Miniature Underwater Animal Tags and Smart Sensors for Civil Engineering Applications

Y. Rosa Zheng, Xiyuan Zhu
yrz218@lehigh.edu
Dept. of ECE, Lehigh University
Bethlehem, PA. 18015, U.S.A

Max Tan
mtan1@exeter.edu
Phillips Exeter Academy
Manlius, NY, 13104, U.S.A.

ABSTRACT

This paper gives an overview of miniature underwater IoT devices recently developed for civil engineering applications: animal tags and underwater smart sensors. The PNNL (Pacific Northwest National Laboratory) fish tag is a newly developed injectable tag that uses acoustic telemetry with hydrophones, set up mostly around dams, to track juvenile salmon. This paper details the decode and detection algorithms that allows for better detection accuracy and range while keeping a low false alarm rate. In addition, three miniature underwater smart sensors are also introduced: the PNNL sensor fish and sensor fish mini, the University of New Hampshire smart grains, and the Lehigh smart pebble. All three sensing devices utilize IMUs (inertial measurement units) to track the acceleration, rotation, and/or water pressure. Speed and position are estimated from 3-axis accelerometer and gyro sensor measurements and the need for rigorous calibration is demonstrated. Finally, the field application examples for the fish tags and smart sensors are described.

CCS CONCEPTS

• **Internet of Things** → **Underwater IoT**; *underwater telemetry*;

KEYWORDS

Underwater animal tags, underwater telemetry, IMU, water pressure sensor, DCM, calibration, Internet of Things, Internet of Underwater Things.

ACM Reference format:

Y. Rosa Zheng, Xiyuan Zhu and Max Tan. 2019. Miniature Underwater Animal Tags and Smart Sensors for Civil Engineering Applications. In *Proceedings of WUWNET'19: International Conference on Underwater Networks & Systems, Atlanta, GA, USA, October 23–25, 2019 (WUWNET'19)*, 7 pages. <https://doi.org/10.1145/3366486.3366543>

1 INTRODUCTION

The rapid advances of cyber-physical systems (CPS) have connected thousands of sensing and control devices to the internet and have enabled large-scale adaptability, efficiency, and autonomy in many application areas. Smart cities, autonomous driving, Unmanned

Aerial Vehicles (UAV), search and rescue, and firefighting are some of the examples showing that CPS are making a profound impact on society. However, the aquatic environment presents a severe barrier for physical devices to connect to the internet because of the difficulties in underwater wireless communications. Very limited works have been reported in the literature on underwater CPS or the Internet of Underwater Things (IoUT). This invited paper is to introduce several preliminary works related to miniature animal tags and data loggers for underwater applications.

Animal tags have been long used to study underwater animal behaviors. However, connecting them to the internet or miniaturizing them into a small form factor becomes challenging. Although many companies produce acoustic tags, only a couple of them produce miniature sensors. Those companies include Advanced Telemetry Systems (ATS, <https://atstrack.com/tracking-systems/acoustic-fish.aspx>), Vemco/HTI (<https://www.vemco.com/>), and Lotek (<https://www.lotek.com/products/arcgeo-series/>). The ATS fish tags are the smallest in size and the technology was transferred from the Pacific Northwest National Laboratory (PNNL). Here, we introduce the PNNL fish tags which uses acoustic communication [1–4], and compare it to the RFID-PIT (Passive Integrated Transponder) tags which use the RFID technology [5, 6] for data delivery. As shown in Fig. 1, both types of tags are small enough to be injected or surgically implanted into small fishes or amphibians. A network of receivers or readers is required to collect data from the animal tags and then relays the data to the internet. Both types of tag systems are used for studying underwater animal behavior.

Figure 1: Acoustic fish tag (reprint from [4]) vs. two RFID PIT tags (<https://www.biomark.com/>)

The biggest difference between the acoustic tags and the RFID PIT tags is the communication distance. Using a very high frequency acoustic transducer, the acoustic PNNL tag transmission can reach 150 meters underwater. In comparison, the RFID PIT tags using a 134.2 kHz reader can reach only 150 cm [6]. The parameters of several models of the two types of tags are listed in Table 1.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

WUWNET'19, October 23–25, 2019, Atlanta, GA, USA

© 2019 Association for Computing Machinery.

