Multi-Modal Sensor Networks for More Effective Sensing in Irish Coastal and Freshwater Environments

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***Abstract*—The world's oceans represent a vital resource to global economies and there exists huge economic opportunity that remains unexploited. However along with this huge potential there rests a responsibility into understanding the effects various developments may have on our natural ecosystem. This along with a variety of other issues necessitates a need for continuous and reliable monitoring of the marine and freshwater environment. The potential for innovative technology development for marine and freshwater monitoring and knowledge generation is huge and recent years have seen huge leaps forward in relation to the development of sensor technology for such purposes. However despite the advancements there are still a number of issues. In our research we advocate a multi-modal approach to create smarter more efficient monitoring networks, while enhancing the use of in-situ wireless sensor networks (WSNs). In particular we focus on the use of visual sensors, modelled outputs and context information to support a conventional in-situ wireless sensor network creating a multi-modal environmental monitoring network. Here we provide an overview of a selection of our work in relation to the use of visual sensing through networked cameras or satellite imagers in three very diverse test sites - a river catchment, a busy port and a coastal environment.**

I. Introduction

Marine and freshwater systems represent vital assets on many levels and need to be monitored and protected. In particular the oceans represent a vital resource to global economies and there exists huge economic opportunity that remains unexploited. However along with this huge potential there rests a responsibility into understanding the effects various developments may have on our natural ecosystem. For example there is much potential for the development of new technologies for exploiting our marine resources in relation to harnessing ocean energy. However alongside this, innovative techniques need to be developed to ensure the protection of these resources and the associated ecology and environmental processes.

These naturally occurring processes can affect issues such as weather, climate and water quality and thus need to be modelled and understood. Modelling and understanding of these processes also leads to invaluable knowledge for future exploitation of marine resources in various sectors and to the development of proactive mitigation strategies for preventing or dealing with environmental events. This requires continuous and reliable monitoring of our marine environment and the potential for innovative technology development for marine monitoring and knowledge generation is huge. Subsequently there lies huge scope for both research institutes and industry to exploit this opportunity.

Ireland has a marine area approximately ten times its land mass, yet the marine economy only represents a very small proportion of GDP [1]. The government hopes to double this to 2.4% per annum by 2030. The ocean represents an enormous national resource that has been to a large extent unexploited up to now. There is huge potential for Ireland to establish itself as a global leader in the marine sector and in the development of marine ICT. This potential has been recognised at a government level through the development of the National Sea Change Strategy 2007-2013 [2][3] and with that an Advanced Marine Technology Program. In 2010, the SmartOcean[1] cluster was established which aims to harness Ireland's marine resources and existing expertise in marine science and ICT to establish the country as a global leader in the development of products and services for the marine sector.

These initiatives at a government level have lead to the development of various SmartOcean Research and Development Infrastructure with the flagship initiative being SmartBay[2] - a national test and demonstration platform situated in Galway Bay, Ireland. This infrastructure enables the development and testing of marine products and services for marine related sectors providing a platform for innovation and collaboration both nationally and internationally among research institutes and industry specialists. The development of SmartBay led from the recognised need for a real and challenging environment for technology development and the Irish coast provides a very suitable test bed for meeting these requirements.

Various initiatives have been supported by national agencies such as the Irish Environmental Protection Agency and the Irish Marine Institute for developing sensor technology for continuous monitoring of coastal and freshwater environments. Some of these initiatives have involved MESTECH and CLARITY researchers at Dublin City University (DCU), Ireland, who have been involved in various technology demon-

[1] http://www.smartocean.org
[2] http://www.smartbay.ie

stration projects e.g. DEPLOY[3] - a technology demonstration project showing the implementation of state of the art technology for continuous real-time monitoring of a river catchment - and the testing of low cost water quality sensors developed in-house on the SmartBay environmental monitoring buoys.

Despite the numerous benefits associated with the use of such sensor technology for environmental monitoring applications, there are a number of challenges such as sensor fouling, data reliability, power, sensor failure, maintenance of sensors in remote locations, cost, communication, lack of redundancy, etc. In our research we seek to develop innovative solutions to increase the effectiveness of such sensors and to create smart environmental monitoring networks. Using national test and demonstration platforms such as SmartBay and other projects such as DEPLOY we seek to develop innovative methods into improving the efficiency of such networks and increasing knowledge generation. In particular we focus on the use of visual sensors, modelled outputs and context information to support a conventional in-situ wireless sensor network subsequently creating a multi-modal monitoring network. Here we provide an overview of a selection of our work in relation to the use of visual sensing through networked cameras or satellite imagers in three very diverse test sites - a river catchment, a busy port and a coastal environment. Off the shelf webcam-type devices are used where the goal is to determine what can be achieved from simply deploying a low cost camera without additional functionalities or modifications to the site. In the following sections firstly the issues with continuous monitoring of aquatic environments and the subsequent objectives of a multi-modal approach are discussed. This is followed by an overview of the work being carried out at the three test sites outlined.

