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AN INTELLIGENT SYSTEM FOR REMOTE MONITORING AND PREDICTION OF BEACH SAFETY.

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ABSTRACT
Remote monitoring of coastal conditions in locations of high public usage is a fast growing application of information technology. Remote mounted CCD camera systems provide a relatively cheap and potentially rich source of information on the state of the near-shore beach zone. The present paper presents a non-technical overview of a system for appropriate feature extraction and integration with other sources of weather and wave data for the purpose of assessing and predicting beach safety conditions using neural network based models. The feasibility of combined image processing and feature extraction routines for providing real-time input to neural network models of beach safety is demonstrated.

KEY WORDS
beach safety prediction, time-stack imagery, predictive neural networks

1 Introduction

1.1 Optical Coast Monitoring

Advances in video image analysis techniques allow for the cost-effective, long-term data collection of near-shore hydrodynamic processes. In recent years, a wide range of algorithms for generating measurements from the temporal and spatial dynamics of video pixel arrays have been reported. Successive collections of arrays of pixel intensities (either single pixel, or cross-shore or long-shore array) are presented as a *timestack*. The ARGUS system [1] for optical monitoring is perhaps the most well known approach, and it demonstrated the utility of video-based methods for measurement of a range of processes, such as wave period and direction [7]. Recent work has demonstrated the utility of video for monitoring long-shore currents [4], wave celerity and near-shore bathymetry [21] and near-shore bar behaviour [23].

In order to obtain quantitative information from the video stream, the reference frames of the image must be related to the actual beach geography. Holland et al [7] demonstrate that this may be accomplished given the technical parameters of the camera (e.g. lens distortion), as experimentally measured. Ground Control Points (GCP's) should also be placed and given three-dimensional coordinates in the beach reference frame to enable solving the problem of mapping of the geography to the reference frame.

Video-based methods have been applied to measurements of: sandbar morphology [7], near-shore fluid processes, sand bar length scales, foreshore topography and drifter motions [7], [8]; intertidal beach profiles [18]; water depth and currents [17]; wave direction [5]; near-shore bathymetry [2], and examination of swash flows using particle image velocimetry (PIV) [8].

1.2 Assessment of near-shore safety

A fact sheet produced by the World Health Organization lists drowning as the second leading cause of unintentional injury death after road traffic injuries. Tourists were noted to be at unacceptably high risk of drowning. A study of drownings in Australia [13] presents a figure of 32% of non-boating related drownings occurring at the surf and ocean with 18% comprising overseas tourists. Of the 88 tourists from 12 countries drowned in Australia during 1992-1997, 89% drowned in the ocean. 61% are noted as drowning at surfing beaches or elsewhere in the ocean. Short [20] ranked Northcliffe, Southport, Surfers Paradise and the Gold Coast Spit as among some of Queensland's most hazardous beaches.

The identification of the potential for rip current formation and other hazardous situations can assist authorities to manage resources related to public safety, while assisting with beach management and erosion control issues. The development of automated methods for monitoring near-shore conditions is important as both a research methodology, and for the public benefit. Automated data-collection techniques can improve real-time predictive capabilities for near-shore circulation and morphology [22].

Australian national bodies have noted the importance of identifying hazards and risk in the coastal zone through integrating advanced technologies such as satellite, airborne and shore-based remote sensing. Other reports note the importance of effective long-term monitoring of fluid and sediment transport processes, breaking waves and induced currents, sand-bar morphology, as well as bottom boundary layers and associated turbulence [22].

There is obvious potential for using data generated from video-based monitoring of the near-shore wave field in order to predict concurrent and future beach safety. The present study details a case-study of a beach monitoring scenario with high- and low- altitude cameras. The application of time-stack analysis to the raw pixel data enables the detection of beach condition variables useful for beach-state and safety predictions.

