Electrical localization of weakly electric fish using neural networks

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Abstract. Weakly Electric Fish (WEF) emit an Electric Organ Discharge (EOD), which travels through the surrounding water and enables WEF to locate nearby objects or to communicate between individuals. Previous tracking of WEF has been conducted using infrared (IR) cameras and subsequent image processing. The limitation of visual tracking is its relatively low frame-rate and lack of reliability when visually obstructed. Thus, there is a need for reliable monitoring of WEF location and behaviour. The objective of this study is to provide an alternative and non-invasive means of tracking WEF in real-time using neural networks (NN). This study was carried out in three stages. First stage was to recreate voltage distributions by simulating the WEF using EIDORS and finite element method (FEM) modelling. Second stage was to validate the model using phantom data acquired from an Electrical Impedance Tomography (EIT) based system, including a phantom fish and tank. In the third stage, the measurement data was acquired using a restrained WEF within a tank. We trained the NN based on the voltage distributions for different locations of the WEF. With networks trained on the acquired data, we tracked new locations of the WEF and observed the movement patterns. The results showed a strong correlation between expected and calculated values of WEF position in one dimension, yielding a high spatial resolution within 1 cm and 10 times higher temporal resolution than IR cameras. Thus, the developed approach could be used as a practical method to non-invasively monitor the WEF in real-time.

1. Introduction

Weakly electric fish (WEF) emit an electric organ discharge (EOD), which travels through the surrounding water and enables WEF to locate nearby objects or to communicate with other individuals. From studying the temporal patterns of EOD, the potential exists to track the location and movement of WEF, which could allow us to understand the sensory motor brain function of vertebrates. WEFs EOD are a time varying current dipole between the head and tail that discharges at a rate of approximately 50 Hz [1]. The head and tail region of the WEF always have opposite current flows, but the polarity can switch depending on the pulse cycle of the EOD. Much like an actual current dipole, the strength of the electric field produced is proportional to the length of the WEF. Previously, the movement of WEF has been detected using infrared (IR) cameras. IR cameras lack reliability when there is a visual obstruction, and thus the tracking of WEF is inconsistent [1]. Here, we aim to use neural networks (NN) to provide an alternative non-invasive means of tracking WEF using their EOD.

2. Methodology

2.1. Overview

We aimed to investigate if WEF can be accurately localized from recordings of their electrical outputs. The method employed was three-fold. Stage I was to create a finite element method (FEM) model of the system with similar stimulation patterns to the WEF. The model (Stage II) was then validated against a phantom electrical impedance tomography (EIT) based system. Once the FEM model had been validated, a database was compiled of corresponding voltage readings and position coordinates. The method of neural networks (NN) was tested with this data. In stage III, real WEF data was acquired and tested using the NN based tracking method as chosen from the FEM system.

2.2. Stage I: FEM Model

In order to create the FEM model of the phantom system, Electrical Impedance Tomography and Diffuse Optical Tomography Reconstruction Software (EIDORS) was used [2]. The FEM model tank was a scaled down version of the phantom tank to reduce computation time. The phantom tank has a height-diameter ratio of 9:7, and the FEM model has a ratio of 1:4. The reason for the reduction in this ratio in the FEM model was because the measurement protocol consisted of positions in the horizontal plane. The FEM tank contained one row of 32 electrodes. In this model, the electrodes were not paired across the tank, but all referenced to a common ground. In order to compare values with those of the phantom, opposite channels could be subtracted from one another. The WEF in the FEM model was created as a cylinder with charged electrodes on the head and tail, with an insulating section in the middle. The charge on the head was positive and the tail was negative like the opposing poles of an actual WEF [3].

2.3. Stage II: Verification of FEM Model

In order to test the tracking method, a database of position and voltage pairs needed to be collected. The database needed to contain a large number of test cases, and have very high precision in the position of the fish. The tank was equipped with four rows of 32 evenly spaced electrodes, and a ground pin at the centre of the base; one level and 16 electrodes were used and connected directly opposite the tank in pairs, providing eight channels for measurements. The phantom WEF was 0.9 mm in diameter and 17 cm in length, in a tank with 28 cm diameter. A measurement protocol consisting of 21 different positions of the phantom was used to obtain consistent and highly inclusive data throughout the tank. Since the WEF containing tank that the phantom system was based on was shallow, the measurement protocol consisted of positions exclusively in the horizontal plane, in line with the electrodes.

