Designing embedded fish sensor for underwater robot

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Commercial fish finders have already been known and widely used in so many real applications. However, sometimes these kinds of instrument are not suitable for underwater robotic or submarine robot applications. The size and the interfacing features are not designed to meet the requirements of underwater robot application purposes. This system relies on an Artificial Neural Network implemented on an embedded microcontroller. By using a proximity ping sensor widely used in mobile robot with some dedicated signal pre-conditioning and processing of extracted features with the proposed algorithm, a fish detection and classification system has been realized. The proposed system gives satisfactory achievement with respective maximum values of 100% for detection and 94% for classification. Also the existence and the type of fish can be known and the behavior of group can also be revealed by statistically interpretations such as hovering passion and sparse swimming mode.

Keywords: fish detection, classification, Artificial Neural Network, ultrasound sensor, marine robot

Introduction

Fish detection is not a new idea; many researches have tried to develop fish detection system. They even expand their ideas to localization of schooling fish which is similar with fish finder. Variety of techniques and algorithms have been developed and implemented, where some of them use ultrasound based fish finder combined with Global Positioning System. A simple smart algorithm embedded into a small light weight device has to be used for a small fish robot or a miniature submarine, which has limited area for equipments.

It is common for fisherman to find fish using a fish finder device which usually consists of ultrasonic transmitter and receiver. The fish finder detects the existence of a group of fish. Certainly, the fish finder detects only fishes in the coverage range of the detector. The corresponding schooling fish generates reflection wave that enables the identification of the existence of a group of fish. Up to now, many researchers have been tried to produce advanced fish detection devices to locate the location of individual or schooling fish. A variety of techniques and algorithms has been proposed and implemented, including ultrasound-based fish finders combined with Global Positioning Systems. For a robotic fish (Zhi. Et al., 2005) or a miniature submarine with a limited area for the detector, a compact detection device has to be deployed, which is smart enough but light weight.

Hence, the fish finder features can still be improved to have the ability to classify the type of fishes, not just their existence, by adding pattern classification algorithm such as Hidden Markov Model, clustering, or artificial neural network (Haralabous, et al., 1998) to the system.

Fish finder used in a fisher boat may not be suitable for a small submarine robot which requires only a small and light enough sensing device. The present study comprises a fish detection and classification system for small fish types which have the behavior to gather or school together. Moreover, the performance of fish finders can be improved by using pattern classification techniques such as Hidden Markov Models (HMMs), clustering algorithms, Fuzzy logic (Handoko, et al., 2007) and artificial neural networks. In other words, not only their existence but also the fish type can be identified. For instance, Lee, et al. [2009] proposed a novel location estimation approach based on maximum likelihood approach to underwater localization based on signals collected by the sound receivers.

The current fish detection devices are expensive and cannot be deployed in many small underwater or submarine robots because they have limited space (Tidd and Wilder, 2001). Therefore, it is necessary to
develop new type of fish detection devices which are cheap and compact in size. This is the main issue to be addressed in this paper.

The rest of the paper is organized as follows. Section II presents a new design for fish detection and classification, including the sensor system used in this design. In Section III, some general procedures are designed for testing and evaluating the proposed fish detector. Section IV presents some experimental results to show the feasibility and performance of the proposed fish detection device. Finally, a brief conclusion and future work are summarized in Section 5.

Materials and methods

1. Classification underwater object

The synthetic system is imitating the ability of human. Some procedural to classify is made or firstly a pre-processing must be conducted to reveal the uniqueness. If the single sample can not be used to make classification then classifying can be done by observing populated sampling. In synthetic system, the sensor to sense and capture the feature is depended on the environment and intrinsic variable. Sensing system in the water environment is not the same as in the air. Water has special characteristic such as pH, conductivity, pressure and clearness. Visual sensor like camera usually can not be used in the water because the light become eagerly demand and lighting effect in the water interferes the acquisition. The suitable sensor in the water is sonar sensor. The sonar sensor is not clearly free error, it is containing noise signal. One ping sonar transmitted signal with spike form will echo multi spike form when reflected to multi normal field (Fig. 1). So, the common sensor to detect the existence of schooling fish in the sea or river is sonar sensor.

