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Design and Development of a Wireless Robotic Networked Aquatic Microbial Observing System

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ABSTRACT

This paper describes the design, development, and initial application of a sensor-actuated network for sensing and sampling microbial communities in aquatic ecosystems. The network consists of ten stationary buoys and one mobile robotic boat for real-time, *in situ* measurements and analysis of chemical and physical factors governing the abundance and dynamics of microorganisms at biologically relevant spatiotemporal scales. The goal of the network is to obtain high-resolution information on the spatial and temporal distributions of plankton assemblages and concomitant environmental parameters in aquatic environments using the *in situ* presence afforded by the network and to make possible network-enabled robotic sampling of hydrographic features of interest. This work constitutes advances in (1) real-time observing in aquatic ecosystems and (2) sensor actuated sampling for biological analysis.

Key words: sensor-actuator network; aquatic microbial observing system; robotic sensor network; plankton dynamics

INTRODUCTION

Aquatic microorganisms (viruses, archaea, bacteria, microalgae, protozoa) play fundamental roles in the ecology and biogeochemistry of marine and freshwater ecosystems. Planktonic cyanobacteria and eukaryotic microalgae produce much of the organic matter that constitutes the base of the food webs in these ecosystems (Falkowski, 1994), while archaea, bacteria, and heterotrophic protists (protozoa) consume or degrade much of this primary production via trophic interactions and decompositional processes (Cole *et al.*, 1988; Sherr and Sherr, 2002). Collectively, microbial assemblages and their processes dominate the biogeochemical cycles of our planet (Karl, 2002; Karl *et al.*, 2003).

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On the other hand, microorganisms can cause ecological damage and present significant risks to human health. Blooms of harmful algae (e.g., red, brown, and green tides) appear to be on the rise globally (Smayda, 1989) and presently result in the loss of tens of millions of dollars annually in the United States due to impacts on commercial and recreational fisheries (particularly shellfish resources) and tourism (Anderson *et al.,* 2000). Similarly, contamination of drinking water supplies, beaches, and other recreational waters with sewage and/or urban runoff causes economic loss and represents an increasing threat to human health (Pruss, 1998). Detection and characterization of these events is improving, but the time scales for responding to impending or emerging problems are still too long to avoid unfavorable and costly outcomes (Corso *et al.,* 2003).

A primary scientific goal in aquatic science is to understand, predict, and ultimately ameliorate the environmental conditions under which specific populations of aquatic microorganisms develop in nature or to identify the sources from which they originate (e.g., in the case of sewage entering aquatic ecosystems). In order to be useful, these measurements must be performed at fine spatial and temporal scales that are relevant to the organisms, their ecologies, and the environmental setting. They must also be carried out in conjunction with approaches that can collect samples for later analyses of microbial presence and/or activity (or, ultimately, for onboard analyses). This level of presence in equatic ecosystems has not been possible using extant technology and methodologic approaches. Only recently have large-scale networks been designed and implemented (Glenn *et al.,* 2000). While these scales of measurement are appropriate for addressing some questions, the observational systems do not provide sufficient spatiotemporal coverage (or concomitant biological sample collection) required to facilitate improvements in our fundamental knowledge of the factors controlling the distributions of planktonic microbes.

Sampling the environment with high resolution in real time using embedded sensor networks constitutes a revolutionary step forward in the study of the ecology of aquatic microbial species (Glasgow *et al.,* 2004; Porter *et al.,* 2005). Combined with a new generation of techniques to rapidly identify aquatic microorganisms (UMCES, 2005), such networks provide extremely valuable tools for the early detection of organisms of human interest and the mitigation of their effects on the environment and human population.

The goal of developing a predictive understanding of aquatic microorganismal distributions warrants a continuous (sensing) presence in the environment to enable real-time acquisition and analysis of chemical and physical data collected at relevant spatiotemporal scales and correlated with measurements of specific microorganisms. However, at the scales required to attain this goal, it is typically infeasible to deploy a set of stationary monitoring stations that will provide sufficient spatial density and continuous monitoring. Conversely, deploying a fleet of mobile autonomous vehicles might provide adequate spatial coverage but insufficient temporal coverage. The concept of deploying a high-density wireless network consisting of both stationary and mobile components to aid each other has been recently introduced (Batalin *et al.,* 2005). Stationary buoys provide low-resolution spatial sampling with high temporal resolution while a mobile robotic boat provides high-resolution spatial sampling with relatively low temporal resolution. Collectively, we believe this network provides unprecedented coverage and thus unique insights into microbial plankton distributions and dynamics. Here we describe our prototype sensor-actuator network consisting of 10 buoys and a robotic boat, equipped with a collection of simple off-the-shelf sensors (GPS, thermistors, fluorometers) that can be deployed *in situ* to gather and analyze relevant data in an aquatic environment. We describe the design of the system and report on data collected from preliminary field trials.

SYSTEM DESCRIPTION

The stationary nodes (buoys) continuously monitor the aquatic environment at the location at which they are deployed and communicate the collected sensor information to a shore-based station and to the robotic boat, which is capable of autonomous navigation and sampling. We begin by giving an overview of the hardware constituents of the system.

