Coastal Fog Detection Using Visual Sensing

Dian Zhang [1,2], Timothy Sullivan[1], Noel E. O'Connor[2], Randy Gillespie[3], and Fiona Regan[1]

[1]MESTECH, Marine and Environmental Sensing Technology Hub, Dublin City University, Glasnevin, D9, Ireland.
[2]INSIGHT, Centre for Data Analytics, Dublin City University, Glasnevin, D9, Ireland.
[3]Fisheries and Marine Institute, Memorial University of Newfoundland, 155 Ridge Rd St John's, NL, Canada.

I. Introduction

Use of visual sensing techniques to detect low visibility conditions may have a number of advantages when combined with other methods, such as satellite based remote sensing, as data can be collected and processed in real or near real time. Camera-enabled visual sensing can provide direct confirmation of modelling and forecasting results. Indeed, fog detection, modelling and prediction are a priority for maritime communities and coastal cities due to economic impacts of fog on aviation, marine, and land transportation. Canadian and Irish coasts are particularly vulnerable to dense fog under certain environmental conditions, and offshore installations related to oil and gas production on Grand Bank (off the Canadian East Coast) for example can be adversely affected by weather and sea state conditions. In particular, fog can disrupt the transfer of equipment and people to/from the production platforms by helicopter. Such disruptions create delays and the delays cost money. According to offshore oil and gas industry representatives at a recent workshop on metocean monitoring and forecasting for the NL offshore, there is a real need for improved forecasting of visibility (fog) out to 3 days. The ability to accurately forecast future fog conditions would improve the industrys ability to adjust its schedule of operations accordingly. In addition, it was recognised by workshop participants that the physics of Grand Banks fog formation is not well understood, and that more and better data are needed.

In Europe, an EU COST action fog project, with objectives of reducing economic loss and fatalities, has also been created to develop advanced methods for very short-range forecasts of fog and low clouds. Key research objectives of the project included methods for determining the optimal combination of satellite and ground-based observations and measurement techniques of fog. These data were then used to develop estimates of fog risk at high spatial and temporal resolutions, however the focus was on satellite observations rather than visual sensing systems [1].

Fog forecasting/nowcasting is typically done using satellite observations, however this can have a number of challenges when mid- and high-level clouds are present, at twilight or when trying to distinguish fog from stratus clouds. Therefore, integration of observations from surface-based sensors, remote sensors, and model data can provide better data for forecasting/nowcasting. Sensors are available for fog detection, however the majority of these are dedicated to measuring visibility distances (diffusiometer, transmissometer) and are expensive and require specialist installation. Moreover, this type of equipment cannot easily be placed on offshore platforms or buoys. However, the increasing use of traffic cameras, CCTV cameras, visual sensing systems both onshore and on offshore platforms can provide real or near real time image data that could potentially be combined with sensors and satellite-based measurements, particularly with regard to field observations that can be used for model verification purposes. Improved availability of marine based observations for verification purposes is particularly required. A number of methods of image processing approaches for detecting periods of low visibility have been attempted. In previous work, visual sensors integrated with in situ water quality sensors to detect and categorise turbidity peaks and pollutant levels associated with shipping in coastal and estuarine locations [2][3] has been demonstrated. In the current work, the utility of visual sensing as a component of a fog detection and nowcasting network is shown.

In this paper, we utilise image datasets obtained from camera systems deployed by Met Eireann (The Irish Meteorological Service) at various measurement points around the coast of Ireland to determine visibility levels using image-processing techniques. A number of image processing methods are compared to determine the most promising and applicable machine learning techniques. These images are taken from static fixed platforms which simplifies the measurement operation given that a reference image is always available, however the objective is to determine methods which provide the most promise for correct classification of images based on visibility. The real technical challenge is to accurately estimate visibility using a camera mounted on an offshore data buoy where the only detectable edges are the horizon and wave edges. In this paper, we provide some preliminary work on this challenge by first comparing image processing methods on real image datasets captured from land-based systems, and assess their suitability for this challenge. The potential of methods of on-platform embedded systems is also discussed for real- time data processing to reduce the amount of data transmission required.

II. Methods

corresponding author: dian.zhang2@mail.dcu.ie

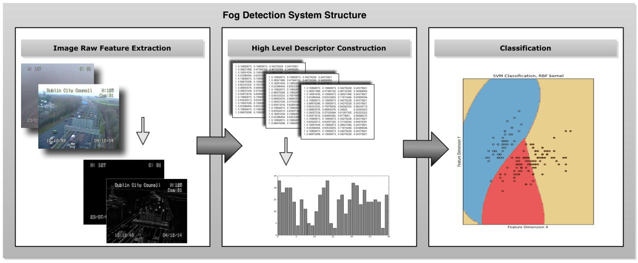

Fig. 1. Block diagram of fog detection system using image processing techniques. Images under clear (no fog) weather conditions provide fine detailed structural information, while fog will lead to a blurry image.

