Augmented Reality Visualization for Sailboats (ARVS)

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***Abstract*—In order to safely operate sailboats, captains often rely on proper interpretation of several marine aspects to make decisions. In this project, we are in the process of developing an Augmented Reality System (ARS) to provide captains of sailboats with a centralized sensor data server and a visualization method. We have deployed an experimental proof-of-concept version of this system on our research vessel, SV Moonshadow. Assistance in navigation is of particular interest for small sailing vessels as they are sometimes sailed by the captain alone. At the same time there are a large number of data inputs such as wind, tide, weather, position, and presence of obstacles such as logs or kelp that have to be considered to choose the proper course of action. We introduce a visualization tool that provides an interface for representing a wide spectrum of relevant marine data. The interface relies on a real-time data server that provides information about the status of the vessel (wind, GPS, gyro, accelerometer, depth sounder etc.) An important component to be integrated in the interface is a debris detector that analyzes data from a camera mounted on the bow in order to warn a captain about a potential collision. We have also examined initial feedback on this tool from a number of users.**

Fig. 1. Research sailing vessel Moonshadow

I. Introduction

According to a US Coast Guard report from 2014 [1], the most common contributing factor of accidents in sailboat operation is operator inattention, followed by improper lookout and operator inexperience. As tempting as it may seem to think that being attentive while operating a sailboat is easy, or natural, the reality is to the contrary; the information needed for proper decision-making is usually acquired through activities that are intrinsically disruptive, such as consulting tide tables and charts, observing wind changes, performing course corrections, monitoring the depth meter or barometer etc. [2] Human captains of sailing vessels make decisions based on a large amount of data, which gives the captain a large cognitive load, especially when critical events occur, such as tacking or navigating in turbulent currents. In order to reduce that cognitive load we propose the use of a centralized *augmented reality system* (ARS), which receives data relevant to navigation and controls the presentation of that data to the captain. In this paper we describe the design and implementation of such a system. An experimental proof-of-concept version of this system was deployed on the SV Moonshadow, seen in Fig. 1. While most of the individual components are active, certain non-MNEA sensors are currently not used, awaiting upgrades.

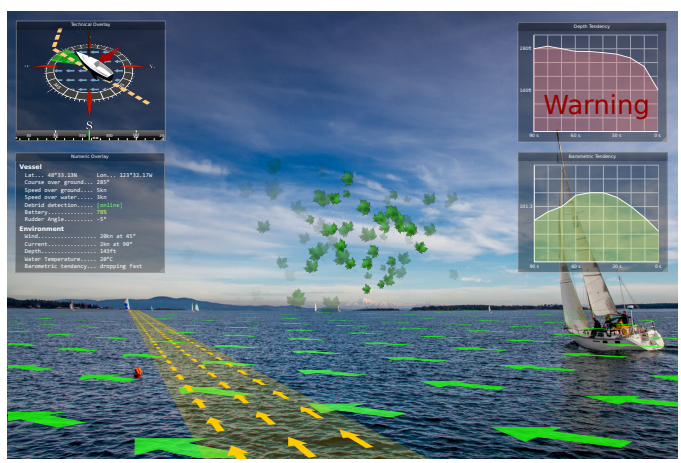

Fig. 2. AR Visualization System

The data needed by the captain to ensure safe vessel operation, includes:

- the position and direction of the vessel
- the direction and strength of the wind and water currents
- or the position of any reefs, plants, debris, marine wildlife, man-made floating navigational aids or fishing gear

For offshore sailing, it is vital that the captain also be aware of the weather changes, by actively monitoring barometric and thermal variations. For coastal cruising, the skipper must consult tide charts in order to predict tidal currents, as well as being aware of temporal constraints such as nightfall, tidal changes, marine wildlife behaviours etc.

The ARS collects data from sensors monitoring a diverse environment, including mechanical, electrical and marine aspects, into a single interface for the captain. The safe operation of a sailboat relies on the real-time acquisition of a large amount of information from different media, together with correct interpretation of this information. This is usually learned through extensive practice and experience.

In this project we endeavoured to create an interface that allows captains to estimate the status of the vessel and its immediate surrounding environment, by using augmented reality and computer vision methods.