ACM ISBN 978-1-4503-7740-9/19/10...\$15.00

<https://doi.org/10.1145/3366486.3366543>

Model	size (mm)	weight in air	comm. range	battery life	reference
JSATS micro V1	15L-3.35Dia	0.216 g	150 m	120 days	[1, 3]
ATS SS300	10.79L-5.26W-3.65H	0.348 g	150 m	45 days	atstrack.com
PIT APT12	12L-3Dia	1 g	0.3 m	no battery	biomark.com
PIT HPT23	23L-5Dia	2 g	0.3 m	no battery	biomark.com

Table 1: Parameters of several miniature animal tags. The RFID PIT tags are passive without a battery.

Model	size (mm)	weight in air	comm.	sensing	sampling rate	data storage
Sensor Fish [2]	89L-24.5Dia	42.1 g	offline	gyro, accel, magnet, pressure	2048 Hz	5 minutes
SF Mini [7]	23 diameter	6.4 g	offline	gyro, accel, magnet, pressure	2048 Hz	2.4 minutes
Lehigh SP [8]	22 diameter	5 g	offline	gyro, accel, magnet	200 Hz	3.4 minutes
Eco-SD [9, 10]	44 diameter	unknown	BLE	gyro, accel	1000 Hz max	2 – 4 minutes
Eco-Micro [11]	8 x 8x 1.5 board	unknown	BLE	gyro, accel	1000 Hz max	1 sec

Table 2: Parameters of several miniature smart sensors

Miniature smart sensors are also desirable in many field applications. With a small form factor though, the sensing capabilities, communication range, and data storage become significant technical challenges. This paper gives an overview of several miniature smart sensors for underwater applications: one is the PNNL sensor fishes [7], one is the Lehigh smart pebbles, and one is the University of New Hampshire (UNH) smart grain [9], as shown in Fig. 2 and 3. These smart sensors have a size less than 90 mm and are used in hydrology studies.

Figure 2: a) CAD drawings of the sensor fish and sensor fish mini, b) real model of SF and SF-mini. Reprint from [7]. **Figure 3: Lehigh smart pebble (diameter = 22 mm) and UNH smart grain (diameter = 44 mm, photo reprint from [9])**

The sensors included in these miniature devices are IMU and/or water pressure sensors. The sensor fish and Lehigh smart pebble currently do not have wireless communication means, while the UNH smart grain has Bluetooth (BLE) capability (RF at 2.4 GHz). Parameters of these smart sensors are compared in Table 2.

2 UNDERWATER ACOUSTIC ANIMAL TAGS

2.1 Acoustic Animal Tag Hardware

The PNNL Juvenile Salmon Acoustic Telemetry System (JSATS) consists of acoustic micro-transmitters (tags) injected in the animals, and cabled microphone-array or autonomous acoustic receivers located in river, lake, ocean, or other underwater environments. The micro-transmitter tag, shown in Fig. 1a, consists of a high energy-density battery, a micro-controller, and a piezoelectric transducer at $416.7 \pm 0.5\%$ kHz carrier frequency. The hardware components are enclosed by epoxy yielding a volume of 0.111 mL. The source level of the micro-transmitter is larger than $+153$ dB re $1 \mu\text{Pa}$ @1 m. At a nominal pulse repetition interval (PRI) of 3 seconds, the micro-transmitter has a life span of 120 days.

The typical JSATS cabled receiver consists of four hydrophones, a four-channel signal conditioner, a DSP+FPGA detector card for data processing, data storage drives, a computer, and power supplies, all mounted in a 17-inch instrumentation rack. The detector card employs a digital signal processor, TMS320C6713, and a field programmable gate array, the Xilinx XC3S1000, Innovative P25M by Innovative Integration, Simi Valley, CA, USA. An energy detector searches for signals that are twice as loud as the background noise. When one is found, it saves 16.384 ms (40960 samples) to a file on a local hard drive. With a 2.5 MHz sampling rate and 4 channels at 8 bit per channel, an hour worth of recording is equivalent to 36 GB. Both data processing and data transferring to the internet become challenging tasks. Therefore, local processing of tag IDs is desirable.

