Electrolocation with an Electric Organ Discharge Waveform for Biomimetic Application

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Abstract
Weakly electric fish use electric organ discharge (EOD) and their electroreceptors to identify prey, explore their surroundings, and communicate with other members of the same species. They are specialized in active electrolocation using a self-generated electric field, and they can sense distortion of their self-generated electric field caused by a target object. Electric fish have many electrosensors on the surface of their body, and the sensor readings from the electroreceptors form an electric image. A correlation exists between features of the electric images and characteristics of a target object. In estimating the location of a target object, the intensity, width, and slope of the electric image must be considered. In this paper, we suggest that periodic EOD signals are helpful to extract localization features from noisy electrosensory signals. Cross-correlation between an efference copy signal and sensory signals in the waveform can produce filtered signals in the temporal domain. For a biomimetic fish robot, we can use two-phase filtering: noise-filtering with cross-correlation in the temporal axis and additional filtering in the rostrocaudal spatial axis. This spatiotemporal filtering can effectively remove noise, thus making it possible to obtain accurate localization features of a target object in an underwater environment.

Keywords
weakly electric fish, electrolocation, spatiotemporal filter, noise filtering, electric organ discharge, biomimetic system

1 Introduction
Weakly electric fish have a particular sensory system: an active electrosensory system that uses their own electric organ discharge (EOD) (Lissmann, 1958). They emit electric discharge in every direction, and detect the reflection of their self-generated carrier signal (Bajcsy, 1988; Heiligenberg, 1991; Moller, 1995). Their own carrier signals are perturbed by objects in the environment, and the electroreceptors can sense the perturbation potential in order to extract environmental information. There are many animals that use active sensory systems to obtain novel information from a reafferent signal, such as bats, dolphins, and mice (Nelson and MacIver, 2006). These animals have different sensory ranges and sensing mechanisms. Bats and dolphins are specialized in echolocation using ultrasonic waves, while mice use their whiskers as tactile
sensors for the exploration of surroundings, navigation, and identification of a target object. The signal-sensing range of electrosensors is relatively small compared to other echolocation systems; however, electrosensors have an omnidirectional range.

Weakly electric fish can identify the location and characteristics of a target object, such as size, shape, and electrical properties (Rasnow, 1996; Assad et al., 1999; von der Emde, 2006). In this context, electrosensing may have potential as an engineering application in an underwater environment in the absence of visual information. Recently, there have been robotic design studies inspired by weakly electric fish (Baffet et al., 2008; Solberg et al., 2007). Applying the electrolocation of a target object that is employed by weakly electric fish to engineering in an underwater environment is challenging, however. There have been many studies of the electrolocation mechanism, but the way in which electric fish accurately obtain localization features of target objects is still poorly understood. In this paper, we focus on the electrolocation mechanism and suggest a possible filtering mechanism for electrolocation in a biomimetic application.

Many aquatic vertebrates have a mechanosensory lateral line system (Goulet et al., 2008; Akanyeti et al., 2010). This lateral sensory system is also found in weakly electric fish. Weakly electric fish seem to utilize multiple non-visual modalities, such as the mechanosensory lateral line, ampullary electroreceptors, and tuberous electroreceptors (Nelson et al., 2000). The lateral line is stimulated by pressure caused by the movements of nearby objects, and the ampullary electroreceptors detect the bioelectric field of prey. The high-frequency electrosensors, that is, tuberous electroreceptors, respond to their own electric field generated by the electric organ. It is believed that the ampullary system detects an external change in the electric field by passive sensing and is also sensitive to a low-frequency electric field. Alternatively, the tuberous system detects an internal change in a self-generated electric field (Nelson et al., 2000).

When a target object is near the body surface, the electric field changes and electroreceptors on the surface sense the perturbation. Next, the sensor readings from the electroreceptors draw a bell-shaped curve along the rostrocaudal and dorsoventral sensory lines, generating two-dimensional sensory images. The stimulus curve derived from a set of electroreceptors is called an electric image (Caputi and Budelli, 2006). The electric image represents the local change in electric potential at the electroreceptors. A closer object has a smaller electric image width with a larger change in electric potential. When a target object moves away from the fish, the width of the electric image increases and the intensity decreases.

