Introducing direction and history into artificial lateral line source localization using neural networks

Bachelor's Project Thesis

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Abstract: Fish are able to detect alterations in water flow velocities with their mechanoreceptive lateral line organ. This organ consists of an array of receptors distributed along the body of the fish. The excitation profiles of such an array can be used to localize nearby moving objects. This organ can be simulated along with its environment. Previous research has shown that using neural networks an artificial lateral line is capable of source localization with high accuracy in a 2-dimensional environment. This research aims to accurately detect the direction of movement of a source. Another aim was to improve localization accuracy by combining angular and temporal information. This research shows that the direction of a source can be predicted accurately and is reliable, with a mean error of 0.13 degrees and a standard deviation of 9.5 degrees. However, when excitation patterns are concatenated over time, utilizing temporal information does not improve localization accuracy. Transformations including angular data of earlier excitation patterns can be used instead of these excitation patterns themselves. When these transformations are concatenated with the current excitation profile the improvement of the localization of a moving source is significant and relevant. The improvement is a factor 1.5.

1 Introduction

Fish are aquatic animals that come in great diversity. Most aquatic species posess an organ called the lateral line organ. This organ aids fish in the detection and localization of nearby bodies. This can be useful for the animal to detect prey or predators. The organ serves schooling purposes as well (Dijkgraaf, 1963). The sense is best described as "feel at a distance".
The lateral line organ consists of arrays of neuromasts. These neuromasts contain mechanoreceptive hair cells which are stimulated by variations in water flow, as described in previous research (Abdulsadda & Tan, 2013, Curcic & van Netten, 2006). These variations in the movement of the surrounding water allow fish to detect moving objects in their environment (Dijkgraaf, 1963; Coombs et al., 1988). A schematic representation of the lateral

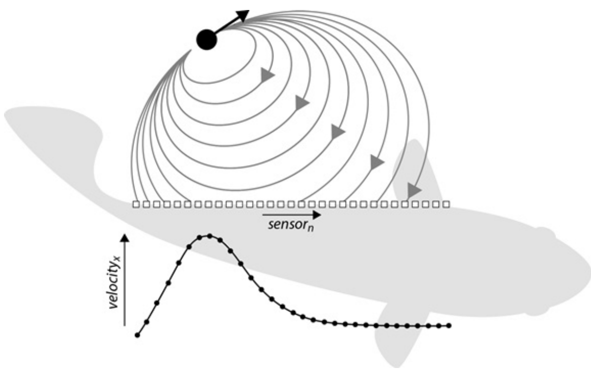

Figure 1.1: Lateral line perception in fish. A moving source creating a flow field is present. In lower part of this figure the excitation profile as measured by the sensors is shown.

line is depicted in figure 1.1[1]. A moving source creating a flow field is shown. The corresponding excitation profile as picked up by the sensors is represented as well. In previous research, excitation patterns along a simulated lateral line have been succesfully decoded for localization using an artificial lateral line and neural networks. This has resulted in the 2D localization of a moving source using water velocities parallel to the simulated lateral line. (Boulogne, 2016). In additional research also water velocities ortogonal to the simulated lateral line were used, and the presentation of excitation profiles was altered to offer more diversity in the input patterns. (Hermes, 2017)

The previous research performed by Boulogne suggested that Extreme Learning Machines are best suited for this task. The current bachelor project is part of a larger project. The aim of this bachelor project is to extend the output with directional information and improve the performance of the artificial lateral line using an extreme learning machine. The results can be used in the future development of the LAkHsMI project. This research thus mainly focused on how to retrieve more information from the artificial lateral line in a reliable manner and how to use this acquired information to improve localization accuracy.

In this research an attempt was made to include the direction of movement in the output of an extreme learning machine and to improve the localization accuracy. For that purpose a temporal component was implemented to incorporate data from previous timesteps. The first question to be answered in this research was the following:

Can the angle of movement of a source be measured using aforementioned techniques? In this investigation a parameter sweep has been performed to determine optimal settings. Another question to be answered was whether incorporating temporal information will aid in the localization accuracy, and whether the effect is larger when angular data is used than when it is not used. Finally, an experiment has been performed with transformations of the excitation profiles. A transformation of an excitation profile is the output of the Extreme Learning Machine given the excitation profile as input. Since this research deals in a temporal setting, the transformations of excitation profiles of previous timesteps are used. These transformations were added to the current profile to investigate whether transformations provide better aid to localization than the previous excitation profiles themselves. A distinction was made between transformations that incorporate angular information and transformations that merely incorporate the previous coordinates of the source. In future research the velocity or size of a moving object may be included in the output, giving a more clear and consise picture of the source. Translated to biology, a fish then has all the necessary information to detect whether it is in danger and to decide on the severity of that danger. When implemented in 3D, this mechanism may offer great practical purposes in deep sea research. For a great part lateral lines could serve to augment sonar in the future.

It can be hypothesized that the first research question is answered positively, because the angle is present in the calculation of the wavelet implicitly. If the network has to learn angular data it learns more about the source, therefore it can be hypothesized that localization may be aided. Therefore the second research question was hypothesized to be answered positively as well. If a network is presented with clearer transformations of input patterns than those patterns themselves it is likely to perform better when angular information is available. Therefore the final experiment was hypothesized to yield improvements with regard to localization.

