Wave Height Estimation Using a Novel Seaweed-Attached Sensor

Masoud Emam, Caroline Press, Hamed Jafarzadeh,
Marco Belcastro, Brendan O'Flynn
Tyndall National Institute
University College Cork (UCC)
Cork, Ireland
Email: [masoud.emam, caroline.peres, hamed.jafarzadeh,
marco.belcastro, brendan.oflynn]@tyndall.ie

Joanne Casserly, Frank Kane
Marine Institute
Rinville, Oranmore
Galway, Ireland.
Email: [joanne.casserly, frank.kane]@marine.ie

***Abstract*— The growth rate of seaweed is significantly affected by wave parameters and sea conditions. The wave characteristics in an aquaculture farm is normally measured using expensive equipment, which is not affordable for many farmers or researchers, and is not easily relocated from place to place to evaluate wave conditions in a variety of locations. In this paper, a sensor fusion method is presented which can estimate wave height using the data logged by a multi modal low-cost seaweed-attached sensor system. The sensor was developed for use in an Aquaculture scenario. This method is based on combination of extended Kalman filter and artificial neural networks. Regarding the importance of studying the impact of wave on seaweeds growth rate, this method will avail many researchers to use wave height data in their study to fill the gap in knowledge of the impact of water motion on aquaculture and maximising of seaweed harvests.**

Keywords; Seaweed attached sensor; Aquaculture; Underwater sensor; Embedded system; Kalman filter; Artificial Neural Network.

I. INTRODUCTION

According to the "*fishery and aquaculture statistics*" published by the Food and Agriculture Organisation (FAO) [1], the contribution from aquaculture to total fish production reached 46.0% in 2018 as compared to 25.7% in 2000. This rapid growth in fish farming activities causes environmental sustainability concerns [2]. As production increases, so two the demand on the environment to provide more nutrients and the waste generated increases. Another impact on economic sustainability comes from the increased maintenance and labour costs associated with increased production.

One promising solution to sustainable aquaculture is to employ the practice of Integrated Multi-trophic Aquaculture (IMTA) . IMTA is an aquaculture farming method where the by-products and wastes of one aquatic species, for example fish, is utilised as food for another species, such as seaweed or shellfish. New approaches, such as those developed in the IMPAQT project [3], aim to integrate the IMTA model, smart systems, and sensors for monitoring, data modelling and intelligent management systems [4].

Seaweed growth rates are considerably affected by water motion and flow rate. In low level water motion, seaweeds absorb less nutrients and CO2, which is limiting the growth. High movement rates, on the other hand, can dislodge kelps and reduced productivity as a result of forcing them to develop larger holdfasts [5]. According to Hurd [6], to understand how water motion can affect the growth rate of seaweeds, the influence of other environmental factors should be measured and accounted for in aquaculture site management and operation.

Several studies have investigated this topic, such as [7], [8], and [9], where water motion rates and wave exposure were not directly measured with wave sensors/loggers, such as Acoustic Doppler Current Profilers (ADCP), wave buoys, but were indirectly measured using wind speed and incidence, and distance to coastline to estimate the wave exposure index [10]. Using this method it was possible to categorise large geographical locations as "high exposure" or "low exposure". According to Lindegarth and Gamfeldt [11], using this categorical variable method instead of a continuous-type variable results in very different explanations of the importance of environmental factors. Furthermore, Focht and Shima [12], found that the correspondence between in-situ measurements by accelerometers and a wave-rider buoy and a priori assessments of wave exposure is limited.

Various research, such as [12]-[14], presented solutions to the problem of measuring water motion using inexpensive sensors developed using commonly available materials. Lyman et al. [14], developed a low-cost open-source pressure transducer to record wave height using a PVC pipe as housing. In [12], fine-scale wave exposure in different locations have been measured using accelerometers, and compared with a nearby deployed wave-rider buoy. Their analysis shows that there was a significant fine-scale variation in the wave movement, as a result of changes in acceleration, timing, and frequency of wave events.

