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A Neural Filter for Electrolocation in Weakly Electric Fish

Miyoung Sim and DaeEun Kim

Biological Cybernetics Lab, Yonsei University,
School of Electrical and Electronic Engineering,
Seoul, 120-749, Corea (South Korea)
e-mail: daeeun@yonsei.ac.kr

Abstract. The weakly electric fish have the electric organ to generate the electric field and electrosensory mechanism to read the change of electric field with their electroreceptors. The electric organ produce a waveform of electric field as their electric organ discharge (EOD). Their active electrolocation system can detect the distortion of the self-generated electric field, which is caused by a target object, and estimate the position of a target object. In this paper, we suggest a hypothesis that the periodic EOD signals are involved to extract localization features from noisy electrosensory signals and then provide a possible neural network to process the noise-filtering to obtain the accurate information of a target position. The neural network has sinusoidal weights to process a time series of sensor readings for each electroreceptor.

1 Introduction

The localization of a target object is an essential mechanism for animals to survive the environment. Animals capture a prey, or detect predators using their own sensory system. Most of them use their visual, auditory or odor information, but electric fish sense their environment with their electrosensory system instead of other sensory systems. Electric fish can use the electric field as a carrier source of sensory system [6].

There are three types of electric fish, strongly electric fish, weakly electric ish, and elasmobranch fishes that can only detect the electric field. Strongly electric fish generate powerful electric field enough to make their prey fainted or threat their enemy. However, an electric field of weakly electric fish is not strong to capture prey or guard from predator. They use their own electric field to explore surroundings, navigate, detect a target, and communicate. It is expected that the study of weakly electric fish can give us a possible developement of electrosensory system [6]. Elasmobranch belongs to the third group that can only detect the electric field. Elasmobranch has ampullary type electroreceptors which are sensitive to external electric stimuli and deliver physical stimuli to the brain system [5].

Weakly electric fish have two types of electroreceptors, tuberous electroreceptors and ampullary electroreceptors [5, 7, 8]. Tuberous electroreceptor organs are specialized to sense modulations of the self-generated electric field that has high frequency characteristic. It is known that Mormyroidei and Gymnotiforms

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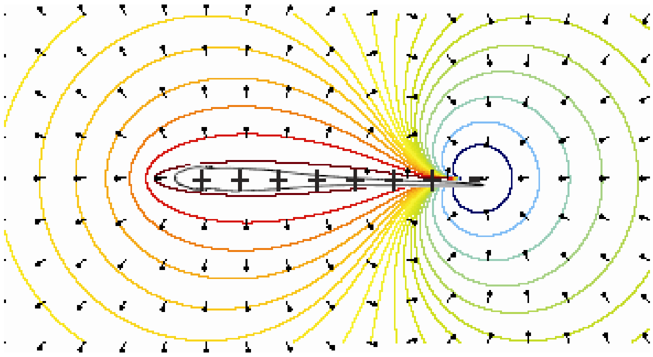

Fig. 1: Electric field with electric organ in weakly electric fish (contours indicate equipotential lines)

havey more tuberous electrosensors than ampullary type. Weakly electric fish which have tuberous electrosensor use active sensing. They can exploit electric field as a self-generated carrier as shown in Fig. 1. The released electric field is distorted by the environmental objects and weakly electric fish detect the change. When there is an object near weakly electric fish, the intensity change is affected by the position, size, and electrical characteristics of an object at each electroreceptor.

In three-dimensional space, weakly electric fish identify the position of a target object in rostrocaudal (from head to tail), dorsoventral (from dorsal part to ventral part), and lateral (from their body to side) axis. In an electric image, the peak amplitude position indicates the rostrocaudal and dorsoventral position of a target object. The lateral position of a target object changes the maximal amplitude, but the maximum intensity is also affected by the size and conductivity of an object. It is already known that the relative slope and full-width at half-maximum (FWHM) of electric image can be a measure of lateral distance. The relative slope is the ratio of maximal slope to maximal intensity in the electric image, and FWHM is the width when the intensity is half in an electric image. If there is no noise in electric image, it is easy to estimate the lateral distance of a target object.

Weakly electric fish have electric organ (EO) that is composed of modified nerve and muscle cells and EO generate a waveform of electric organ discharge (EOD) [2, 5, 4]. A waveform of a lot of Gymnotiformes and most of Mormyriforms is a pulse-type waveform with large intervals. The EOD has a periodic form in time domain. We use this electric sequence in time domain to extract accurate distance measure. In this paper, we suggest a neural network to reduce noise in the electric image. The neural network has sinusoidal weights to process a time series of sensor readings for each electroreceptor and thus remove a high-frequency noise. Then a collection of sensor readings along the rostrocaudal axis can estimate the distance of a target object.