II. Issues with Continuous Monitoring of Marine and Freshwater Environments

Coastal and freshwater zones are generally dynamic environments affected by a range of anthropogenic factors as well as naturally occurring processes. Accurately monitoring the quality of these waters can prove very difficult since the associated environmental processes often demonstrate high frequency spatial and temporal variation and are extremely heterogeneous. Observing these processes with high fidelity allows us to create models, make predictions and better manage our environments [4]. Undersampling on a temporal scale can result in masking the variability caused by processes occurring at higher frequencies than the sampling rate [5]. Sampling at a limited number of points spatially in the environment can mask the dynamics or trajectory of a phenomenon. From an operational perspective, high spatial and temporal monitoring allows the development of rapid detection and response systems to deal with environmental threats such as flooding, harmful algal blooms (HABs), pollution or oil spills [6].

New technologies are emerging in order to enable remote autonomous sensing of our water systems and subsequently meet the demands for high temporal and spatial monitoring. In particular, advances in communication and sensor technology has provided a catalyst for progress in remote monitoring of our water systems [7]. This has developed into the concept of wireless sensor networks (WSNs) and involves a diverse range of sensing technologies which autonomously sense their environment and gather and transmit sensed data. Environmental monitoring applications essentially require large-scale low-cost sensor networks that can operate reliably and autonomously over extended periods of time. However, despite much progress, there is still a significant gap between the current state of the art in both in-situ WSNs and the analytical instruments used for sensing, and what is needed to realise this overall vision [7] [8]. Sophisticated analytical instruments may not be suitable for scaled-up deployments over many months or years in terms of their sustainability, reliability or cost [7]. Also in times of extreme events such as flooding, such instrumentation is prone to failure.

In our work we extend our conventional understanding of a sensor network or a community of sensor nodes to include diverse data sources and multiple sensing modalities in order to create a smarter water monitoring network. In particular we focus on the use of visual sensors to complement and enhance the use of an in-situ WSN. Webcam-type CCTV devices can provide continuous daylight data for periods extending to decades at a very low cost, effectively quantifying coastal and river parameters with high resolution in space and time. They can also provide surrogate measurements for parameters otherwise obtainable with sophisticated in-situ instrumentation e.g. a change in depth may indicate run-off which may indicate nutrient loading etc. On a larger scale satellite information can be used to characterise a wide spatial area proving invaluable information regarding a number of different parameters and details regarding the trajectory of an event. The following describes in more detail the benefits of such an approach and a selection of the studies carried out in the various test sites.

III. Objectives of a Multi-Modal Approach

The two main issues with conventional in-situ sensor networks can be summarised in terms of scalability and reliability:

- **Scalability -** In-situ wireless sensor networks or analytical instruments are generally not suitable for scaled up deployments suitable to meet the demands of certain marine environmental monitoring applications.
- **Reliability -** Sensor nodes are subject to failure or damage, especially when not maintained regularly. Failure of in-situ sensor networks may result in faulty data or gaps in coverage.

Here it is discussed how environmental monitoring applications at three very different test sites benefit from the use of a network incorporating diverse sensing modalities such as visual sensors, modelled outputs and context information alongside the more conventional in-situ wireless sensor networks. The intelligent coordination of a diverse range of additional low-cost data sources creates a smarter network with increased

[3] http://www.deploy.ie

Fig. 1. DEPLOY sites on the river Lee. The site in Cork city circled on the map is the site chosen for this study. Source: Google Maps and www.deploy.ie.

awareness while optimising the nodes already in place and creating greater efficiency in the network. For example the adjustment of the sampling rate when contextual information suggests something of interest is taking place may render such devices more efficient and thus more scalable. Contextual information may also help with the optimum placement of the more costly sophisticated nodes.

A multi-modal approach may also allow missing data values to be inferred from the use of models and additional contextual information to compensate for the failure of a node where there is no redundant identical node in the network to replace its operation. This is often the case due to budgetary constraints, hence the ability to optimise the network to replicate its behaviour is extremely desirable and could create huge efficiencies. Characterisation of a site through multiple dimensions with invisible 'software' sensors is an example of what is to be achieved. In the following this notion is discussed in relation to the three different test sites - the River Lee, Poolbeg Marina and Galway Bay.

IV. River Lee

The River Lee represents one of the largest rivers in the southwest of Ireland. It and its main tributaries drain a catchment area of approximately 1,100km^2 upstream of Cork City [9]. The site chosen for our study is the point of the river where it flows into the sea commonly referred to as the Lee Maltings (See Figure 1). It represents a very interesting but challenging site to monitor, near the upper end of the estuary on a left hand bend of approximately 70 degrees. Water levels at the site are influenced by spillage from the Iniscarra dam and the site is also tidal with a tidal range of approximately 4 metres.

The River Lee was used as a demonstration site for the DEPLOY[4] project [10]. DEPLOY began collecting data from five sites on the River Lee at 10-15 minute intervals from April 2009 until May 2010. One of the DEPLOY stations was located at the Lee Maltings site with others located at different points of the catchment representative of varying conditions along the river. The range of sensors deployed at the Lee Maltings site included sensors for monitoring conductivity, dissolved oxygen, temperature and water depth.