1.3 Intelligent techniques for prediction and interpretation of video imagery

Intelligent techniques such as artificial neural networks (ANNs) have emerged as powerful tools for many real-world applications. ANNs have featured prominently in the areas of coastal management, ocean engineering and other environmental applications [11] [16]. In recent times, ANNs have been frequently used for the purpose of prediction and forecasting in the area of coastal/ocean processes. Krasnopolsky and Chalikov [10] used ANNs for to approximate for nonlinear interactions in wind wave models. Lee [12] used a simple backpropagation ANN trained on 69 tidal constituents to predict long-term tidal levels. Aitkenhead et al. [15] proposed a novel 'local interaction' ANN-based method for time series prediction of various variables in a stream (i.e. flow rate, temperature etc.). They found that their technique outperformed the commonly used backpropagation algorithm and simulated annealing. Deo and Jagdale [14] used a traditional backpropagation ANN for the prediction of breaking waves. For training they used three inputs including deep-water wave height, wave period and the seabed slope. Their network had two outputs producing the breaking wave height and the water depth at the time of breaking. The authors found that using the ANN-based model, they obtained better predictions for the aforementioned variables than with traditional empirical schemes. Finally, Altunkaynak and Ozger [3] presented a wave height prediction technique using perceptron Kalman filtering. They used past measurements of significant wave height and wind speed variables for training their model. It was then employed to predict significant wave height values for future time intervals based purely on wind speed measurements.

Another important area related to this project that has benefited from neural-based techniques is that of object detection and image analysis from still and video images. Schofield et al. [19] used ANNs for background scene identification in video images for the counting of persons. As an application for autonomous vehicle navigation, Wohler and Anlauf [24] employed an adaptable time-delay ANN to analyse complete image sequences for the purpose of driver assistance through the detection of overtaking vehicles. Ha et al. [6] have employed a neural-based edge detector for vehicle detection and traffic parameter estimation in their image-based traffic monitoring system. Finally, Kingston et al. [9] have employed a standard feedforward ANN trained with the Levenberg-Marquardt algorithm for providing estimates of sandbar location from remote sensed video imagery. The data used to train their network consist of simultaneous measurements of the near shore bathymetry and video imagery of the double bar system at Egmond aan Zee, the Netherlands.

1.4 Towards an beach safety monitoring system

The significant amount of scientific and engineering progress in remote monitoring methods for coastal monitoring demonstrates the potential for a completely automated system for generating estimates and predictions of beach safety from remote monitoring systems. Such a system is under development at G.C.C.M., Griffith University, and as well as providing a system-wide overview, the present work demonstrates the feasibility of certain algorithms for automatically extracting essential information of beach state from remote optical sources in real time.

Referring to the system overview given in figure 1, the key descriptors of the beach condition monitoring system are:

integration: it draws together data from a variety of sources, incorporating remote optical measurements, and information from meteorological and other sources, such as current and future offshore swell height and directions, and tide forecasts.

distribution: the system comprises components at remote physical locations, and draws upon information from 3rd parties.

intelligence: it generates and utilizes internal models of the relationship between integrated feature vectors and beach safety from observation of the data using neural networks.

modularity: the system comprises a heterogenous family of subsystems:

- low level hardware routines, i.e. video capturing and archiving, network queries for 3^{rd} party networks and time-stamping routines
- pure image processing systems, i.e. template matching, edge detectors
- statistical routines for generation of feature vectors, i.e. mean, standard deviation and skewness measures for characterizing break profiles