2.2 Animal Tag ID Detection

The micro-transmitter tags are configured to transmit a 31-bit message containing a 7-bit Barker code as a preamble, a 16-bit tag

ID code, and an 8-bit CRC (cyclic redundancy check)-bits generated with the Dallas CRC8 polynomial. The tags use BPSK (Binary Phase Shift Keying) as a passband modulation scheme. A typical example of the received signal is shown in Figure 4a, which suffers significant interference from multipath echo and Doppler spread. As shown in Fig. 4b, severe multipath echo exists in the 31 bit tag code presenting significant challenges for channel estimation, equalization, or error correction decoding.

Figure 4: Example JSATS signals at passband and baseband.

The first challenge is accurate carrier frequency estimation and Doppler compensation. This is overcome by a coarse search in the Fourier transform of the received signal squared, as shown in (1), then a fine tuning ± 305 Hz around the detected peak [1].

$$f_c = \frac{1}{2} \max_{|f-2f_0| < 2f_{max}} F(v^2(t)) \quad (1)$$

where $v(t)$ is the received passband signal, F is the Fourier transform, f_0 and f_{max} are the nominal carrier frequency and the maximal frequency offset, respectively.

The second challenge is the symbol-frame synchronization using the 7-bit Barker code. The 7-bit barker code $72_{oct} = 114_{dec}$ is short and its normalized cross correlation with other 7-bit codes is shown in Fig. 5, where M is the 7-bit codes in decimal format. Without any interference or noise, there is another code pattern $M = 13_{dec}$ whose cross-correlation is $|R_{uv}| = 1$, and there are 14 other 7-bit code patterns that have a cross-correlation $|R_{uv}| = 0.7146$ with the 7-bit barker code. Assuming all the 7-bit patterns where $M = 13_{dec}$ and $M = 114_{dec}$ are excluded from the 24-bit tag ID + CRC codes, the probability is very high that the synchronization due to interference and noise messes up the 14 other 7-bit patterns in the tag ID codes, yielding false detection. When this happens, the different ping rates for different tag IDs may be used in the post processing to rule out the false positives.

The third challenge is the multipath interference, as demonstrated in Fig. 4. The strong echos may alter the tag ID code, generate ghost signals, and result in false positives. Unfortunately, due to the short barker code and weak CRC encoding, it is extremely

Figure 5: Cross correlation of 7-bit Barker code with all possible 7-bit sequences, assuming baseband BPSK bit-to-symbol mapping.

ill-conditioned to estimate the channel impulse response and design a channel equalizer. Great effort has been invested in utilizing the CRC for error correction decoding, as well as joint optimization of channel estimation and equalization with the known Barker code.

3 UNDERWATER SMART SENSORS

As shown in Table 2, smart sensors often consist of a coin battery, inertial measurement unit (IMU) sensor or/and water pressure sensor, and a microcontroller with interface to computer. This section describes the three types of smart sensors in details, with some emphasis on the calibration process of IMU sensors.

3.1 Smart Sensor hardware

Fish Sensor and FS Mini

The SF and SF mini are autonomous sensors that can record acceleration, rotational velocity and pressure. Specifically, the sensor package contains a 3-axis linear accelerometer (ADXL377, Analog Devices, Inc.), gyrosensor (ITG-3200, InvenSense, Inc), and orientation sensor through an eCompass module (LSM303DLHC, STMicroelectronics). In addition to these kinetic sensors, a water pressure sensor (MS5412-BM, Measurement Specialties, Inc.) is attached to the device which can measure over a range of 12 bars (174 psi (absolute)). A temperature sensor (TC1046, Microchip Technology Inc) is also included in the SF and can measure over a range of -40 to +125 °C. Each sensor samples at 2048 Hz and the microcontroller can communicate with a computer through a serial port at 921,600 baud rate. Apart from the size and weight differences, other differences [2] between the SF and SFmini are: 1) the flash memory sizes of the SF and SFmini are 128 Mbits and 64 Mbits, respectively, making their data recording capabilities approximately 292 seconds and 146 seconds, respectively. 2) The SF has a dedicated temperature sensor, while the SF mini uses a built-in sensor on the microcontroller. 3) The SF has an RF transmitter at a carrier frequency of 146 MHz but SF mini has no RF transmitter. 4) The battery capacities of the two sensors are 110 mAh and 50 mAh, respectively.