[4]http://www.deploy.ie

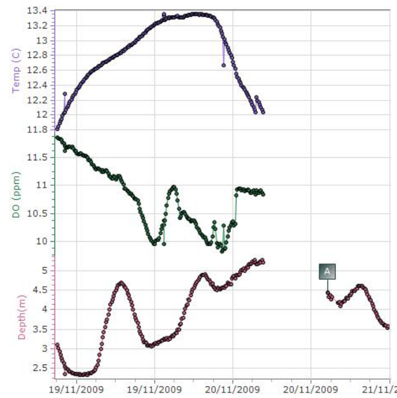

Fig. 2. Data from the Lee Maltings site of DEPLOY during a period of flooding. Source: DEPLOY

A. Issues

Despite the numerous benefits provided by the in-situ sensors, there are issues which have been highlighted throughout the deployment. These include gaps in the sensing and irregularities with the sensor data itself. This may be due to the fact that the sensors needed to be maintained more regularly or may have suffered from the harsh conditions that are often associated with deploying sensors in such an environment. Biofouling is often a major problem especially during the warmer summer months. Power failures or technical issues with the sensors were also an issue. However intermittently erroneous data is a fact of life for real world sensing.

In November 2009, there was a flooding event at the Lee Maltings where the River Lee burst its banks. This resulted in the depth sensor along with other in-situ sensors going offline demonstrating that in-situ nodes often cannot withstand extreme events. Figure 2 shows data from the temperature, conductivity and depth sensors during this time period. The depth can be seen to continually rise during this period of increasing depth. It subsequently goes offline. By the time the sensor is back online again water levels have subsided. Furthermore these sensors are only monitoring one specific point of the site when an overall characterisation of events at multiple points may be desirable.

These issues reinforce the benefits outlined in Section III of adopting a multi-modal approach to monitoring. For example during periods of extreme events such as flooding, a camera overlooking the water will continually collect data. Thus it provides a back-up sensing modality in the network. It can also be used dispute or validate in-situ readings from a sensor network when it is unclear whether events are 'real' or due to errors with the in-situ sensor node. Modelling approaches which optimise the use of all available information in order to infer missing values would also be extremely beneficial where a sensor goes offline. As previously outlined contextual data may also be useful for controlling the operation of a sensor node in order to elongate its use in such an environment. For example a sophisticated chemical sensor such as the device

Fig. 3. The angle of the images captured by the camera.

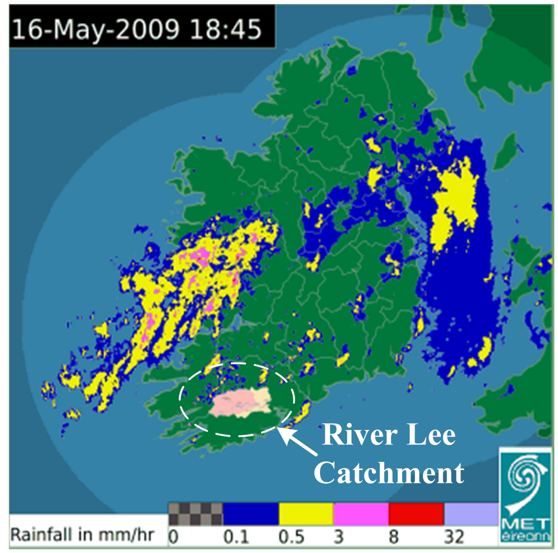

Fig. 4. Rainfall radar image and the catchment range for the River Lee.

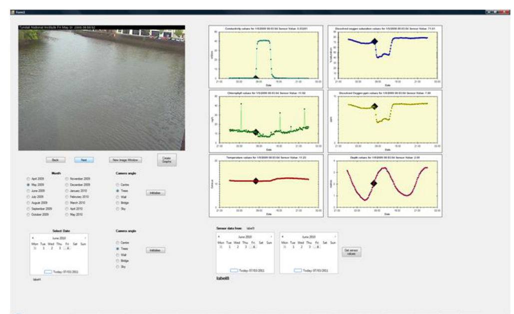

Fig. 5. Visual sensor analysis tool - enables the analysis of visual data alongside in-situ sensor readings in order to examine features and relationships between features and in-situ sensor data.

described in [11] would benefit from an adaptive sampling rate based on surrounding events. In the following a selection of studies carried out into a multi-modal context based approach for optimising the monitoring ability of the network are described.

B. Adoption of a Multi-Modal Context Based Approach

In May 2008 an AXIS PTZ Network camera was deployed overlooking the banks of the River Lee at the Tyndall Research institute, Cork, Ireland. It pans to four different positions every minute in order to capture the site from four different angles (See Figure 3) . Rainfall radar imagery is also captured from the Met Éireann - the Irish meteorological service - web site [5]. These images show the precipitation distribution and dynamic development over Ireland and are useful sources of information for estimating overall precipitation in a river catchment area (See Figure 4).