Hardware

Each stationary node consists of a stargate board, an ADC board, a battery, a fluorometer, and an array of six thermistors, which are mounted on a wooden chassis and sealed inside a waterproof container (Fig. 1). The Stargate board (Fig. 2e) uses Intel 400 MHz XScale processor (PXA255; Crossbow Technologies, San Jose, CA) and an 802.11b wireless card for inter-node communication. It locally logs sensor data received from the ADC board and transmits such data back to a base station. The ADC board (Fig. 2d) consists of a basic stamp module (24 pin microcontroller BS2sx from Parallax Inc., (Rocklin, CA) (Fig. 2c) and two ADC chips (16 bit single channel ADS1100 and 12 bit 8 channel ADS7828 from Digi-Key, Analog Devices, Norwood, MA). We use the basic stamp to control the two ADC chips to obtain data from the sensors.

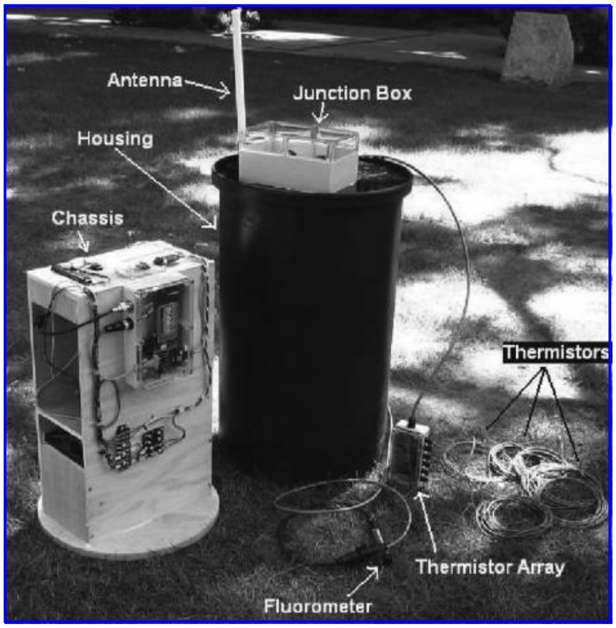

Figure 1. The hardware configuration of a stationary buoy node. A wooden chassis holds the computer and interface boards and is mounted within a waterproof housing.

The ADC board is connected to the Stargate board through a USB/Serial converter.

The present node configuration uses two types of sensors: fluorometers and thermistors. A fluorometer (Fig. 2a) estimates the concentration of chlorophyll *a*, which is indicative of the density of photosynthetic microorganisms in the environment. We use the CYCLOPS-7 submersible fluorometer from Turner Designs (Sunnyvale, CA) for chlorophyll *a.* It has three user settable gain ranges, which provide a wide measurement dynamic range of 0.03 to 500 μg/L. The thermistors (Fig. 2b) have an accuracy of 0.1°C. They are covered with a custom titanium coating for corrosion resistance. The sensors are suspended from the buoy into the water. The fluorometer is lowered to a specified depth while the six thermistors are uniformly deployed from 0.15 to 2.65 m below the water surface. Each buoy is powered by a car battery, which can be recharged via an external solar panel. Without recharging, a buoy can operate continuously for approximately a week. Preliminary measurements indicate that connecting the solar panel could potentially meet the power requirements of a buoy indefinitely, with attendance reduced to accommodating the service schedule of the sensors.

The robotic boat is a modified RC airboat (Fig. 3). An air propeller provides propulsion and minimizes disturbance to the water. All processing modules are connected to the main processor (the Stargate board) via the RS-485 bus (Fig. 4), which allows integration of additional modules without affecting the existing modules. The boat is equipped with a GPS (Garmin 16A, Olathe, KS) (Fig. 5a) and compass (V2XE 2-axis digital compass, PNI Corp., Santa Rosa, CA) (Fig. 5b) for navigation. The sensor suite on the boat consists of a thermistor and a fluorometer that are interfaced with the boat via the ADC board similar to the one on the stationary nodes. In addition, the boat is equipped with a six-vial sample collection cartridge that can acquire six 3 mL samples in-

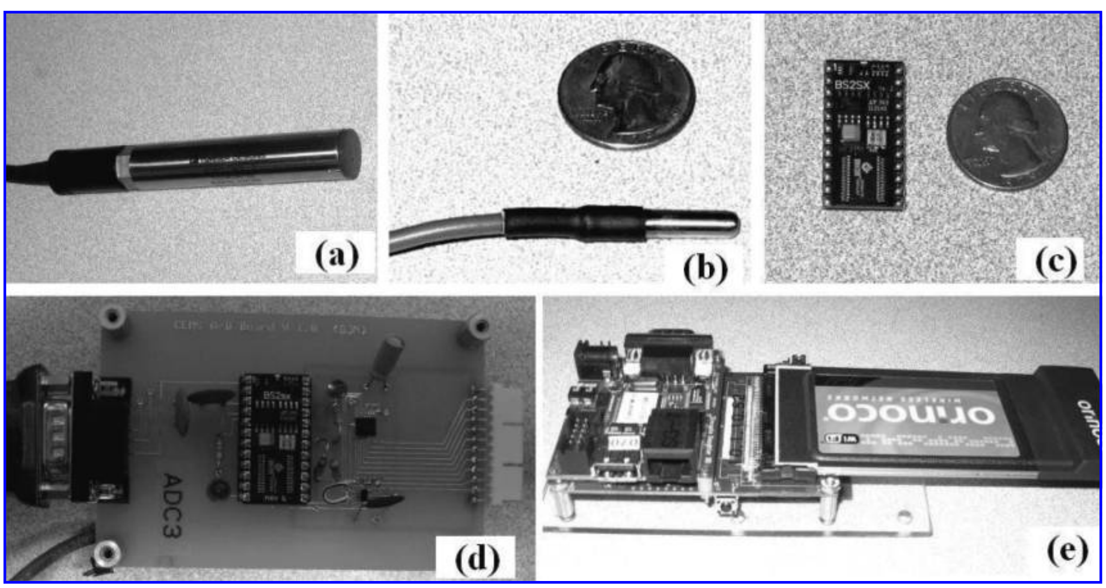

Figure 2. Sensing, communication, and processing hardware on each buoy and the robotic boat. **(a)** Fluorometer; **(b)** thermistor; **(c)** basic stamp; **(d)** ADC board; **(e)** Stargate board.

