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Development of Monitoring and Classification Systems for Wave Energy

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Abstract

In this paper, we proposed a novel approach to develop a monitoring module for nearshore wave energy converting (WEC) device. The monitoring module is composed of a gyro-accelerometer sensor, Arduino microcontroller and RF transceiver. The nearshore WEC device has a floating buoy to capture the energy transferred by the ocean wave and power generators. The monitoring module is designed to be attached on the top of the floating buoys to record and transmit the collected movement information. In the experiment, we used Scorsby motion table to simulate different kinds of wave patterns. The collected dataset was analyzed to develop a classifier which categorizes ocean wave strengths. Preprocessing techniques were employed on the dataset before it was utilized using machine learning algorithms. In addition, signal segmentation and feature extraction were applied to generate representative feature sets. Three supervised machine learning algorithms: Support vector machine, Random forest, and Artificial neural network were investigated for better performance. The experimental results showed that the SVM classifier outperformed the others. The monitoring module turned out to be effective for nearshore WEC device. For future work, the movement information can be extended to predict the actual power that can be generated from the wave energy harvesting stations.

Keywords: *wave energy converting system, machine learning, monitoring module, support vector machine, prediction*

1. Introduction

The world has been relying on the conventional energy sources for a long time. The primary source of these conventional energies are fossil fuels such as coal, petroleum and natural gas. However, the known reserves of the fossil fuels have depleted to a large extent because of its continuous and heavy use. Unless it is diminished, there is a risk of complete exhaustion. Furthermore, the use of these resources results in a serious impact on the environment including global warming and climate change problems [1].

Since renewable energy sources have practical advantages in addressing air pollution and global warming problems, recently many countries put efforts to replace the conventional sources with renewable ones [2]. To support these green energy notions and sustainable development of countries, the United Nations has declared 2014-2024 as the Decade for Sustainable Energy for all. The resolution emphasized on the development of affordable, reliable and environmentally sound energy sources. It also stressed on the improvement of renewable energy shares [3].

The popular types of renewable energy sources include wind, thermal, solar, geothermal and wave. Since the oceans cover 71% of the earth's surface and contain a vast amount of untapped energy, harvesting ocean wave is a viable alternative green

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energy. To harvest energy from the oceans, several methods were developed in different parts of the world. These methods are categorized according to the locations: offshore, nearshore and onshore. Despite their difference in location, directional characteristics and operational principle, most of the wave energy harvesting devices capture the kinetic energy transmitted by the ocean wave and convert it into usable electrical energy [4].

The energy transmitted by the ocean wave is manifested by the movement of water near the surface of the sea. Approximately 95% of the wave energy is located between the water surface and one-quarter of the wavelength below the surface [6]. When this energy interacts with the floating buoys, the wave exerts a considerable amount of force that will cause buoys to move in various directions. To capture the movement information of the buoys, we developed a monitoring device.

To find the optimal site of wave power plant, it is necessary to measure the wave energy near the site location. This paper addressed the development of monitoring module which can be used to assess the amount of wave energy and build a classifier to categorize it into groups.

Figure 1 depicts the schematic diagram of the WEC device developed by INGINE [5]. The WEC has three main components: energy absorbing, energy transferring, and power generating units. The energy absorbing device is a floating buoy located 80 meters away from the coastal line. It is anchored to the seabed by a pulley, which creates a stationary base to absorb the energy transferred by the ocean wave. The device uses the movement of the ocean surface between the crest and trough to create tension force on the connecting rope and to convert it to tension force. The energy transferring device connects the energy absorbing and power generating devices. It also serves as a bridge to transfer the tension force produced by the energy absorbing device.