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2 Method

2.1 EOD waveforms and object perturbation

We simulate the electrosenses at a collection of electrosensors on the skin surface. For simulation, we set the body length to 21cm and the length of electric organ to 15.47 cm, and fix the density of electric pole to 10 poles /cm, following the body model from other works [3, 1]. The number of electric poles is approximately 155, and these poles lie along the midline of fish. All poles are positive except the negative pole at the end of tail. Each electroreceptor measures the perturbation of transdermal potential caused by an object near the fish body.

The EO can be composed of a collection of electric poles and electric field is the total sum of electric potentials of electric poles [3]. When there is a sphere object near weakly electric fish, the perturbation effect of an object at a position of an electroreceptor is reflected on the sensor readings $\Delta V(\vec{x})$,

$$\Delta V(\vec{x}) = \chi \frac{a^3 E(\vec{x}_{obj}) \cdot (\vec{x} - \vec{x}_{obj})}{|\vec{x} - \vec{x}_{obj}|^3} \tag{1}$$

where E is the electric field vector of perturbation potential caused by a target object, a is the radius, and $\vec{x}_{obj}$ the center of a spherical target object. The symbol χ electrical property -1 for a perfect conductor and 0.5 for a perfect insulator of an object.

Gymnotiform fishes generate continuous periodic waveform. It is known that A. albifrons generates such EOD waveforms which have about 1kHz frequency [7]. In our experiments, the simulated EOD waveform with 1kHz frequency and the corresponding sensory signal are processed. In three-dimensional space, the rostrocaudal and dorsoventral positions are directly indicated by the position of peak amplitude because of the distribution of sensors all over the skin surface. A collection of electrosensory signals along the rostrocaudal line will form an electric image. This electric image determines the lateral distance of a target object, using the relative slope, that is, ratio of maximum slope to maximum amplitude. Each electroreceptor has noisy sensor signal as shown above, and the noisy signal influences the estimation of distance badly. Noise-filtering is required for accurate estimation of distance of a target object.

3 Neural filter model

We build a neural network model to calculate the cross-correlation between the emitter signal and the receiver signal. We argue that the cross-correlation over an electric image can find de-noised electric image by removing noise in temporal domain and thus more accurate distance estimation can be obtained. Here, cross-correlation can be calculated at each electroreceptor over the two signals, the self-generated EOD waveform and the signal distorted by a target object and noise. We take the maximum of cross-correlation results for each electroreceptor. The cross-correlation can effectively reduce noise with auto-correlation function.

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$$Output = \max_t \sum_{i=1}^{q} b(i) * x(q+i-t)$$

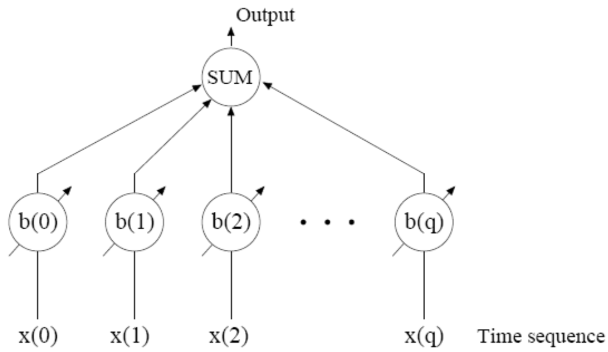

Fig. 2: Neural network model to represent cross-correlation mechanism

A time series of signals should be consecutively considered for the calculation and the neural network model shown in Fig. 2 can handle this cross-correlation. Here, the self-generated EOD waveform has a regular form of sinusoidal signal and thus the waveform is encoded in the neural weights, $b(0), b(1), ..., b(q)$. We set the neural weight $b(k) = A_0 sin(2\pi k/N)$ where A_0 is the amplitude, N is the number of weights, f is the EOD frequency, and k is an integer. If we have a different model for the EOD, then we can use that activation for the weight sequence. The original EOD waveform of weakly electric fish can be interpreted as a weight sequence of the neural network as represented as $b(0), b(1), ..., b(q)$ when q is length of an EOD wave for a cycle. When temporal electric potentials are detected at each electroreceptor, a time series of observed sensor signals pass through this neural network as remarked in $x(0), x(1), ..., x(q)$ for a cycle of EOD waveform. Initially, the sensor reading, $x(0)$, will be weighted with $b(q)$. After time $t1$, a sequence of sensor readings $x(0), x(1), ..., x(t1)$ will be multiplied with weights, $b(q - t1), b(q - t1 + 1), ..., b(0)$. We take maximum of weighted sum and the output at each electroreceptor generates denoised electric image for a collection of electroreceptors.