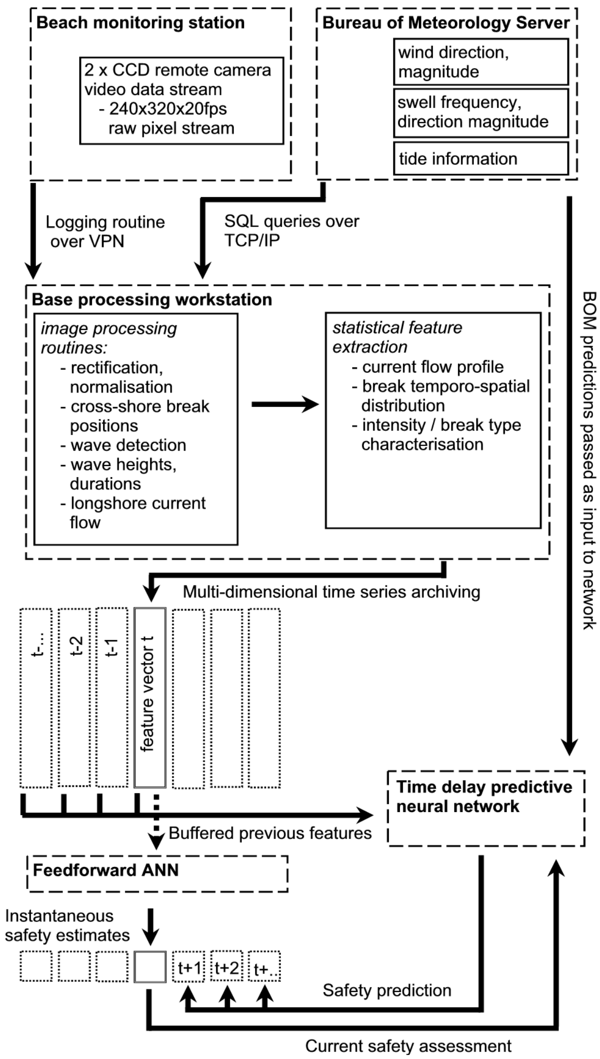

Figure 1. Flowchart detailing the beach condition monitoring and prediction system.

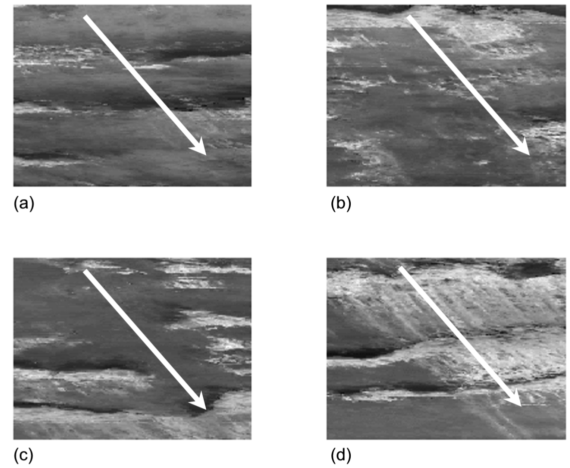

Figure 2. Typical horizontal time-stacks taken at random times in a test video recording. The white arrows indicate the angle of current flow over time. This flow is not evident when sufficient particles do not exist on the water surface (a,b,c), but quite clear after a breaking wave leaves swash on the surface (d).

- two neural network modules with independent inputs and outputs

Such a complete system is necessarily of a relatively high degree of complexity. As well as providing a general overview of the complete system, the present paper focuses on the use of image processing routines for the purpose of feature extraction in the context of a wider intelligent system.

2 Method

2.1 Site and Infrastructure

The remote monitoring site is situated at Narrowneck beach, located just north of Surfers Paradise at the northern end of the Gold Coast, Queensland. It is a typical open coast, east Australian beach usually consisting of a bar-trough topography and experiencing a net northward littoral drift of approximately 500,000 m^3/yr. A Sony SSC-DC393P cameras with 7-70 mm vari-focal auto iris zoom lens is mounted on a lifeguard tower directly in front of Narrowneck beach, Gold Coast, Australia. The camera is located 20 metres in front of the high water line, at an elevation of 10 metres above mean sea level. A second camera is installed on the roof of a nearby residential tower.

The CCD cameras are connected to local PCs acting as streaming servers through video capture cards. Raw video data is captured at 320x240 pixel resolution for 10 minutes each hour and transmitted to the distal base archiving PC over a virtual private network (VPN). A second relatively powerful PC serves as the main analysis PC, accessing files on the archive computer for image processing and generating and archiving feature vectors in real-time. A final separate machine is intended to be used for neural network simulation and training.