UNH Smart Grains

UNH, in collaboration with National Tsinghua University, has developed a couple of miniature smart sensors in the recent years. The EcoSD contains a triaxial accelerometer (LIS331DLH) on-board and a triaxial accelerometer on another PCB connected via an

expansion module, measuring along six degrees of freedom in acceleration[10]. The expansion module also contains a 16-Mbit flash memory (S25FL016K) for data logging via a 100 MHz SPI serial bus. The microcontroller unit (MCU) of the EcoSD is a Nordic nRF24LE1/nRF24LE1+, an 8-bit 8051-compatible SoC (system on a Chip) with an integrated radio that provides 2.4 GHz Bluetooth (BLE) connectivity. The $4 \times 4 \text{ mm}^2$ QFN package is used to achieve the small form factor of a microSD card. The EcoSD can be reprogrammed via the wireless link. Its program also contains a threshold detector that detects the outputs of the accelerometers and compares them with two thresholds. It wakes up the sensor when the outputs exceed the high threshold, and puts the sensor into sleep when the outputs drop down below the low threshold. The EcoSD also employs a wireless charging and power management subsystem that consists of wireless coil and charging management chip (LTC4054, Linear Technology). During charging, a magnetic switch (AS-M15TAN-R, Murata Technology) disconnects the battery power from the EcoSD node.

A later development yields the EcoMicro, mainly by the National Tsinghua University [11]. The MCU on EcoMicro is DA14580 from Dialog Semiconductor and is roughly $2.436 \times 2.436 \text{ mm}^2$ in a WLCSP package. The MCU has an ARM Cortex-M0 Core and an integrated BLE radio (Bluetooth low energy for wireless transmission of data) [11]. The IMU in EcoMicro (ICM20948, InvenSense) is a 9-axis sensor with a 3-axis accelerometer, gyroscope, and magnetometer. It also includes a Real-Time Clock (AM1805) to keep a calendar time and power gating. EcoMicro is powered by energy harvesting through two solar cells (CPC1822) connected in series. The harvested energy is maximized in efficiency and storage through a maximum power point tracker (MPPT) chip (BQ25504, Texas Instruments) as the ultra low power boost converter.

Even though the newly developed EcoMicro is more energy efficient than the previous EcoSD, it lacks in certain areas. The small size of the solar cells and low-capacity batteries limits the capabilities of the sensor. Also EcoMicro uses the on-board flash only instead of an external flash memory, requiring data streaming via the BLE at all times which may not be effective for underwater communication.

Lehigh Smart Pebbles

Similar to other smart sensors, the Lehigh smart pebble contains a coin battery powering a small micro controller. Attached to the microcontroller board is a 9-axis Motion Processing Unit (MPU-9150, InvenSense Inc.). The MPU has a triple-axis MEMS gyroscope, accelerometer, and magnetometer. To increase run time, only the gyroscope and accelerometer data were recorded into the on-board flash memory of the MCU (MSP430F5596, TI). The hardware is encased inside a 3-D printed waterproof cover roughly 22 mm in diameter [8].

To program the smart pebble, a JTAG debugger is needed to connect the sensor to a PC. Data is retrieved through a UART-USB connection with a computer. A GUI has been designed to send and retrieve the data through the UART connection. A sensor calibration procedure is needed to estimate the sensing errors and then the field measurement data is compensated to yield results on 3-dimensional acceleration, velocity, orientation, and positional vectors. Sensing error model and calibration method are presented in Sec. 3.2.

