low number of objects classified as sailboats (in the case of I2 – 2 out of 14 and II2 – 1 out of 14).

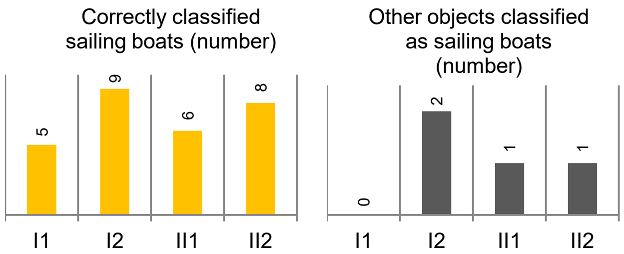

Figure 5. Classification of sailing boats (first test set)

In connection with the results discussed above, the authors then decided to double-check the classification for the I2 and II2 normalizations on the new test data set (second test data set). In this case, the goal was only to select objects that were sailboats. Two classes were established (sailboats – 17 objects, and other vessels – 23 objects); the results are presented in Figure 6. The difference in the obtained classification accuracy (in the two approaches) was not great. The classification accuracy of 90% is satisfactory at this stage of research. The difference between the classification quality in these two cases (I2 and II2) for such a small set of test data is not significant. It is only 1 more sailboat correctly classified (in the case of II2). In order be able to say which of the normalization assumptions is better, tests should be carried out on a larger test set.

It turned out to be necessary to change the set of classes to two for the identifying features and classifications of the developed algorithm. The proposed approach does not allow detection of the other 8 proposed classes. For this purpose, it will be necessary to examine other methods of selecting the features of images that represent vessels. Current research allows for the classification of subsequent classes. Their goal will be to not only recognize other ships, but also to increase the accuracy of sailing boat classification. In addition to methods for emerging features, other test methods are also planned, such as decision trees and artificial neuron networks.

Conclusions

Classification of vessels based on an image is a difficult and complex task. Obtaining the answer of which vessel is in the image requires the combination of several methods. The set of features on which the classification is made should be extensive. Work on developing an accurate and reasonable swift algorithm will take a long time. The preliminary results, on the other hand, are promising. The

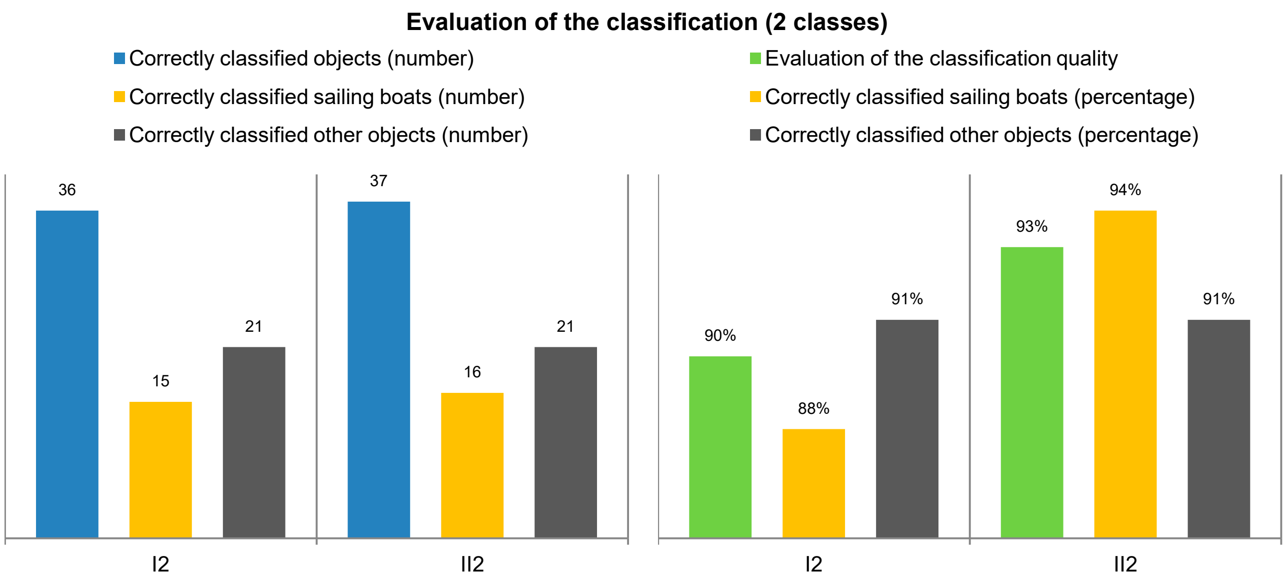

Figure 6. Classification of sailing boats (second test set)

results presented in this article show that by using the Hough transform it is possible to develop a set of features that will allow the classification of sailing boats, among other units. Methods based on the analysis of the histogram, Gabor filtration, and object shape analysis are currently being tested; these will allow the identification of other features of ships allowing for classification on other ship types. The next step will be the consolidation of all the feature extraction methods used for the purpose of covering all defined vessel classes.

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