A. Problem Statement

The process of operating a sailing vessel under sail implies a considerable effort put in by the captain, and requires having a clear understanding of both vessel status and also its surrounding environment. Reading and estimating the behaviour of the marine environment is complex, even with all the information readily available. Yet, in an overwhelming majority of sailboats in use today, the information required by the captain is provided by accessing a number of fundamentally different media such as paper or electronic charts, tide tables, wind indicators, barometers, thermometers etc. Fortunately, using standards like the NMEA0183 (National Marine Electronics Association) (and the newer NMEA2000 [3]), some of the information relaying the status of the vessel and its immediate environment can be centralized (e.g. GPS position and speed over ground, wind information, speed over water, depth). Some modern GPS units feature 2D interfaces that can integrate this data.

The problem addressed in this research is to create a technological solution which simplifies the complex task of integration of navigational and environmental data to enable better decisions-making for operators of small vessels.

B. Contributions

This research aims to provide a captain with a real-time augmented reality system that will centralize most of the relevant information about the vessel and its environment, thus relieving the effort of obtaining this data in real-time, as well as greatly reducing the risk for human error in the process of switching between media.

The main contributions of this work are:

- An augmented reality system whose purpose is to reduce cognitive load on the captain and enhance the sailing experience.
- An animated 3D visualizer that uses particle systems to create an immersive impression, as opposed to a static representation.
- An experimental method for detecting debris on the water using image acquisition and processing.

II. Previous Work

Advances in ship-based sensor technology, better ship-to-shore communication connectivity and increases in vessel traffic necessitate advances in automation for maritime navigation. Data fusion, including integration of ship-based data, electronic charts and remote sensing data, such as satellite [4] and coastal RADAR offer new possibilities for enhanced safety in navigation. Initiatives such as the "Chart of the Future," which aims to enhance paper charts by incorporating bathymetry and shoreline imagery have been in development for over a decade [5]. Despite these technological advances, navigation, especially aboard small vessels, is often still done with paper charts and relies on human interpretation of sensor data.

Many systems have been introduced for enhanced visualization of sensor data, yet we are not aware of the existence of any augmented reality visualization interface designed exclusively for operators of small sailing vessels, either in academia, in the industry or as a commercial product. We briefly describe a few existing systems in the following.

The problem of interface design for ship bridge operation is addressed in [6]. In this paper, the author explores several aspects for integrating more and more navigation systems such as the ARPA/ECDIS. Our system builds on the existing 2D interface attempts by introducing an augmented reality interface.

As of early 2015, Rolls Royce [7] announced the intention of developing an augmented reality based interface for controlling various aspects in the command, navigation and operation of cargo ships. A design concept was released to the press, however, no articles or research reports have been published yet.

The open-source navigation software OpenCPN (as well as several other commercial products) has among its features a plug-in called Dashboard, that successfully integrates and displays NMEA-available information in a minimal 2D window system. While said plug-in approaches the same problem, displaying information from NMEA sensors, it does so in a 2D windowed paradigm, using a rudimentary 2D geometric and numeric approach. Our approach is processing the same data and rendering it as animated 3D layers in an augmented reality system.

The final aspect of the system is an experimental image acquisition and processing method for detecting debris on the water, which poses a navigational risk. A method of obstacle detection against a dynamic sea background has been proposed in [8] using dynamic textures. We have been inspired by

various existing state-of-the-art saliency detection algorithms ranging from simpler contrast based to more complex learning based algorithms [9], [10], [11], [12]. These methods do not always lead to robust results, as often certain bright areas in the water, reflected spots or small particles floating on the surface are detected as being salient.

The learning based saliency detection approach proposed in [12] method is based on the Adaboost ensemble classification algorithm. It uses colour and texture orientation features and combines them across multiple scales in a nonlinear manner, with the implementation of the Adaboost classifier, which performs automatic feature selection, thresholding and weight assignment.