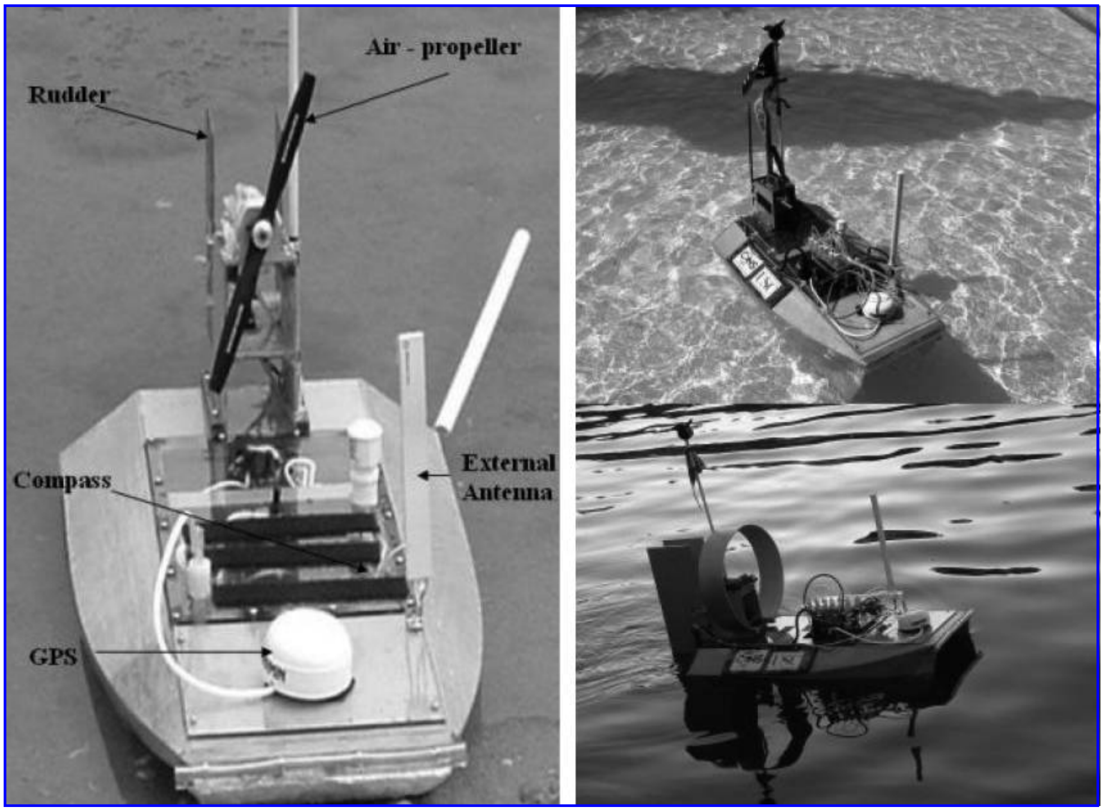

Figure 3. External views of the robotic boat. The airboat configuration minimizes stirring of the water during experiments.

dependently under instructions provided to the boat through the network (Fig. 5c). Sample collection is controlled by a basic stamp module through a motor controller (a 36 vial version is under development).

Communication with other nodes takes place via an 802.11b wireless connection. The boat is powered using rechargeable NiMH batteries, which at present give it an approximate lifetime of 4-6 h of continuous operation.

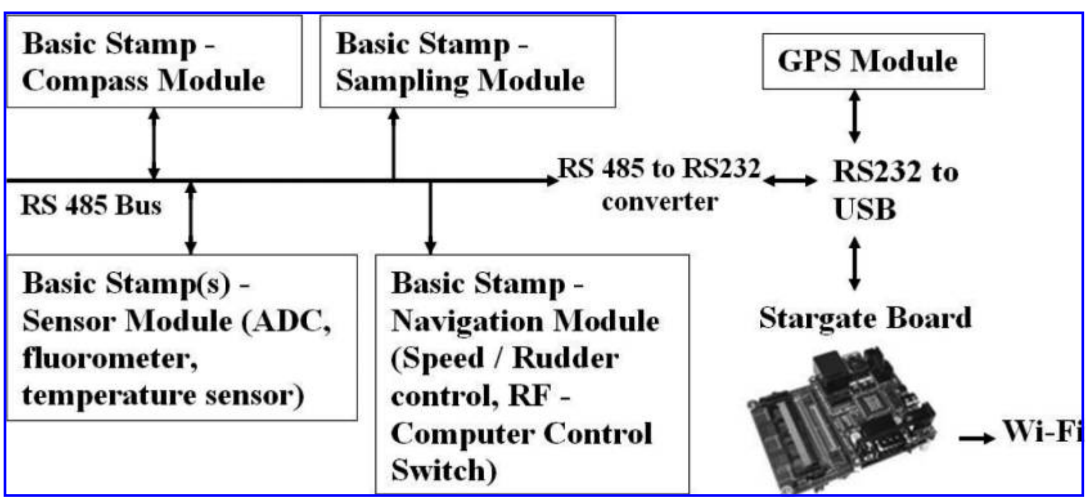

Figure 4. Overall system architecture of the robotic boat. The main processor (Stargate) communicates with the peripheral systems over a shared bus. Each peripheral system is controlled using a basic stamp module. All communication with the base station and buoys is over WiFi on the main processor.

