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MODELING AND INSPECTION APPLICATIONS OF A COASTAL DISTRIBUTED AUTONOMOUS SENSOR NETWORK

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ABSTRACT

Real time in-situ measurements are essential for monitoring and understanding physical and biochemical changes within ocean environments. Phenomena of interest usually display spatial and temporal dynamics that span different scales. As a result, a combination of different vehicles, sensors, and advanced control algorithms are required in oceanographic monitoring systems. In this study our group presents the design of a distributed heterogeneous autonomous sensor network that combines underwater, surface, and aerial robotic vehicles along with advanced sensor payloads, planning algorithms and learning principles to successfully operate across the scales and constraints found in coastal environments. Examples where the robotic sensor network is used to localize algal blooms and collect modeling data in the coastal regions of the island nation of Singapore and to construct 3D models of marine structures for inspection and harbor navigation are presented. The system was successfully tested in seawater environments around Singapore where the water current is around 1-2m/s.

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INTRODUCTION

This study presents the autonomous sensor network being developed at the Center for Environmental Sensing and Modeling (CENSAM) in Singapore and its applications to coastal environments. Ocean observing and prediction systems present challenges for vehicles, sensors, motion planners, data assimilation and predictive models. In addition, coastal environments have particular challenges such as low depths and commercial vehicle traffic which increase the likelihood of collisions. Our group is developing a distributed heterogeneous autonomous sensor network that combines underwater, surface, and aerial robotic vehicles along with advanced sensor payloads, planing algorithms and learning principles to successfully operate across the scales and constraints found in coastal environments. Its effectiveness relies on the seamless operation of all vehicles, their safe interaction with each other and the environment, the capability of collecting pertinent data, and the capability to analyze the collected data and use information within to optimize the sampling process. The two applications explored herein portray examples of basic tools for these objectives. The study first presents a description of the configuration and components of the autonomous sensor network developed by our group and subsequently two applications are described in detail: a procedure for algal bloom monitoring and 3D surface reconstruction. Preliminary results

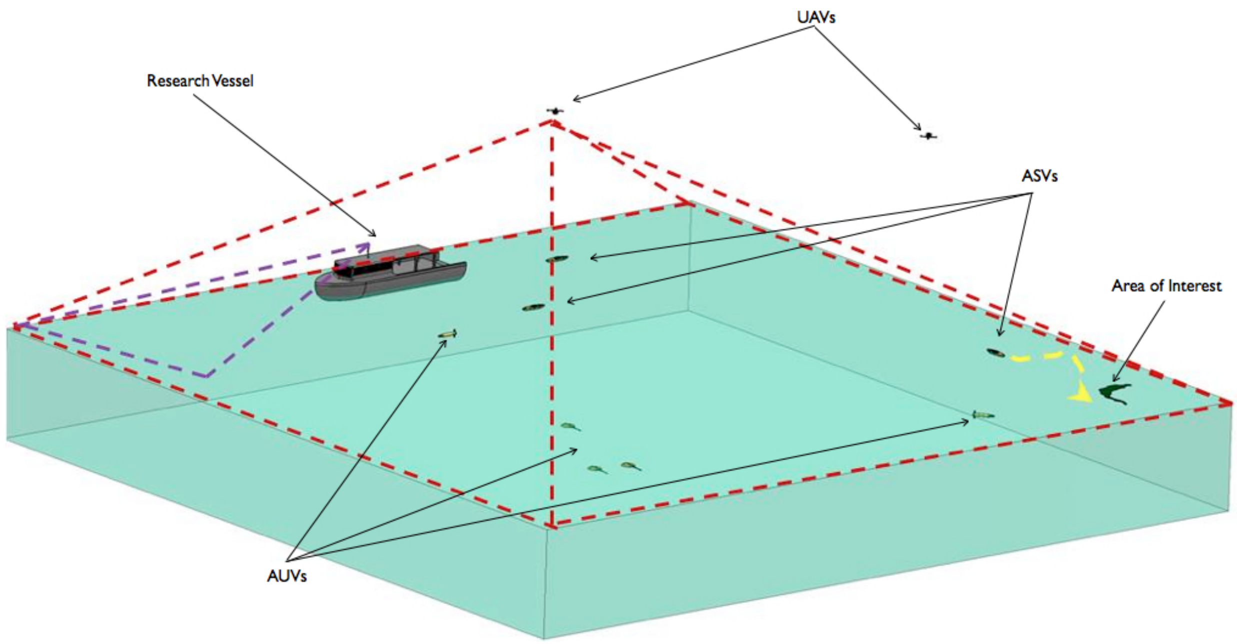


FIGURE 1. Stratified heterogeneous sensor network. Aerial, surface and underwater vehicles along with research vessels are used to span different spatial and temporal scales and optimally scan and monitor coastal regions. Dashed colored lines denote vehicle scanning range.