3.2 Sensor Calibration Procedures

Based on the inherent structure of the MEMS sensors, each sensor may exhibit errors, as modeled in Fig. 6, where the two parameters, the bias B and the scaling factor K , can be estimated in the calibration procedures and be compensated in field measurements. The nonlinearity effect of the sensor error is often avoided by limiting the maximum range of the measurement.

Figure 6: Errors in IMU to be calibrated: the bias B and scaling factor K in the output voltage U vs. the input force s for the accelerometer.

Accurate estimation of the bias and scaling factor for each IMU sensor in each direction is essential and is often performed offline before each field experiment. The PNLL utilizes a rigorous calibration procedure involving precision instrumentation and reference sensors [2, 4]. A mechanical test track is used to hold the sensor fish and reference instruments which are moved and/or rotated together. The sensor fish measurements are compared with the reference instruments to estimate the bias and scaling factors. The reference instruments used for acceleration and rotation sensors are B&K accelerometer and high speed digital camera (Photron PCI Fast-CAM 1280; Photron USA, Inc.), respectively. The motion-tracking software package (Visual Fusion 4.2; Boeing-SVS Inc., Albuquerque, New Mexico) is also used to calibrate the rotation and orientation sensors. The temperature sensor is calibrated with the digital thermocouple thermometer (DT8852, General Tools and Instruments, New York, NY).

The precision instruments control the sensor with specific inputs (acceleration, angular velocity, and orientation), then record the sensor outputs and process the input-output model. Those precision instruments may be costly but yield excellent accuracy and precision. The calibration can match the linear operation region as well as the nonlinear region, as shown in Fig. 7. The measurements can then be calibrated through a lookup table (LUT) and interpolation.

Another error source is the non-orthogonality of the three spatial axes, as shown in Fig. 8. The desired Cartesian axes (x_d, y_d, z_d) are orthogonal, and the MEMS sensor axes (x_a, y_a, z_a) after the calibration of the scaling factor and bias may match the center but still differ from the desired axes. The orthogonality error is measured by aligning the x_a with x_d and aligning the (x_a, y_a) plane with the (x_d, y_d) plane. The angle between y_a and y_d is then α_{yz} , the angles between z_a and z_d projected on the (x_d, z_d) and (y_d, z_d) planes are α_{zx} and α_{zy} , respectively.

Figure 7: Result of classic calibration: the circled points are measurements from precision instrumentation, the dashed line is the interpolated calibration curve.

Figure 8: Non-orthogonal axes in the 3-D accelerometer. The gyroscopes measure the angular velocities along these axes.

(a) Octahedral shell

(b) Related directions

Figure 9: Gravity points to eight different directions when it is placed on different surfaces.

Without using a precision mechanical platform, Lehigh University extended the method in [12] and developed a low-cost procedure for calibration. The procedure includes multiple raw measurements at known locations and different orientations, estimating the gravity, and then solving for the bias and scaling factor via a nonlinear least squares approach. First, the pebble is placed in an

octahedral shell, as shown in Fig. 9a, which is then placed in several different positions. At each position (or location), measurements are taken in different orientations. This way the gravitational vector can be measured accurately in 8 different direction, as shown in Fig. 9b. By using three different angles of every surface, a total of 24 inputs are collected. Considering Let $\mathbf{U} = [U_x, U_y, U_z]^T$ denote the measured force vector from the accelerometer without calibration, and the superscript T denotes the vector transpose. Let $\mathbf{s}$ be the calibrated force vector. The calibration follows

$$\mathbf{s} = \mathbf{P}^{-1} \mathbf{K}^{-1} (\mathbf{U} - \mathbf{B}) \quad (2)$$

where $\mathbf{B} = [B_x, B_y, B_z]^T$ is the bias, $\mathbf{K} = \text{diag}(K_x, K_y, K_z)$ is the scaling factor matrix, and the axes nonorthogonality matrix $\mathbf{P}$ is

$$\mathbf{P} = \begin{bmatrix} 1 & 0 & 0 \\ -\alpha_{yz} & 1 & 0 \\ \alpha_{zy} & -\alpha_{zx} & 1 \end{bmatrix} \quad (3)$$

