Identification of River Hydromorphological Features Using Histograms of Oriented Gradients Cascaded to the Viola-Jones Algorithm

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***Abstract*—In this paper, a quadcopter equipped with a camera was used to capture images from a river. These captured images were used as training data in the automated detection program used to identify the hydromorphological features in the area of the river such as trees, roofs, roads and the shore. The histogram of oriented gradient with support vector machine classifier was cascaded with the Viola Jones Algorithm in order to recognize hydromorphological features. Testing was done using different images to verify the effectiveness of the detection system compared with previous studies. System evaluation and success of the cascaded system was determined using the percentage of correct detected features in the image. The results showed that the cascaded system has increased the accuracy compared to the implementation with only the Viola Jones Algorithm.**

***Index Terms*—quadcopter, hydromorphological, viola-jones algorithm, histograms of oriented gradients, support vector machine**

I. Introduction

Disaster Prevention is one of the most pressing issues in the world today and is currently an area of extensive research [1][2][3]. Some of the advancements in this field are surveillance and monitoring of areas that are deemed to be prone to disaster. Surveillance and monitoring is a critical component of disaster prevention. Constant surveying and monitoring of all the objects and areas in a given place are critical in knowing and preparing for a possibility of a coming disaster. At times, only few minutes of neglect can cost a lot of lives when disaster occurs. One of the areas where disaster may occur is in streams of rivers. There are many hydromorphological features in a river such as trees, roofs of houses and buildings, roads, shorelines and the river water. These features are often monitored and are constantly checked for changes or disturbances. When disturbances occur, there is a possibility of disaster happening [4]. The idea of disaster prevention has created many methodologies or approach into tackling this problem. One approach that is commonly implemented is via in-situ mapping [5]. Another approach is aerial imagery assessment [6]. This approach relies on visual or automated identification of key river characteristics from image captured or acquired. In this approach, the quality of the assessment depends upon the accuracy of the classification approach and the characteristics of the imagery. This approach relies on the expertise of the surveyor identifying hydromorphological features and does not allow for the objective re-assessment of records after survey completion. Problems such as practicality of time and cost makes this approach difficult to repeat at high frequencies and they have a common limited accessibility [7,8,9]. Therefore, an automated approach to the problem is needed.

There are three types of image classification techniques, such as object-based image analysis, unsupervised and supervised image classification. The first technique is the object-based image analysis which relies on multi-resolution segmentation. They are able to generate objects of different shapes and scales by grouping the pixels of similar characteristics. Unsupervised classification groups pixels based on their reflectance properties while supervised classification is based on the concept of segmenting the spectral domain into areas that can be associated with features of interests. This method requires training process by which samples are used and are identified to classify the entire image. There are a lot of algorithms for this kind of task, algorithms such as Gaussian mixture models, minimum distance, network classifiers and object detection algorithms [10-16]. Other recent studies focused on pattern recognition and feature extractions techniques [17-20].

This study presents a new hydromorphological feature extraction technique using a cascaded Histogram of

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Oriented Gradients with Support Vector Machine to a Viola Jones Algorithm to extract river features. The algorithm shows effectiveness of up to 94% during the automated implementation.

II. Methodology

The hydromorphological features in this study was detected using Histograms of Oriented Gradients with Support Vector Machine as classifier, This section show the overall methodology together with the system block diagram of the algorithm.

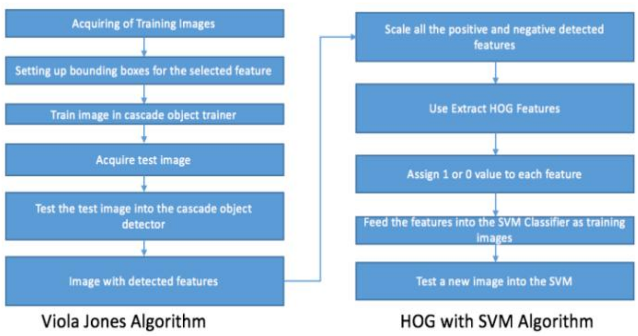

Figure 1. System Block Diagram

The system block diagram can be seen in Fig. 1 and it has two parts. The first part is the Viola Jones Algorithm block diagram and then right next to it is the Histograms of Oriented Gradients with Support Vector Machine as classifier algorithm. It can be noted that the HOG with SVM Algorithm can be directly cascaded to the Viola Jones Algorithm in order to improve system performance. In this study, there are currently 80 pre selected images of the river. Each of the images contains the features that the program wants to be detected. Such features include the water from the river, trees, roads, roofs, shore and the sky.

Figure 2. Image with bounding box

Before the actual training, there is a need for the features in the images to be identified, they will be identified by putting bounding boxes in each images depending on the selected feature. Fig. 2 shows an image with a bounding box. The program will allow the user to put bounding boxes on each of the 80 pre selected images to the selected feature. Each of the 80 images will be identified with the selected feature until all images had an identified feature for the selected feature. It can be seen in Fig. 3, three different images from the 80 pre selected images with bounding boxes of the same feature identified.

Figure 3. Different Images with the Same Feature Bounded

When a trainer data set is created, it can be now set as test image for the detector of the Viola Jones Algorithm block. A test image is used which will output another image with bounding boxes trying to detect the correct feature. In Fig. 4, it shows the output from the Viola Jones Algorithm block, it is an image with detected features. This is an example of the road feature detector. the output bounding boxes shows some correct feature detected and some incorrect ones

Figure 4. Image with detected road features

At this point, the performance result of the Viola Jones Algorithm block shows very low correct feature detection, only the tree feature detector was able to reach the 70% correct feature detection goal. So in order to gain better performance results and accuracy for the detection and recognition of the selected features, this study came up with cascading the results from the Viola Jones Algorithm block with the block that contains the Histograms of Oriented Gradients with Support Vector Machine as classifier.