2.4. Stage II: Neural Networks on FEM Data

Using the FEM data, the inverse solution was accomplished using NN. Measurements were made around the FEM model tank, and the electrode voltages for each trial had pseudorandom noise added up to ±10 % of the maximum channel voltage. The position data was packaged into coordinates of the head and tail of the fish in Cartesian coordinates, with the real length of the fish as 23 cm. A cascade forward network was declared using the Matlab NN toolbox and was trained with the data acquired from the simulation in the format of 32 signed voltages as inputs, and two sets of (x, y) coordinates as outputs.

2.5. Stage III: Experimental Data

The measurement data was acquired using a restrained WEF (with length of 23 cm) within a tank (1.5 m in diameter) surrounded by eight graphite electrodes and filled with water (17.5 cm in depth). In

order to obtain accurate WEF datasets, the WEF was restrained near the surface of the tank with a Styrofoam harness [1]. The measurement data were acquired based on (i) positions for full tank, (ii) positions for half of the tank. The WEF dataset contained 299 data points compared to the 1196 of the simulated data, so interpolation had to be performed to maintain a high quality result. The first set of data tested used the full tank. The dataset contained 299 data points, which were interpolated to be 29,900 data points. The second set of data tested used a half tank dataset, which consisted of the same 299 data points, which was interpolated to be the 15,210 positive x data points.

The computer used for processing had 6 GB of memory and a quad-core processor running at 2.67 GHz.

2.6. Stage III: Neural Network on Real WEF Data

Voltage values were taken across symmetrically paired electrode channels, thus a mirroring issue presented itself across the x-axis of the tank. Since voltages are measured between two points, the voltage read across a channel when the WEF was at x = ±2 cm, for example, would be the same. In order to proceed with using the NN and obtaining reasonable results, it was necessary to only train and test points that fell on either side of x = 0. The positive x-axis was selected. The NN was trained with two datasets in order to show the constraints of the physical system on which the experiments were performed.

3. Results

Though the performance of the NN was analyzed for the FEM data, it was largely for verification purpose, so only the real WEF data analysis of the NN is shown below.

Figure 1a shows the performance of a pseudo-randomly generated NN with full tank data. As calculated from Figure 1a, the percentage of calculated head or tail positions, which fell within 1 cm of the true location, was 54.45 % and that the results had a mean squared error (MSE) of 5.53 mm. This is a very high MSE and low percentage of accuracy, neither of which is desirable.
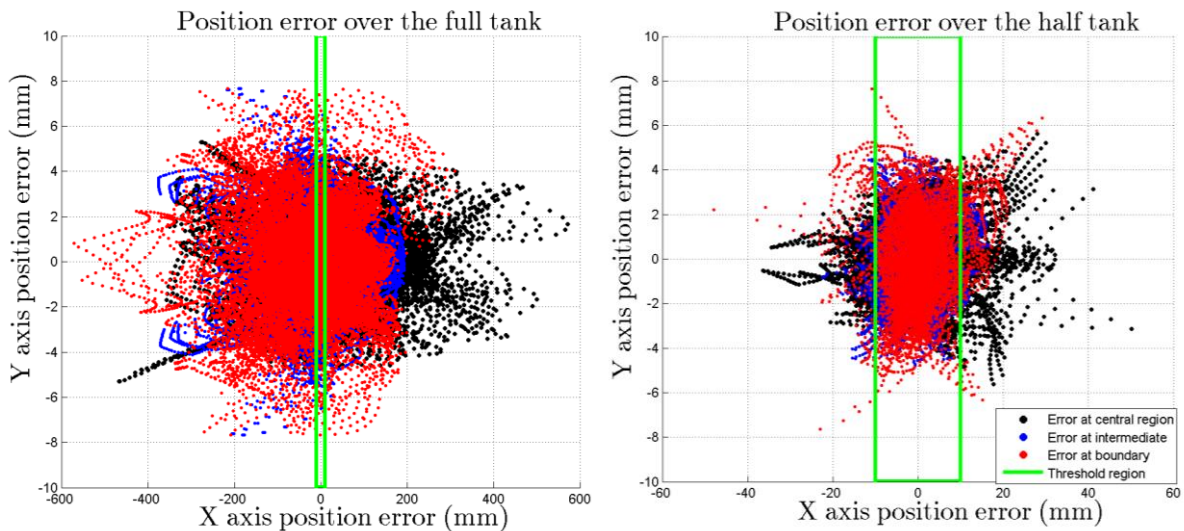

