River Water-level Estimation Using Visual Sensing

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Abstract. This paper reports our initial work on the extraction of environmental information from images sampled from a camera deployed to monitor a river environment. It demonstrates very promising results for the use of a visual sensor in a smart multi-modal sensor network.

1 Introduction

Water management is an important part of the monitoring of the natural environment and includes monitoring the water quality of coastal and inland marine locations. Our belief is that the use of visual sensing can help to overcome some of the problems associated with in-situ wireless sensor networks [3] and provide context to what is being sensed. It can help lead to a smarter sensing environment whereby resource-constrained sensors can be used more efficiently. In essence, we believe that the singular use of any of these devices is not sufficient for effective coastal monitoring and that the development of a smart multi-modal sensor network will lead to a more robust and effective environmental sensing system. In this paper, we report our initial work on using visual sensing to monitor a river environment. We demonstrate its use in the estimation of water-level from images sampled from a camera. However, from a broader perspective, the overall objective of our work is to investigate how visual sensing from cameras and satellite imagers can be used as part of a multi-modal sensor network alongside traditional in-situ wireless sensor networks.

2 Related work

In previous studies, camera sensor systems have been identified as effective tools for coastal monitoring. A prime example of this is a major European research project entitled CoastView [2] which demonstrates the use of fixed video remote sensing systems to partially ameliorate some of the problems associated with in-situ measurements of waves, currents, and morphological change. However, Davidson et al. [2] point out that despite the potential to improve monitoring of coastal zones with coastal video systems, that there are many coastal management issues that may only be addressed adequately through the integration of additional data sources and expert knowledge alongside the image data. We are investigating the integration of image data with additional sensor sources, as the overall long-term objective of this work. Other studies have also investigated the use of imagers not only in the context of monitoring a marine environment but also in other forms of environmental monitoring applications such as for monitoring avian nesting behaviour[1] and for phenological monitoring [4]

3 Water-level estimation

In our work, an AXIS PTZ Network camera was deployed overlooking the banks of the river Lee at the Tyndall Research Institute, Cork, Ireland [5] . The Smart-Coast multi-sensor system for water quality monitoring is deployed at this location [6]. Various problems were identified with the in-situ sensors and we believe the camera represents a low-cost smart sensing device that can provide contextual or alternative information to that provided by the in-situ sensors. A pilot study was undertaken whereby we exploit the appearance of rocks along the banks of the water to provide a rough estimation of water level. The approach we have developed for water level estimation is suitable for any marine environment where the water-land boundary is visible, without interference on the the site in question. The amount of rock visible in the images was divided into 5 classes, from no-rock-visible (high water level) to high-rock (low water level).We captured 2800 daylight images in July 2008 for training and used 80 images from September and February as our test set.This allows the performance of the system to be tested for other time periods demonstrating diverse environmental and river conditions. We investigated three classifiers, for determining the class of an image which are described in the following section.

Fig. 1. Examples of the challenging image data we are using, demonstrating disparate appearance due to varying river conditions.

3.1 Classifiers

Each classifier works in a similar manner; using statistical (data) models representing each class, a query image is classified by computing the similarity between the image to each each class model and the most similar class is selected. Classification algorithim 1 (C_1) used a Gaussian model for classification. A pixel-based log-likelihood (LL) model was computed using hue and saturation values from the training data Given an image, an LL coefficient is calculated for each pixel based on their hue and saturation values. A class-based Gaussian model was built from the mean and standard deviation image of LL values using training images for each class. We compute the similarity between a test image, I, and class models, $\{M_1, .., M_5\}$, using:

$$S(I, M_k) = \frac{1}{N} \sum_{i=1}^{N} e^{-0.5 \times \frac{(I(i) - \mu_k(i))^2}{\sigma_k^2(i)}} \quad (1)$$

where μ and σ are the pixel mean and standard deviation in the LL image models (top 2 rows of figure 2) and N is the number of pixels. The second classification algorithm (C_2) is similar to C_1 except it uses normalized cross correlation (NCC) to calculate the similarity between the query image and the class models The final classification algorithm (C_3) uses a different statistical model to represent each class than C_1 and C_2. For each class, we computed the mean image using the raw pixel values. A test image is then classified by selecting the class with the highest NCC value to the test image (see figure 2). We also investigated the use of texture features, however they did improve results. We intend in future to use more advanced classifiers such as SVMs.

Fig. 2. Models used by the the third classifier for each of the 5 water-level classes. Each of these images represents the mean image (raw pixel mean) for its respective class.

4 Experimental Results

4.1 Overall accuracy

The best performing classifier was C_3, classifying 75% of the test images correctly. This is quite good considering the subjective nature of the depth-class human annotation and the fact that the test images originate from different times periods demonstrating extremely diverse conditions (See figure 1). We see a more detailed analysis of the results in Figure 3, which shows the confusion matrices for the classifiers we investigated. When classifier C_3 does not correctly estimate the class of an image, it is clear that it is usually quite close, since most of the test images lie close to the diagonal of the confusion matrix. It also has very high accuracy at classifying the more extreme events (i.e. no-rock and high rock) which is promising since these tend to be more distinguishable than the other levels even to the human eye.

5 Conclusions

In this paper we developed and evaluated algorithms for classifying river images to identify the water depth, in order to investigate the viability of using a

C_1

	Estimated Class				
	1	**2**	**3**	**4**	**5**
1	58	9	2	11	0
2	1	1	65	13	0
3	0	1	49	23	7
4	0	0	1	47	32
5	0	0	0	48	32

C_2

	Estimated Class				
	1	**2**	**3**	**4**	**5**
1	74	5	1	0	0
2	5	57	18	0	0
3	2	1	72	5	0
4	21	6	12	34	7
5	17	2	2	3	56

C_3

	Estimated Class				
	1	**2**	**3**	**4**	**5**
1	74	6	0	0	0
2	6	55	12	4	3
3	1	2	62	13	2
4	0	1	8	33	38
5	2	0	1	1	76

Fig. 3. Confusion matrices for the three classifiers that were evaluated, illustrating the challenging nature of the testing data.

low-cost visual sensing device for environmental monitoring. We found that the best performing classifier used a mean image as the model and NCC for classification.It performed quite well considering the challenging image data and the use of test images from alternative seasons to the training set. We believe that the use of visual sensing holds great promise as a low-cost complementary sensing modality. Its use in the development of a smart multi-modal sensor network forms part of our future work.

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