The identification of a target object from electric images has been studied (Rasnow, 1996; Assad et al., 1999; von der Emde, 2006). It has been shown that the change in electric field is inversely proportional to the distance of an object (Rasnow, 1996; Chen et al., 2005; Babineau et al., 2006). In order to identify the size and shape of an object, we need to consider the relative width and peak amplitude of the electric image, as well as the phase shift in the EOD waveform. The phase shift of the EOD waveform also provides us with the impedance information of a target (von der Emde, 1993; von der Emde, 1998; von der Emde, 1999; Fujita and Kashimori, 2010). Thus far there is no direct measurement that can tell us the size, shape, and impedance of a target object. However, it is possible to localize a target object irrespective of its size and electrical properties. When the electric image is seen along the rostrocaudal sensory line, the location of the peak amplitude indicates the rostrocaudal position of a target object. The relative slope and Full-Width at Half-Maximum (FWHM) in the electric image could be used to estimate the lateral distance of a target. The relative slope is the ratio of the maximal slope to the maximal amplitude, and the FWHM is the width of the electric
image when the electric potential is half of the maximum intensity. Interestingly, these distance measurements are independent of the size and conductivity of a target object (von der Emde et al., 1998; von der Emde, 1999; Schwarz and von der Emde, 2001; Assad et al., 1999; Chen et al., 2005; Babineau et al., 2006). Kashimori et al. (2001) showed a neural network model of an electrosensory system where the EOD pattern distorted by an object can induce the modulation signal depending on the distance.

The electric organ (EO) is composed of transformed nerves and muscle cells (Bennett, 1971; Zimmermann, 1985; Bass, 1986; Zakon, 1988; Kramer, 1996; Kramer, 1999). It is located in the tail area and generates a waveform of electric discharges. There are two main types of waveforms, pulse and wave type. Most African Mormyriiformes emit pulse-type EODs, which are a combinational form of short electric pulses and long intervals between pulses. Some South American Gymnotiformes emit continuous wave-type electric signals, while others emit pulse-type EODs, similar to Mormyrids (von der Emde, 1999). It is believed that electric fishes use a waveform of EODs to recognize other electric fishes (Bastian, 1999). Furthermore, the pulse type of weakly electric fish may have the advantage of communication efficiency, using low duty cycles to avoid congested signals (Kramer, 1999). In contrast, wave-type EODs may presumably help electrolocation rather than the communication efficiency. However, this principle has not yet been proven.

The distance estimation of a target object from clean electric images can simply follow relative slope or FWHM. However, noisy electric images provide an erroneous measurement for electrolocation. In a noisy environment, a filtering process is required in order to accurately localize a target object. Low-pass filtering over sensor readings in the rostrocaudal axis is a simple solution for filtering out noise in the electric image. In this paper, we consider both spatial and temporal structures in an electric image. Using periodic EOD waveforms that weakly electric fish generate, a regular interval of temporal information can be integrated into the noise reduction process. A collection of the maximum number of cross-correlation outputs between an efference copy signal and the sensory signals can effectively remove high-frequency noise. In addition, the cross-correlation can easily determine the phase-shift of the waveforms.

In this paper, we present two-phase filtering, which consists of a temporal filter with cross-correlation for each electrosensor followed by a spatial low pass filter of the temporal filter results from the electoreceptors along the rostrocaudal line. The preliminary report has been presented at the conference (Sim and Kim, 2010). Herein, we will apply the spatiotemporal filtering method to various types of EOD waveforms, including pulse-type and wave-type waveforms, and evaluate the electrolocation performance. We consider the application of the suggested filtering method to the electrolocation process of a fish-like robot in an underwater environment. Our simulation experiments using the biological model show significant improvement in noise-filtering performance. We will first introduce a model of an electric field with sensor readings from electoreceptors. We will then explain the method of low-pass filtering along the rostrocaudal axis, temporal filtering based on cross-correlation, and spatiotemporal filtering as a combined model. We will also provide experimental results with varying levels of noise in the electric images, and discuss the effect on electrolocation.