III. Vessel and Immediate Environment Sensor Data

The sailboat is equipped with a number of sensors and a data server that reads, processes, logs and provides status information to one or more visualizers, as shown in Figure 3. The information gathered by the server is about aspects regarding the vessel itself and also about the immediate surrounding environment. The boat server also provides stored marine data such as tidal levels and currents and charts, as well as astronomical data such as sunrise or moonrise.

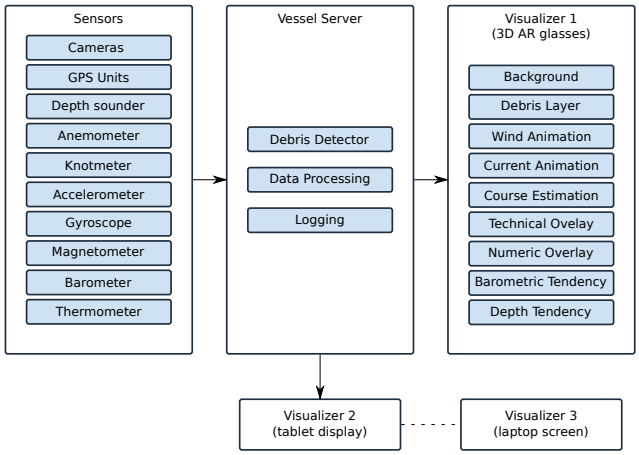

Fig. 3. System Design Overview

A. Sensors

The sensors located on-board the sailing vessel are used to collect data regarding the vessel and its immediate environment. Currently, most of the individual components have been tested and integrated. Yet, the functionality of the prototype is only partial, awaiting the upgrade of the last batch of NMEA sensors (depth sounder and knotmeter).

1) Location: GPS information is collected using two or more GPS units (one on the bow of the ship, one on the stern and another optional one amidships). This provides the boat server with the location of the boat relative to true north and with a speed over ground (SOG) estimation. Given a typical GPS error of under 2m and a ship's length of over 8m, even when the ship is not moving at all, the orientation of the ship can still be determined by computing a vector between the after and forward GPS units.

2) Boat heel: A 3D accelerometer is used for determining the roll (heel) and pitch of the vessel relative to the ground, as well as determining the upright direction in the unfortunate case of a vessel capsize.

3) Motion: A 3D gyroscope is used for determining the yaw, pitch and roll variation, relative the vessel's previous position.

4) Orientation: A 3D magnetometer is used for determining vessel orientation relative to magnetic north. Using a static calibration of the vessel's magnetic deviation and a continuous adjustment of the magnetic variation (computed based on the GPS coordinates), the magnetic north orientation reading is translated to a true north orientation.

5) Atmospheric Pressure: A barometer is used for monitoring the tendency of the atmospheric pressure. This information is vital for off-shore cruisers for mid and long-term weather predictions. In costal sailing it can still be very useful for predicting incoming storms or sudden weather changes.

6) Speed Over Water: A knotmeter is used for determining the speed over water (SOW) - i.e. the speed of the vessel relative to the water underneath; this is different than the SOG readings from the GPS unit, which reflects the speed relative to the ground below. By measuring the SOG and the SOW, an estimate can be made about the speed and direction of the water currents the vessels is sailing on. E.g. if the vessel is traveling with a SOW of 2kn over a current in the same direction of 3kn, then the SOG will be 5kn.

7) Water Depth: A depth sounder is used for determining the water depth under the boat. By computing the tendency of the water depth over time, an estimate can be made about the danger of running aground.

8) Wind Direction and Strength: An anemometer is used for determining the apparent wind direction and strength, relative to the motion and orientation of the boat. If the vessel is traveling downwind at 5kn, in 10kn winds, then the apparent wind is 5kn. Yet, if the vessel were to go in the opposite direction, the apparent wind would be 15kn.

The sensors 6 through 8 are currently awaiting to be upgraded to NMEA sensors to ease the data acquisition process.

B. Image Acquisition and Processing

The image acquisition mechanical components are still in an experimental stage, with upgrades being currently performed. The vessel uses two standard bow-mounted cameras for stereographic vision, in addition to a camera without an infrared filter used for debris detection. Following the photo-capture, the data is collected by the ship's server and passed on to the visualizer for the 3D background layer of the ARS (see IV). As soon as the debris detection module moves from an experimental stage to a real-time deployment, the ship's server will supply this module with a similar live feed of captured data.