Some pre-treatment to echoes signal should be done like filtering, de-noising and feature extraction. After that, the detection and classification procedures can be conducted (Brehmer et al. [2006][2007]). The pre-conditioned sonar signal then being analyzed with some classification algorithms. There are various methods of pattern classification such as Hidden Markov Model as mentioned before. This method compares the output sequences of an interrelated input model with the corresponding state condition as reference pattern. Some state conditions are determined before the classification process using the related clustering data. Other method which is easier to train is fuzzy min max neural network classification method which combines the fuzzy logic (Hu, et al., as inferential tools with Artificial Neural Network (ANN) as classification method). Input patterns represent the fish types which are available as ultrasound echo signals.

The feature extraction tool also becomes the important step to get successful classification. Some methods of feature extraction run on time domain rather than on frequency domain. Kulichenko, et al propose two techniques of feature extraction. Feature extraction in time domain may take shape of signal, present of peak, local maximum or minimum, average maximum amplitude and duration as the representative features. In frequency domain, the feature is obtained by transforming time domain echo signal to frequency domain representation using Fast Fourier Transform. Range of maximum amplitude in frequency domain will be the corresponding observation variables. Fuzzy logic can also be used as a classifier tool using fuzzy C-means and fuzzy nearest prototype (Estévez, et al., 2003, Hu, et al., 1998). In this paper the detection tools rely on in time domain computation. All echo ultrasound data is extracted to get significant features and then inserting the result to Artificial Neural Network (ANN) (Haralabous, et al., 1996).

2. Sensory system

The sensory system is designed by using modified ping ultrasound sensor Maxsonar EZ-1 which is widely used in mobile robot as proximity sensor working at frequency of 42 KHz. To make the sensor waterproof, it needs a protection layer which can transmit and receive ultrasound signal but hinder water entering the sensor housing. Thin rubber is used as waterproof media and it is very useful.

The sensor output has three type of data i.e. analog, digital and PWM (Pulse Width Modulation). Serial format digital data can be easily linked to other digital port such as microcontroller or computer port. For Basic Stamp microcontroller, the configuration of sensor connection can be shown as in Fig. 2.

This sensor is suitable for detection of small fish in the range of 10 to 100 cm. It is shorter than the

Figure 1—Transmitted and received signal
detector used in air caused by uncoupling buffer between protection thin rubber and water. The sensor will produce serial digital echo signal when there is an obstacle reflects the transmitted signal. The sensor is a type of proximity sensor so that the distance information of the signal will also affect the inputs to the detection system.

3. Embedded artificial neural network

Embedded Artificial Neural Network (EANN) is an artificial neural network algorithm that is specially designed to meet the requirements that it must be downloadable object into microcontroller. The method applies continuous function artificial neural network which is simply derived from the corresponding discrete function.

Continuous algorithm of ANN is similar with back propagation algorithm with no hidden layer architecture such that it can be rewritten as follows:

\[
\hat{y}_j = f(b_i + \sum x_iw_{ij})
\]

\[
f(.) = \frac{1}{1 + e^{-\alpha x}}
\]

\[
\Delta w_{ij} = \alpha \frac{df}{dx} (\tilde{t} - \hat{y})
\]

\[
= \alpha (\tilde{t} - \hat{y}) f(.) (1 - f(.))
\]

In this case, the exponential function in sigmoid function (Equation 2) can be represented as follows:

\[
e^x = 1 + x + \frac{1}{2!} x^2 + \frac{1}{3!} x^3
\]

Experimental procedure

The experimental procedures are divided into three stages. The first stage consists of data acquisition and preparation of good feature extraction from raw sensory data. The second stage is learning stage that uses artificial neural network as offline supervised procedure relied on MATLAB toolbox.

Feature extraction and data acquisition is done by Basic Stamps II microcontroller (Fig. 3). The role of microcontroller in preparation stage is to transfer echo signal sensor to computer. Simple visual basic program can be downloaded from website. The last stage is testing the detection and classifier algorithm that has been downloaded to EEPROM microcontroller.

The sensor subsystem is installed in a board with rotating shaft that allows the board to be rotated according to its axis. The rotating mechanism is mounted at fixed thin plywood. The other plywood divides the water into two areas, with and without fish areas respectively. The existence or absence of fish is simply done by rotating the shaft (Fig. 4). If the sensor faces to non fish area, it will be set up as it is to
have no fish condition but on the other hand to have the existence of fish it just only needs to rotate the shaft. The distance between the sensor and fishes is about 25 cm.

Feature extraction is considered to localize any echo signal which represents the existence of fish i.e. the big amplitude and it is separated from raw data as independent signal. This data is processed by statistical tool such as mean or maximum value. The extracted feature is fed to Artificial Neural Network as learning tools with learning rate $\alpha = 0.1$, standard deviation $\sigma = 0.003$, target vector $t$, and activation function $f(.)$. The idea is to have the realization of Artificial Neural Network on microcontroller. This is done by representing some continuous non linear activation function with a linear-fraction of function.