Figure 1 illustrates an overview structure of the fog detection system. The framework follows the standards three-tier image classification structure, which includes image acquisition, feature extraction and classification. The image acquisition tier gathers image data from imagery devices and the feature extraction tier extracts a set of feature (refers as descriptor of the image) from input image. These input images are then categorised into sub groups by a pre-trained classifier. In this work, the following image features, which are widely used in Content Based Information Retrieval (CBIR) systems, have been tested: CEDD, EHD, Gabor, FCTH, FOH, Joint Histogram, Scalable Color, SCH, Tamura.

- Color and Edge Directivity Descriptor (CEDD) [4]: It incorporates colour and texture information in a fixed 54 byte histogram per image. One of the most important attribute of the CEDD is the low computational power needed for extraction. Its main functionality is image-to-image matching and the intended use is for still-image retrieval, where an image may consist of either a single rectangular frame or arbitrarily shaped, possibly disconnected, regions.
- Edge Histogram [5]: It is a descriptor from the MPEG-7 standard. An image is first divided into 4x4 sub-images and five type of edges, which include no directional, vertical, horizontal, 45 degree, and 135 degree diagonal edges, are extracted from each sub-block. EHD provides primitive information on the edge distribution in the image.
- Gabor [6]: It is a set of feature that obtained from passing an image through Gabor filer. Gabor descriptor have been found to be particularly appropriate for texture representation and discrimination.
- Fuzzy Colour and Texture Histogram (FCTH) [7]: FCTH is a low level feature that combines colour and texture information.
- Fuzzy Opponent Histogram (FOH) [8]: This is a combination of three 1D histograms based on the channels of the opponent colour space. The intensity of an image is represented by channel one and the colour information is represented by the other two channels.
- Joint Histogram [9]: A joint histogram is created by selecting a set of local pixel features and constructing a multidimensional histogram. Each entry in a joint histogram contains the number of pixels in the image that are described by a particular combination of feature values.
- Scalable Colour [10]: It is another standard MPEG-7 colour descriptor, which is derived from a colour histogram defined in the HueSaturation-Value (HSV) colour space with fixed colour space quantisation. It uses a Haar transform coefficient encoding, allowing scalable representation of description, as well as complexity scalability of feature extraction and matching procedures.
- Simple Colour Histogram (SCH) [11]: It represents the global distribution of the composition of colours in an image. The simple colour histogram shows the brightness distribution of each of the three (RGB) colour channels.
- Tamura [12]: This descriptor is a combination of three features corresponding to coarseness, contrast and directionality. It takes into account of size, shape and the orientation in the texture.

Classification is performed using Support Vector Machines (SVM) [13]. In its simplest form, a SVM finds a linear separating hyperplane with the best possible separation between two classes. SVM is widely used in many research areas such as machine vision [14], audio processing [15] and text categorisation [16]. Generally, there are two steps to perform SVM classification: determining which kernel to use and selecting an optimal set of parameters. In this work, a Radial Basis Function (RBF) kernel was applied as it can handle a non-linear decision boundary. Parameter optimisation is performed using Grid Search [17] method.

III. Experiments and Results

The image data used for the following experiments were kindly provided by Met Éireann[1]. The dataset contains a total of 321 images captured from six cameras at three weather observing stations (Mace Head, Roches Point and Malin Head) cross Ireland between 31-Nov-2011 and 08-Feb-2015. In order to build and evaluate a simple classification model, these images were annotated as three categories corresponding to either no fog, light fog and heavy fog. Figure 2 shows an example image corresponding to each of these categories.

When training a SVM with the RBF kernel, two parameters must be considered: C and γ. C a soft margin parameter for all SVM kernels, which develops a trade off between misclassification of training examples against simplicity of the decision surface. A low value of C makes the decision surface smooth, while a high value of C aims at classifying all training examples correctly. γ is a free parameter (for RBF kernel) that defines how far the influence of a single training example reaches, where low values mean ‘far’ (the influence of a single training entry is significant to the decision boundary) and high values means ‘close’. To obtain an optimised set of parameters, Grid Search was applied. Grid search is one of the standard methods of performing hyper-parameter optimisation. Various pairs of (C, γ) values are tried and the one with the highest

[1] http://www.met.ie/

Fig. 2. Sample of image data from each categories. Top row (left to right) : sample images with no fog, light fog and heavy fog respectively at Roches Point weather observing station. Bottom row (left to right): sample images showing no fog, light fog and heavy fog from various weather observing stations, demonstrating the range of foreground and background features that can be expected in image datasets provided from weather monitoring stations.