2 Methods
2.1 Electric Field
The electric organ can be modeled with many electric poles (Rasnow, 1996; Chen et al., 2005). Although strongly electric fish generate a pulse discharge having monopolar
characteristics, weakly electric fish produce bipolar EODs (Kramer, 1996).

For \( n \) electric poles, \( m \) positive poles and \( n - m \) negative poles can be taken along the midline axis of weakly electric fish and the electric potential, \( V(\vec{x}) \) is given by

\[
V(\vec{x}) = \sum_{i=1}^{m} \frac{q_i}{|\vec{x} - \vec{x}_{ip}|} - \sum_{i=1}^{n-m} \frac{q_i}{|\vec{x} - \vec{x}_{in}|}
\]  

where \( \vec{x} \) is the sensor position, \( \vec{x}_{ip} \) is the position of the \( i \)-th positive electric pole, and \( \vec{x}_{in} \) is the \( i \)-th negative electric pole. \( q \) is the scaled electric potential, depending upon the species (Chen et al., 2005). The magnitudes of a positive pole and a negative pole are \( q/m \), and \(-q/(n-m)\), respectively. The total sum of the potential of all the electric poles is zero. For simulation, we set the body length equal to 21cm and fix the electric pole density to 10 poles/cm, following the biological body models (Chen et al., 2005; Babineau et al., 2006). There are approximately 155 electric poles, and these poles lie along the midline of the fish. All poles are positive except for the negative pole at the end of the tail. As shown in Figure 1, the electric field \( E(\vec{x}) \) at position \( \vec{x} \) is the gradient of the electric potential given by

\[
E(\vec{x}) = \sum_{i=1}^{n-1} \frac{q_i}{|\vec{x} - \vec{x}_{ip}|^3} (\vec{x} - \vec{x}_{ip}) - \sum_{i=1}^{n-m} \frac{q_i}{|\vec{x} - \vec{x}_{in}|^3} (\vec{x} - \vec{x}_{in})
\]

The component of the incident electric field normal to the skin surface of weakly electric fish, \( V_{id}(\vec{x}) \) can be estimated such that

\[
V_{id}(\vec{x}_s) = E(\vec{x}_s) \cdot \hat{n}(\vec{x}_s) \frac{\rho_{\text{skin}}}{\rho_{\text{water}}}
\]

where \( \hat{n}(\vec{x}_s) \) is the normal vector at the electroreceptors on the skin, while \( \rho_{\text{skin}} \) and \( \rho_{\text{water}} \) are the resistivity of the skin surface and water, respectively.

The potential perturbation caused by a spherical object (Rasnow, 1996; Chen et al., 2005), \( \delta V(\vec{x}) \), is given by

\[
\delta V(\vec{x}) = \chi \frac{a^3 E(\vec{x}_{obj}) \cdot (\vec{x} - \vec{x}_{obj})}{|\vec{x} - \vec{x}_{obj}|^3}
\]
and the transdermal potential difference due to an object, $\Delta V_{td}(\vec{x}_s)$, is calculated with a gradient of object perturbation as follows:

$$\Delta V_{td}(\vec{x}_s) = -\nabla (\delta V(\vec{x})) \cdot \hat{n}(\vec{x}) \frac{\rho_{\text{skin}}}{\rho_{\text{water}}}$$  \hspace{1cm} (5)

where $a$ is the radius, $\chi$ is the electrical contrast, and $\vec{x}_{\text{obj}}$ is the center of the target object. We assume that electrorceptors can read a change in electric potential caused by a neighboring object, which is given in equation (5). The change is affected by the size of an object with radius $a$, the electric contrast and the electric field at the center of an object.

2.2 Electric Organ Discharge

We simulate the electrosensory mechanism, and six types of EOD waveforms are tested for electrolocation in a noisy environment. The six types of EOD waveforms are classified into two classes: pulse type and wave type. The waveforms shown in Figure 2 are models of EODs that employed by weakly electric fish (Stoddard and Markham, 2008). Figure 2 (a)-(c) shows pulse-type waveforms with a period of 4 ms, and Figure 2(d)-(f) shows wavetype waveforms with a period of 1 ms or 2 ms. Figure 2(c) and 2(f) are realistic models following EOD waveforms of some weakly electric fish.