Evans and Abdo in [13], designed a structure that is attached to a HOBO Pendant G acceleration data logger, moored to the seafloor, and deployed adjacent to a wave-rider buoy. They showed that the wave motion data logged by the accelerometer is correlated with the daily average, maximum Wave-Rider Buoy (WRB), tidal data and found it to be highly correlated with daily average total wave height. The authors discussed that using a faster sampling rate for accelerometer (with increased data storage), more detailed water movement parameters, such as velocities, forces, and wave period; could be measured and determined. It would also enable a more detailed analysis of the data using spectral analysis. They conclude that, their method allows researchers to collect additional water movement data where advanced devices are not available or too costly.

In another study by Mullarney and Pilditch [15], the HOBO Pendant G Accelerometers is attached to the kelp stipe by tying it at fixed intervals up the stipe bundle. Pressure and velocities were measured by an Acoustic Doppler Current Profilers (ADCP) for this study. The objective of the research was to find the response of kelp to the wave movement.

According to the review of literature that has been presented, measurements of wave height and/or water motion is critical in aquaculture and has been studied in many research publications. However, all the solutions and research discussed above have problems in common, such as the typically large size of the sensors systems that limits the deployment method; power requirements such as cables, external power supplies, and data recovery. On the other hand, a low-cost miniature wave measurement solution has been presented in [16] and [17]. To aid in in-situ monitoring for IMTA aquaculture farm sites, a seaweed monitoring device was developed, which is described in detail in [18].

In this paper, a method based on sensor fusion and Artificial Intelligence (AI) is proposed in order to estimate current and wave using data recorded by the attached seaweed sensor presented in [18]. This method can avail many researchers to use wave height data in their study and fill the gap in knowledge of exact impact of water motion on aquaculture. To achieve this method, the seaweed-attached sensors have been deployed in an IMTA site and the correlation between the data recorded by the sensor and wave height have been studied. The results showed a strong correlation and the next step is to train a neural network to estimate wave height using data logged by seaweed-attached sensor.

The remainder of the paper is organised as the following. In Section II, the methodology of suggested method is presented and feasibility of the method is investigated in Section III where the initial result from a deployment is studied. At the end, in Section IV, the paper is concluded.

II. METHODOLOGY

The seaweed attached sensor, AquaBit (see Figure 1.), has been originally designed to measure ambient parameters relevant to seaweeds, such as light, temperature, depth, and motion [18]. However, this sensor has significant potential to be used in indirect measurement of other parameters based on fusion of the readings from different sensors embedded in AquaBit. In this section, a method is proposed to estimate current strength and wave height.

The embedded IMU sensor consists of a 3-axis accelerometer and a 3-axis gyroscope. The accelerations and angular velocities are sampled with the frequency of 12.5 Hz and recorded in the internal flash memory of AquaBit. This sampling frequency provide much higher accuracy in comparison with a data buoy which normally operate with a very long sampling interval in range of minutes.

Motion and displacement of the seaweed-attached sensor is the result of current and wave. Faster motion is the result of stronger wave or current [19]. Therefore, if we can calculate the motion of the attached sensor, we can estimate the strength of current or wave. Theoretically, acceleration is the second time-derivative of position, and vice versa, position is the second integral of acceleration. Therefore, we should be able to calculate the position of AquaBit easily from the accelerations measured by the IMU. However, this calculation results in huge position error as the consequence of measurement noise.

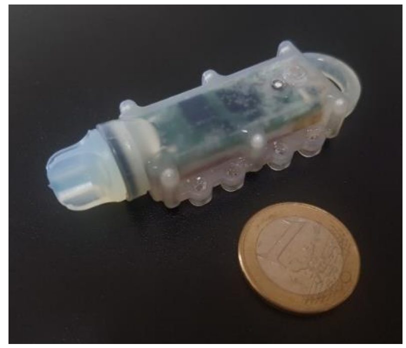

Figure 1. Seaweed attached sensor, AquaBit Unit

On the other hand, it is very hard to find the exact function that maps the motion of attached sensor to wave or current. The main reason is that the AquaBit is attached to seaweed blades and to establish the function, the exact hydro dynamic model of seaweed blades and AquaBit are needed which is hard (or even impossible) to find in the context of the fast growth of seaweeds.