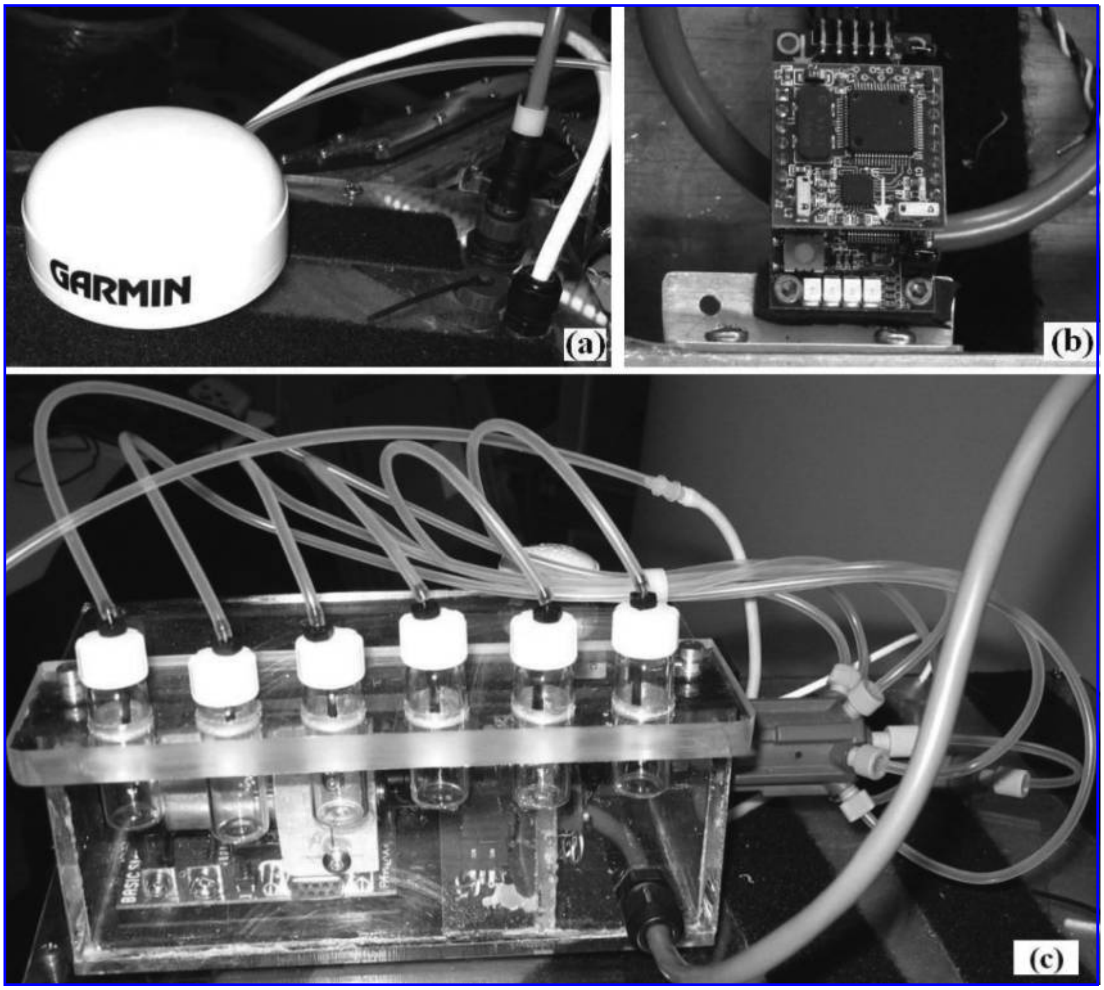

Figure 5. Sensing and sampling on the boat. **(a)** GPS; **(b)** compass; **(c)** 6-vial custom water sampler.

Software components and algorithms

Our software system is built atop EmStar, a software system for developing and deploying wireless sensor networks involving Linux-based platforms (Girod *et al.,* 2004). There are three principal components. The first reads, logs, and transmits sensor data. The stationary nodes are configured to run in *ad hoc* mode. A multi-hop protocol is used to create a dynamic routing tree, which can reliably route packets through the network. This component is also responsible for time synchronization that is essential for time stamping the gathered sensor data. The second component is the interface between the sensor network and the users. This component communicates with the first component running on the stationary nodes and forwards packets between the network and users. The third component is a toolkit to visualize the sensed data. This toolkit is built with Matlab and Java, provides a graphical interface for the system, and can be used to initialize and stop the process of data collection. Finally there is a set of miscellaneous software tools for retrieving and visualizing the data logged on the stationary nodes.