Each electrorceptor has noisy sensor readings. The sensor readings, even for a single electrorceptor, have noisy signals in their temporal axis (Figure 3). The sensor values are proportional to the potential level of electric organ discharge. A waveform of EODs thus produces a waveform of reafferent sensor readings, but the sensor readings can be influenced by the conductivity of a target object. The conductive material near the body surface can distort the shape of the waveform itself, as well as shift the phase of the EOD waveform (von der Emde and Zelick, 1995; von der Emde, 1998). For our experiments, we assume that a target object is an insulator without conductance. We focus on obtaining localization information for a target object from noisy signals. For the purpose, we will see the effect of cross-correlation between the EOD waveform and the sensory values.

2.3 Distance Estimation from Electric Images

When a target object is near a weakly electric fish, sensor readings along the rostrocaudal sensory line draw a bell-shaped curve, and this electric image can be utilized to localize a target object. In the electric images along the rostrocaudal sensory line, the position of maximum amplitude indicates the rostrocaudal position of a target object because the intensity increases when the distance between the target object and the sensor decreases (Rasnow, 1996; Chen et al., 2005). (Rasnow, 1996; Chen et al., 2005). The dorsoventral position of the target object is also obtained from the electric image along the dorsoventral sensory line. When the rostrocaudal and dorsoventral position of the target object is given, the lateral distance of the target can be determined.

The electric potential is affected by the position, size, and conductivity of a target object. If there is a large object near a weakly electric fish, the width and intensity of the electric image increase. In order to estimate both the size and distance of a target object, we first need to determine the distance using the width and maximum intensity of an electric image. The relative slope is the ratio of maximal slope to maximal amplitude in the bell-shaped curve of an electric image (Schwarz and von der Emde, 2001). It provides a cue for the lateral distance of a target object. In this paper, we use the relative slope to estimate the lateral distance of a target object.
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Figure 2: EOD waveforms; pulse- and wave-type waveforms (a) sine pulse (b) cosine pulse (c) pulse of *Brachyhypopomus pinnicau-datus* (d) sine wave (e) sine wave with DC offset (f) waveform of *Eigenmannia virescens* (reprinted from (Stoddard and Markham, 2008))

Figure 3: Sensor readings of an electroreceptor with 10% uniform random noise for a waveform of EOD; (a) sine pulse (b) cosine pulse (c) pulse of *Brachyhypopomus pinnicau-datus* (d) sine wave (e) sine wave with DC offset (f) waveform of *Eigenmannia virescens*

Figure 4 shows the pattern of relative slopes depending on the lateral distance and rostrocaudal position of a target object. For varying object sizes, the relative slope remains unchanged. Three different markers represent spherical objects with varying radii of 0.8, 1.0, and 1.2 cm, respectively. The relative slope is only affected by the rostrocaudal and lateral position of a spherical object. If an electric image is generated, then the rostrocaudal position of the target can be measured by the location of peak amplitude, and we can then subsequently estimate the lateral distance using the relative slope curve in Figure 4.
Electrolocation with Periodic Electric Organ Discharge

3 Noise Filtering in the Spatiotemporal Domain

The electroreceptors experience electric potential distortion in the vicinity of a target object, background objects, and noise. Accurate electrolocation of an object in a noisy environment is crucial for weakly electric fish. Low pass filtering is a basic method that can be applied to sensor readings of electroreceptors in the spatial or temporal domain. Sophisticated temporal processing is required in order to remove noise and extract accurate localization information for a target object. We test a low pass filter for the sensor readings in the spatial domain and use cross-correlation in the temporal domain. We suggest a combination of the two filtering types for noisy sensor readings, which we call spatiotemporal filtering. We demonstrate the effectiveness of the suggested method in tests of two methods using the six different types of EOD waveforms shown in Figure 2.

**Method 1**: Apply a Butterworth low-pass filter to sensor readings in the spatial domain along the rostrocaudal sensory line.