2 Methods

An object making its way through an aquatic environment applies pressure to its surrounding. The source acts as a dipole when potential flow is assumed. The surrounding water is pressurized creating a flow field. This field can be measured by a lateral line system such as an artificial lateral line as utilized in this paper. The flow field can be decoded to determine the location of the source.

The methods used by Boulogne (2016) and Hermes (2017) apply to the current paper to a large extent.

[1] Adapted from B.J. Wolf (2016), http://www.rug.nl/research/alice/autonomus-perceptive-systems/research-and-projects/phd-project-lateral-line-based-sensing-and-imaging

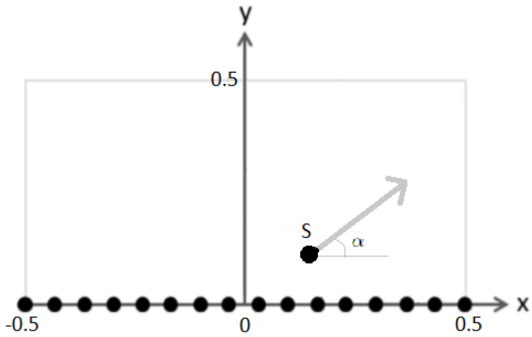

Figure 2.1: Visual representation of the simulated environment with a moving source. Adapted from Hermes (2017).

2.1 The Environment

This research took place in a simulated environment.[2] The environment is a 2-dimensional aquarium of which the width is two times as large as the length. The sensors are in equidistant distribution along the bottom of the aquarium. This setup is similar to previous research (Hermes, 2017), (Boulogne, 2016), as viewed in figure 2.1.

2.2 The Stimulus

The stimulus is a moving source in the aquarium. It follows a path and is programmed in such a way that it can not leave the aquarium. The algorithm for the movement of the source was taken from Boulogne (2016) and altered. The algorithm that Boulogne created allowed the source to collide into the borders. This produces unnatural data that is highly likely to disrupt the course of the source. Alterations were made in such a way that the source averted collisions with the borders, resulting in a more natural path. The altered algorithm for this is described in algorithm 2.1.

[2]This project was implemented using MATLAB R2016A on a 64-bit platform running Windows 10. The code is based on the work of Boulogne (2016)

Algorithm 2.1 create path

```
x ⇐ random[−0.5, 0.5]
y ⇐ random[0, 0.5]
α ⇐ random[0, 2π]
speed ⇐ 0.1

for i = 1 to n do
store(x, y)
calculate velocity pattern ((x, y), α)
α ⇐ α + random[−1, 1]
if too close to border then
   turn away with maximum randomness per timestep
end if
update(x, y)

end for
```

In this algorithm x and y are the horizontal and vertical coordinates respectively. α is the angle of movement in radians. *speed* is the speed of the source. It can also be viewed as the sampling rate or step size. Step size, speed and sampling rate are interrelated in this research. The step size is the distance between a sample and the next. The step size is influenced by the speed of the source. Decreasing the step size inbetween samples is synonymous to decreasing the speed of the source. Increasing the sampling rate is synonymous to decreasing the step size inbetween samples and decreasing the amount of movement randomness from one sample to the next sample. When the step size is decreased, the amount of randomness in angular change needs to be decreased as well to maintain the turning radius. The step size has an inverse relationship with the effective sampling rate. For the remainder of this research the terms step size and maximum angular change are used.
The source is allowed random movements with a maximum change in direction while it is within one turning radius away from the borders. It is described in algorithm 2.1 as maximum randomness. This turning radius was taken to be the step size divided by its maximum angular change:

$$R = S/\phi. \qquad (2.1)$$

At times that the source is approaching a border too closely the angular change is in the direction averting the border in the case that there is

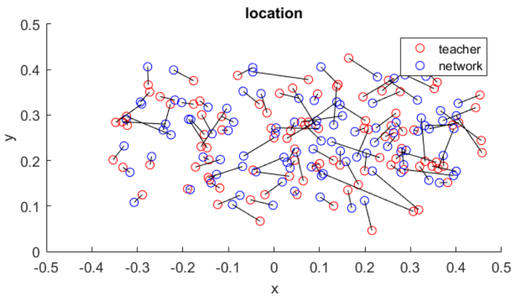

Figure 2.2: The original step size and maximum angular change.

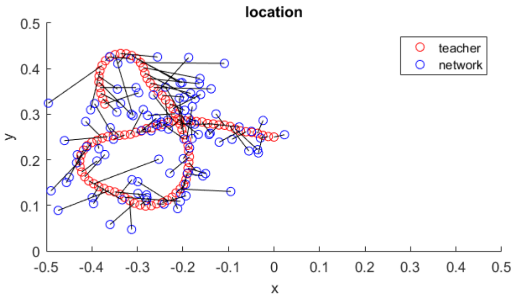

Figure 2.3: The smaller step size and maximum angular change.

any form of parallel movement alongside a border. When the source is moving ortogonal to the border the angular change is maximal in random direction. The maximum angular change per step is set at the beginning of the program. Different values for the step size were utilized to investigate the effect of a smoother path. In figure 2.2 the path of 100 samples is shown with the step size as used in Boulogne (2016). Figure 2.3 shows a decreased step size with 100 samples. Decreasing the step size creates a smoother path, which is expected to aid in localization.