There are two fishes used in this experiment: banded fish and gapi fish. The size of fish is about 3 cm length and 1 cm height. All types are tested separately.

1. Feature extraction

Feature extraction procedure processes raw data, i.e. echo sensor signal $c(t)$ (shown at Fig. 5), into some variables by which the existence of fish can be clearly represented and in other side the non fish obstacle can be eliminated too.

Kulinchenko, et al.\textsuperscript{2} use the range of minimum to maximum of temporal data as a feature that may represent fish existence. The technique is called later by the shape parameter. The shape of the echo provides a great deal of information about the reflecting object. The slope of the echo’s leading edge reveals how hard the reflecting surface is. The trailing edge reveals information about the absorption of the echo by the target and the target’s resonant structure.

In this paper, the output of feature extraction process is an existence vector with $[2 \times 1]$ dimension and a directional vector with $[4 \times 1]$ dimension, where they are symbolized as $\bar{E}$ and $\bar{D}$ respectively:

\[
\bar{E} = \left[ \sum_{i=1}^{N} c_i ; \forall c \in [u_k, v_k] \right], \quad k = 1 \text{ to } 3 \quad \ldots (5)
\]

\[
\bar{D} = \begin{bmatrix}
\min(\tau) \\
\max(\tau) \\
\sum_{i=1}^{N} d_i \quad ; \quad f_1(d) \\
\sum_{i=1}^{N} d_i \quad ; \quad f_2(d)
\end{bmatrix}
\]

With

\[
f_1(d) = \sum_{i=1}^{N} d_i \quad ; \quad f_2(d) = \sum_{i=1}^{N} d_i
\]

The value of $\tau$ represents the time distance between two neighbor amplitudes and $d$ is a amplitude distance between two neighbor amplitudes, as can be shown in Fig. 6. The value of $[u_k, v_k]$ for each percentile can be shown in Table 1 where $N$ is the number of data for one detection.

Table 1 becomes a template or matching table for the detection of the existence of fish. The number of amplitude, as mentioned before, represents the variety of distance obtained from schooling fish. These numbers can represent the change of distance in some certain time. This indirectly represents the motion

![Figure 5—Echo sensor signal $c(t)$ (normalized to 1) obtained by directly connecting the ping sensor to computer serial port](image1)

![Figure 6—Calculation of $\tau$ and $d$ value](image2)
The amplitude of signal $c(t)$ actually represents the distance between sensor to object. Hence, the distribution of $d_i$ represents the static or dynamic object in forth to back direction. If the fish tendentiously hovering or remain stay then the thirteen signal transmitted by sonar will all back to receiver, and also it is happened when the signal reflected by massive wall. The value of $d_i$ will be small or near zero. If the fish is swimming closely to receiver; or far away from the sensor the value of $d_i$ will not be near zero. So the $d_i$ can be represented the radial direction. In order side, $\tau$ represents the mobility of fish in angle direction, if in every transmitted signal period (40 ms) the peak is always there, it means the group of fish is not moving out from angle of sonar beam i.e. The location detected always not vacant. When the shoaling fish is not in angle of sonar beam the value of $\tau$ are 20 n ms with n integer value greater than one. Transmitted period $T$ is 40 ms. The relation between $d_i$ and $\tau$ heuristically can be represented in Table 2.

### Table 2—Relation between variable $d_i$ and $\tau$

<table>
<thead>
<tr>
<th>Condition</th>
<th>$d_i$</th>
<th>$\tau$</th>
<th>Approximating condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>$=0$</td>
<td>T</td>
<td>Boundary condition or the fish hovering or there is a static obstacle</td>
</tr>
<tr>
<td>B</td>
<td>$&gt;0$</td>
<td>T</td>
<td>The fish going away from sensor but maintain in angle of beam</td>
</tr>
<tr>
<td>C</td>
<td>$&lt;0$</td>
<td>T</td>
<td>The fish come close to sensor but maintain in angle of beam</td>
</tr>
<tr>
<td>D</td>
<td>$=0$</td>
<td>nT</td>
<td>The fish is going out from area of angle beam and coming back exactly at the same place</td>
</tr>
<tr>
<td>E</td>
<td>$&gt;0$</td>
<td>nT</td>
<td>The fish is going out from area of angle beam and being detected again in the area angle of beam at nT time with position further than before</td>
</tr>
<tr>
<td>F</td>
<td>$&lt;0$</td>
<td>nT</td>
<td>The fish is going out from area of angle beam and being detected again in the area angle of beam at nT time with position closer than before</td>
</tr>
</tbody>
</table>

2. **Detection and classification procedure**

The existence of fish is detected by checking the vector $\vec{E}$ while the fish type is detected by inserting the vector $\vec{D}$ that is produced by feature extraction to Artificial Neural Network algorithm. The whole process can be shown in a flowchart as shown in Fig. 7.