The boat is directed by information collected and processed within the network to identify features of biological interest. The Stargate board on the boat receives and processes the inputs from the GPS, compass, sensors, and network, makes decisions, and sends appropriate navigation commands to the navigation module. The basic stamp in the navigation module converts these into appropriate commands for the motor controllers, which are connected to the rudder and the propeller. By sending appropriate commands, the boat can navigate in both forward and reverse directions. The robotic boat operates in three modes. In the radio-controlled mode, the boat is controlled using RF control from the shore. In the computer-controlled mode, appropriate control commands can be sent from the base station to the boat over the *ad hoc* network. In the autonomous mode, the boat uses GPS waypoint locations (set by a human user or the buoy network) and sensor information to compute control commands. Autonomous navigation over water is not trivial since wind and water currents affect the boat's heading and speed. Limited GPS availability and inaccuracies in sensor information (both GPS and compass) introduce further problems and are an area of ongoing research. We use a PID controller to compensate for disturbances and sensor errors while performing waypoint following. Based on the accuracy of the GPS, the system dynamically adjusts its error tolerances for waypoints, resulting in reliable waypoint following in varying conditions. Figure 6 gives a high-level pseudocode description of the waypoint navigation and control algorithms. Location tracking relies on the onboard GPS system. In the absence of GPS, a call is made to the function GetStateEstimate() that filters inertial data and motor commands to estimate location. Similarly, heading tracking relies on the onboard compass. In the absence of reliable compass readings, a call is made to GetStateEstimate(), which filters inertial data and motor commands to estimate heading.

The boat collects position and time-stamped measurements of both temperature and fluorometry data, which are transmitted to the network for further analysis. It can also be programmed to collect water samples at designated GPS locations for further lab analysis.

EXPERIMENTS AND RESULTS

Initial field tests of the robotic boat were carried out at Shelter Island, NY, during May 2004, and subsequently

Algorithm 1 Navigation and sampling.

Input: A boat equipped with a GPS and compass as sensors. A set of GPS locations ($location_{target}$) for the boat to follow in the order specified.
{INITIAILIZATION: Obtain initial GPS fix. Calibrate compass.}
Output: (i) Path traversed by the boat. (ii) Position and time-stamped temperature and chlorophyll data and water samples.
{Select a GPS way-point as the target for the boat}

while more gps way-points specified **do**
  select next way-point as ($location_{target}$)
  repeat
    $location_{current}$ = GetCurrentLocation()
    $heading_{current}$ = GetCurrentHeading()
    GenerateControlCommand($location_{current}$, $location_{target}$, $heading_{current}$)
    CollectSample($temperature$, $chlorophyll$)
  until ($location_{current} = location_{target}$)
  CollectSample($water$)
end while

Algorithm 2 GetCurrentLocation(). Get the current Latitude and Longitude of the boat.

Input: A boat equipped with a GPS sensor.
Output: Current location of the boat ($location_{current}$).

$gps_{currentReading}$ = Read(gps)
if ($gps_{currentReading} \neq gps_{previousReading}$) **then**
  $location_{current} = gps_{currentReading}$
  {Current location is the new state of the boat}
  SetState($gps_{currentReading}$)
else
  $location_{current}$ = GetStateEstimate($location$)
end if

Algorithm 3 GetCurrentHeading(). Get the current heading of the boat with reference to geographical North.

Input: A boat equipped with a compass.
Output: Current heading of the boat ($heading_{current}$) wrt. geographical North.

$compass_{currentReading}$ = Read($compass$)
if ($compass_{currentReading} \neq compass_{previousReading}$) **then**
  $heading_{current} = compass_{currentReading}$
  {Current heading is the new state of the boat}
  SetState($compass_{currentReading}$)
else
  $heading_{current}$ = GetStateEstimate($heading$)
end if

Algorithm 4 GenerateControlCommand(). Set Rudder.

Input: Current location of the boat ($location_{current}$), specified target location ($location_{target}$), current heading of the boat ($heading_{current}$)
Output: Turn command for rudder ($command_{turn}$).

$error_{latitude} = location_{target}.lat - location_{current}.lat$
$error_{longitude} = location_{target}.lon - location_{target}.lon$
{Desired heading from North direction}
$heading_{desired}$ = 90 - atan($error_{latitude}$, $error_{longitude}$)
$heading_{error} = heading_{desired} - heading_{current}$
$heading_{PID-fix}$ = PIDCorrection($heading_{error}$)
$command_{turn}$ = GenerateCommand($heading_{PID-fix}$)

Figure 6. Algorithm 1 is the main loop for navigation and sampling, which makes calls to Algorithms 2 (location tracking), 3 (heading tracking), and 4 (rudder control). Location tracking relies on the onboard GPS system. In the absence of GPS, a call is made to the function GetStateEstimate(), which filters inertial data and motor commands to estimate location. Similarly, heading tracking relies on the onboard compass. In the absence of reliable compass readings, a call is made to GetStateEstimate(), which filters inertial data and motor commands to estimate heading.

in Echo Park, Los Angeles, CA, and Lake Fulmor, San Jacinto Mountains, CA. Three larger-scale field deployments of five or more stationary nodes and the boat were carried out in Lake Fulmor in May (4 days), July (2 days), and October (4 days) 2005. The stationary network continuously monitored and recorded temperature and fluorometric data while simultaneously providing real-time visualization of chlorophyll *a* and temperature across the surface of the lake (Fig. 7). Real-time streaming of data and coalescence of the data from individual buoys into

