Demo Abstract: An Underwater Sonar-Based Drowning Detection System

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ABSTRACT

Drowning is a major cause of unintentional deaths in swimming pools. Most swimming pools hire lifeguards for continuous surveillance, which is labor-intensive and hence unfeasible for small private pools. The existing unmanned surveillance solutions like camera array requires non-trivial installations, only work in certain conditions (e.g., with adequate ambient lighting), or raise privacy concerns. This demo presents SwimSonar, the first practical drowning detection system based on underwater sonar. SwimSonar employs an active ultrasonic sonar and features a novel sonar scanning strategy that balances the time and accuracy. Lastly, SwimSonar leverages a deep neural network for accurate drowning detection. Our experiments in real swimming pools show that the system achieves 88 % classification accuracy with a scan time of 1.5 seconds.

CCS CONCEPTS

• **Computer systems organization** → **Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability.

KEYWORDS

drowning detection, sonar, sensor system

1 INTRODUCTION

According to World Health Organization, drowning is the third leading cause of unintentional death around the world, which is estimated to incur 236, 000 cases annually [6]. Lack of close supervision is one of the major reasons for drowning accidents [2]. Even in public swimming pools with on-duty lifeguards, drowning incidents may still occur due to human errors or non-ideal environmental conditions such as obstruction of lifeguards' view. In addition, drowning may happen underwater or only exhibit subtle motions, which are hardly noticeable by people [3, 8]. Thus, an effective autonomous drowning detection system is highly desirable for improving public safety.

Recent work [7] installs multiple cameras under the water and uses a deep neural network (DNN) to detect drowning individuals. However, cameras are vulnerable to low-light conditions and occlusions. Moreover, the cameras also raise privacy concerns, especially for public facilities. Ultrasonic sonars are widely used for underwater ranging and communication because of their excellent sensitivity and lower energy attenuation in the water. Previous work [4] uses sonar to classify swimming styles in a small pool, which cannot detect drowning people.

In this demo, we propose *SwimSonar*, a drowning detection system that can classify swimming and drowning events with a DNN. SwimSonar has two design objectives: First, SwimSonar can detect people in the water. Second, the system can recognize drowning people in the water.

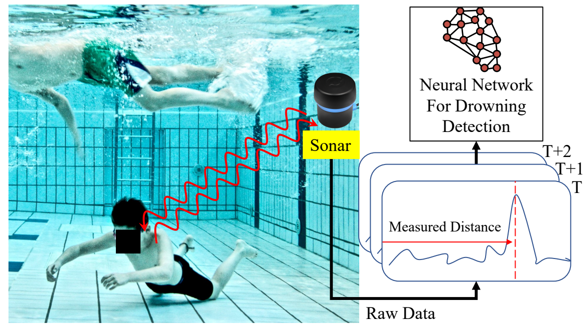


Figure 1: System overview of the SwimSonar.

2 SYSTEM OVERVIEW

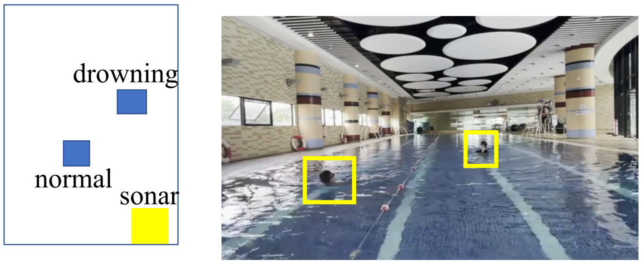
Figure 1 shows the overview of our drowning detection system, i.e., SwimSonar. We place an active sonar (BlueRobotics Ping360 [1]) under the water at the corner of the swimming pool. Our objective is to detect people's struggling in the water, which is the typical behavior of drowning people [2, 3, 8]. The sonar achieves real-time detection based on the echo reflected by the individuals. The details of the active sonar will be introduced in Section 2.1. Since the sonar can only detect objects at a narrow angle at a time, we design a novel sonar scanning strategy to achieve real-time detection, which will be described in Section 2.2. Finally, we use a DNN for classification, which will be depicted in Section 2.3.

2.1 Active Underwater Sonar

Active scan sonar comprises a motor for rotation and a transducer for transmitting and receiving ultrasonic signals. For each frame of scanning, the transducer can only detect the objects within a sector of one degree. The raw data of each frame is the correlation between the receiving signal and the transmitted signal over time. The distances to the objects are computed based on the elapsed time till correlation peaks, which indicates the existence of objects. The motor on the sonar can rotate the sensor for multiple scans and hence cover a wide view. Combining the results of various angles, the sonar can aggregate the result in a 2D image.