The proposed method of this paper is to use an Extended Kalman Filter (EKF) and Artificial Neural Network (ANN) to estimate current and wave base on the readings from IMU sensor. The EKF is employed to cope with the noise in measurement and the ANN is trained in such a way that maps the accelerations to current and wave states.

The EKF is a well-known optimal state observer for nonlinear systems, which can estimate the state of system using noisy measurements of system output [20]. EKF has also been widely employed as a sensor fusion method to estimate the orientation of an object using angular velocities and linear acceleration experienced by the object, [21][22].

The proposed method is to feed IMU measurements to an EKF to estimate the orientation of the IMU with respect to an Earth-Fixed coordination Frame (EFF). The EEF is a three-dimension orthogonal coordination frame fixed to the earth. The X-axis is aligned with the North direction in the opposite direction of gravity, Y-axis is aligned with the West direction, and Z-axis is the cross product of X and Y, which is in the opposite direction of gravity. Using the orientation of the IMU w.r.t. EFF, we will be able to reject the effect of gravity on measurements of accelerometer and estimate the accelerations in EFF.

Artificial intelligence, or more specifically Artificial Neural Networks (ANN), is a good solution when it is difficult to directly measure a physical parameter but some other related parameters are more accessible and easy to measure. For example, in the case of the scenario described in this paper, it is impossible to measure wave height on each seaweed growth line in an aquaculture farm. However, it is possible to measure the acceleration and angular velocity experienced by seaweeds using AquaBit. Therefore, we can train an ANN to estimate wave height from AquaBit measurements.

To train the ANN, AquaBit units will be deployed as close as possible to a current meter or wave logger/sensor. Then, using the IMU measurement of AquaBit, as inputs, and the data logged by current meter/wave sensor, as outputs, are joined to shape a dataset. This dataset is used to train and test the ANN. Then, this ANN is used to map acceleration to current or wave.

III. PILOT RESULTS

To test the feasibility of the proposed method, data collected in one of the AquaBit deployment in the Marine Institute aquaculture research site (Lehanagh Pool), Galway, Ireland is used. In this deployment, AquaBit units have been attached to artificial seaweeds, as shown in Figure 2.

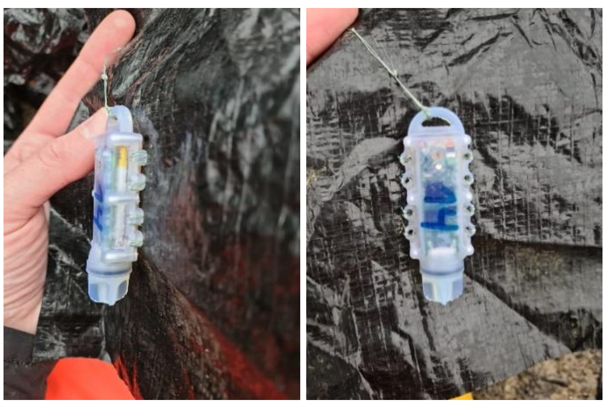

Figure 2. An AquaBit unit attached to artificial seaweed.

The data recorded by the IMU sensor of AquaBit in this deployment have been compared with tilt data recorded by the data buoy of the same site.

To evaluate the feasibility of the proposed method the correlation between magnitude of tilt data and the magnitude of reading from AquaBit gyroscope in frequency domain is studied using Pearson correlation coefficient.