Figure 1. Difference between position of the WEF and equivalent calculated positions as generated by the Neural Network. (A) The performance of the full tank trained network. (B) The performance of the half tank trained network. Black dots stands for errors in the central region, blue dots are for errors in the intermediate region and red dots are for errors in the boundary region.

In the case of computing positions for half of the tank, we saw an improvement. The data set contained 299 data points, which was interpolated to be 15210 data sets. Shown in Fig. 1B is the

performance of a pseudo-randomly generated NN trained with the half tank data set. We can see from this plot that the percentage of the calculated head and tail positions within 1 cm is 94.2 %, with a MSE value of 0.02 mm. The x-coordinate errors are much less in Fig. 1B.

The average computation time for the 15210 sample dataset was 4.7 msec. This computes to a 213 Hz frame rate. The speed at which the NN operates increases with respect to number of consecutive operations and peaks at approximately 213 Hz.

4. Discussion and Conclusion

A verified FEM model was required in order to test possible strategies of WEF localization. The average difference of voltages was 0.129 V between the model and the phantom system. This value had a standard deviation of 0.181. On a range of 0 - 2.5 V these values are relatively low, so it was concluded that the FEM model acted as a reasonable substitute for the phantom system and could be used for investigating three dimensional tracking in future research.

The full tank data shown in Fig. 1A had an accuracy of 54.45 % within 1 cm, and a MSE of 5.53 mm. This accuracy is very low. The largest errors in the x direction were nearly 60 cm. All regions of the tank show consistently high errors. The poor quality of these results was anticipated because of the symmetry of the electrode channels. In order to remove the symmetry issue, a non-symmetric electrode channel (not paired at 180°) could be introduced or a tracking algorithm employed.

The modification made to improve the tracking accuracy was eliminating positions on the x < 0 half of the tank. If the mirroring issue was resolved for the entire tank, results as seen below could be expected for the full tank. Fig. 1B shows the distribution of errors for the half tank solution. The accuracy of the half tank was 94.3 % within 1 cm and a MSE of 0.02 mm. This accuracy is higher than that of the IR cameras, which have a 1 cm resolution. It can be seen on Fig 1B that the area of the tank in which there is lowest accuracy is the centre third at 89.9 %. The middle and outer third sections have accuracies of 96.6 % and 96.1 %, respectively. The accuracy is lowest at the centre of the tank because the EODs from the WEF have travelled the furthest distance, and are therefore have more interference.

The current means of tracking WEF uses IR cameras with a frame rate of approximately 20 Hz. The frame rate of the NN for a large trial was 213 Hz. This frame rate is nearly 10x that of the previous means of tracking. Regardless of the length of the trial, determined by number of samples analyzed, the frame rate of the NN did not vary significantly. Testing 10 samples yielded a frequency of 209 Hz, and testing over 15,000 samples yielded a frequency of 213 Hz.

The use of neural networks for localization of WEF appears to be a viable alternative to IR camera tracking. NNs advantages over IR cameras are both an increase in the temporal resolution or frame rate, and increased spatial resolution. The NN can localize the WEF within 1 cm in one dimension for 94.3 % of cases with a MSE of 0.02 mm. The frame rate of the NN was approximately 213 Hz, which was a temporal resolution of 10 times that of the IR camera. State of the art IR cameras have a frame rate of 1 kHz, but the image processing is much more costly to compute than the NNs raw data analysis and has a lower spatial resolution than NN. NNs could serve as a practical real-time method of tracking WEF non-invasively.

References
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