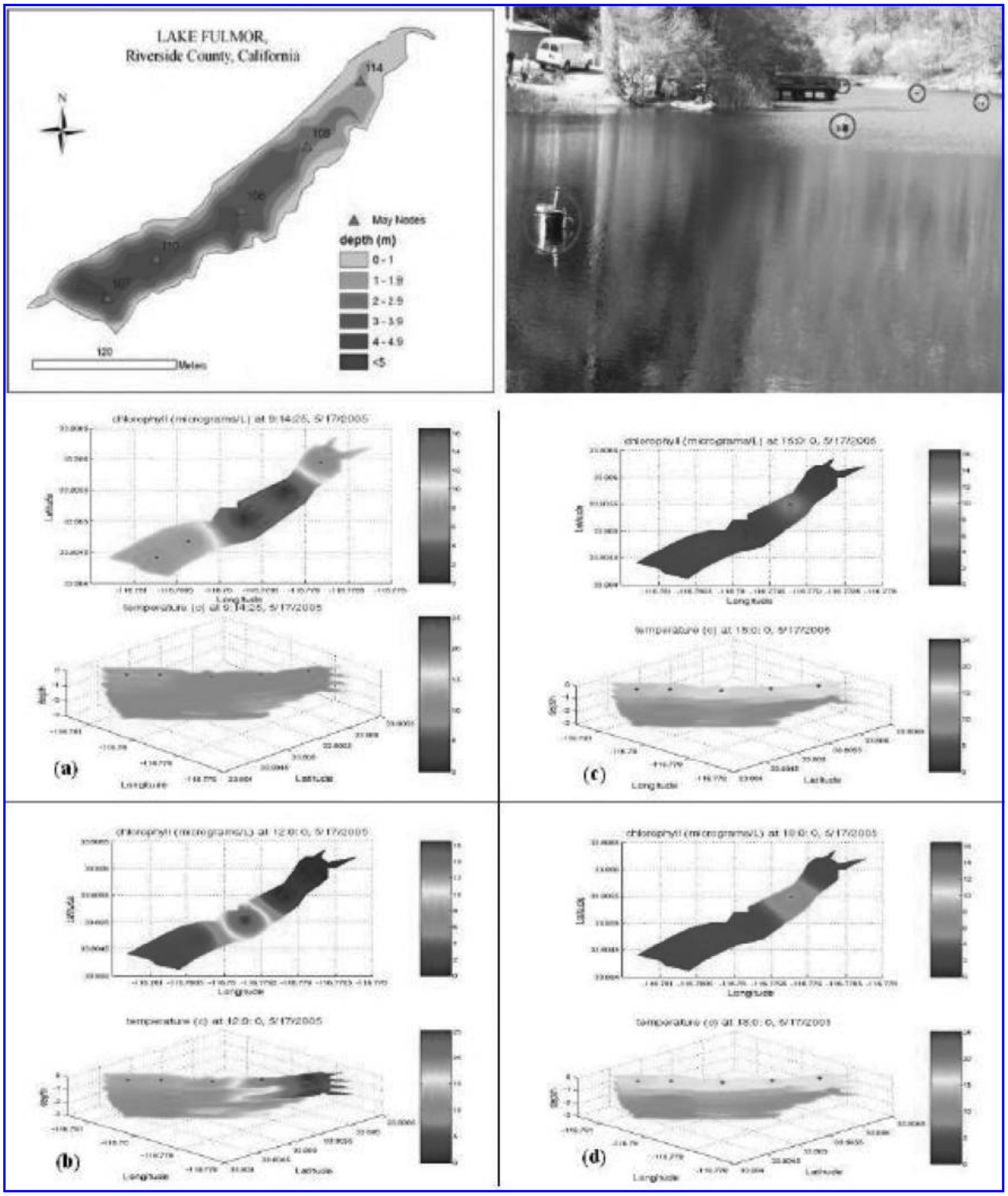

Figure 7. Fluorometric and temperature data from NAMOS deployment in Lake Fulmor on May 17, 2005. *Top left:* Lake bathymetry with node locations indicated by triangles. *Top right:* Photograph of the lake showing stationary nodes (circles). Patterns of chlorophyll (upper figure) and temperature (lower figure) downloaded from the stationary sensor network at ~0900 h **(a),** ~1200 h **(b),** ~0300 h **(c),** and ~0600 h **(d).**

spatial patterns of chlorophyll and temperature from this number of buoys has not been accomplished previously to our knowledge. The top sub-picture in each visualization depicts the chlorophyll *a* distribution in the lake while the bottom picture shows the vertical and horizontal patterns of temperature in 3-D. The pattern of chlorophyll distribution was synthesized within the network, then transferred to the boat to direct sample collection.

In each of the Lake Fulmor deployments, relative chlorophyll concentrations varied spatially along the surface and temporally on daily cycles, apparently indicating a phytoplankton population that was actively migrating in the water column and/or affected by mixing within the water column (for a preliminary assessment of the significance of these data, see Stauffer *et al.,* 2005). Briefly, changes in chlorophyll concentrations at 0.5 m revealed substantial spatial heterogeneity across the whole lake, with a mid-lake maximum in chlorophyll fluorescence during the morning and midday. In addition, substantial differences in chlorophyll fluorescence were also observed during a 24 h period throughout the lake (compare chlorophyll data in panels in Fig. 7). High spatiotemporal variability in chlorophyll concentrations within the lake during the July and October deployments were also observed, although the specific patterns differed among the deployments. These results indicated a plankton assemblage that was highly dynamic seasonally, but also (unexpectedly) over short space and time scales within each deployment.