The amplitude is obtained by recording the echo amplitude in multi interval by ignoring fish-swimming direction. By using a simple statistics, the corresponding range is sorted into table, and subsequently the detection can be done by using table matching approaches.

3. **Density of shoaling fish**

Vector $\vec{E}$ is summing every the discrete signals which has a value between certain range so this is a cumulative distribution. The range can be equal interval or non-equal interval. In schooling and also in shoaling fish this vector is represented the size or density of group fish as shown in Fig. 8.

Then the density can be found by modified $\rho$, used in$^2$ to the form of $\vec{E}$ as follows:
The amplitude range classifier is based on observation of the amplitude range of temporal data where the magnitude is normalized in the range of 0 to 1 (Table 1). It should be remembered that this range which is represented by vector $\vec{E}$ also contains distance information of fish as the ping ultrasound sensor itself is also used as a proximity sensor. So the amplitude of echo signal measured in this vector truly represents the distance between sensor and the fish. However, this information is not useful and should not eliminate the main goal, i.e. the information of fish existence.

The value $\tau$ and $d$ in Equation (5) represent the interval time and amplitude difference which may indicate moving objects. The directional vector $\vec{D}$ can not exactly detect the real fish direction but it only expresses the changing direction caused by fish schooling pattern such as approaching or going far away from the sensor.

The number of echo is counted with the same sampling time for each 1 minute measurement. The range of maximum amplitude and number of (echo) amplitude will be the inputs for separation process. The range is simply defined by dividing the total range of amplitude into three equal part of percentile obtained from 20 experiments. The disturbance signal coming from the edge and the wall of aquarium can be eliminated by increasing the starting boundary value and decreasing the final boundary value respectively.

The ANN supervised learning algorithm which is done with MALTAB. Using 20 training data, the ANN’s learning process has achieved successful optimization with MSE = 0.1. The weighting variable as the product of this process is inserted into ANN microcontroller algorithm. Results from 20 real-time tests indicates that the proposed system gives good achievement as can be shown in Table 3. The successful criteria of the classification are represented in percentage of total test.

The present result will reveal that by using the existence vector $\vec{E}$ and the cumulative amplitude pre-designed table, the proposed low cost fish detection has already successfully been realized. The classification success rate of fish type II is only 80% and less than fish type I. It is also shown that the pattern of direction which is represented by directional vector $\vec{D}$ is more reliable in fish type I. The ANN easily obtains its corresponding optimization value in tenentious similar pattern or in very non similar pattern. Hence, for the case of fish type II, the pattern of directional vector for each learning samples do not have distinction power or significant distinction.

If $\tau_i$ and $d_i$ values are tabled and then the variability based on the standard deviation can be calculated and finally it will be found that fish type II has greater value than fish type I.

Table 4 reveals that the mean value of $d$ has almost the same value for the two types of fish. It indicates that the average of amplitude neighborhood distance in two types is similar. It means that the two groups of fish have tendency to gather in the steady location and have little passion to wander or make hovering swim. Fish type I has mean $\tau$ greater than that of type II. This is caused by the size of fish type I that is bigger than type II so the schooling fish type I is detected more often and it is also shown by smaller value of $\tau$-standard deviation. The value of $d$-standard deviation represents the sparse group of fish. In a group, the schooling fish type II has sparse swimming mode and has more density (individual per area) than type I.

Table 5 comprises the value of average density and the bias and also the condition of shoaling fish. Group fish type I have behavior to swimming in a group (almost like schooling fish) their center of the group always change but they keep the group to stay together. So the density is bigger than type II. Group fish in type II has condition D as their habit.
swimming mode (Sfakiotakis, et al., 1999). The existence and the type of fish that can be known through the present study. The behavior in group can also be revealed by statistically interpretations such as hovering passion and sparse swimming mode. The most conditions captured are hovering and running away condition. The variation of mobility and agility may be quantized by thoroughly observing the directional vector and the density changes. The size of the fish, the intensity distribution of the sonar, absorption and noise are not discussed yet.

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