The tilt data are recorded as the maximum and minimum value of tilt experienced around X- and Y-axis (EEF) during a 10 minute period. The magnitude of tilt is calculated as in (1) and (2).

$$Tilt_{max} = \sqrt{Tilt\_X_{max}^2 + Tilt\_Y_{max}^2} \quad (1)$$

$$Tilt_{min} = \sqrt{Tilt\_X_{min}^2 + Tilt\_Y_{min}^2} \quad (2)$$

On the other hand, the magnitude of readings from gyroscope is calculated as in (3) and (4).

$$W_{max} = \sqrt{w\_x_{max}^2 + w\_y_{max}^2 + w\_z_{max}^2} \quad (3)$$

$$W_{min} = \sqrt{w\_x_{min}^2 + w\_y_{min}^2 + w\_z_{min}^2} \quad (4)$$

where, w_x_{max}, w_y_{max}, and w_z_{max} are the maximum angular velocity around X-, Y-, and Z-axis (sensor coordination frame) during a 10 minute period. Note that, the time period for maximum/minimum calculation is exactly the same for data buoy and AquaBit.

Since these measurements are compared in frequency domain, the Fast Fourier Transformation (FFT) is used to transform tilt and angular velocities into frequency domain.

The Pearson correlation coefficient for the FFT of $Tilt_{max}$ and the FFT of W_{max} is 0.84 with p-value of 5×10^{-97}; and for the FFT of $Tilt_{min}$ and the FFT of W_{min} is 0.85 with p-value of 1×10^{-99}, which means the variation in tilt can be calculated using angular velocities by a linear function. The tilt values from the data buoy approximately represents wave height – the higher the wave height the more tilt measured by the buoy measures. As the tilt measured by the buoy is correlated with the angular velocity measured by the sensor device, we conclude that the wave height could be estimated by the angular velocity. This supports the expectation that a sensor fusion algorithm for accelerometer and gyroscope could provide good estimates of wave height and energy.

IV. CONCLUSIONS AND FUTURE WORK

In this paper, we presented a work in progress, a novel method of estimation of wave height for cost effective research project. The method translates the data collected by a 6 Degree of Freedom (DoF) IMU (accelerometer and gyroscope) into wave height by combining EKF and ANN. The data analysis of a pilot trial showed that the angular velocity is strongly correlated to tilt values recorded by a wave-rider buoy. In other words, wave height or other wave statistical parameters could be estimated using readings from the embedded IMU of AquaBit. The next step is to figure out an ANN and train it to estimate the wave height using the data recorded by the embedded IMU of AquaBit. The hypothesis will continue to be investigated in Flume Tanks [23] (dedicated infrastructure for wave measurements) and the algorithms developed to establish wave height from IMU readings attached to seaweed lines in aquaculture oriented deployments.

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References

[1] F. Yearbook, "Fishery and aquaculture statistics 2016," *Rome: FAO*, 2019.

[2] M. Føre *et al.*, "Precision fish farming: a new framework to improve production in aquaculture," *biosystems engineering*, vol. 173, pp. 176-193, 2018.

[3] "IMPAQT Project." https://impaqtproject.eu/about-impaqt/ (accessed Sep. 17, 2021).

[4] I. A. Iglesias. "Can integrated multi-trophic aquaculture (IMTA) make an IMPAQT in Europe?" https://thefishsite.com/articles/can-integrated-multi-trophic-aquaculture-imta-make-an-impaqt-in-europe (accessed Sep. 17, 2021).

[5] P. D. Kerrison, M. S. Stanley, M. D. Edwards, K. D. Black, and A. D. Hughes, "The cultivation of European kelp for bioenergy: site and species selection," *Biomass and bioenergy*, vol. 80, pp. 229-242, 2015.

[6] C. L. Hurd, "Water motion, marine macroalgal physiology, and production," *Journal of Phycology*, vol. 36, no. 3, pp. 453-472, 2000.

[7] W. Visch, G. M. Nylund, and H. Pavia, "Growth and biofouling in kelp aquaculture (Saccharina latissima): the effect of location and wave exposure," *Journal of Applied Phycology*, vol. 32, no. 5, pp. 3199-3209, 2020.