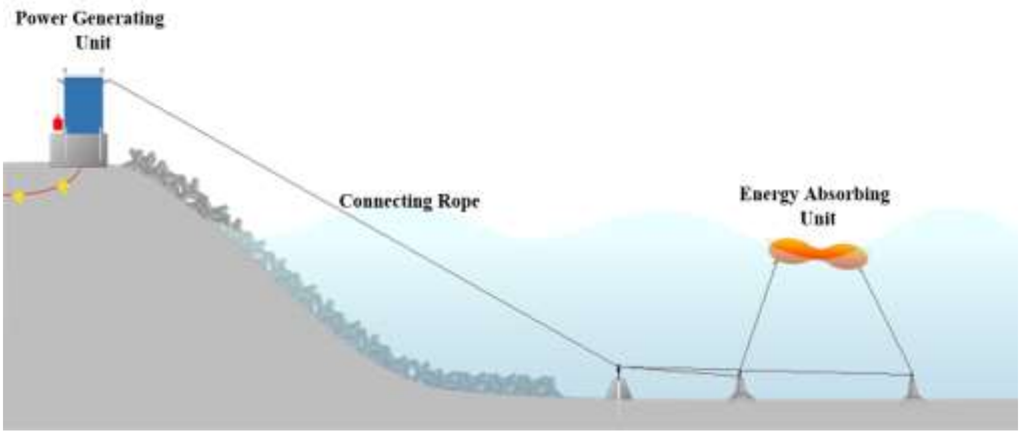


Figure 1. Nearshore Wave Energy Converting Device

The power generating unit contains generators, energy storing devices, and power converters. The system converts the transferred tension force into electrical energy through the generators. The WEC generates power only when the connecting rope is pulled towards the water side or when buoy rises. On the other hand, when the buoy descends, the rope is pulled towards the land side, the counter weight (equalizer) maintains the tension on the rope and keeps the floating buoy on the designated position.

2. Monitoring Module

The proposed monitoring system deals with data collection using the monitoring module.

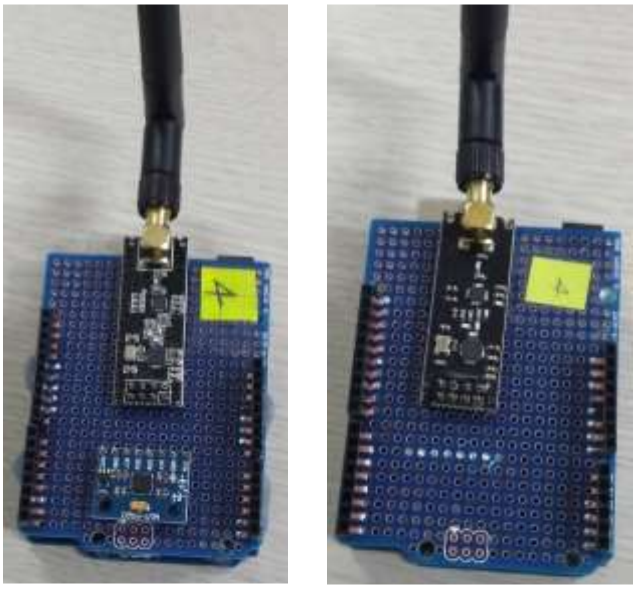
2.1. Data Collecting Module

The data collecting module has three main functions: sensing and converting the movement of the buoys to electrical signals, processing the collected data signals, and lastly transmitting the processed data to the land side where data receiver and PC stationed. The sensing device used for this study is MPU-6050, a tri-axial gyro-accelerometer sensor manufactured by InvenSense. The device incorporates a gyroscope and accelerometer sensor as well as a digital motion processor (DMP) [7].

It is possible to use either gyroscope or accelerometer sensor as a sensing device for this study but the degree of accuracy is lower than that of the combined one. Since using multiple sensors information will result in more reliable and accurate information, it's better to use both gyroscope and accelerometer sensors for data acquisition module [8].

We can observe the movement of the buoys using the MPU-6050. This sensor is widely used to detect the movement and orientation of objects. Especially it is embedded in smartphones and tables to enhance user experiences. Furthermore, we can analyze the movement information to correlate it with the generated out power. The information from the sensor is linear accelerations and angular velocities in the x, y and z axes. These six measurements are used to determine the movement and orientation of objects at a specific time and for a specific type of wave strength.