C. Sensor Data Processing

The vessel's sensors are connected to a ship's server that performs most of the data processing. Using the information provided by this server, any number of visualizers can be used (e.g. augmented reality full-3D glasses, 2D tablets, static 2D display). The data from the magnetometer, gyro and accelerometer is filtered and integrated to offer a very accurate reading on the orientation of the vessel relative to magnetic north. This data is processed together with the true north orientation computed using the different GPS units.

IV. Debris Detection Method

We propose a method for detecting objects on the water (e.g. logs) using computer vision techniques. The detection system makes use of a monocular camera attached to the bow, overlooking the water surface ahead of the vessel. To analyze the captured data, we have to take into account the dynamic nature of the marine environment. Several challenges need to be overcome, such as the shifting texture of water, strong surface reflections and the complex shore features. The current state of this module is experimental, with all the results being drawn from real data, but not implemented for operation in real time, yet.

A. Implementation

The goal of debris detection is to detect debris afloat on the water surface by implementing a system that follows the following steps: feature extraction, training, classification and post-processing.

A computer vision algorithm has been implemented where we use features that are suitable for the classification. The extraction of features is the process of isolating colour and energy and edge texture information for every image. This information is structured as a feature vector.

The colour features consist of the intensity channel (I) and two chromaticity channels (RG, BY). A similar approach was presented in [13]. If r, g, b denote the red, green and blue channels respectively, I, RG and BY are calculated as:

$$I = r + g + b$$
$$RG = r - g$$
$$BY = b - \frac{r\ +\ g}{2} - \frac{min(r,g)}{2}$$

In order to obtain the texture information in RGB, we are using Laws' texture masks to compute the texture energy values by employing 9 masks, as presented in [14]. In addition to these, we are using another 2 masks to extend the feature space, by using the method presented by Michels in [15]. We transform the images into YCbCr colour space and use the Cb and Cr colour channel information to compute the final energy values.

We are employing Gabor filters to extract features for the edge information using 4 different angles $(0°, 45°, 90°, 135°)$. [16]

The feature values are combined into a feature vector: $f(x) = [f1(x)\ \ f2(x)\ \ f3(x)..fn(x)]$ where each of $f1(x),\ f2(x)..fn(x)$ represent a feature.

We are extracting feature vectors out of a set of background images and object images. Then these feature vectors are fed into the classifier during the training process.

We use the Adaboost statistical machine learning algorithm [17] for the training and classification step. It is a linear classifier that combines several weak classifiers (learners) used to construct a final strong classifier. The weak learners are weighted in favor of those instances misclassified by previous classifiers. The Adaboost algorithm with decision trees is well-suited for our problem because it is less susceptible to overfitting and it has a good generalization property. It uses the method of boosting for improving the accuracy of any learning algorithm. The output obtained from the classifier after training and classification is represented as a binary image where white pixels represent the object and black pixels represent the background. Next, in post-processing we recognize if a desired target object in the binary image has been detected.

As part of the post-processing step, a shape analysis is performed. Detected objects are constrained to certain shape characteristics, such as a pre-defined area and eccentricity threshold. For example, we impose an area constraint of less than 40% of the image size and an eccentricity threshold of 0.8, values which are optimal for detecting logs.

The process has been represented by the block diagram in Figure 4.

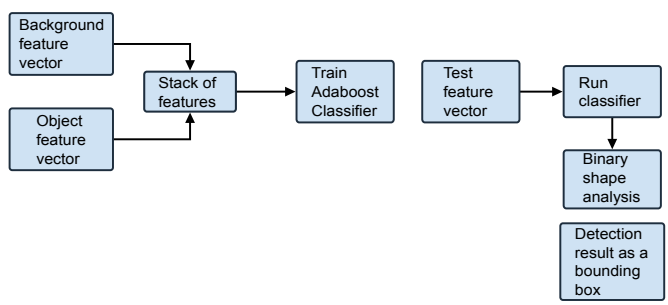

Fig. 4. Steps of training and classification module

B. Results

For an evaluation of the off-line implementation, we have used a set of 5 scenes. Each scene used 10 background images containing no objects and 10 object images for training, in addition to 20 images for testing.