The next step is to extract all of the features detected from the test image and scale them to have the same size. Upon doing so, one should extract the HOG features and then collate each one of them and assign each feature with 1 or 0, with 1 being a positive feature and 0 a negative feature. These data of features that have assigned 1 or 0 with them will then be fed into the Support Machine Vector classifier as training images, the detected features with 1 will be used as the positive images or will be the basis for the training while those with 0 will be used as a comparison to the 1s in order to carefully differentiate the features from one another. When this is done, one can now use the test image to the SVM classifier, in this case, the test images that were used in the Viola Jones Algorithm block were also used as the test images for the HOG with SVM block. The output will be an image with output boxes to detect the correct selected feature. Though in this case, there are still some features that are incorrectly detected or classified by this block. These data will now be compared to only the Viola Jones algorithm.

III. RESULTS AND DISCUSSION

To test the HOG with SVM algorithm success, when cascaded into the Viola Jones Algorithm, all of the six features were tested in three separate images and the percentage of the correct feature detected over the total feature detected was evaluated. The correctly detected feature using the Viola Jones Algorithm will be compared to the correctly detected feature when it is cascaded with the HOG with SVM Algorithm. Table 1 shows the data collected from the SEA Feature detector of both the Viola Jones Algorithm Detector alone against the one with cascaded system. The table shows that a marked improvement in the feature detection using the cascade system.

TABLE I. RESULTS OF SEA FEATURE DETECTOR

IMG	Viola Jones only			Cascaded System		
SEA	# feat	√ Feat	%	# feat	√ Feat	%
1	47	13	27.6%	42	35	83.3%
2	118	34	28.8%	102	87	86.2%
3	327	11	3.3%	297	213	71.7%

It is also noted that in the Viola Jones Algorithm part of the system, whether cascaded or not, the merge threshold used is 3. In the previous experiments, the correct feature detected is compared and analyzed by changing the merge threshold of each test and the results shows the using a merge threshold of 3 would give the optimal and highest accuracy for the feature detectors. The merge threshold of 3 shows the highest accuracy in all of the feature detectors except that of the tree feature detector. The tree feature detector obtained its highest accuracy with a merge threshold of 1, but since the difference of the results of the Viola Jones Algorithm block part of the system has only 5-8% difference to the merge threshold of 3, it is safe to assume that this study can also use the merge threshold of 3 in all of the feature detector, this is also viable for simplicity purposes and streamlining of all the feature detectors having the same characteristics. Table II shows another comparison of the correct feature detected of the Tree feature detector.

TABLE II. RESULTS OF TREE FEATURE DETECTOR

IMG	Viola Jones only			Cascaded System		
TREE	# feat	√ Feat	%	# feat	√ Feat	%
1	1251	983	78.3%	1132	1027	90.7%
2	1141	808	70.4%	1065	934	87.6%
3	702	457	65.0%	642	486	75.7%

The next table, Table III, shows the road feature detector from the viola jones algorithm system and the cascaded system.

TABLE III. RESULTS OF ROAD FEATURE DETECTOR

IMG	Viola Jones only			Cascaded System		
ROAD	# feat	√ Feat	%	# feat	√ Feat	%
1	321	162	50.4%	267	213	79.7%
2	432	91	21.0%	378	272	71.9%
3	301	69	22.2%	278	202	72.6%

Table IV shows the test results of the remaining feature detectors, the roof, shores and sky feature detector. There will be a sky feature to be detected because it is a common mistake that the sky is often mistaken as a sea image because of the quality of the image, and for that reason, there is a need to try and detect the sky if the sea will also be detected by it.

TABLE IV. RESULT OF ROOF, SHORE AND SKY FEATURE DETECTOR

IMG	Viola Jones Only	Cascaded System
ROOF	% of √ Feature	% of √ Feature
1	8.8%	72.4%
2	10.2%	83.4%
3	6.4%	71.3%
SHORE	% of √ Feature	% of √ Feature
1	16.6%	77.5%
2	20.3%	84.6%
3	3.9%	70.3%
SKY	% of √ Feature	% of √ Feature
1	10.5%	81.3%
2	5.5%	70.6%
3	87.0%	94.1%

As seen in the test, it can be observed that when the system is un-cascaded and only contains the Viola-Jones Detection Algorithm, all of the percentage of correct detection accuracy is very low except for the tree detector, this is because the Viola-Jones Detection Algorithm is mainly used for face detection and when it is used in object detection, it has a low correct detection rate because of many factors including the need to have many training data. When the system was cascaded with the Histograms of Oriented Gradients with Support Vector Machine as classifier in the system, it can be seen that there is a significant increase in the accuracy of the hydromorphological features detected, most especially with the features that have very low detection rate.

IV. CONCLUSION

The detection of hydromorphological features of a river were initially detected using the Viola Jones algorithm. However, due to the significant number of wrong detections, it is cascaded with Support Vector Machine using Histogram of Oriented Gradient. The results showed that the Viola Jones detection algorithm with the HOG and SVM algorithm achieved high detection, classification and identification of river hydromorphological features.

In the future, researchers may establish the relationship of increasing the training images with the accuracy of the feature detector. Also, the use of other algorithms combined with the present system is also being considered to increase effectiveness. The accurate detection of hydromorphological features can be used in the segmentation of the said features.

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