Using these additional data sources along with currently available in-situ information from the network, a number of studies were carried out. These were as follows:

1) Visual Sensing: In order to analyse the relationship between the sensor readings and features in the images, a tool was developed to enable visualisation of the sensor readings and the closest corresponding images. This enabled visual identification of the possible relationship between the two sensing modalities and how they could be used in a complementary manner (See Figure 5). Using a low cost non-specialised visual sensor limits the parameters to be directly detected from the camera and the conditions at the site also result in challenging image data e.g reflections on the water, changes in weather conditions and poor visibility etc. (e.g. See Figure 6).

However there are a number of events which can be directly detected and additional features which may provide surrogate measurements for non directly detectable parameters e.g. changes in freshwater levels may indicate nutrient loadings etc. As described in [12] a number of features were identified for detection e.g. boats, objects floating on the water, water turbulence, water depth etc. Subsequently a detailed outline of the estimation of depth from the camera images was provided due to its importance as an indicator of conditions at the site and the ability to link it to the in-situ sensor readings. A number of features appeared to correlate with different levels of depth and algorithms were developed for the detection of each of these features (See Figure 7). These features are rocks at the trees, rocks at the far wall. rocks at the near wall and the appearance of an island feature in the middle of a the water. As outlined in [12] the results indicated that each of the depth features could be detected to a very high accuracy and the classifier had a high ability to distinguish between the classes. Each of the models were evaluated using the standard machine learning technique of ten-fold cross validation.

In a further study models were similarly developed for each of the four depth features based on data sampled across a different 12 day period in May 2009 and the models were tested on data from both similar and alternative times of the year. Additionally a 2-class model (feature present, feature not present) and a 3 class model (feature present, feature not

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

Fig. 6. Examples of the challenging image data we are using, demonstrating disparate appearance due to varying river conditions.

Fig. 7. The features highlighted in the image become visible in order with changing depth.

present, feature intermediately present) were examined. It was found that the 2-class model is the best option as it produces the highest accuracies in relation to the detection of each of the depth features and it is really only positive and negative detections that are of main concern.

The resulting four depth feature models were evaluated on two unseen datasets - one containing data from May and the other combining data from November, January and February (*novjanfeb*). Accuracies of 89.2%, 85.38%, 98.63% and 79.25% were achieved on the May test data on a test set of 800 instances (400 positive, 400 negative) for each feature. The results were poorer for the *novjanfeb* test data with accuracies of 67.08%, 79.6%, 94.58% 53.75%. However due to the weather conditions a smaller number of instances of these lower depth features were available for testing (250 positive and 250 negative instances for depth features 1 and 2, 120 positive and 120 negative instances for depth features 3 and 4). From visual inspection of the data, the time period of the second test set displayed very different visual signatures to that of the May test set. An evaluation carried out on data from this time period suggests that better accuracies may be achieved by training models with data specific for this time period. This is subsequently the approach adopted when using these models at a later stage in our study. As outlined in [12], further improvements could be achieved by referencing images from the three alternative camera angles which effectively represent additional data streams in the network. Also the addition of another camera to the network would still render the deployment very cost effective while increasing knowledge about events at the site.

There are also additional features that could also be investigated. These four features were originally chosen as a proof of concept. For example it may be worthwhile investigating into the use of another feature to give an indication of when higher waters levels are changing. A sample feature is a varying appearance of the wall depending on the height of the water. Three different levels can generally be depicted through the appearance of three different lines of colour. Figure 8 shows three images - the first image demonstrates when three lines of colours are visible due to a lower water level, the second image demonstrates when two lines of colour are visible due to a higher water level and the third image demonstrates a really high water level when only the top colour of the wall is visible.

A model was developed in a similar fashion to those developed for the four depth features outlined in [12] using 800 samples of each of the three classes from the *novjanfeb* dataset. It contained images with a larger number of sample instances of the higher water levels. Ten-fold cross validation was used in evaluating whether the model had the ability to differentiate between these different appearances of the wall depending on the water level. The model achieved an accuracy of 82.29% and was especially accurate in classifying the higher water levels which is most important considering this could indicate a flood alert.

Subsequently ways in which to relate these features back to the in-situ depth data were evaluated. Using the initial four depth features a variety of methods were examined resulting in a number of visual sensor streams. Figure 9 shows the range of water depth values corresponding to the various features where *rocks-trees* indicates rocks at trees only, *rocks-trees-wall* indicates rocks at trees and the far wall but no rocks at the other two features etc. From this graph it can be seen that there is a distinction between the range of depth values associated with different depth features, except for the features *rocks-trees-wall* and *rocks-trees-wall-near-wall* which occur in similar ranges. This distinction was used in order to align the two data streams. This approach can benefit from the fact that often it is not a precise measurement that is relevant but a general estimation of conditions.