The Figures 5 through 10 and Table I below show some detection results. The two correctly identified logs in fig. 5 (one close to the shore and the other further away) are shown enclosed within the red bounding box in fig. 6. True positive results have also been shown in fig. 8 and fig. 10. Figure 12 shows a false positive detection along with the detected log for the frame in fig.11.

The algorithm has been evaluated by the precision and recall measures, which are defined as:

$Precision = \frac{TP}{TP+FP}$; and $Recall = \frac{TP}{TP+FN}$, where TP is True Positives, FP - False Positives and FN - False Negatives.

The precision is the fraction of retrieved instances that are relevant, while recall is the fraction of relevant instances that are retrieved. High precision and recall values indicate a low false alarm rate. For example, in Sample set 1, Fig. 5, we have a precision of 86.95% and recall of 100% which means that it has a high accuracy and low false alarm rate. A large number of false negatives occur due to the object being far away and too small. Larger objects are detected with comparatively higher accuracy. The average computational times for recognition have also been tabulated in Table I.

The results of the detection method have been promising and we are currently planning to start deploying a real-time implementation of the method.

Set #	Comp. Time (S)	No. of Samples	TP	FP	FN	Precision	Recall
1	4.7426	20	20	3	0	86.95%	100%
2	4.7258	20	10	4	10	41.66%	50%
3	3.3967	20	10	0	10	50%	50%
4	3.6553	20	5	0	15	40%	40%
5	4.6324	20	16	6	0	84.21%	80%

TABLE I
DEBRIS DETECTION RESULTS

Fig. 5. Debris detection Sample 1 - Original

Fig. 6. Debris detection Sample 1 - Result

V. VISUALIZER

The visualizer is a component that receives processed sensor data from the vessel server and displays it using a visualization method.

A. Video (See-Through) Capture

The background of the visualizer is either a 2D or 3D image of the terrain ahead of the vessel.

Fig. 7. Debris detection Sample 2 - Original

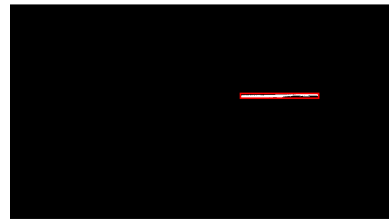

Fig. 8. Debris detection Sample 2 - Result

Fig. 9. Debris detection Sample 3 - Original

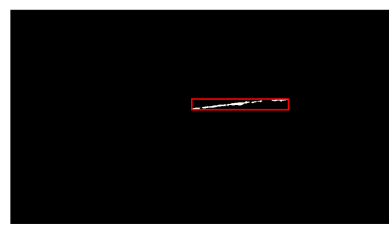

Fig. 10. Debris detection Sample 3 - Result

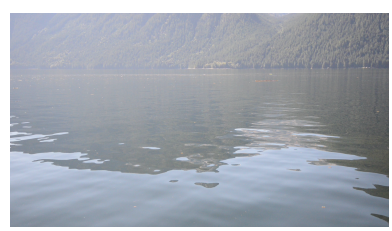

Fig. 11. Debris detection Sample 4 - Original

B. Debris Layer

The debris layer highlights the results from the debris detection process as a layer in the visualizer. Water objects identified as potential debris are highlighted as semi-transparent in bright red. Based on the data collected from the sensors and from the static mechanical position of the camera, the 3D position of the detected debris is estimated and displayed as

Fig. 12. Debris detection Sample 4 - Result

3 dimensional objects when using augmented reality glasses. In the current state of the project, the debris detection is still in an experimental, off-line stage. Following the most recent assesments of the detection results, a real-time detector implementation is in an early planning stage.

C. Wind and Current Animation Layers

The wind and current animation layers are designed to give the user immediate information on the strength and direction of the wind and current, using 3D particle systems. Our implementation is based on a flow model similar to the ones in [18]. The problem with typical visualization systems for wind or current, often represented as an arrow or windsock, is that the visualization is generally quite static; that is, only changing if there is a change in the data. A particle system is never still unless there is no wind or current, in which case it should be still; the stillness itself instantly providing a significant amount of information at a brief glance. The particle system is also much more adept at displaying the information in the same (or similar) coordinate system to which the user is seeing themselves; an arrow is 2D in nature, making it less suitable for use in a 3D coordinate system.