4 Experiments and Results

To evaluate the noise-filtering methods, uniform random noise is added to the electric image. Fig. 3 shows noisy sensor signals in spatiotemporal domain. We use three types of methods to process noisy electric image for periodic EOD waveforms, and the methods are applied in time domain to see the effectiveness of the neural network model.

- Method1: take average of intensities at the regular point for one period at

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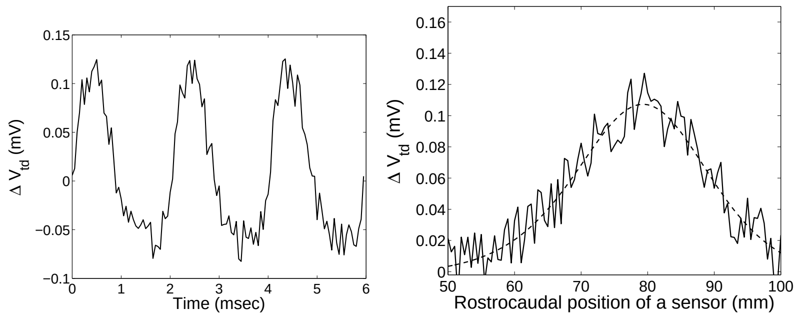

Fig. 3: Noisy sensor signals (a) Sensor signal of an electroreceptor in time domain (b) sensor signals along the rostrocaudal axis

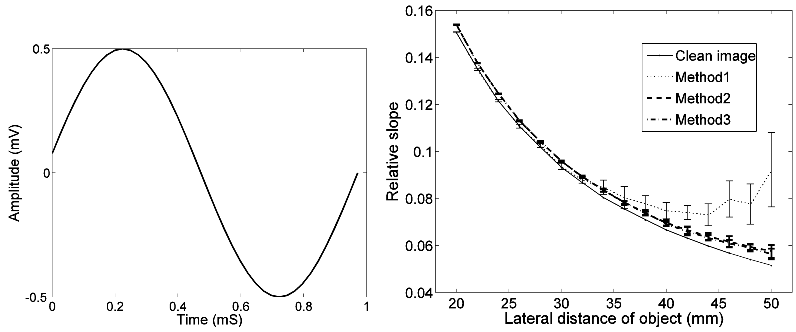

Fig. 4: EOD waveform and relative slope (a) sine pulse (b) relative slope for the pulse; when a weakly electric fish generates EOD waveform as shown in the left side the electric image is corrupted by uniform random noise and each method filters out noise

each electroreceptor

- Method2: take cross-correlation for several cycles at each electroreceptor
- Method3: take the neural network model at each electroreceptor.

EOD waveforms have periodic characteristics and we use five cycles per iteration in simulation for the test. Fig. 4 shows an EOD waveform and the relative slope for distance estimation of a target object with three different methods. The relative slope is the ratio of maximum slope to maximum amplitude of an electric image along the rostrocaudal axis. From the relative slope curve, we can estimate the distance of a target object. The self-generated electric signal of a weakly electric fish is distorted by a target object and noise, the above three methods can initiall obtain an electric image, and then the relative slope is calculated for each case. As shown in Fig. 4, the result of two methods, method 2 and method 3 produce almost the same performance. The noise filtering with

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method 2 and method 3 using cross correlation is more effective than method 1 and is close to the original relative slope curve without noise.

In this paper, we concentrate on noise filtering in time domain. Our neural network model is based on the cross-correlation and it exploits periodicity of EOD waveform. Here, the neural weights are encoded in advance, but if there are feedback signals of desired outputs, we can adaptively change the weights. There are two types of EOD waveforms, pulse type and wave type. Here, only wave-type waveform result is demonstrated, and the similar result is obtained for the pulse-type waveform.

5 Conclusion

Weakly electric fish are very specialzed in active electrolocation. In this paper, we consider a noise filtering method with neural networks in time domain. This filtering method can allow to estimate the distance of a target object accurately. Our neural network model with sinusoidal weights processes the cross-correlation effect on noisy sensory signals. It is effective to different EOD waveform types, pulse type and wave type as well as the distance measure with relative slope.

What kind of neural mechanisms or what types of biological process are available for the cross-correlation operation is an open question. Also, it is still unknown whether or not weakly electric fish use the cross-correlation operation or similar. Our neural network suggests a possible network structure for the cross-correlation.

Acknowledgments

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