For a stable wireless communication between the transmitter and receiver, nRF24L01 RF device was used. This device is a bidirectional RF transceiver for ultra-low-power wireless communication. It operates in the global ISM frequency band from 2.4 to 2.4835 GHz [9]. The selection of this device relies on the range of distance that it covers. Since the floating buoys are located around 80 meters away from the coast, we need a stable wireless communication to transmit the data for the desired distance.



(a) (b)

Figure 2. The Data Collecting Module (a) Transmitter Module (b) Receiver Module

The gyro-accelerometer sensor and the RF transceiver are connected to Arduino microcontroller. Since Arduino boards have small computing capacity and low power consumption they can be applied for remote sensing applications which require low power intake. The boards have a microprocessor, memory and extendable digital and analog input/output pins. Our Arduino board selection was motivated by its open source platform which is supported by a large community of developers and designers. Furthermore, there are many projects and applications already implemented using these boards, which makes Arduino board a suitable platform for our project.

For the experiment, a pair of transceiver modules was built. The transmitter module consists of the MPU6050 gyro-accelerometer sensor, nRF24L01 RF device, and Arduino board, while the receiver module has the same except MPU-6050. The purpose of the receiver is to collect the incoming signal and transfer the data to the host PC. The host PC analyzes the incoming data and store it for further processing. Figure 2 shows the transmitter and receiver modules.

2.2. Working Principle of the Proposed System

The data collecting module is intended to convert the movement information of the buoys to a meaningful dataset. The dataset carries a significant information about the wave strength and the amount of power that can be harvested from the WEC device. In the proposed system, we designed the sensor to sample the buoys movement with a sampling frequency of 12HZ. Each sample contains three angular velocities and three linear accelerations.

The gyroscope is supposed to find roll, yaw and pitch angles of objects from angular velocities via a simple set of equations which is usually difficult to solve. However, angular velocities as well as accelerations are good enough to describe the wave strength without using roll, yaw and pitch angles. It is because the latter express the static orientation position of objects. Figure 3 shows direction of movement of floating buoys.

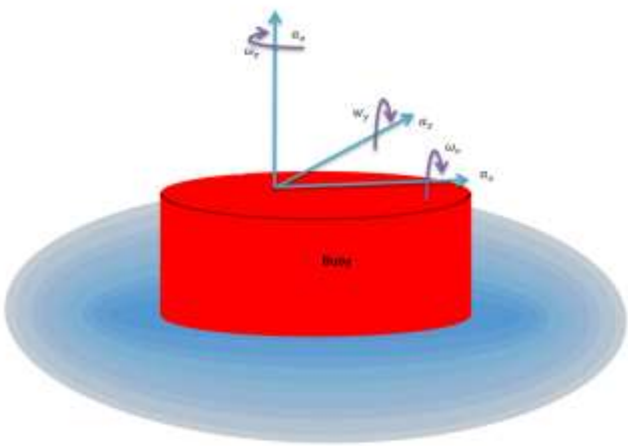


Figure 3. Direction of Movement of Floating Buoys

Figure 4 shows the architecture of the proposed monitoring system. The system integrates modules located on the water side and land side. To track the movement of the buoys from the water side, the data collecting module is firmly mounted on the top of the buoys as shown in Figure 4.

The collected movement information is transmitted to the land side using RF transceiver unit. Both the transmitter and the receiver are configured to communicate seamlessly within the desired range of distance. On the land side, we attached the receving module to a computer located in the power plant. We have developed an application to retrieve the information from the receiver module and store it in a structured database. Storing the incoming data into the database makes it more convenient and easier to query information for further analysis [10].