The two visualization implementations, based on particle systems, the wind and current are overlaid on top of the camera and debris layers, and generates particles that move through 3D space relative to the boats orientation; that is, if the wind is blowing from the east, and the boat is pointed to the north, then the particles will be moving across the visualizer screen from right to left. The strength of the wind/current is represented by the speed of the particles; though it could also be represented by the colour or shape as well. Since the visualization implementations are rendered in 3D with a perspective projection, the user can very easily see the direction of the wind and current with respect to the boat, even if they are travelling parallel to the boat. The visualization implementation is also constantly in motion, which ensures that no area of the first layer of the visualization is ever constantly being covered; this also ensures that neither the wind nor current visualisations can obscure potential hazards. The visualizer also has the potential to communicate even more information to the user through the look and behaviour of the particles themselves. For instance, the wind particles could change based on the weather conditions (if its rainy, snowing, cold, hot, etc.). Using a 3D particle system enables us to provide the user with a very intuitive and unobtrusive method of displaying information that is crucial for a sail boat.

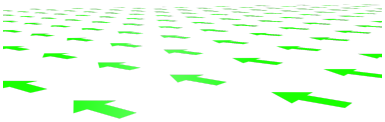

Fig. 13. Current Animation Pattern

Fig. 14. Wind Animation Pattern

D. Course Estimation

The course estimation is a visual representation of the actual course of the boat (as opposed to the heading or bearing) represented by a 3D plane overlaid onto the previous visualization layers. The course estimation is displayed as a 3D plane, where the boat represents the origin of the coordinate system, and the plane stretches to the horizon. The horizon is determined from the camera image upon which the plane is overlaid. The plane is rendered with a perspective transform so that it appears to be lying on top of the water surface, giving the user immediate information as to where the boat is travelling. The plane is textured with moving arrows, in order to indicate the direction of travel along the plane.

E. Technical Graphics Overlay

The technical graphics overlay (Fig. 15) provides the user with a number of layers representing the current, wind, heel, compass heading etc. The first of these layers provides the user with a detailed 3D technical overlay of the boat. The technical overlay consists of a 3D model of a boat placed in a compass rose along with additional directional information to provide precise information of the direction of the boat as well as outside forces such as the wind. Currently, the technical overlay provides the user with quick information about the heading, course and bearing, as well as the wind and current strengths and directions. The technical overlay also provides the user with a real-time visualization of the movement of the boat in three dimensions, rotating the boat to show the heading, pitch and roll. The orientation of the boat in the technical overlay can be fixed to allow the compass and indicators to instead rotate around the boat, which can provide the user with a more natural coordinate system. The 3D technical overlay

window provides the user with a quick, and easy to interpret, display of important situational information.

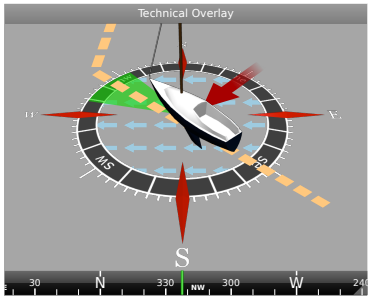

Fig. 15. Technical Graphics Overlay

F. Numeric Overlay

The numeric overlay (Fig. 16) is a layer used to display all the collected data in a precise numeric form using a simple text format. The data displayed in the numeric overlay consists of the following: the boats position, orientation, speed and course; the wind direction and strength; the current direction and strength; the barometric pressure; and the depth.

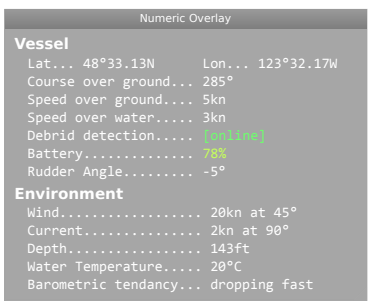

Fig. 16. Numeric Overlay

G. Barometric Tendency

The barometric tendency is a layer (Fig. 17) that displays a 2D graph of the barometric pressure over the past few minutes. The barometric tendency graph allows the user to easily see how the pressure is changing.