are summarized within each section and concluding remarks and future work are outlined.

AUTONOMOUS SENSOR NETWORK

Ocean observing and prediction systems have inspired both theoretical and experimental work. The Autonomous Ocean Sampling Network (AOSN) project [1, 2] outlined the significant challenges for the practical implementation of such systems. Other studies since have explored both hardware (vehicles and sensors) [3, 4] and software (motion planners, data assimilation, predictive models) [5–7] for use in robotic sensor networks to observe and forecast conditions in marine environments. This study presents an update on the autonomous sensor network being developed at CENSAM [8] and its applications to coastal environments. Fig. 1 shows a diagram of the typical spatial distribution of the active network nodes within CENSAM's network, which include research vessels, autonomous surface vehicles (ASVs), autonomous underwater vehicles (AUVs), and unmanned aerial vehicles (UAVs) of a quad-rotor design. The autonomous vehicles are shown individually in Fig 2. Large distances ($\sim 10^3$ meters) are covered by the quadrotors whose mission is to rapidly scan areas of interest and identify potential target zones. In addition to navigation related hardware, quadrotor sensor payloads include digital and infrared cameras. If a quadrotor identifies a feature of interest its location is geo-tagged and relayed to the rest of the network, subsequently a research vessel deploys autonomous underwater vehicles (Iver2 submarines from Oceanserver) and autonomous surface vehicles (SCOUT ocean kayaks equipped for oceanographic and undersea testing) within the vicinity of the areas of interest ($\sim 10^2$ meters). The AUVs and ASVs perform finer scanning passes inside the target zones to provide denser data for further analysis. In addition to inertial navigation and communication equipment, the surface and underwater vehicles are equipped with oceanographic sensors to measure pH, temperature, conductivity, chlorophyll, rhodamine, turbidity, and dissolved oxygen. Spectrophotometers (AC-9 from Wetlabs) are also used to measure the absorption and attenuation coefficients of the elements within the sampled zones.

ALGAL BLOOMS

The first application discussed for the robotic sensor network is the location and scientific survey of algal blooms in the coastal regions of Singapore. Harmful algal blooms are an increasing problem in the coastal waterways surrounding Singapore due to urban development as well as longer term climate changes. A toxic algal bloom in December 2009 resulted in 200,000 fish killed in the Pasir Ris area alone, and a second bloom by a different algal species occurred a month later in the same location. An understanding of the underlying ecological, chemical, tidal, and hydrodynamic factors is needed to develop

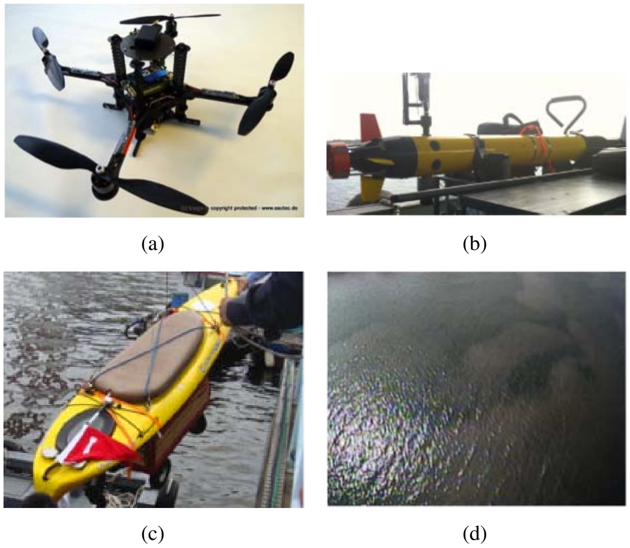


FIGURE 2. The quadrotor (a), AUV (b) and ASV (c) measurement vehicles and a bloom captured by the quadrotor's aerial camera in the Johor Straight (d).

