A proposal for a new method of fish species and size prediction by recognizing fishing vibration pattern using machine learning

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1. Introduction

In recent years, a fishing as a sport has become popular accompanied with developments of fishing gadgets. The gadgets combined with cutting-edge technologies keep being designed and improved. For example, some fishing products have an ability of sensing an impact [1] when a fish touches a rod and when the nod recognizes the impact it notifies by using a led light which is attached on the rod. Many researchers and developers are trying to come up with a more useful fishing equipment.

In this paper, we will design and develop a new technology for developing a new fishing device. Our aim is to investigate if we can develop a device which finds out a size and species information of a fish when the fish bit the rod. This will be realized by using a machine learning analysis with a movement of the rod and features of information given by a fish.

The contents of this paper is structured as follows. In Section 2, the existing studies related to the proposed work will be presented. In section 3, features of fishes when they swim will be introduced based on the result acquired by experiments. In section 4, the method to realize our goal will be described. The plans for the future experiment will be covered in section 5 and finally a conclusion is given in section 6.

2. Related work

Many studies have been carried out on recognition of species and size of fishes so far. Strachan et al. tried to acquire these kinds of information by using a pattern recognition method [2]. They investigated feasibility of their method based on the data bank of pictures that they collected for the analysis. Although the approach is different from our work since they used a static data for the recognition while dynamic data are analyzed in our work, they could distinguish the type of fishes with a relatively high accuracy. It gives an intuition that static data could be applied to distinguish species of fishes.

White et al. used a computer vision technique to identify a fish [3]. They used the dynamic data collected from fishes passing a conveyor underneath a digital camera. Although they only succeeded to distinguish whether the fish is a round type or a flat type, it was meaningful since they used the dynamic data to recognize a fish.

Randy and Johnson have patented light-emitting fishing float [4]. They attached the sensor of lighting on a hook of a rod where the switch responses when a fish contacts a hook.

As mentioned above, there are many existing studies to identify fish in the context of fishing, however, to the best of our knowledge, there was no research paper dealing with a method to find the fish's species by using a rod. Therefore, in this work, we try to implement a sensor device which can be attached to a fishing rod to capture information of a fish, and identify the size and species of the fishes through analysis of the captured data through the rod taking into account the traits of fishes.

3. Features of fish swimming

Some swimming features of fishes are created depending on the differences in vibration and the movement of a rod. Those features of swimming may help predict the fish species and its size. The fish swimming traits which are related to our research will be described as follows.

Firstly, various swimming forms of fishes are described. The swimming forms are categorized by which parts of the body (fin) the fishes use and the way of swimming using those parts.

Secondly, the fast-start, a brief behavior which is a sudden acceleration caused by reaction, is discussed.

The report by Beamish [5] defined three major categories of swimming activities: sustained (over 200 min), prolonged (20s to 200min) and burst (under 20s). In our case, the fast-starts are included in burst swimming. Because we are focusing on burst swimming, the other swimming activities are excluded from our target swimming styles.

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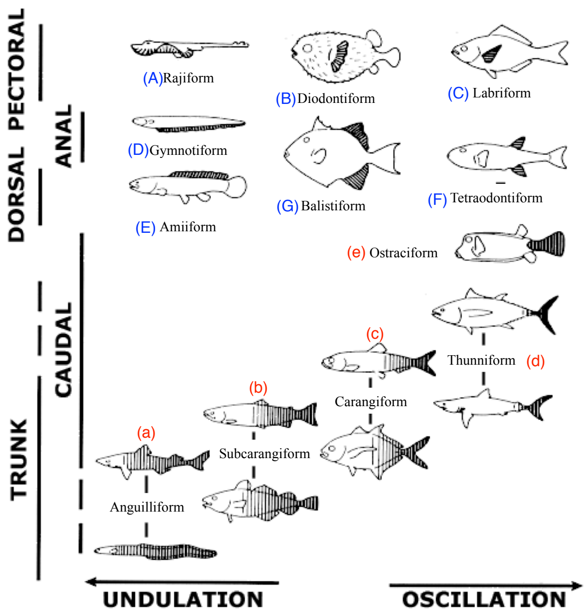

Fig. 1: Fish swimming style [6]