**Method 2**: Apply cross-correlation to sensor readings in the temporal domain, and then low pass filtering in the spatial domain.

3.1 Method 1: Low-Pass Filter

Here, we use a fifth order Butterworth filter to remove noise for the sensor readings along the rostrocaudal line, $x_1, x_2, ..., x_n$. In our experiments, we set the cut-off frequency of the filter to 0.1, since smaller cut-off frequencies tend to distort the shape of the original electric image, thereby producing an incorrect estimation of the distance with the relative slope.

3.2 Method 2: Temporal Cross-Correlation with a Spatial Low-Pass Filter

We investigate the cross-correlation method with various types of EOD waveforms, pulse-type and wave-type waveforms. The sensor signal, $b_k(t)$, of the $k$-th electrore-
ceptor can be modeled as follows:

\[ b_k(t) = h_k(t) \ast a(t) + n(t) \quad \text{for } k = 1, \ldots, N \] (6)

where \( h_k(t) \) represents the perturbation signal caused by a target object, \( a(t) \) is a periodic source signal, \( n(t) \) is a noise signal, ‘\( \ast \)’ denotes the convolution operator, and \( N \) is the number of electroreceptors along the rostrocaudal line. The cross-correlation between the emitter signal and the receiver signal is given by

\[ a(t) \ast b_k(t) = a(t) \ast (h_k(t) \ast a(t) + n(t)) \] (7)

\[ = [a(-t) \ast a(t)] \ast h_k(t) + a(-t) \ast n(t) \] (8)

\[ = [a(t) \ast a(t)] \ast h_k(t) + a(t) \ast n(t) \] (9)

where ‘\( \ast \)’ is the cross-correlation operator. The cross-correlation between the periodic emitter signal \( a(t) \) and the receiver signal can improve the output signal-to-noise ratio with a matched filter in order to obtain electric images. Cross-correlation can obtain the perturbation signals \([h_1(t), h_2(t), \ldots, h_N(t)]\), or electric image, when the maximum output is selected in the time series for every electroreceptor. Cross-correlation between the emitter signal of the electric field and the receiver signals can provide a de-noised electric image and also accurately estimate the phase-shift of the receiver signal from the emitter signal.

Figure 5 shows a schematic diagram for cross-correlation in the temporal domain. The cross-correlation uses the periodicity of EOD waveforms in the time domain. Ten cycles of EOD waveforms are given as a source signal in our experiments. Ten cycles of self-generated EOD waveforms and the observed perturbation potential at an electroreceptor are multiplied in a serial order with respect to time. For the discretized signal,

\[ c_k = \max_m \sum_i a[i] b_k[m + i], \] (10)

where \( a[i] \) is the efference copy signal generated by the electric organ at the \( i \)-th time step, \( b_k[i] \) is the sensory afferent signal detected at the \( k \)-th electroreceptor along the rostrocaudal sensory line, and \( c_k \) is the maximum output of cross-correlation. Here, the source signal is the EOD waveform, which is a common source to all of the electroreceptors.

Figure 6 shows patterns of cross-correlation outputs in a time course. Several peak amplitudes are observed, and each peak appears when two electric signals are in the same phase. At each electroreceptor, we choose a maximum value from the sum of the multiplication of two temporal sequences, as seen in equation (10). As mentioned above, a collection of maximum values form a de-noised electric image along the rostrocaudal sensory line.

The spatial low-pass filter can be applied to the above temporal cross-correlation results for more refined electric images. We will call this combinational method (i.e., spatiotemporal filter) Method 2 in the experiments.

4 Results

For our experiments, we use six types of waveforms for the electric organ discharge, as shown in Figure 2. The two methods mentioned above are tested in order to determine the effect of spatiotemporal filtering. In our simulation experiments, varying levels of uniform random noise in the sensor readings are considered. We use three different random noise levels, the 10%, 30%, and 50% level of the maximum perturbation
Figure 5: Schematic diagram of cross-correlation for an electric image; a spherical object with a radius of 8 mm was tested with 10% random noise in the EOD waveform.