A diel pattern in chlorophyll *a* observed at individual buoys during May was supported by temporal changes in the pattern of chlorophyll *a* across the lake (Fig. 7). A broad maximum in chlorophyll *a* concentration near the middle of the lake was present at 0900 h on May 17, 2005. The spatial extent of this peak in chlorophyll *a* concentration decreased in size by 1200 h although peak concentrations remained high at the center of the feature. Chlorophyll concentrations near the surface throughout the lake were greatly reduced by 1500 h and remained low at 1800 h. These decreases in chlorophyll concentration were approximately an order of magnitude. The patterns of chlorophyll and temperature obtained from the sensor network provided a unique view of the temporal and spatial heterogeneity of plankton biomass in the lake. This "whole lake" assessment has generated hypotheses that integrate the contributions of water movement, light adaptation, and diel vertical migration by the phytoplankton assemblage as major factors controlling the standing stock and vertical distribution of phytoplankton in the lake.

The daily pattern in water temperature in Lake Fulmor during May 2005 was featureless in the morning (0900 h) both horizontally and vertically (Fig. 7a, lower picture). The temperature at that time was relatively constant throughout the lake at approximately 12–14°C. This pattern changed dramatically by 1200 h, with substantial heating of water at the northeast end of the lake, but little change in the lower two-thirds of the lake. Maximum temperature at the northern edge of the lake approached 25°C. Water enters the lake at the northeast end and passes through an adjacent marsh area before reaching the lake proper. Temperatures at 1500 and 1800 h indicated uniformly warm surface waters (range of $\sim$14–16°C) horizontally across the lake, presumably due to wind-driven spreading of warm waters from the northeast section of the lake. It is unknown at this time how these substantial heterogeneities in the spatial and temporal patterns of surface water temperatures may have affected the distributions or activities of planktonic microbes, but these are topics of active research.

The robotic boat successfully operated in conjunction with the stationary network performing autonomous GPS waypoint navigation between the nodes collecting sensor data as it moved. Figure 8 shows a typical path followed by the boat while moving from one GPS waypoint to another. The navigational capabilities of the robotic boat, coupled with the chlorophyll information collected from the network of stationary nodes, enabled the collection of water samples at pertinent biological features (e.g., chlorophyll maxima) for lab analysis.

DISCUSSION

Deployments of the NAMOS system in Lake Fulmor, CA, afforded a constant *in situ* presence, which yielded information from several locations in the lake throughout the 2 to 4 day deployments. This level of observations enabled a "whole system" approach to understand physical/chemical processes taking place in the lake and thus useful information for developing hypotheses regarding ecosystem level processes and an excellent setting for future experimental tests of those hypotheses. Although our network employed relatively simple off-the-shelf sensor technology, the incorporation of more sophisticated or more specialized sensors will provide a rich data environment for detecting and characterizing features and processes of interest. The incorporation of sensors for dissolved oxygen, pH, photosynthetically active radiation, and selected nutrients will significantly improve the ability to provide an environmental context for explaining the distributions and abundances of planktonic taxa. In addition, the construction of the next generation of robotic boat (now underway) will incorporate a winch for vertical profiling of these environmental parameters.