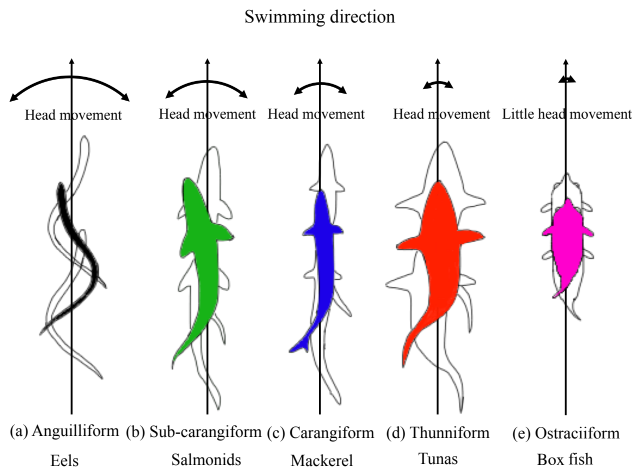

Fig. 2: Caudal trunk swimmers

3.1 Fish swimming style

There are a varieties of fish swimming styles. ESI (Environmental Science Investigation) [6] divided fishes into twelve groups based on the percentage of used body parts which are calculated based on movement in swimming (Fig. 1).

On the other hand, Sfakiotakis [7] reviewed some paper regarding fish swimming modes. According to the paper, some fishes move their body and caudal fin to generate propulsion. Some other species move forward by using their median and paired fins movement. The fishes involved in the former group swim faster so that they can easily hunt or escape from a predator. However, they are not able to turn around rapidly, resulting in a difficulty of hiding from a predator. In the case of latter group, on the contrary, they swim relatively slowly but they can make a rapid change of direction. Thus, they can live in coral reefs.

We describe the details of those swimming styles as follows. The twelve groups shown in Fig. 1 are categorized into two groups. One group is using median and paired fin while the other group is using body and caudal fin.

3.1.1 Propulsion using Median and Paired Fin

Targeting seven fishes which are (A) Rajiform, (B) Diodontiform, (C) Labriform, (D) Gymnotiform, (E) Amiiform, (F) Tetraodontiform and (G) Balistiform, are formed of one group based on its body parts which are using the median and paired fin for swimming (Fig. 1).

The first one is Rajiform (Fig. 1-(A)) locomotion which uses horizontal pectoral fins and moves like a wave. For example, rays, especially mantas use this sort of locomotion. Secondly, Diodontiform (Fig. 1-(B)) locomotion also uses the pectoral fins, however, it moves vertically and a porcupine fish is one example of this locomotion. Thirdly, Labriform (Fig. 1-(C)) locomotion also uses vertical pectoral fins but it is rather stiffer than the former groups. Therefore, they drag the fins through the water like a rowing motion for swimming. Fourthly, Gymnotiform (Fig. 1-(D)) fishes use undulations of a long anal fin and a knife fish shows this kind of motion. Fifthly, Amiiform (Fig. 2-(E)) locomotion uses a long dorsal fin which can move undulate for swim and Bowfin is included in this motion. Sixthly, Tetraodontiform (Fig. 1-(F)) uses anal fins and dorsal to swim. They flapped their anal fins and dorsal simultaneously. Lastly, Balistiform (Fig. 1-(G)) also uses both anal and dorsal fins. The differences in median and paired fin propulsion swimming styles result in differences in the frequency of a fin vibration, and the magnitude of force of fin movements. It can also be extracted as one of features made from vibration of the rod.

3.1.2 Propulsion using Body and Caudal Fin

Targeting five fishes, which are (a) Anguilliform, (b) Sub-carangiform, (c) Carangiform, (d) Thunniform and

(e) Ostraciiform are involved in one group based on its body part such as a body in general and a caudal fin (Fig. 1).

First of all, an Anguilliform (Fig. 1-(a)) fish has a long and thin body such as eels. They move like a wave as it utilizes the entire body called undulation. Therefore, the range of their head movement is significantly wide compared to the length of their body (Fig. 2-(a)). Secondly, a Sub-carangiform (Fig. 1-(b)) fish also swims like a wave as well, but their body is stiffer than Anguilliform fish in general (Fig. 2-(b)). So they are able to swim faster than the former group but they have low mobility (such as salmonids) (Fig. 2-(b)). Thirdly, a Carangiform (Fig. 1-(c)) fish is stiffer and they can swim faster than the former groups. Their movement is concentrated on the caudal and fin. Thus, they rapidly oscillate their tail like a fan when they are swimming. For instance, a Mackerel uses the carangiform (Fig. 2-(c)). Fourthly, a Thunniform (Fig. 1-(d)) fish has a large and crescent-shaped tail. They rapidly oscillate the tail with strong peduncle which connects the body and tail (such as tunas and a shark) (Fig. 2-(d)). Therefore, they can make a high speed and long-distance swim which enables them to chase a prey and run away from a predator. Lastly, an Ostraciiform (Fig. 1-(e)) fish only uses the fin oscillating for swimming. Therefore, the range of their head movement is significantly small compared to the former groups (Fig. 2-(e)). For instance, a boxfish uses the ostraciiform.