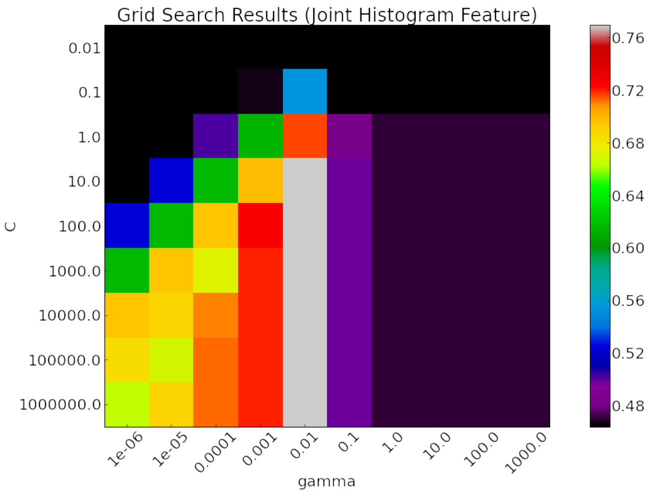

Fig. 3. A sample of Grid Search results (Joint Histogram) shows the accuracies of different C and γ parameter value pairs.

evaluation accuracy is picked. In [17], the author suggests that trying exponentially growing sequences of C and γ is a practical method to identify good parameters. Thus, we set the range of C from $1e^{-2}$ to $1e^{7}$ and the range of γ from $1e^{-6}$ to $1e^{4}$. To avoid over-fitting, 5 fold cross validation is applied. A sample of Grid Search results is shown in Figure 3.

The optimal sets of C and γ for each tested feature are shown in table I. The classification accuracy score, which is the ratio of correctly classified instances to the total number of instances, is used to determine the optimal pair of kernel parameters. The classification accuracy scores of each selected descriptor are illustrated in Figure 4. As can be seen from the graph, the Joint Histogram descriptor achieves the best classification performance. Overall, both Scalable Colour and Edge Histogram techniques achieve the second best results, however, the Scalable Colour descriptor has a lower standard variation than the of the Edge Histogram technique.

TABLE I. OPTIMAL SET OF C, γ FOR EACH TESTED FEATURE

Feature	C,γ	Feature	C, γ
CEDD	$1e^{1}$, $1e^{-2}$	Joint Histogram	$1e^{3}$, $1e^{-6}$
Edge Histogram	$1e^{1}$, $1e^{-2}$	Scalable Color	$1e^{1}$, $1e^{-4}$
Gabor	$1e^{6}$, $1e^{-5}$	SCH	$1e^{3}$, $1e^{-4}$
FCTH	$1e^{0}$, $1e^{-1}$	Tamura	$1e^{1}$, $1e^{-5}$
FOH	$1e^{4}$, $1e^{-6}$		

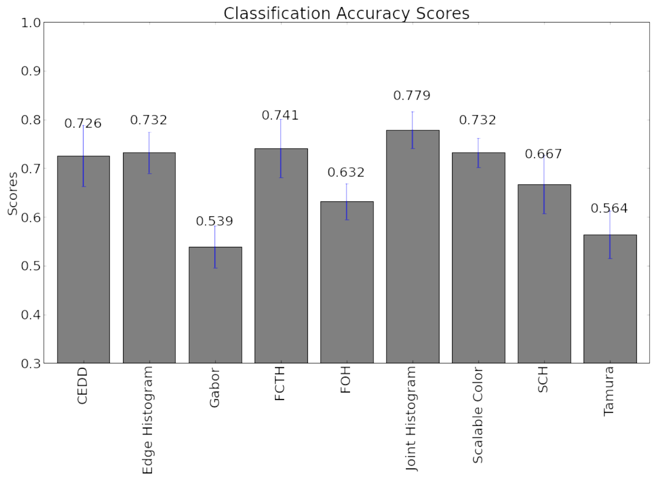

Fig. 4. Classification scores of selected image descriptors.

By examining the classification results, it has been found that majority of the error occurs between adjoining categories. Figure 5 and Figure 6 show two incorrectly classified examples. Figure 5 is annotated as no fog but classified as light fog. The classification output of Figure 6 is no fog but manual assessment of the image reveals light fog.

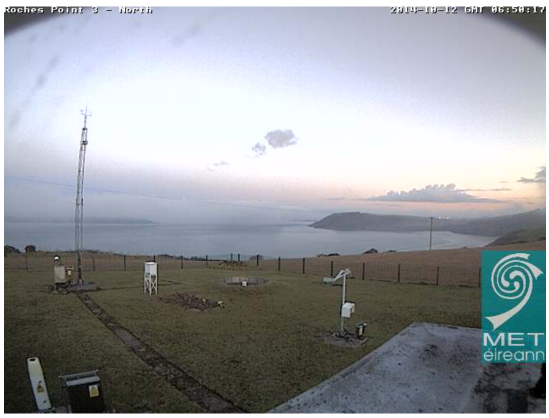

Fig. 5. Example of incorrectly classified image. Image is annotated as no fog but classified as light fog.

Fig. 6. Example of incorrectly classified image where the image is annotated as light fog but classified as no fog.

IV. Conclusion

In this paper, we propose and evaluate a visibility estimation framework using multiple image datasets captured by visual systems that provides contextual information that can be used to complement current fog prediction systems. We have assessed the potential of a range machine learning methods to classify camera images on the basis of visibility. From these results, and based on the training sets provided, the Joint Histogram method provides the highest classification accuracy, closely followed by....These initial results will be used to further develop an offshore fog detection platform based on image analysis methods.

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