Figure 6: Cross-correlation results (ten cycles of EOD waveforms without noise were tested using a spherical object with a radius of 8 mm); (a) pulse type (Figure 3(c) EOD waveform), (b) wave type (Figure 3(f) EOD waveform).

potential found when a spherical object is located in a lateral distance of 5 cm. Uniform random noise is in the interval $[0.0073 mV, 0.0073 mV]$, $[0.0219 mV, 0.0219 mV]$, or $[0.0365 mV, 0.0365 mV]$, known as level 1 (low level), level 2 (medium level), and level 3 (high level), respectively (we define $\sigma$ as the maximum at a given noise level). When a waveform of EOD is given, the sensor readings at each electroreceptor still follow a periodic curve with a noise component, as shown in Figure 7. The electrolocation process must use a spatial distribution of sensor readings along the rostrocaudal axis.

Figure 8 shows the electric image result after the cross-correlation operation with varying EOD cycles of the Eigenmannia-type waveform. We used a medium level of noise (level 2) for this test. Inspecting more cycles of EOD waveforms can produce a
smoother electric image since the cross-correlation calculates the sum of the products of two temporal sequences during a longer time period. Six types of EOD waveforms were also tested with the cross-correlation operation. Even without low-pass filtering in the spatial domain, the cross-correlation seems to work well for all types of periodic EOD waveform models. Table 1 shows the root mean squared error (RMSE) between a clean electric image without noise and the de-noised electric image when uniform random noise is introduced to the sensor readings. The maximum level of the filter outputs are scaled to the maximum intensity of a clean electric image. In Table 1, cross-correlation using longer temporal sequences shows better results and the wave-type waveform model performs better than the pulse-type model. The error of the wave-type waveform models ((d), (e), and (f) models in Figure 2) is smaller than that of the pulse-type waveform models. The duration of sinusoidal signals in a wave-type waveform model is longer than that in a pulse-type waveform, and thus provides a cleaner image. Based on the above results, we used ten cycles of EOD waveforms for all of the cross-correlation experiments.

The de-noised electric images closely approximate the original clean image. The relative slope for distance estimation requires two factors: the maximum amplitude and the maximum slope in the electric image. The slope calculation involves differentiation with respect to the rostrocaudal axis. Small bumps in the image may cause a deviation in the spatial slope in the electric image curve, which significantly influences the relative slope estimation. A collection of temporal cross-correlation outputs of elec-
Table 1: RMS error between the clean electric image and the scaled de-noised electric image using only cross-correlation in the time domain with six EOD waveform (a) sine pulse (b) cosine pulse (c) pulse of Brachyhypopomus pinnicaudatus (d) sine wave (e) sine wave with DC offset (f) waveform of Eigenmannia virescens

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Table 2: RMS error between the clean electric image and the scaled de-noised electric image using Method 2 in the spatiotemporal domain with six EOD waveform (a) sine pulse (b) cosine pulse (c) pulse of Brachyhypopomus pinnicaudatus (d) sine wave (e) sine wave with DC offset (f) waveform of Eigenmannia virescens

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Figure 9 shows electric images from two different noise filtering methods. The original electric images are restored closely, and the spatiotemporal filtering (Method 2) shows a better result. For each method, we can extract the maximal amplitude, maximum slope, and relative width. In order to estimate the distance of a target object, we can use the relative slope from the electric image. Table 2 shows the error performance with spatiotemporal filtering (Method 2). The performance is improved compared to the result of cross-correlation alone (Table 1 compared to Table 2). Similar to the re-
Figure 9: De-noised electric image with Method 1 and Method 2 (a) noisy electric image (level 1) (b) Method 1 result (c) Method 2 result (d) noisy electric image (level 2) (e) Method 1 result (f) Method 2 result (g) noisy electric image (level 3) (h) Method 1 result (i) Method 2 result (each row indicates a noisy image, the Method 1 result and the Method 2 result for the noisy image, dashed: ideal electric image without noise; solid: cross-correlation result which is scaled to the electric image level).

result of cross-correlation, the wave-type waveform is more effective than the pulse-type signal for restoring the original electric image.