An in-situ depth reading is taken every 10 minutes, where as an image is produced from the camera sensor approximately

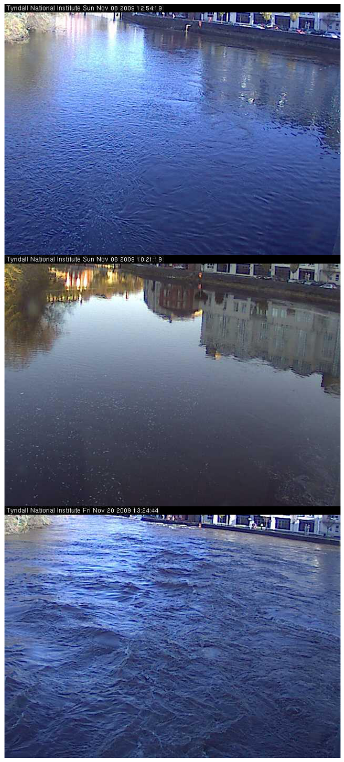

Fig. 8. Features on the wall showing changes in higher water levels.

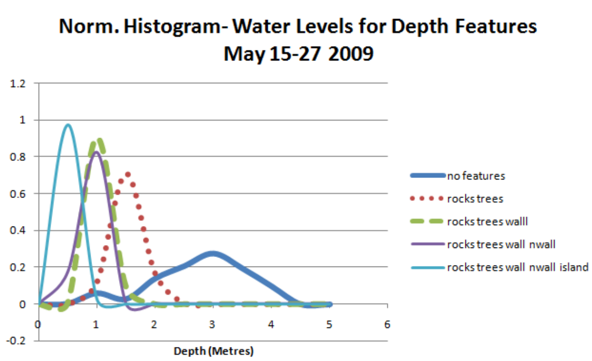

Fig. 9. Normalised histogram of water levels for depth features for a selection of images from May 15-27 2009

every minute. Hence for each in-situ depth reading the images (i.e. the classifications for each of the depth features) that are within 10 minutes of this reading are aligned with the time of the depth value. Two approaches are then used in order to decipher the appropriate classification for each of the depth features for this particular time-stamp. In the first scenario a maximum approach is used whereby if there are any positive instances at all within the classifications, then the classification for this time is considered to be positive. In the second scenario, a majority approach is used whereby the classification for this time for a particular feature is the majority classification of all the classifications aligned with this time. The majority approach was the most appropriate considering that one poor classification in the other approach may result in an error. The output of either approach is an array consisting of the timestamp, the depth sensor value, and the classification for each of the depth features (i.e. present, not present) using the approach in question.

Next it needs to be determined how a cooperative relationship can be established between the two outputs for determining whether they are in agreement. Ideally after the appearance of one feature the subsequent appearance or disappearance of the next appropriate feature should be seen relevant to whether depth is moving down or up. From examining the training data, it is apparent that if the water is below or between certain levels certain features should be appearing and others not appearing, hence a thresholding approach is used. If there is water between a certain level and the appropriate relevant features are detected and there is no detection of the non-relevant features, then a positive cooperation value of ’1’ is assigned, or else a negative cooperation value of ’0’ is assigned to this input. Further studies have also been carried out which use this type of output in a trust and reputation framework to determine the most reliable visual sensor stream at a particular point in time where different approaches are being evaluated and the influence of various depth features on the output of the algorithm. However this is outside the scope of this paper.

At the Poolbeg test site we further this work by examining methods to obtain more precise depth readings from the visual sensor stream in the network. However it must be reinforced that the goal is to determine what can be achieved from simply deploying a low-cost camera without additional functionalities or modifications to the site.

2) Adaptive Sensing Using Contextual Information: As previously outlined, an ideal scenario is whereby contextual information can be used in order to improve the efficiency of the sophisticated in-situ sensor nodes. In the work outlined in [13] we describe a study whereby rainfall radar images and information from a water depth sensor are used as input to an Artificial Neural Network to dictate the sampling frequency of a phosphate analyser at the Lee Maltings site. Specifically we investigate a methodology for incorporation of pixel information from rainfall radar images and in-situ depth data into an ANN and the subsequent use of this network to predict average freshwater levels at a dynamic point of the river. The site is tidal and affected by the dam which makes this non-trivial. However a prediction of change in freshwater levels may indicate runoff from further upstream and subsequent nutrient loading. At this point the sensor should be sampling more regularly. However when no events of interest are occurring the sensor should limit the use of its resources and operate more intelligently.

This involved the examination of a number of different issues such as the most effective way to present rainfall radar information extracted from a simplified digital image representation to the network, the effects of rainfall from different points of the catchment on the model and the effect of differing lag times on the model. However the study demonstrated that with limited training data, a system for controlling the sampling rate of the nutrient sensor can be established quickly and cost effectively at a deployment and can improve the efficiency of the more sophisticated nodes of the sensor network.

3) Redundancy in the Network: In other work we are examining the ability of heterogeneous sensor nodes to provide redundancy within the network for an alternative sensor node in the case of node failure. We are investigating a variety of models incorporating data from different combinations of nodes and examining their ability to predict values from an alternative node in the network. We are examining essentially what can be achieved with limited data sources into replicating the activity of a sensor whilst there may be a possible gap in the data or fault in the network, and whether we can estimate the missing data values in a very low cost manner. The initial results from this work are extremely promising using regression trees with input models consisting of one or more alternative parameters and a limited number of preceding values.