3.2 Fast-start

Fast-start is a brief and sudden acceleration made by fish. This action is very important for fishes when encountering a predator or prey. Domenici [8] analyzed those fast-start actions by the kinematics and performance. Fast-start determines the outcome of a predator, prey interactions in terms of feeding success or survival. Weihs [9] divides fast-starts into three kinematic stages (Fig. 3):

stage 1 : the preparatory stroke

stage 2 : the propulsive stroke

stage 3 : continuous swimming or coasting

These three stages will be of great help to determine the range of extracting features.

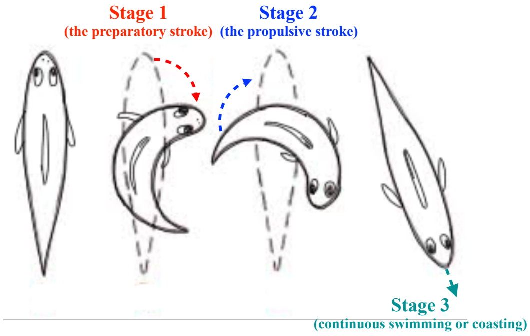

Fig. 3: Sequence of the fast-starts

4. Methodology

The method proposed in this paper, the fish species and its size are going to be predicted by a 9-axis sensor using machine learning. Firstly, we describe about the 9-axis sensor which will be attached to the fishing rod. Secondly, we discuss about two types of features extracted from sensor data. One is time-based extraction and the other is a frequency-based extraction. Finally, we will describe the details of machine learning approach regarding how to predict the fish species and its size.

4.1 Sensor

In our proposed method, we use two sensors. We use a small sensor board called Senstick [10, 11, 12, 13] and attach it on the tip of fishing rod. SenStick is tiny and light (3g including a battery) and can measure the 9-axis acceleration and communicate with a smartphone through BLE. The attached position of Senstick is a tip of a rod since the tips are the most fluctuating point of the fishing rod. The sensitivity of Senstick can be set to 1G, 2G, 4G and 8G. Therefore, it is adaptable to various situations.

Moreover, the fishing vibration data will be obtained using a smart device which is attached near the fishing rod. The type of the smart device is iPod touch manufactured by Apple Inc. [14]. It has an acceleration sensor, gyro sensor and compass. The attachment position of both devices are shown in Fig. 4.

Sampling frequency of iOS App running on iPod touch and Senstick is 100 Hz. This frequency was determined by our preliminary experiment that catches two Hera-huna fishes. One is length of 350mm and the other one is 280mm. In this experiment, we obtained the vibration data from sensors observing acceleration on the iOS app with sampling frequency of 10 Hz. With this sampling rate, however, it was not enough to visualize the frequency spectrum of fish vibrations because the maximum resolution of FFT is only 5 Hz. Thus, it is difficult to compare the differences of fish species and its size by the fish vibration frequency only.

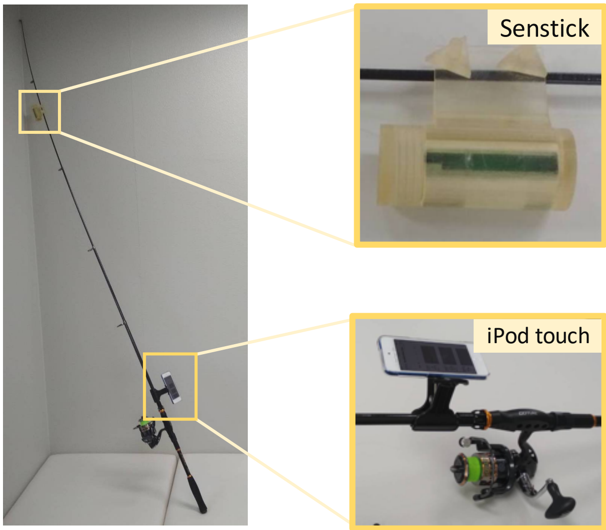

Fig. 4: The position of sensors

4.2 Features extraction

As we described the fish swimming styles, there are several patterns which are related to the fish species and the shape of fish. Therefore we will predict the fish species and its size by using those patterns with our feature extraction method. In the plan of our feature extraction, there are two types of features extracted from acceleration data. One is time-based extraction and the other is frequency-based extraction. Time-based extraction set the first 10 seconds time-series sensor data to the target.

Time-based extraction is calculated by using 10 seconds time-series data with the statistical function such as average, standard deviation, maximum and so on. These features are able to describe how the fishes fight with the rod and the line and how strong their strength is when they pull the line. We considered that the fish size and weight affect the vibration amplitude and the turning reaction of fishes because a big fish swims stronger than a small fish while the big fish is harder to turn around compared to tiny fishes.