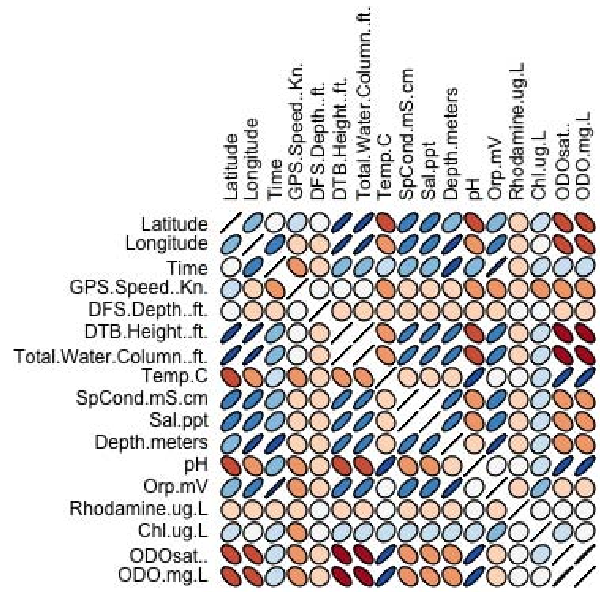
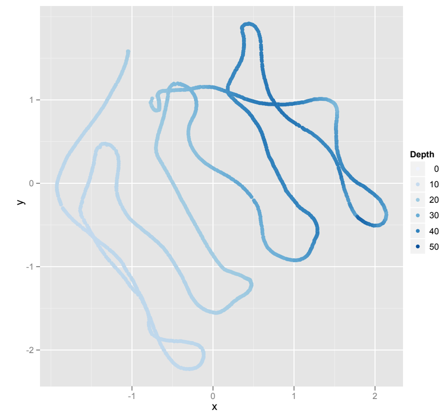


FIGURE 3. Correlation matrix of measured data assembled from multiple test sites along the northern coast of Singapore. Correlations between all the sensor variables have been shown to highlight major correlations, including the total height of the water column, the water temperature, the pH, conductivity, chlorophyll, rhodamine, and dissolved oxygen. The shape and color of the ellipse indicates if the correlation is weak (white circle) strongly positive (blue front leaning) or strongly negative (red back leaning), from [12].

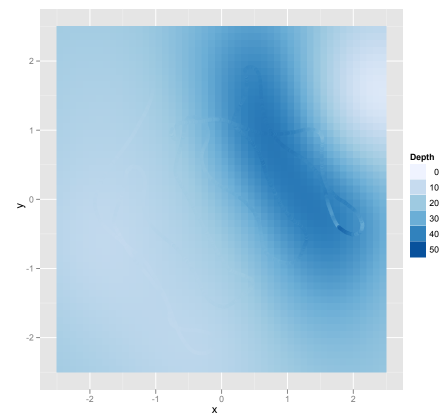
reliable models of these events. However, modeling a system with so many features and such a broad range of time and length scales is extremely difficult, and an autonomous network of sensing vehicles is an ideal approach to capture the data essential to develop such models. Using flexible kernel regression methods, seemingly disparate data sources can be combined in a meaningful way with heavier weighting given to more accurate data sources (such as GPS position data of the ASVs). Once compiled, this kind of information can be used to establish correlations between measured parameters across vehicles and to map out distributions of key parameters such as chlorophyll. As described in the previous section, quadrotors, equipped with digital and thermal cameras, scan large distances to identify areas of interest, in this case potential bloom zones. A research vessel deploys AUVs and ASVs within the vicinity of the areas of interest. The AUVs and ASVs perform finer scanning passes inside the target zones to provide denser data for further analysis. The vehicles are shown in Fig 2 along with one identified algal bloom in the Johor Straight between Singapore and Malaysia. Data from the quadrotor cameras and the in-situ measurements taken along the paths of the AUVs and ASVs must then be assembled into a coherent picture of a bloom.