The calibration has to estimate the nine parameters in (2). Assume the local gravitational acceleration is g . The acceleration measurements taken when the sensor is rested on a test position have to ensure that $\|\mathbf{s}\| = g = 1 \text{ G}$. With more than nine measurements taken when the sensor is stationary resting on different sides of the octahedron, the nine unknown parameters are solved by the least squares method that minimizes the mean squared error between the estimates $\hat{\mathbf{s}}(t) = \mathbf{P}^{-1} \mathbf{K}^{-1} (\mathbf{U}(t) - \mathbf{B})$ and $\mathbf{s}$ for all time instants t that fall in the valid data periods. With a large number of measurement samples, the minimization is calculated by the Newton method [12] and care shall be taken to ensure the convergence and avoid ill conditions. An example of the calibration measurement setup is shown in Fig. 10. The raw measurements converted by the scaling factors of the data sheet and the calibrated data are shown in Fig. 11. The valid data periods are extracted by setting a small threshold on the variance of the measurement data. The utilization of the octahedral shell helps to obtain measurements at all directions of the sensor and ensure all parameters are estimated with good accuracy.

Figure 10: A setup of ten test positions for calibrating the smart pebble.

The gyroscope measurements are calibrated similarly as the acceleration, but the desired angular velocity is zero when the sensor is stationary. After calibration, the specific force from gravity is removed to obtain an accurate representation of acceleration without gravity. To solve for the position of the smart pebble, the

Figure 11: Measured data shows a few periods of small variance, which correspond to sensor resting on a surface. Those periods also correspond to $\|s\| = 1$ G, and are used for parameter estimation.

calibrated acceleration data and angular velocity measurements are used to first compute the speeds $v(t)$ and then the positions $l(t)$, where t denotes the time instant. Since the IMU coordinate system is different from the local coordinate system or the earth gravity coordinate system, the angular velocity data at each time instant is to adjust the acceleration vectors. To reduce the error accumulation due to double integration of the acceleration, the method of quaternions [13] is used as a means of accurate rotation calculation. Quaternions are numbers that extend into the complex number system and can be applied as rotations. A quaternion q can be written as

$$q = q_0 + q_1i + q_2j + q_3k \quad (4)$$

where q_0, q_1, q_2 , and q_3 are real numbers, and i, j , and k are the fundamental quaternion units. Given orientation quaternion q_t at time t , we can then find the derivative of the quaternion at t to compute the quaternion at time $t + 1$ [14]

$$\dot{q}(t) = \frac{1}{2} q(t) \odot \bar{\omega}(t) \quad (5)$$

$$q(t + 1) = q(t) + \dot{q}(t)\Delta t \quad (6)$$

where $\bar{\omega}(t)$ is the calibrated angular velocity from the gyroscope measurements, $\dot{q}(t)$ is the derivative of $q(t)$, and the operator $\odot$ is the quaternion multiplication. The inertial quaternion $q_0 = q(t = 0)$ is estimated by utilizing the direction of gravity $s_0 = s(t = 0)$ when the IMU device is static. We calculate q_0 by

$$\min_{q_0 \in R^4} \left[q_0^\dagger \odot d \odot q_0 - s_0 \right] \quad (7)$$

where $d = [0, 0, 0, 1]^T$ and the superscript $\dagger$ denotes inverse of the quaternion.

The gradient descent method [14] is then used with the accelerometer and gyroscope measurements to achieve the minimum square error estimation of the orientation and position.

Furthermore, the underwater dynamic behavior of smart pebbles improves the accuracy of the position estimation. Lehigh smart pebbles can identify the periods of static motion and use them to calibrate the position result using the same method as shown in Fig. 11. After the calibration procedure, the position estimation errors can be reduced to 10^{-2} . As shown in the example in Fig. 12, the total calibration length is 120 cm, the root mean squared error was 4 cm and the maximal error was ± 2 cm.

Figure 12: The calculated positions of the pebble during laboratory test.