V. Poolbeg Marina

Poolbeg Marina is located on the lower part of the estuary of the River Liffey, in Dublin, Ireland. It is a busy port subject to large amounts of recreational and commercial activity and the port is heavily used with a high amount of ship traffic. It has quite a diverse ecosystem. Due to the large amount of activity at the site and its importance from an environmental and ecological perspective, a multi-paramter in-situ sensor equipped with turbidity, dissolved oxygen, temperature, conductivity and depth probes was deployed at the site. A visual sensing sensing system was also deployed at the site similar to the deployment at the Lee Maltings test site. The visual sensor continuously sends images back to a cloud server at a frame rate of approximately 1 frame every 10 seconds.

At this site our investigation into visual sensing is moved forward from studies and experiences to date at the Lee Maltings test site. However it represents a very different site with very different characteristics, dynamics and issues that require monitoring. In turn this requires new approaches to analysing images from the site in order to extract the relevant events of interest that can complement and enhance the use of the in-situ sensors deployed at the location. In the following a brief overview of a small selection of these studies are described in order to provide an indication of the potential of such a system.

A. Visual Sensing

From an environmental monitoring perspective ship traffic at the port greatly affects the aquatic ecosystem. Propeller contact, noise, movement and turbulence from from the propulsion systems can have multiple effects on the ecosystem including increased turbidity. There are many negative impacts of increased turbidity on the ecosystem which are well documented in the literature [14]. As outlined in [15] analysis of the sensor data demonstrates that ships entering the port often coincide with spikes in data from the turbidity sensor. The same effects are not seen with the activity of small boats in the area. Hence a study was carried out to detect ship traffic from a visual sensor.

Fig. 10. Images from Poolbeg Marina displaying an empty scene along with images displaying boats and ships at the site.

Aside from the obvious benefits of being able to monitor traffic in and out of the port from a visual sensor e.g. security, logistical monitoring etc., automatically extracting information on ship traffic from a database of images can provide a more precise indication of its effect on turbidity. It also may be able to provide surrogate measurements if the in-situ sensor were to fail or indicate when the sensor is producing inaccurate readings and may require maintenance. Similar to the case with the Lee Maltings site the image dataset is challenging which renders the accurate detection of ships in all scenes difficult. However using a selection of computer vision techniques ships can be detected in the seen with an extremely high accuracy, details of which are outlined in [15]. Figure 10 shows examples of an empty scene, along with images displaying boats and ships at the site.

In other work at the Poolbeg Marina site, initial work from the Lee Maltings site is also being furthered at this site in relation to depth estimation. As opposed to using a number of individual localised features at the site we are investigating the use of more global features in the images for depth estimation in order to render the system more transferable between sites. Features which may give us a more precise estimation of water depth are also being evaluated. With no water depth sensor at the site online tidal information is being relied upon to provide a ground truth. Even though this work is in the early stages the initial results have been extremely promising. Figure 11 displays images from the site at different tides - low, mid and high tide and Figure 12 shows a graph displaying the predicted versus actual water levels from a model developed using global image features.

VI. Galway Bay

Galway Bay is located on the west coast of Ireland (See Figure 13) bordered by Co. Clare to the south and Co. Galway to the north. It is approximately 62 km long from

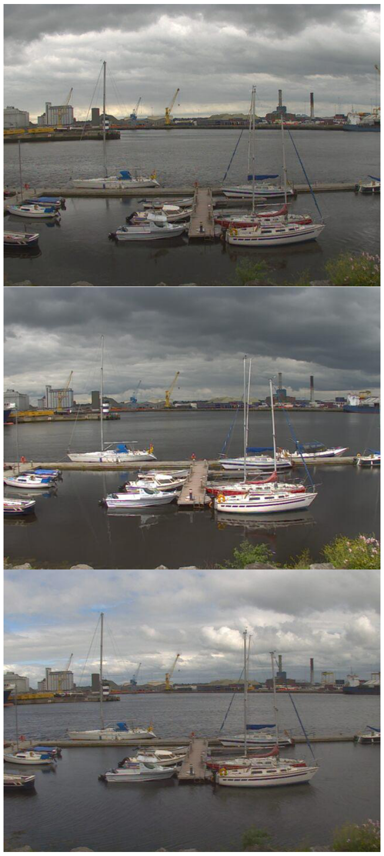

Fig. 11. Images from Poolbeg Marina displaying from top to bottom - low tide, mid tide and high tide.