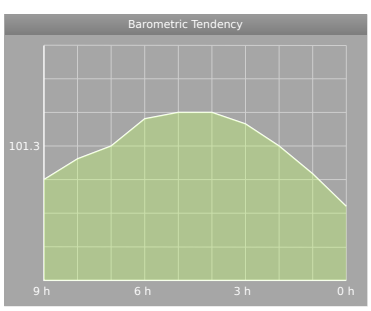

Fig. 17. Barometric Tendency Overlay

H. Depth Tendency

The depth tendency is a layer (Fig. 18) that displays a 2D graph of the depth over the past few minutes, similar to the barometric tendency layer. The depth tendency graph allows the user to easily see how the depth is changing, and could be set to alert the user if the depth is rising very rapidly, which may indicate that the boat is approaching a dangerously shallow area.

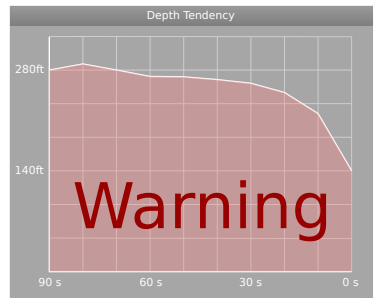

Fig. 18. Depth Tendency Overlay

VI. Evaluation

We worked with a number of experienced captains and determined their needs (reduce sources of data, standardize data, centralize and integrate all available information into an intuitive interface). Following an evaluation of the proof of concept software, three of the experienced sailors have been consulted and they made positive comments regarding the ease of access to simulated real-time data and the intuitive way of representing the data. The sailors have expressed interest in using the fully developed version of the software, when it will be ready. Feedback was received about a need to be able to customize the interface (adjustable particle density and texture, moving, hiding and stacking windows, customizable colours and others).

The prototype was met with largely good and enthusiastic remarks, together with suggestions on how it can be improved. A general consensus among those who have experienced the system first hand was a general eagerness to see it move on to beta-testing and hopefully towards turning it into a product that can be purchased and installed.

In the future a controlled user study will be conducted to determine if captains using ARS will be less likely to have accidents due to inattention.

VII. Limitations and Future Work

A. Shore Detection

In order to achieve satisfactory results in debris detection, we are currently considering a future implementation of a method for detecting the shore based on terrain data from both marine and terrestrial charts and height maps. Using the boat's real-time position and orientation, it would be possible to render a 3d model of what the surroundings should look like. This rendered terrain image would then be used to identify

the shore. The terrain features that are not on the water will be subtracted from the real-time video feed. This way we aim at eliminating the possibility of shore features causing false detections.

B. Autonomy

This research project is a work in progress and in its future phases some aspects of this system could serve as inputs to an automatic navigation systems. Connecting a linear actuator to the helm would allow the implementation of an electromechanical system that will act as an autopilot; yet, in order to be able to experiment with vessel automation, it is vital that the shore and debris detectors perform satisfactorily.

C. Smart-glasses Deployment

We are currently in the starting phases of experimenting with deploying the ARS on a pair of smart-glasses (e.g. Google Glass), that add another camera, plus sensors relating to the device orientation. Using smart-glasses changes slightly the paradigm of the interface, focusing on an immersive experience of the environment and the boat separately. In this phase, the bow-mounted camera is replaced with two stereographic cameras and the smart-glasses interface will be represented completely in 3D, including background, debris highlights, wind and current animations and overlays.

VIII. Conclusion

We have presented the design of an augmented reality system to provide captains of sailboats access to vital data from a wide variety of sensors. A few sailboat captains have experienced a partial implementation of the system and comments have in general been favourable.

In the development process, from the early design beginnings and all the way throughout implementation, we have been in constant touch with experienced sailors who provided constant valuable feedback. Despite the potential to include various types of information, priority was given to selecting and displaying the information that is the most relevant and important.

IX. Acknowledgements

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