The geo-tagged and time-stamped data are processed to identify correlations between the measured variables to help develop models of the bloom activity based on more easily predicted or measured variables such as temperature, local water depth, and tidal dynamics. An example of such data is presented in Fig 3 for all the sensor variables over all the data collected in one season. Because the sensors are not uniform across the vehicles and sensors occasionally malfunction, these correlations must be made between pairwise observations using Pearson's method.

While this kind of correlation information is important for model building, the data from the ASVs and AUVs must be tied back in to data from the quadrotor cameras and samples taken from research vessels. These sources of data are crucial for locating the ASVs and AUVs relative to the bloom activity which is identified visually (as in Fig 2(d)) or through positive identification of a harmful bloom species in a water sample. This requires that the sensor data from individual paths be extrapolated over the whole region as in Fig 4 where data from an AUV sampling path is extrapolated using regularized kernel regression, specifically the νSVR (Support Vector Regression) of [10] and [9]. As shown, the method expands the useful domain of the data from the path to the full region. The method also acts to filter out noise, such as the spurious spike at $t = 1200$, regularizing the signal without loosing the physical peaks.



(a)



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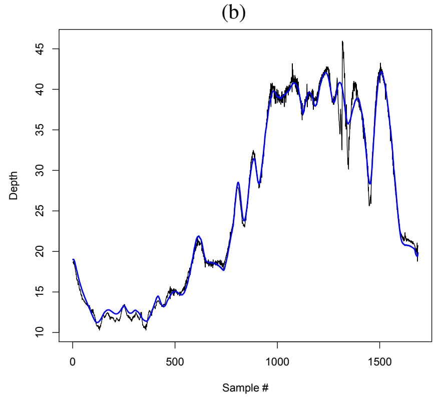


(c)

FIGURE 4. Depth data from a single AUV run. Figure (a) shows the path of the AUV and the data collected. Figure (b) shows the 2D reconstruction using regularized kernel regression with Figure (a) data overlay ([11]). Figure (c) shows the raw data (black) and kernel regression (blue) which shows that signal is regularized without loosing the physical peaks.

SURFACE RECONSTRUCTION

Another application of the robotic sensor network is to construct 3D models of marine structures. Marine structures are structures that are partially submerged. For safety, marine structures need to be inspected regularly for wear and tear. Manual inspection is tedious and even a small oversight can have severe consequences for the structure and the people inside or around it. A robotic system that can construct 3D models of marine structures would enable remote inspection and allow human field inspectors to focus on higher risk areas. This inspection strategy reduces the likelihood of oversights and improves the safety of marine environments. In this section we present the hardware and software infrastructure to construct 3D models of marine structures. Our current system uses a single ASV with multiple sensors. The hardware setup can be easily implemented on multiple ASVs to speed up inspection of large marine structures whenever necessary. Various multi-robot mapping algorithms, such as [13], can then be used to merge the 3D scan data from different ASVs.

Hardware setup

Due to the water currents and wakes that may move the ASV adversely, we would like to use a scanning sensor that can finish each scanning cycle quickly and has a relatively wide field of view. The high scanning frequency allows each scanning cycle to be completed before the ASV drifts significantly far from the position where the scanning cycle was started. This reduces the need to adjust different points within a single scan according to the ASV movement, and hence simplifies 3D model reconstruction. The wide field of view provides significant overlaps between subsequent scans of the environment, despite the unintended movement of the ASV due to water currents and wakes. Significant overlaps between subsequent scans allows merging subsequent scans into one coordinate system without knowing the scanner pose when the scans were taken, which is an important capability for 3D model reconstruction when the accuracy of the robot's positioning sensors is low. Note that the above sensor requirements do not need to be satisfied by both the sensor that scans above the waterline and the underwater part of the structures. When one of these sensors satisfies the above requirements, we can use the information for merging the scan data from one of the sensors to help the merging process of the scan data generated by the other sensor. In this work, the above requirements are satisfied by the sensor that scans the above the waterline part of the structures. To scan the above the waterline we use a Velodyne HDL-64E S2, a 3D LiDAR (Light Detection and Ranging) that finishes each scanning cycle in 0.1 seconds. In each scanning cycle, the LiDAR captures the entire 360^0 horizontal and 26.8^0 vertical field of view with $0.09^0 \times 0.4^0$ resolution. Unfortunately the Velodyne LiDAR cannot be mounted in its standard configuration on the ASV. When the LiDAR is