4 APPLICATIONS

4.1 Application of PNNL Animal Tags

The PNNL acoustic animal tags and Sensor Fishes have been primarily used to track fish near dams or monitor fish behavior, evaluate fish passage through structures, and understand the physical conditions. Extensive field experiments have been conducted over the last decade. Examples of the experiments include Columbia and Snake River hydropower systems, Davenport Farmers Screen at Hood River, Oregon, etc. Figure 13 shows one of the typical field studies where the stationary points marked in color were tag locations. The 32 hydrophones were arranged under the spill way and the power house. Both tag IDs were detected and their locations were estimated.

Figure 13: Animal tag river experiment setup at Little Goose Dam, Snake River, WA. reprinted from [1].

In real fish tracking studies, the survival of fish near dams, spillway, and turbines, etc are of interest. Care was taken to reduce the false positive rate to below 10^{-5} so that the survival rate would not be over-estimated. Due to the strong correlation among the short codes and severe multipath interference, the detection rate was also low when the false positive rate was set low. Survivability rates of Chinook Salmon was investigated [3] from the Lower Monumental Dam and comparison between injectable and surgically implanted tagging methods showed that the smaller injectable tags had better survival rate than the surgically implanted tags.

4.2 Application of Smart Sensors

The PNNL sensor fishes were used in field experiments at Davenport Farmers Screen [7] and the results were compared with previously conducted experiments at several dams and spillways. The purpose of the experiments is to identify severe acceleration events when a fish passes the civil infrastructure. The PNNL has found via laboratory test that an acceleration of 95g would be considered as a severe event for the Chinook Salmon. Field measurements of sensor acceleration were taken with the sensor fishes and live fishes under different water discharge rates and results demonstrated that the Sensor Fish and SF mini provided accurate estimation of acceleration.

The University of New Hampshire (UNH) has used the smart sediment grain (SSG) as a detection device for the incipient motion of underwater grains. They were able to test their SSG at small and large scale flumes at the OH Hinsdale Wave Research Laboratory, Oregon State University, Oregon, USA. In both experiments they assessed that the onset of motion correlated with the increase of the Sleath parameter (S) which quantifies the effect of the pressure gradient of the flow of water. Therefore their experiments indicates that incipient motion is caused by pressure gradients rather than shear stress[9].

The Lehigh smart pebble is also intended for sediment studies in storm water management. The raw measurements may be translated to water force, flow speed, and particle locations. Besides calibration, the challenges of data processing include inaccurate timing, mapping errors, and synchronization with other measurement instrumentation such as optical/laser imaging systems.

5 CONCLUDING REMARKS

This paper reviewed several miniature acoustic animal tags and smart sensors for underwater civil engineering applications. The PNNL tags and sensors are clearly the best developed with a Technology Readiness Level at about 7 – 8 TRL. The smart sensors developed by the universities are of smaller size, but their TRLs are at most at 3 – 4 TRL. Extensive optimization of circuits, programs, and packaging is needed to further improve these smart sensors.

For future work, communication signaling and data processing algorithms remain active areas of improvement for both acoustic animal tags and smart sensors. In particular, with very short data package length and ultra-low power requirements, efficient signal designs for acoustic tags would achieve the best balance between cost, power consumption, and performance. Advanced decoding and detection algorithms may yield better performances under sparse channel conditions, but may also suffer from ambiguities. For

smart sensors, combining acoustic communication capability with the sensing capability would be a challenge when a small form factor is required. Wireless connectivity via Bluetooth is an alternative only when the sensors are in very shallow water or are collected out of water. Data storage, battery size, sensing capabilities, and other functionalities are also a difficult trade-off with size limitations.

In summary, the demand for underwater smart sensors is high and the research community has a long way to go to achieve an Internet of Underwater Things.

ACKNOWLEDGMENTS

The work of Y.R. Zheng is supported by the National Science Foundation of USA under CPS-1853257 and IIP-1853258. The authors would like to thank Dr. Zhiqun Daniel Deng of PNNL and Dr. Pai Chou of National Tsinghua University for helpful discussions during the writing of this paper and for allowing the use of their figures. Max Tan wishes to thank the conference and NSF for a student travel grant that supports him to attend the conference.