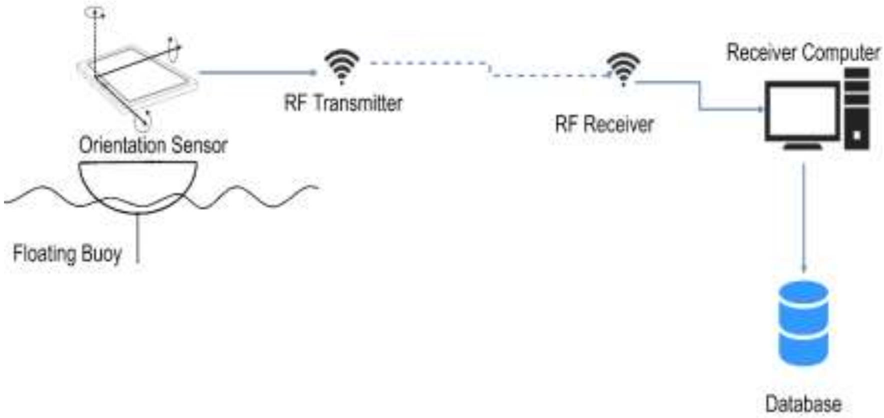


Figure 4. Architecture of the Proposed Monitoring System

3. Data Collection

In this study, we analyzed the movement information of a motion table to simulate the motion of buoys and examined the collected dataset to build an effective classifier. The previous section describes a monitoring module to collect the movement information of the buoys. The acquired data is a time series that can fully represent the movement of the buoy at a given specific time. For the experiment, we simulated the wave motion using Scorsby motion table as shown in Figure 5. The table can make a circular motion with options of tilt angles and rotation speeds. Therefore, the table simulates the motion that can be observed on the ocean and the circular motion with options can represent various wave strengths in a laboratory.

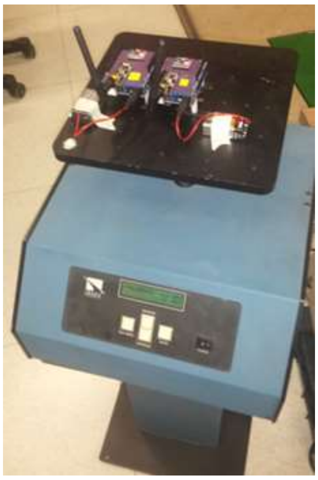


Figure 5. Scorsby Motion Table Used in the Experiment

The motion table has an advantage in reducing the prototyping time for new products and minimizing the cost of implementation. The maximum rotation speed for this device is 20 rpm. Furthermore, the tilt angle can vary from 0 to 30 degrees. The rotating shaft generates sinusoidal motion for each axis, and they cannot be controlled individually [11].

Figure 5 shows the experimental setup. The data collecting module was mounted on the top of the motion table during the data collection process. To reduce noise during data acquisition, the motion table was also firmly attached to a stationary base. Six different motion patterns were generated by varying the tilt angle and rotation speed. For the experiment, we considered scenarios with multiple combinations of tilt angles and rotation speeds. The tilt angle was varied between 5 and 20 degrees and also the rotation speed was varied between 5, 15 and 20 RPM. The experiment for each scenario lasted for 2 minutes. The details of the wave patterns generated are shown in Table 1.

Table 1. Wave Patterns Generated for the Experiment

	RPM	Tilt Angle
Wave pattern 1	5	5
Wave pattern 2	20	5
Wave pattern 3	5	20
Wave pattern 4	20	20
Wave pattern 5	15	5
Wave pattern 6	15	20

4. Wave Strength Classification

The movement of the floating buoys greatly various with the strength of ocean wave. This section explains a method to identify the strength of ocean wave using machine learning by analyzing movement information. Three supervised machine learning algorithms were utilized to generate a classifier based on the data obtained from the buoys. The algorithms use labeled data to build a predictive model and make predictions about new instances of similar data using the generated model [12]. The proposed approach is depicted in Figure 6.