Queries are made to 3^{rd} party Bureau of Meteorology servers that provide real-time local WW3 model readings and forecasts at 1, 3, 6 and 12 hours for wind heading and speed, and estimates of swell frequency, magnitude, and direction. Queries are also made to electronic versions of tide tables, providing current, and predicted tide levels corresponding to each of the WW3 prediction time frames.

2.2 System Architecture

Figure 1 illustrates that the system architecture may be broadly described in four functional stages:

1. Raw data is gathered from distal locations, in 10 minute sections, time-stamped and archived. At this point a vertical *time-slice* consisting of a single column of pixels, arranged as a Y-Time matrix over the 10 minute time period.

2. Image processing routines generate the first level of abstraction from the raw pixel data, generating intermediate representations, such as break locations in Y-Time matrix (see Figure 4).

3. Extraction of statistical properties of intermediate features (e.g. standard deviation and skewness of cross shore position of breakers) and creation of a time series of multi-dimensional features.

4. Instantaneous neural network estimation of overal beach safety (trained using human expert judge ments). A second network performs prediction of fu ture beach safety states using a combination of het erogenous inputs: meteorological model output, ex tracted features, and current beach state.

The present study reports in more depth items 2 anc 3 above: algorithms for image processing and extraction o wave field features suitable for presentation to a supervisec learning module.

3 Algorithm and Results

As stated above, the present paper presents in detail the per formance of two inter-related feature extraction algorithm: designed to extract and quantify the characteristics of thc breaking wave field and long-shore currents, creating output suitable for use as input to a neural network. Figure 2 illustrates that long-shore currents are evident as diagonal 'streaks' in the time X-Time image after the passage of white-water through the slice (2.d), but are much less

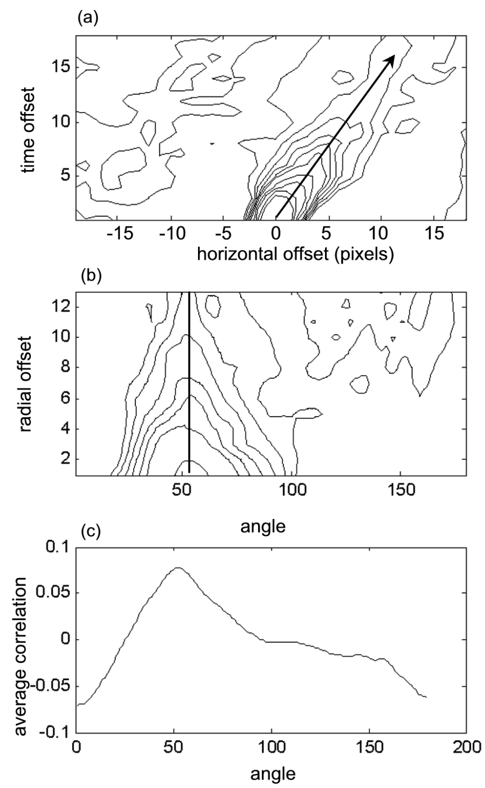

Figure 3. Contour of pixel cross-correlations with point $c(0,0)$ (a), converted to radial format (b) and averaged (c), yielding a maxima (in this case) at $53^o \equiv 0.17m/s$.