(a) (b) (c)

FIGURE 5. (a) The ASV setup for scanning the above and underwater parts of a marine structure. Note that additional pontoons are attached to the ASV to improve its stability. (b) The Velodyne LiDAR and the mounting platform for placing the LiDAR in an inverted configuration on the ASV. (c) The BlueView MB2250 micro-bathymetry sonar mounted in a sideways configuration.

mounted in its standard configuration, it sits low on the water relative to the structures we would like to scan. Since the LiDAR's vertical field of view spans from -24.8^0 to $+2^0$ and its range limit is 50m, in its standard configuration, the LiDAR can only scan parts of the marine structures from the water surface up to around 2 meters above the water surface. This is insufficient for our purpose. To overcome this difficulty, we mount the LiDAR in an inverted configuration, thereby generating a vertical field of view that spans from -2^0 to $+24.8^0$ and enables the LiDAR to scan parts of the marine structures from the water surface up to around 20 meters above the water surface.

However, mounting the LiDAR in an inverted configuration makes the ASV less stable. Since the LiDAR is quite heavy (around 13 kilograms) and its center of gravity lies near its bottom, which would sit high up in an inverted configuration, mounting the LiDAR in an inverted configuration significantly raises the center of gravity of the entire system. As a result, the ASV becomes less stable, especially in roll, and vulnerable to capsizing when operating in rough water environments. To mount the LiDAR in an inverted configuration and maintain stability, we designed a platform to mount the LiDAR in an inverted configuration on the ASV with two primary considerations: vehicle stability and sensor visibility. Fig 5(b) shows the mounting platform. The entire mounting structure is made with lightweight aluminium extrusions. The four posts bearing the weight of the sensor are tied together with triangulating pieces in the hull of the ASV to create a rigid platform to mount the LiDAR that is robust to motion in all directions. Furthermore, the four posts are narrow so that they have a minimal effect on the data collected by the LiDAR. Experiments with the LiDAR in this mount show that these posts cast insignificant shadows on the LiDAR returns. In order to ensure the stability of the ASV, we keep the centroid of the craft low by mounting the LiDAR as low as possible without encroaching on the sensor's field of view. Additionally,

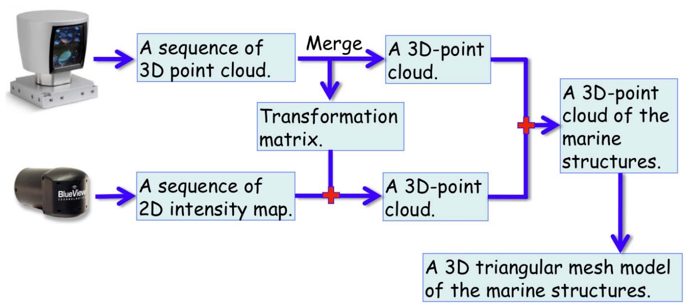
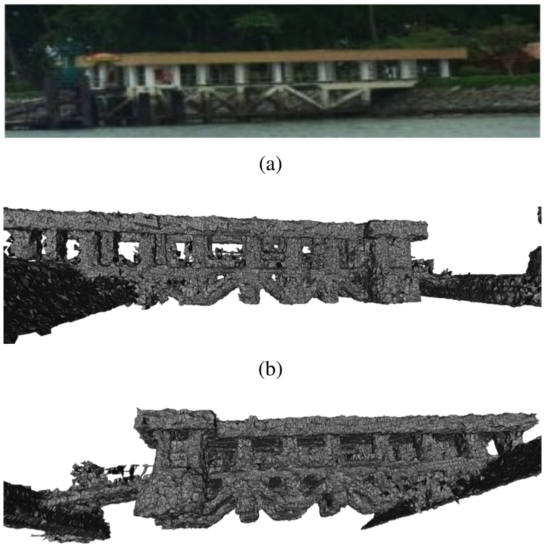


FIGURE 6. Processing steps for 3D model reconstruction of partially submerged marine structures.

to protect the ASV from rolling, its most vulnerable direction, we attach port and starboard stabilizers. These stabilizers consist of buoyant pontoons mounted on an aluminum square extrusion assembly that is fixed directly to the LiDAR's mount. The pontoons are streamlined to minimize the added drag. To scan the underwater part of the marine structure of interest, we use a 3D Microbathymetry sonar from BlueView (model MB2250-45). The MB2250-45 sonar uses 256 beams with one degree beam width in the elevation. Since we are interested in mapping marine structures, instead of mounting the sonar in the default forward-looking configuration, we mount it sideways on the vehicle (Fig 5(c)). The overall setup of is shown in Fig 5(a).