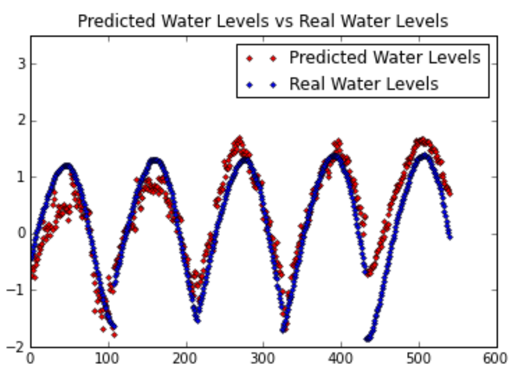

Fig. 12. A graph displaying real versus predicted values of depth at Poolbeg marina using a model developed from image features.

the Brannock Islands (situated just north west of the Aran islands) in the west to Oranmore in the east. The main rivers entering the bay are the River Corrib at Galway and the Owenboliskey River at an Spidéal. It is quite an important resource supporting a range of maritime activities with many research institutes and organisations using Galway Bay as the basis for research programmes and projects, most notably the Irish Marine Institute located in Oranmore, Co. Galway. Galway Bay is the location of the SmartBay national test and

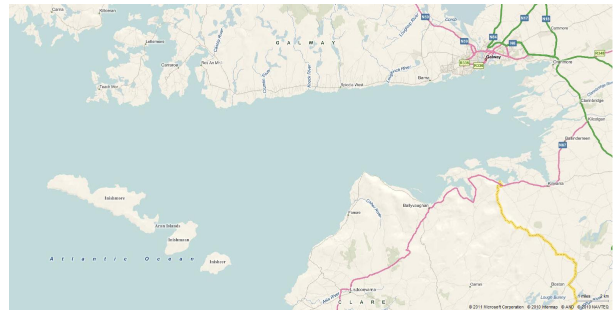

Fig. 13. Galway Bay. Source: Bing Maps

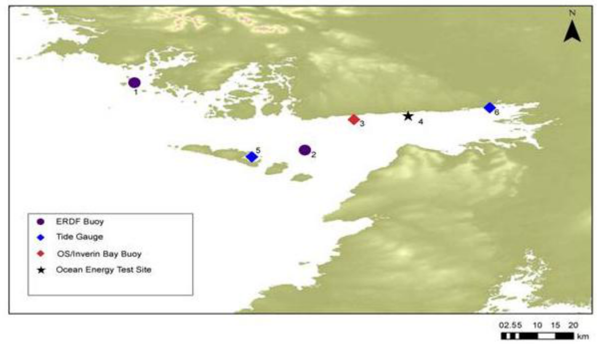

Fig. 14. SmartBay Pilot Project in 2008. Source: Marine Institute

demonstration facility. In 2008 a number of environmental monitoring buoys were launched as part of the the SmartBay pilot project. It is data from these buoys that were used in our initial analysis described below (See Figure 14).

A. Visual Sensing

The multi-modal aspect of our research in Galway Bay has mainly focused on the use of visual sensing from satellite imagers to complement the data from the SmartBay environmental monitoring buoys. This is due to the vast location area. However we have also begun investigating the use of web cam data currently available around Galway port. In [16] we describe a study demonstrating the need for both satellite and in-situ sensors for monitoring Sea Surface Temperature (SST). We also investigated the use of satellite ocean colour data. However throughout our analysis we found difficulties in searching for available satellite imagery due to issues such as cloud cover. Subsequently as part of our research we developed a system for the efficient browsing of MODIS chlorophyll data described in [17]. Three different interfaces for the search system were created with one of these shown in Figure 15.

Following the difficulties with the reliance on data from a singular satellite sensor, an investigation into the use of satellite data products that produce an analysis based on the combination of many satellite and in some cases in-situ data streams and/or model output was carried out. In [18] the ability of these data sources to provide contextual awareness, redundancy and increased efficiency to an in-situ sensor network is investigated. More specifically, the potential

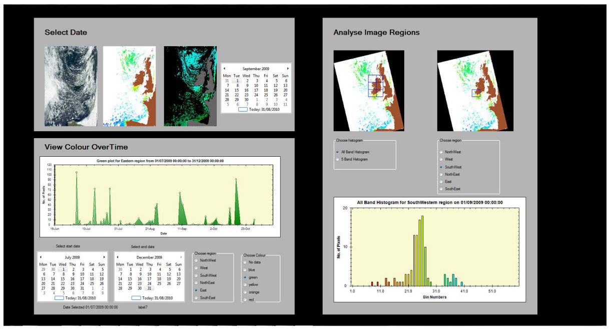

Fig. 15. Satellite image analysis and search system.

use of a variety of chlorophyll and SST data products as additional data sources in the SmartBay monitoring network in Galway Bay, Ireland is analysed. Overall it was found that while care needs to be taken in choosing these products, there is extremely promising performance from a number of these products that would be suitable in the context of a number of applications especially in relation to SST. It was more difficult to come to conclusive results for the chlorophyll analysis. Further work is investigating this with new deployments as part of the SmartBay test and development platform and the integration of other satellite sensor data aside from ocean colour and SST e.g. sea surface roughness, along with model data and other sensor data available from the Irish Marine Institute.

VII. Conclusion

Here we have provided an overview of the importance of continuous remote monitoring of our marine and freshwater environments along with the issues with the singular reliance on in-situ sensor networks. While they provide an enormous step forward for continuous and real-time monitoring of the aquatic environment, there are still a number of issues with the current state of the art. Complementing these networks with additional data sources such as visual sensors and contextual information can greatly improve their efficiency and performance most importantly in terms of *scalability* and *reliability*.