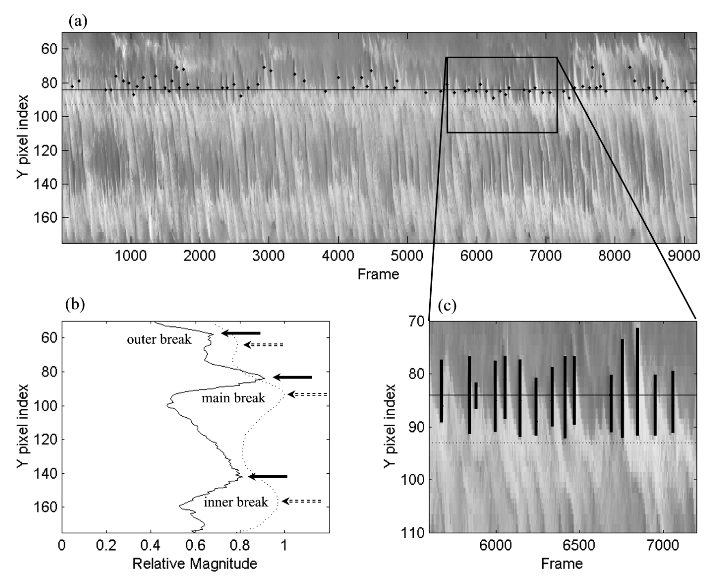

Figure 4. Vertical slice video time-stack with detected break zones, breakers, and break heights.

evident at other times. This presents a challenge for the issue of measuring the velocity of the long-shore current flow, which is a critical determinant of safety to bathers and leads to difficulty in implementing particle image velocimetry (PIV) techniques, which rely on correlations between consecutive snapshots with a small time offset. After filtering the raw pixels in the 320x9000 pixel X-Timewidth image with a Prewitt edge detector, this issue is overcome by creating randomly sampled data set of 10,000 samples comprising pixel pairs with a range of time and horizontal offsets. Figure 3.a shows a contour map of the correlations with the random coordinate pixel $p(x, t)$ and the corresponding displaced pixel $p(x + dx, t + dt)$. After converting to radial coordinates with respect to $p(x, t)$ (3.b) and estimating the maxima with respect to radial distance independently, the estimates using the range of radial distances from $p(x, t)$ may then be averaging to provide an overall estimate (3.c). The estimated long-shore current may be derived from the angle correlation maxima using straight-forward calibration methods. Further, since the estimated angles over the range of radial offsets are themselves (for the present purpose) independent samples, a confidence estimate of the mean may be calculated using standard statistical methods. This is important because at times where surface textures are rare or non-existent, any particle-correlation method will perform poorly, and has the potential to feed spurious features to neural network models in subsequent processing stages.

Safety assessment models require information regarding the bathymetry (contour of the ocean floor) off a beach, as this substantially affects the potential for rip current formation. The well known ARGUS monitoring systems demonstrated that bathymetry may be effectively estimated from the locations of the white-water. Breaking wave sizes, rhythms and patterns are also potentially important predictors of beach safety, are often a function of local bathymetry and geography. Hence, estimation of these parameters from the locally mounted cameras is preferred to relying on large scale meteorological and oceanographic models. Figure 4.a displaying detected individual breaks in the main break zone (shown with a horizontal line). The break detection method is based on defining a breaking wave in cross-shore position - time space as a coherent high contrast change from dark to light over time. Figure 4.a shows that it effectively detects the time - cross-shore position over 95% of breaking waves. Figure 4.b illustrates that estimating simple mean and standard deviations over pixels with respect to cross-shore position may provide an acceptable profile of the cross-shore bathymetry. Figure 4.b plots the mean (solid line) and standard deviation (dotted line) over Y pixel index, with local maxima indicating the break and swash zones of the three break zones. As would be expected, the standard deviation maxima (solid arrow - representing high contrast breaking wave phenomena) is followed in each case by an average maxima(dotted arrow - representing white water). The three detected sand-bars may be seen visually in 4.b. The number and positions of the bars are useful indicators of beach safety. Figure 4.c illustrates the method of detecting the height of individual breakers through detecting transitions from dark to light pixels over time. The mean and other parameters of the wave height distribution of interest as beach condition features.

4 Conclusions

A non-technical discussion of an ongoing project for the automatic assessment and prediction of beach safety has been provided. Advances in image processing methods applied to environmental monitoring situations has dramatically increased the quality and quantity of data that may be collected from CCD cameras. By combining these data gathering methods with other sources of environmental data, appropriate feature extraction routines and neural network based models, we are developing a system that relies on distributed resources to provide accurate, real-time estimates of beach safety. Similar systems may be developed for scientific, environmental, or security based applications.

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