2.2 Sonar Scanning Strategy

Existing work [9] typically requires a full sonar scan and treats the data as a greyscale image. However, this is not feasible for drowning detection since a full scan can take up to 20 seconds. In our system, we process every frame (i.e., a small angle of view) of the sonar instead of waiting till the end of the full scan. The final result is the combination of multiple successive frames.



(a) Detection result of SwimSonar. **(b) Onsite photo.**

Figure 2: An example of SwimSonar with one swimmer and one drowning person.

Each frame of scan contains the motion data with a duration of only 0.05 seconds, which is too short to detect a drowning event accurately. We scan the object repeatedly to capture temporal information after the first scan of the object is completed. In addition, when there is no detected object, we speed up the rotation by three times to save time.

2.3 Data Processing and Classification

For each detected object, we use a DNN to classify its states into four activities, i.e., swimming, drowning (i.e., struggling with the whole body while the location is not changing), submerging (i.e., full body submerge), and still (i.e., staying still with the help of a floating object). We format the input data as a three-dimensional tensor with the shape of $C \times H \times W$, where C refers to the rescan times, H is the distance along echo direction, W denotes the angle of the scanned sector. For each 2D sonar image, we first filter out scatters whose sizes are outside a predefined range. This can remove noises like wall reflections and environmental objects whose sizes are different from a normal human. Meanwhile, our predefined range can also filter out normal swimming people because they have significantly larger or smaller scatter sizes when moving farther or closer to the sonar, respectively. When there are multiple individuals in the proximity of each other, their size is irregularly large since they are recognized as a single object. In such a case, we filter them out since a drowning accident around other swimmers is more likely to be noticed. We normalize each image and resize it to (36×24). We design a DNN based on LeNet [5], using 4 convolutional layers and 3 fully connected layers with a cross-entropy loss.

3 EVALUATION AND DEMONSTRATION

We implement SwimSonar using Pytorch 1.6 on a laptop with CPU i7-8700. Since there is no existing open-source drowning detection system or dataset, we recruit multiple volunteers to collect our dataset of the four states corresponding to the output of our model. We place the sonar on the edge of a public swimming pool, whose size is 30 m (length) $\times$ 10 m (width) $\times$ 2 m (depth). The duration of the experiment is around 20 minutes, and each of the states has an equal amount of data. We ask the volunteers to stay in a small region without instruction and then manually record their location as ground truth. The distance between the volunteer and sonar varies from 3 meters to 15 meters. We record the experiment in a video and label the location and status of people manually. Figure 2 shows one example frame of SwimSonar. The left figure shows the detection result from SwimSonar, while the right figure shows the corresponding photo.

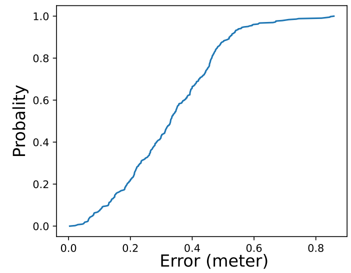


Figure 3: CDF of localization error.

We first evaluate the localization accuracy. Figure 3 shows the cumulative distribution function of localization error. SwimSonar can localize volunteers accurately with less than 0.8 meters error, which is acceptable for swimmers in the pool. We further classify the volunteers' states of detected objects and evaluate the accuracy with various scan times. The scan times are the number of repeated scanning for each object, when we alter the scan time to 3 (i.e., 1 second), 4 (i.e., 1.4 seconds), and 5 (i.e., 1.7 seconds), the classification accuracy is 82%, 88%, and 81%, respectively. To balance the delay and accuracy, we select the scan times to 4.

During the demo session of the conference, we plan to show a prototype of SwimSonar with a water container. The tentative size of the water tank is 50 cm (length) $\times$ 30 cm (width) $\times$ 20 cm (depth). We will showcase the real-time image of sonar and the detection result of the object's movements. A video of the experiment in real swimming pools will also be presented.

4 CONCLUSION

This demo presents SwimSonar, which is a novel drowning detection system. SwimSonar collects the data from a single underwater sonar and detects drowning events with a DNN. In addition, a sonar scanning strategy is designed to balance the detection time and accuracy in the water. We evaluate SwimSonar in a real-world public swimming pool and achieve 88 % accuracy for drowning classification.

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