For the next experiments, we applied two filtering methods, Method 1 and Method 2, and varied the distance of the target object. We measured the performance of the distance estimation by comparing the relative slope from filtered electric images to that of clean electric images. We calculated the RMS error of the relative slope and its standard deviation. Method 1, or low-pass filtering, considers a spatial distribution of sensor readings only at a static moment. Here, we use the peak amplitudes in the time domain for each electroreceptor, since larger amplitudes can have a higher signal-to-noise ratio. The temporal domain provides more information, and the cross-correlation is able to process the data in the temporal domain. When we use both spatial and temporal filtering methods, we can obtain more accurate relative slope curves than with a single domain filtering alone, as well as a small standard deviation. We found that low pass filtering after cross-correlation can effectively filter out noisy components in an electric image.
Figure 10: Relative slope with varying lateral distances by two noise filtering methods (six EOD waveform models tested) (a) sine pulse (b) cosine pulse (c) pulse of *Brachyhypopomus pinnicaudatus* (d) sine wave (e) sine wave with DC offset (f) waveform of *Eigenmannia virescens* (random noise $[-0.005mV, 0.005mV]$)

Figure 10 shows the relative slope curves depending on the two filtering methods with a given level of random noise $[-5\mu V, 5\mu V]$. We tested varying distances using ten trials for each configuration, and measured the average performance. If the lateral distance increases, the signal-to-noise ratio decreases, and the estimation of relative slope becomes inaccurate. The spatial low-pass filtering alone shows that its relative slope pattern is quite different from that of a clean electric image. It cannot be used
Figure 11: Relative slope with a spherical object with a radius of 8 mm at a fixed distance of 5 cm by two noise filtering methods (six EOD waveforms tested); (a) sine pulse (b) cosine pulse (c) pulse of Brachyhypopomus pinnicaudatus (d) sine wave (e) sine wave with DC offset (f) waveform of Eigenmannia virescens for electrolocation at a far distance from a target object. However, spatiotemporal filtering closely approximates the original relative slope, although it does not produce a perfect performance. Figure 11 shows the relative slopes with varying levels of random noise; the lateral distance of a target object is fixed at 5 cm and the noise level changes from 0µV to 45µV. For each noise level, ten trials were tested to calculate the
average relative slopes and the standard deviations. The discrepancy between clean electric images and the de-noised images increases as the noise level increases. Method 1, or spatial low-pass filtering on its own, performs poorly at a high level of noise. In contrast, Method 2, or spatiotemporal filtering, has remarkable performance in filtering out noise even when the target object moves far away from the body surface or the noise level increases.

5 Discussion

The electric signals generated by other underwater animals or other noise components may be mixed up with the electric signals that an agent produces. In that environment, it is important to extract the perturbation potential purely caused by a target object from the electric image. We could simply apply low-pass filtering to a spatial distribution of sensor readings along the rostrocaudal axis, but our experiments show that this method may not be sufficient to obtain smooth electric images. Temporal signal processing with cross-correlation can further refine the electric image.

Cross-correlation is a measure of the similarity of two signals using a time-lag function of one signal. It has many applications in template matching or pattern recognition in an auditory or visual system. If two periodic signals have different frequencies, the cross-correlated sum has a small value. Consequently, cross-correlation has the advantage of being able to separate the self-generated electric signals from disturbance signals. It can prevent communication congestion in the electric field environment.

We used six different EOD waveform models for noise filtering. Despite the fact that there has been no reliable evidence about the advantage of electrolocation in wave-type EODs, our experiments show that the wave-type waveform model has smaller RMS error in restoring original electric images. Additional biological observations and experiments are required in order to verify the relationship between the electrolocation mechanism and EODs.