In frequency-based extraction, we use the FFT (Fast Fourier Transform) [15] for the analysis of fish vibration frequency. The FFT converts a time series of equally separated values from the discrete time domain to the discrete frequency domain. Vibration frequency data includes the information of fish's swimming style. We consider that fish vibration consists of fish's head movement, body and caudal fin propulsion. Generally, user's rod movement is also considered as noise.

4.3 Model building

The purpose of our research is to predict the fish species and its size with machine learning model. The flow of model building is shown in Fig. 5. Firstly, it starts at feature extraction from the vibration data. Secondly, we concentrate on sorting features data and collect ground-truth labels (fish species and size) to prepare training data for machine learning. Thirdly, two models are built on the data collected. One is the model which predicts the fish species. The other model is to predict the fish size. Lastly, the test will be done by intentionally inputting features data without labels and see if the fish species and size are predicted correctly by the learned model.

Several machine learning models will be used to compare prediction results by the models. In this case, machine learning methods such as supervised learning models, Decision Tree, Random Forest and SVM (Support Vector Machine) will be implemented.

Decision Tree [16, 17] is a graph that uses a branching method to illustrate every possible outcome of a decision. Random Forest [18, 19], which is one of the strong machine learning models. Random forest consists of a large number of individual decision trees that operate as an ensemble. Each individual tree in the random forest results in a class prediction and the class which is the most appeared becomes the model's prediction result. Therefore, Random Forest can learn the various types of features based on many trees. SVM [20] is a supervised machine learning algorithm which is used for classification or regression problems. It uses a technique called the kernel trick to transform data. And then it utilizes these transformations to find an optimal boundary between the possible outputs.

5. Experiment plans

In order to collect various species of fish data, a lot of fishing spots will be visited with the sensing devices such as the Sensticks and the smart device. To minimize the effect of waves, choice for a non-floating fishing spot is desired. Also, when the fish bites the rod, the line between the tip of the rod and the fish will

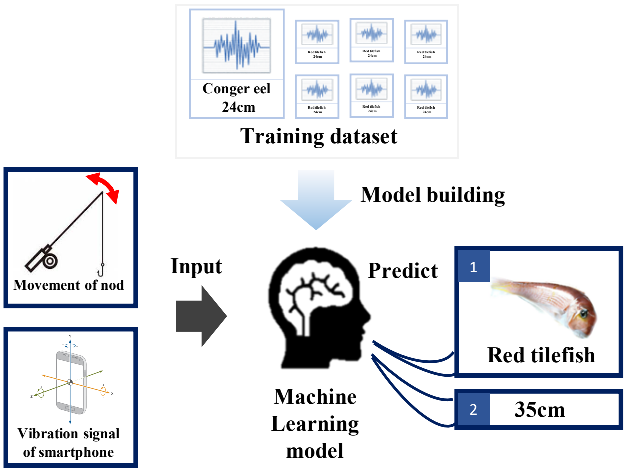

Fig. 5: The procedure of model building

be stretched strongly and straight. At that time, the condition is not including the wave vibration because the line is straight.

Our fishing style is "single-hook fishing" which can hit only one fish at one time. At least five species fish data will be collected and more than ten fish will be needed for one species. Thus, the total number of fish data is expected to be more than fifty.

In evaluation of machine learning model, the features such as accuracy, precision, recall, and F-measures are used as numeric indexes. Also, to review the predicted details, we calculate a confusion matrix. Confusion matrix is often used to describe the performance of a classification model on a set of test data that the true values are already known. Evaluation method is 5-hold cross validation [21].

6. Conclusion

In this paper, we proposed a method for predicting the species and the sized of fishes from the vibration of the fishing rod. To capture the vibrations and movements transmitted from the fishing rod, we attach a Senstick and a smart device to specific positions of a rod.

There is a potential problem in the proposed method that the vibrations and movements which are delivered through the fishing rod are likely to contain a bit of noise by many factors such as waves, currents, and bumps of obstacles. Moreover, there are undesired noises which are made by a fisher such as an unnecessary touch to the rod and shakes generated when the fisher hook a fish. The noises generated from hooking induces vibrations and result in the fish doing fast-start. So, it should be considered regarding the method to minimize the noises. This would be resolved by installing a force sensor or acceleration sensor in the reach of a human hand and observing the noises from human motion. Finally, we expect this research paper to contribute to a fishing community by sharing the refined data which is collected for the experiment. Furthermore, it is expected to have positive effects by helping people collect information of fish individually.

Acknowledgment

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