[8] L. Kregting, A. J. Blight, B. Elsäßer, and G. Savidge, "The influence of water motion on the growth rate of the kelp Laminaria digitata," *Journal of experimental marine biology and ecology*, vol. 478, pp. 86-95, 2016.

[9] T. Bekkby, E. Rinde, H. Gundersen, K. M. Norderhaug, J. K. Gitmark, and H. Christie, "Length, strength and water flow: relative importance of wave and current exposure on morphology in kelp Laminaria hyperborea," *Marine Ecology Progress Series*, vol. 506, pp. 61-70, 2014.

[10] M. T. Burrows, R. Harvey, and L. Robb, "Wave exposure indices from digital coastlines and the prediction of rocky shore community structure," *Marine Ecology Progress Series*, vol. 353, pp. 1-12, 2008.

[11] M. Lindegarth and L. Gamfeldt, "Comparing categorical and continuous ecological analyses: effects of "wave exposure" on rocky shores," *Ecology*, vol. 86, no. 5, pp. 1346-1357, 2005.

[12] R. C. Focht and J. S. Shima, "Acceleration loggers reveal fine-scale heterogeneity in wave exposure along an open coast," *Estuarine, Coastal and Shelf Science*, vol. 233, p. 106507, 2020.

[13] S. Evans and D. Abdo, "A cost-effective technique for measuring relative water movement for studies of benthic organisms," *Marine and Freshwater Research*, vol. 61, no. 11, pp. 1327-1335, 2010.

[14] T. P. Lyman, K. Elsmore, B. Gaylord, J. E. Byrnes, and L. P. Miller, "Open Wave Height Logger: An open source pressure sensor data logger for wave measurement," *Limnology and Oceanography: Methods*, vol. 18, no. 7, pp. 335-345, 2020.

[15] J. C. Mullarney and C. A. Pilditch, "The differential response of kelp to swell and infragravity wave motion," *Limnology and Oceanography*, vol. 62, no. 6, pp. 2524-2537, 2017.

[16] D. Kennedy, M. Walsh, and B. O'Flynn, "Development of a miniature, low-cost wave measurement solution," in *2014 Oceans-St. John's*, 2014: IEEE, pp. 1-6.

[17] D. Kennedy, M. Walsh, and B. O'Flynn, "Low-cost inertial measurement of ocean waves," in *2014 IEEE Sensor Systems for a Changing Ocean (SSCO)*. 2014: IEEE, pp. 1-2.

[18] C. Peres, M. Emam, H. Jafarzadeh, M. Belcastro, and B. O'Flynn, "Development of a Low-Power Underwater NFC-Enabled Sensor Device for Seaweed Monitoring," *Sensors*, vol. 21, no. 14, p. 4649, 2021.

[19] M. Denny and B. Gaylord, "The mechanics of wave-swept algae," *Journal of Experimental Biology*, vol. 205, no. 10, pp. 1355-1362, 2002.

[20] Q. Li, R. Li, K. Ji, and W. Dai, "Kalman filter and its application," in *2015 8th International Conference on Intelligent Networks and Intelligent Systems (ICINIS)*, 2015: IEEE, pp. 74-77.

[21] J. L. Marins, X. Yun, E. R. Bachmann, R. B. McGhee, and M. J. Zyda, "An extended Kalman filter for quaternion-based orientation estimation using MARG sensors," in *Proceedings 2001 IEEE/RSJ International Conference on Intelligent Robots and Systems. Expanding the Societal Role of Robotics in the the Next Millennium (Cat. No. 01CH37180)*, 2001, vol. 4: IEEE, pp. 2003-2011.

[22] A. M. Sabatini, "Quaternion-based extended Kalman filter for determining orientation by inertial and magnetic sensing," *IEEE transactions on Biomedical Engineering*, vol. 53, no. 7, pp. 1346-1356, 2006.

[23] "LiR National Ocean Facility " http://www.lir-notf.com/ (accessed 2021).

[24] "IMPAQT project." https://impaqtproject.eu/ (accessed 2021).