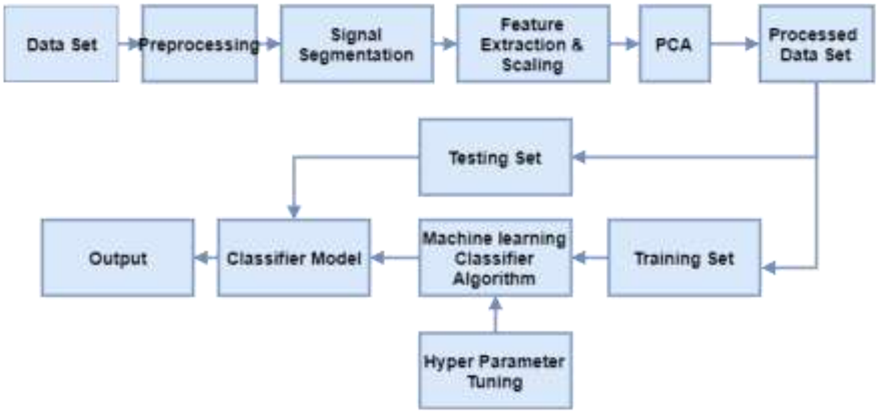


Figure 6. Method for Classifying Wave Strength

Data collecting module including a gyroscope and an RF transmitter was used to obtain an experimental dataset from the motion of the Scorsby table. The dataset contains angular velocities and accelerations in three axes. We applied preprocessing techniques to take care of outliers and noise during the data acquisition. Signal segmentation was done to transform the raw data to appropriate feature set so that it can be applied directly to the classifier. Feature extraction and principal component analysis techniques were also exploited to extract important variables from the preprocessed dataset.

The dataset was split into training and testing set, we have used 70 % of the dataset to train our prediction model and the remaining for testing the model. Classifiers were build using three different machine learning algorithms: support vector machine (SVM), random forest (RF) and artificial neural network (ANN). For each classifier algorithm, we applied hyperparameter tuning technique. This technique searches for optimum values for user configurable parameters which enhances the accuracy of the classifiers.

5. Result and Discussion

5.1. Analysis on Features

The simulation was done to demonstrate that the proposed system was suitable in classifying the wave into distinct groups according to its strength. To assess the performance of the classifier, six different wave patterns were generated using the motion table. From each scenario, time series of three angular velocities and three acceleration were recorded. And the magnitude of angular velocities and that of acceleration were derived from the data. From a total of eight time series, we obtained the mean and the variance of each series using the sliding window. As a result, the new dataset had 16 variables

Each variable was analyzed to examine its impact on class separation. Figure 7 is the distribution of clusters of the six wave patterns in terms of variance of the magnitudes of angular velocity and acceleration. The cluster number in Figure 7 is corresponding to the wave pattern in Table 1.

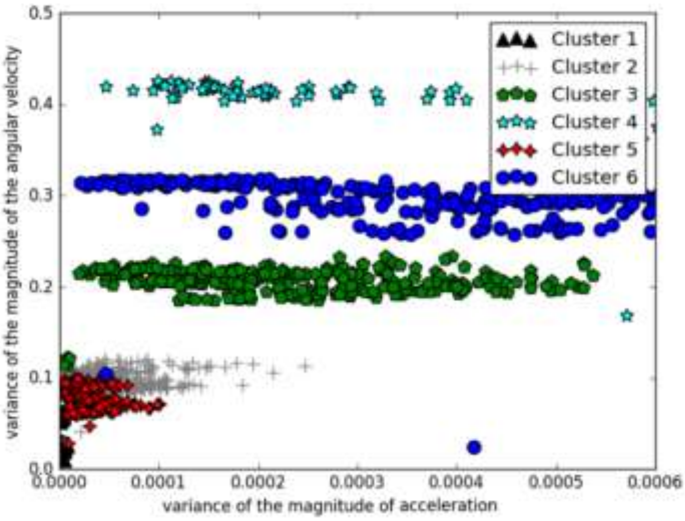


Figure 7. Magnitude of the Angular Velocity versus the Variance of the Magnitude of the Linear Acceleration

It is evident from the figure that as the strength of the wave increases or the rotation speed raise, the variance of the angular velocity also upswings. For instance, cluster 4 has 20 RPM and 20o tilt angle, which are the maximum values for our experimental scenarios. This group showed the highest variance. The graph signifies the potential of the feature sets in identifying different clusters. In general, we can deduce that the combination of the feature set can enable the predictive model to adequately classify the strength of the wave.