In weakly electric fish, the transdermal potential on the skin surface is influenced by the EOD waveform and the perturbation potential caused by nearby objects. We assumed that the impact of EOD-related potential at each electroreceptor can be reduced by reafference cancellation (Caputi, 2004; Bastian, 1995). From this fact, we focused on the perturbation potential caused by objects in our experiments. The way in which the phase shift can be detected from the sensor readings and the mechanism underlying the filtration of noisy sensor readings in weakly electric fish are largely unknown. We suggest that cross-correlation between the self-generated electric discharge and observed sensor readings in the time course might provide the filtered signal and phase information together. The kind of neural mechanisms or types of biological processes that are involved in the cross-correlation operation are also unknown. Herein, the cross-correlation operator was tested with an efference copy signal and sensory signals. Instead of the efference copy signal, the motor command patterns can be coded with sinusoidal weights if the EOD waveform has a regular rhythm for electrolocation. Subsequently, the neural structure with a time series of sensory signals may have a similar effect with cross-correlation.

For a time sequence of cross-correlation outputs, we only considered instances in which phases of the efference copy signal and the sensory signals matched each other exactly in order to obtain the maximized sum of multiplication. The phase-shift of the signals can provide the impedance property of a target object (von der Emde, 1993; von der Emde, 1998; von der Emde, 1999; Fujita and Kashimori, 2010). For future work, we will use cross-correlation to verify various material properties.
Biological reports seem to indicate that electric fish are unaware of their own exact waveform in the presence of an object. Simple spatiotemporal integration of EOD distribution on electroreceptors could sufficiently provide the target features. Results of the current study using the efference copy signals suggest that self-generated EOD waveforms may be more useful for a fish-like robot performing electrolocation rather than explaining how weakly electric fish process noisy sensor signals.

6 Conclusion

Weakly electric fish have an electrolocation mechanism that is related to their active electroreceptive system. This mechanism must process noisy sensor readings, but it is not well-known how noise is filtered from the electric image. We suggest that the periodic EOD waveform might help process noisy sensor readings at each electrosensor. The cross-correlation between an efference copy of the EOD waveform and sensory signals in the temporal domain can efficiently determine the phase-shift of sensor readings caused by a conductive object, and also restore the original electric image from noisy sensor readings.

To our knowledge, there have been few studies investigating temporal sensor readings as an electrolocation process. In order to evaluate electrolocation performance, we applied two methods: low-pass filtering in the spatial domain alone and spatiotemporal filtering with cross-correlation. We observed electric images and the corresponding relative slopes, that is, the slope-to-amplitude ratio over the electric images, for each filtering method. Direct measurement of the relative slope over raw electric signals can produce an incorrect estimate of the distance of a target object. We used two-phase spatiotemporal filtering, consisting of a cross-correlation operation in the temporal domain, followed by low-pass filtering in the spatial domain. Six different types of EOD waveforms were tested in order to validate the spatiotemporal filtering method. According to the simulation experiments, spatiotemporal filtering can successfully obtain de-noised electric images that are quite close to the original clean images. Neither temporal cross-correlation nor spatial low-pass filtering alone is sufficient to obtain a similar level of performance. The suggested filtering method would be suitable for obtaining accurate localization features in the underwater environment.

The electroreception of weakly electric fish can be applied to a robotic system for the localization of a target object underwater. The electric field can spread in every direction, and it can be used to detect not only the location of a target object but also its shape and size (Rasnow, 1996; von der Emde et al., 1998; von der Emde, 1999; Schwarz and von der Emde, 2001). For future work, we will test the electrolocation system with a robotic fish and demonstrate the possibility of applying electrosensors in the submarine system using the suggested filtering approach. It is not known whether or not the suggested filtering mechanism can be found in weakly electric fish. In order to support the validity of our proposed approach, detailed neurophysiological or anatomical studies are required. However, the mechanism can at least be applied to a biomimetic system or robot.

The electroreception of weakly electric fish can be applied to a robotic system to localize a target object in the underwater. The electric field can spread in every direction, and it can be used to detect not only the location of a target object but also shape and size (Rasnow, 1996; von der Emde et al., 1998; von der Emde, 1999; Schwarz and von der Emde, 2001). For the future work, we will test the electrolocation system with a robotic fish and show the possibility of application of electrosensors in the submarine system with the suggested filtering approach. It is an open question whether the sug-
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gested filtering mechanism is available in electric fish. To support the validity of our suggested idea, detailed neurophysiological or anatomical studies are required. Yet at least the mechanism can be applied to a biomimetic system or robot.

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References


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