REFERENCES

- [1] J.M. Ingraham, Zhiqun Deng, Xinya Li, Tao Fu, Geoffrey McMichael, and Brad Trumbo. A fast and accurate decoder for underwater acoustic telemetry. *Review of Scientific Instruments*, 85:074903–074903, 07 2014.
- [2] Z. D. Deng, J. Lu, M. J. Myjak, J. J. Martinez, C. Tian, S. J. Morris, T. J. Carlson, D. Zhou, and H. Hou. Design and implementation of a new autonomous sensor fish to support advanced hydropower development. *Review of Scientific Instruments*, 85(11):115001, 2014.
- [3] Zhiqun Deng, T. J. Carlson, Huidong Li, J. Xiao, M. J. Myjak, J. Lu, Jayson Martinez, Christa Woodley, M. A. Weiland, and M. B. Eppard. An injectable acoustic transmitter for juvenile salmon. *Scientific Reports*, 5, 01 2015.
- [4] Zhiqun Deng, Jayson Martinez, Huidong Li, Ryan Harnish, Christa Woodley, James Hughes, Xinya Li, Tao Fu, Jun Lu, Geoffrey McMichael, M A Weiland, M B Eppard, J R Skalski, and Richard Townsend. Comparing the survival rate of juvenile chinook salmon migrating through hydropower systems using injectable and surgical acoustic transmitters. *Scientific Reports*, 7, 03 2017.
- [5] Jean-Marc Roussel, Alex Haro, and R.A. Cunjak. Field test of a new method for tracking small fishes in shallow rivers using passive integrated transponder (PIT) technology. *Canadian Journal of Fisheries and Aquatic Sciences*, 57(7):1326–1329, 2000.
- [6] Michael Hamed, Hamed Virginia, Dale P Ledford, and Thomas F Laughlin. Monitoring non-breeding habitat activity by subterranean detection of ambystomatid salamanders with implanted passive integrated transponder (pit) tags and a radio frequency identification (rfid) antenna system. *Herpetological Review*, 39:303–306, 09 2008.
- [7] Aljon Salalila, Zhiqun Deng, Jayson Martinez, Jun Lu, and Lee J. Baumgartner. Evaluation of a fish-friendly self-cleaning horizontal irrigation screen using autonomous sensors. *Marine and Freshwater Research*, 07 2019.
- [8] X. Zhu, W. Shih, and Y. R. Zheng. Underwater datalogger for accurate position and location estimation and tracking. In *16th Annual IEEE International Conference on Sensing, Communication, and Networking (SECON)*, pages 1–2, June 2019.
- [9] Donya Frank, D Foster, Pai Chou, Y.-M Kao, J Calantoni, and I.-M Sou. Direct measurements of sediment response to waves with ‘smart sediment grains’. In *OCEANS 2013 MTS/IEEE - San Diego*, pages 1–5, 10 2013.
- [10] Y. Kao, D. Frank, D. Foster, K. Huang, C. Kao, and P. H. Chou. An in-situ motion measurement system for underwater sediments tracking. In *2014 IEEE International Conference on Internet of Things (iThings), and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom)*, pages 360–367, Sep. 2014.
- [11] Cheng-Ting Lee, Yun-Hao Liang, Pai H. Chou, Ali Heydari Gorji, Seyede Mahya Safavi, Wen-Chan Shih, and Wen-Tsuen Chen. Ecomicro: A miniature self-powered inertial sensor node based on bluetooth low energy. In *Proceedings of the International Symposium on Low Power Electronics and Design, ISLPED '18*, pages 30:1–30:6, New York, NY, USA, 2018. ACM.
- [12] Isaac Skog and Peter Händel. Calibration of a mems inertial measurement unit. In *XVII IMEKO world congress*, pages 1–6, 2006.
- [13] Gernot Hoffmann. Application of Quaternions, 2002.
- [14] Sebastian OH Madgwick, Andrew JL Harrison, and Ravi Vaidyanathan. Estimation of IMU and MARG orientation using a gradient descent algorithm. In *2011 IEEE international conference on rehabilitation robotics*, pages 1–7. IEEE, 2011.