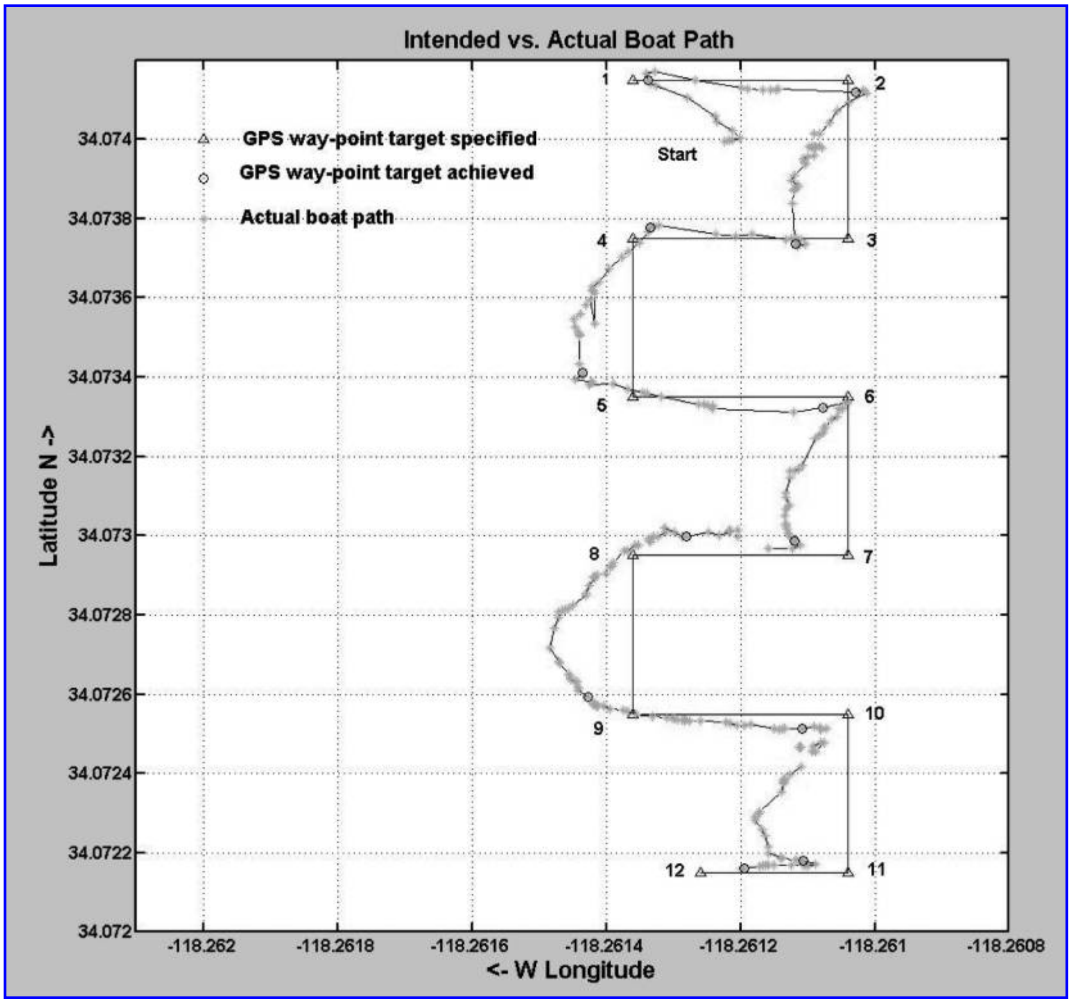

Figure 8. A radiator pattern navigation trace for the boat operating in autonomous waypoint-following mode.

Equally important, the presence of the wireless network allowed the utilization of spatial information collected and synthesized from the stationary nodes to guide the boat to locations that best optimized sampling effort. The ability to collect samples from aquatic ecosystems presently surpasses the capacity to process samples for most biologically meaningful parameters. Therefore, use of the sensor network to optimize the sampling effort of a mobile sampling robot constitutes a significant improvement in cost efficiency and labor allocation to identify and sample features of biological interest. The use of wireless sensor networks in ecological research is now recognized as a feasible and highly informative means of acquiring information on natural ecosystems (Porter *et al.,* 2005). To date, however, most of these systems exist or are envisioned as networks that would encompass spatial scales much larger than those controlling individual aquatic microbial populations. The buoy system described here represents a network that can be deployed at a variety of scales, including those that can capture the small-scale processes affecting the success or demise of planktonic populations. The use of the robot within this network further improves the ability to characterize, respond to, and sample small-scale ephemeral events that might significantly affect microbial distributions in nature.

The addition of solar panels to recharge batteries should increase the duration of deployments to periods dictated by the requirements of the sensors rather than the need to recharge batteries, thereby producing longer-term data on the temporal distribution of phytoplankton in the lake. In addition, the cooperative function of the autonomous boat with the stationary network allows for more specific interrogations of the environment and the collection of samples, which are essential to the characterization of phytoplankton populations. In the three Lake

Fulmor deployments described in this paper, for example, different species were found to be dominant in samples collected by the autonomous boat. A mixed microalgal assemblage was widespread in May, while samples collected in July were heavily dominated by the cyanobacterium *Anabaena spheriodes,* and a diverse cyanobacterial community was present in October. These patterns of succession imply significant shifts in the environmental conditions, which in turn dictate the composition of the phytoplankton community. However, characterizing the parameters responsible for these patterns of succession here or in other aquatic environments has been difficult. The use of our sensor network provides, for the first time, the technological capability to sufficiently characterize the physical and chemical environments on the appropriate scales of time and space to facilitate fundamental understanding of these plankton dynamics.

CONCLUSION

We describe herein the design and use of a sensor-actuator network for an aquatic observing system. We have designed a network to establish patterns in sensed data and use that information to guide a mobile boat and recover samples as features of interest (as determined by the pattern generated by the network). Our fieldwork demonstrates the basic functionality of the system, which constitutes a major step forward in the use of embedded networked sensing in aquatic ecosystems. The data collected from the deployments have revealed interesting spatiotemporal patterns of chlorophyll and temperature and were useful to validate the design of the buoys and the boat.

Documenting the distributions, abundances, and activities of microbial species and understanding the factors that dictate their distributions are dominating themes in modern aquatic biology. The ephemeral nature of aquatic ecosystems, and our limited ability to observe these environments directly, thwarts the development of unifying theories for understanding and predicting the dynamics of these communities. The technology described here will enable studies to characterize the relative contributions and interplay between microbial growth, physiology/behavior, and physical processes in determining the distributions and activities of planktonic microbes.

Our wireless sensor system allows the characterization and monitoring of environmental and biological parameters at a resolution previously unattainable in traditional approaches of aquatic biology. The technological approach described here will provide real-time presence that will stimulate new hypotheses and novel approaches. These capabilities include multi-scale sensing approaches that will provide unique insights into microbial population dynamics, allow the observation and documentation of key features of aquatic ecosystems that will facilitate the construction and parameterization of models predicting microbial dynamics, and address specific needs for ecosystem monitoring and surveillance. Specific questions generated from our recent deployments involve the interplay between photoadapation by phytoplankton, swimming behavior (i.e., diel vertical migration), nutrient status, and physical processes (wind-induced water movement) as local stimulants of phytoplankton growth and contributor to the development of algal blooms. Applications in other settings might include localizing point-source contamination of drinking water sources, monitoring water quality at swimming beaches, or examining the timing, extent, and causes of hypoxic events in freshwater and marine ecosystems. Thus, we believe this technology has far-reaching application.

Deployments and experiments have been scheduled for the future, designed to further investigate microbial abundances. Ongoing work includes improving autonomous boat navigation and improving the stability of the boat to withstand and compensate for stronger air and water currents. A significant portion of our future work is the design and testing of adaptive sampling algorithms, allowing the buoys to guide the sampling process.

ACKNOWLEDGMENTS

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