5.2. Motion Pattern Classification

Machine learning algorithms can be applied to solve various kinds of real world problems including regression, classification, and clustering. In this study, supervised classification algorithms were used to categorize wave strength based on the motion of the buoys. Three classifiers were generated using SVM, RF and ANN algorithms. The performance of each classifier was evaluated using metrics such as accuracy, precision, recall, and F1-score.

Accuracy indicates the proportion of observations which are predicted correctly. It quantifies the ratio of the correct classification to the total number of predictions made

[13]. Precision is the measure of positive classification that is correctly categorized. It is the ratio of correct positive classification to the total number of positive predictions, which include the true positive and false positive predictions. Recall specifies the fraction of positive observation predicted correctly. It measures the fraction of correct positive predictions to the actual positive observation. F1- score metrics is the harmonic mean of precision and recall [14].

$$\mathrm{accuracy}(y, \hat{y}) = \frac{1}{n_{\mathrm{samples}}} \sum_{i=0}^{n_{\mathrm{samples}}-1} 1(\hat{y}_i - y_i) \quad (1)$$

$$\mathrm{precision} = \frac{t_p}{t_p + f_p} \quad (2)$$

$$\mathrm{recall} = \frac{t_p}{t_p + f_n} \quad (3)$$

$$\text{F1-score} = 2 * \frac{\mathrm{Precision} * \mathrm{recall}}{\mathrm{Precision} + \mathrm{recall}} \quad (4)$$

where y_i = the actual value, $\hat{y}_i$ = the predicted value, t_p= true positive, f_p = false positive, f_n = false negative.

Table 2. Experimental Results

	Accuracy	Precision	Recall	F1-score
SVM	99.48	99.50	99.44	0.9946
RF	99.13	99.09	99.10	0.9909
ANN	98.86	98.64	99.13	0.9883

We have applied three classifiers based on SVM, RF, and ANN algorithms. The performance of each of the classifier was analyzed using the metrics defined above. The detailed result of the classification experiment is presented in Table 2. Furthermore, we have analyzed the performance of the best classifier by thoroughly investigating the confusion matrix of the classifier.

The performance of the classifiers presented has an acceptable range of accuracy. However, it is clear from the table that the SVM classifier performs better than RF and ANN. Table 3 is the confusion matrix of the SVM classifier. It shows a breakdown of correct and incorrect prediction count of each class. Each row of the matrix represents the instances in a predicted class while each column represents the instances in an actual class. As we can see from the table, most of the prediction error occurs when classes have close rotation speed and tilt angle values. For instance, the classifier predicted WP 5 instead of the WP 2. Both of these classes have a tilt angle of 5 degree but the rotation speed is 15 and 20 rpm. In general, the prediction error of the classifier is minimal, and it's promising to use this model for further applications.

Table 3. Confusion Matrix of SVM Classifier

Predicted Class	True Class					
	WP 1	WP 2	WP 3	WP 4	WP 5	WP 6
WP 1	131	0	0	0	0	0
WP 2	0	97	0	0	1	0
WP 3	0	0	87	0	0	0
WP 4	0	0	0	88	0	0
WP 5	0	2	0	0	76	0
WP 6	0	0	0	1	0	95

6. Conclusion

In this study, we developed a monitoring module for the nearshore wave energy converting device and proposed an approach for ocean wave strength classification. The monitoring module consists of a gyro-accelerometer sensor, microcontroller and RF transceiver device. The module uses the gyro-accelerometer sensor to capture the movement of the floating buoys. The data was processed by Arduino microcontroller and transmitted to the land side wirelessly using RF transceiver device. To simulate the wave patterns, an experiment was conducted using Scorsby motion table.

The collected data was preprocessed and analyzed using machine learning techniques such as SVM, RF, and ANN. Based on the experimental results we found out that the SVM classifier shows better classification accuracy as compared to the others. Therefore, we claim that the proposed monitoring module can be applied for monitoring nearshore WEC system, and it is suitable to gather information about the movement of the floating buoys. Furthermore, this procedure can be extended to relate the motion of the buoy and the actual power generated from the wave power plant.

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