Software for 3D model reconstruction

The main difficulty in 3D model reconstruction is that GPS signals are often blocked by the structures themselves during operation. Furthermore, we need to merge the 3D scan data of the above the waterline part of the structures with 2D scan data of the underwater part of the structures. To overcome the lack of GPS information, we use a scan matching technique to construct the

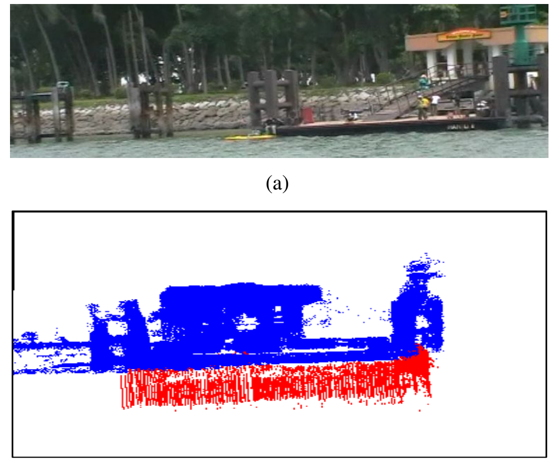


(a)

(b)

(c)

FIGURE 7. Mesh-based map for the above the waterline part of the jetty.



(a)

(b)

FIGURE 8. Point clouds map for the above and underwater part of the jetty.

3D model for above the waterline part of the structures. We then use the transformations, computed by the scan matching algorithm for the above the waterline part, to construct the 3D model of the underwater part of the structures. We combine the 3D model of above the waterline and underwater parts to construct a complete 3D model of the partially submerged marine structure. A diagram of this process is shown in Fig 6.

Experimental Results

We have tested our system successfully to construct a jetty in Pulau Hantu, Singapore. The water currents during operation were around 1-2m/s. The reconstructed 3D model can be seen in Fig 7 and Fig 8. Higher resolution mesh-based maps are shown in Fig 7, while lower resolution point cloud maps are shown in Fig 8. The maps can be used for inspection (high resolution) or navigation in cluttered environements (lower resolution).

CONCLUSIONS AND FUTURE WORK

The vehicles and operational configuration of the coastal distributed autonomous sensor network being developed at CENSAM were presented in this study. Two applications showcasing important tools for ocean surveys and modeling were described: algal bloom monitoring and 3D surface reconstruction.

Algal blooms represent a major concern in coastal environments as they have significant humanitarian and economical impacts. Our group uses the exploration and monitoring capabilities of a sensor network along with statistical analysis to enable increasingly accurate models of bloom activity. Aerial, surface, and underwater vehicles were combined to sample and detect biochemical preconditions for algal blooms in the coasts of Singapore. A wealth of biochemical data (ph, chlorophyll, temperature among others) is being analyzed using learning models to understand and predict algal bloom occurrences.

Inspection and operation in cluttered environments requires 3D maps to facilitate the operation of autonomous vehicles. 3D feature reconstruction of a medium sized marine structure (jetty) was successfully tested using surface vehicles equipped with LiDAR and sonar. Both low and high resolution maps can be generated with the presented approach which can be used for either navigation or inspection depending on mission goals. In the current setup, the LiDAR's sampling rate and its relatively wide field of view allow each scanning cycle to be completed before the ASV drifts significantly far from the position where the scanning cycle began, even in currents as high as 1-2m/s. However, further tests are still needed to find the actual operating limits and reliability under stronger environmental disturbances (e.g. wind and wave conditions) typically encountered in marine applications.

Our group will continue testing these tools in larger scale missions involving more vehicles and more severe environmental disturbances as well as developing further tools for oceanographic studies.

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