We provided an overview of a selection of our work in relation to three diverse test sites - a river catchment, a busy port and a coastal zone - to provide an indication of ways in which these additional data sources have been incorporated into the network. The general focus was on the use of visual sensing as a complementary sensing modality and the optimisation of nodes in the network so that they can operate more efficiently and compensate when a particular node intermittently fails. Each of the test sites are representative of very different issues and have a variety of different available data sources. Therefore our studies have strived to reflect the needs of the site whilst also attempting to drive the research forward. Our results demonstrate that these additional data sources and models may prove as extremely effective tools for optimising future environmental monitoring networks.

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References

[1] Irish Government report - Inter-Departmental Marine Coordination Group (MCG), "Harnessing Our Ocean Wealth - An Integrated Marine Plan (IMP) for Ireland," July 2012.

[2] Marine Institute, "Sea Change 2007-2013 Part I: A Marine Knowledge, Research and Innovation Strategy for Ireland," 2006, [Accessed 29-Aug-2012].

[3] ——, "Sea Change 2007-2013 Part II: Marine Foresight Exercise for Ireland," 2006, [Accessed 29-Aug-2012].

[4] D. Estrin, "Refections on wireless sensing systems: From ecosystems to human systems," in *IEEE Radio and Wireless Symposium*, Long Beach, CA, January 2007.

[5] K. Johnson, J. Needoba, S. Riser, and W. Showers, "Chemical sensor networks for the aquatic environment," *Chemical Reviews*, vol. 107(2), pp. 623–640, 2007.

[6] H. B. Glasgow, J. M. Burkholder, R. E. Reed, A. J. Lewitus, and J. E. Kleinman, "Real-time remote monitoring of water quality: a review of current applications, and advancements in sensor, telemetry, and computing technologies," *Journal of Experimental Marine Biology and Ecology*, vol. 300(1-2), pp. 409–448, 2004.

[7] D. Diamond, S. Coyle, S. Scarmagnani, and J. Hayes, "Wireless sensor networks and chemo-/biosensing," *Chemical Reviews*, vol. 108, no. 2, pp. 652–679, 2008.

[8] P. Moscetta, L. Sanfilippo, E. Savino, R. Allabashi, and A. Gunatilaka, "Instrumentation for continuous monitoring in marine environments," in *OCEANS '09: MTS/IEEE: Marine Technology for Our Future: Global and Local Challenges*, 2009.

[9] Office of Public Works (OPW), "Lee CFRAMS: Lee Catchment Flood Risk Assessment and Management Study, Hydrological Report April 2008," 2008, [accessed 29-Aug-2012].

[10] A. Lawlor, J. Torres, B. O'Flynn, J. Wallace, and F. Regan, "Deploy: a long term deployment of a water quality sensor monitoring system," *Sensor Review*, vol. 32(1), pp. 29–38, 2012.

[11] C. Slater, J. Cleary, K.-T. Lau, D. Snakenborg, B. Corcoran, J. Kutter, and D. Diamond, "Validation of a fully autonomous phosphate analyser based on microfluidic lab-on-a-chip," *Water Science and Technology*, vol. 61(7), pp. 1811–1818, 2010.

[12] E. O'Connor, A. F. Smeaton, and N. E. O'Connor, "A multi-modal event detection system for river and coastal marine monitoring applications." in *IEEE Oceans '11, 6-9 June 2011, Santander, Spain.*, 2011.

[13] E. O'Connor, A. F. Smeaton, N. E. O'Connor, and F. Regan, "A neural network approach to smarter sensor networks for water quality monitoring," *Sensors*, vol. 12, pp. 4605–4632, 2012.

[14] C. Newcombe and D. MacDonald, "Effects of suspended sediments on aquatic ecosystems," *North American Journal of Fisheries Management*, vol. 11(1), pp. 72–82, 1991.

[15] D. Zhang, E. O'Connor, N. E. O'Connor, F. Regan, and A. F. Smeaton, "A visual sensing platform for creating a smarter multi-modal marine monitoring network," in *ACM International Workshop on Multimedia Analysis for Ecological Data, in conjunction with ACM Multimedia 2012*, In Press.

[16] E. O'Connor, J. Hayes, A. F. Smeaton, N. E. O'Connor, and D. Diamond, "Environmental monitoring of galway bay: fusing data from remote and in-situ sources." in *Remote Sensing for Environmental Monitoring, GIS Applications, and Geology IX, SPIE Europe's International Symposium on Remote Sensing (ERS09)*, 2009.

[17] E. O'Connor, J. Hayes, C. O'Conaire, A. Smeaton, N. O'Connor, and D. Diamond, "Image processing for smart browsing of oceancolor data products and subsequent incorporation into a multi-modal sensing framework," in *RSPSoc Remote Sensing and Photogrammetry Society Annual Conference with Irish Earth Observation Symposium*, Cork, Ireland, 1-3 Sept 2010.

[18] E. O'Connor, A. F. Smeaton, N. E. O'Connor, and F. Regan, "Investigation into the use of satellite remote sensing data products as part of a multi-modal marine environmental monitoring network," in *SPIE Remote Sensing 2012*, In Press.