2.3 The Extreme Learning Machine (ELM) Architecture

The ELM used in this paper has vast similarities to a MLP (Multilayer perceptron), as discussed in Boulogne (2016). As opposed to the MLP there can only be one hidden layer in an ELM. After random initialization the weights from the input to the hidden layer are not modified by training (Huang et al., 2006). This means that there is no backpropagation; instead this network applies one-shot learning. Therefore training is faster than other networks previously investigated (Huang et al., 2006). Therefore an ELM was expected to be the most suitable for this paper.

2.4 Alterations to the Simulation Architecture

For the purpose of this research several alterations to the simulation of Boulogne (2016) were necessary. To teach an ELM the angle of movement, the angle needed to be represented differently than on a scale from 0 to 2π. If this representation was not altered the network would not be able to learn the angle due to the step from 2π to 0. For instance, while the outcome 6.27 is very close to 0.01, the network will not notice this as such. To maximize compatibility with the capabilities of the network, the angle of movement of a source is represented by sine and a cosine values. The consequence for the program is that the network now has four output nodes, namely the x-coordinate, the y-coordinate, the sin-value and the cos-value. The code for generating the dataset has been altered accordingly. These angular estimates were scalable to investigate the influence of errors in angle prediction on the performance of the localization.

The implementation of the temporal component required the concatenation of excitation patterns of multiple steps. The size of the history is the number of previous excitation patterns to be concatenated with the current excitation pattern. When adding history, a buffer time is needed to fill said history. The following process describes how this works:
At time $t = 0$ there can be no memory. In the case that the memory parameter is set to one, there is one extra training and testing sample, and the sample at $t = 0$ will be discarded. The input at $t = 0$ includes zeros at the locations where the values of the previous excitation patterns would be. This example describes the underlying structure of the extra input that also applies when the memory size is larger. The history size can be set at the beginning of the program.

2.5 Further alterations: the two-pass model

For the final experiment it was necessary to make additional alterations to the program. The concept of recurrent connections was of great influence in the alterations described below. The set of values of the output nodes can be viewed as the transformation of the input pattern. These transformations give a more concrete view than the original patterns. It was therefore useful to investigate whether an ELM would perform better on the task of localization when the excitation patterns of previous steps were represented more concrete. However, an ELM does not have recurrent connections, therefore it would not be suitable for this final experiment. An MLP or ESN would be useful for this experiment. However a Multilayer Perceptron or an Echo State Network may take days to train on such sizable problems. Since training an ELM is much faster, this paper introduces a different approach. A first ELM is trained and tested as if it had no memory. The transformations, or values of the output nodes of said first ELM, are stored. Depending on the amount of history, various sets of transformations of previous steps are concatenated with an excitation pattern, which will in turn serve as input pattern for a second ELM. The scheme describing the two-pass model is depicted in figure 2.4. This is a form of explicit memory representation which requires a second ELM to be trained and tested in this research. Although the plausibility and practicality of such a construction is questionable, it is a promising concept.

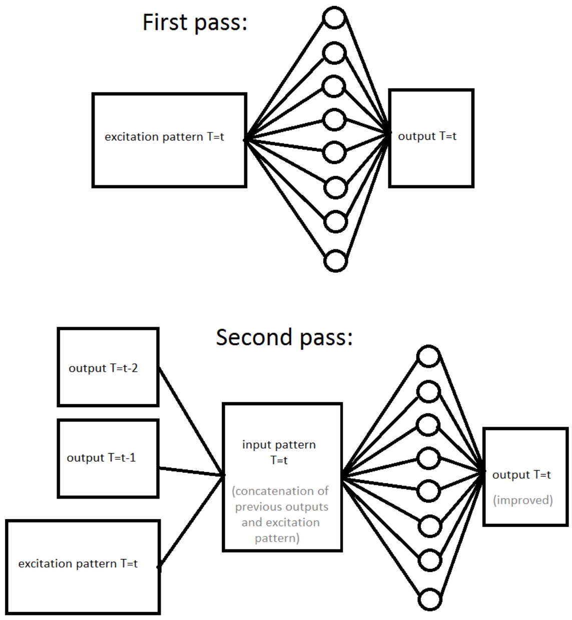

Figure 2.4: The two-pass model

3 Results

3.1 Angular scaling

In determining the best settings for the network with regard to the additional output, a parameter sweep was performed on the scaling of the *sin*- and *cos*-output nodes on different training sizes. The test size was kept at 200. The result of this parameter sweep is depicted in figure 3.1. In this figure the estimation error is shown in mean euclidian distance error. One can observe the large error bar around a training size of 4000. This observation is in accordance with the findings of Hermes (2017). This is an intrinsic property of the ex-

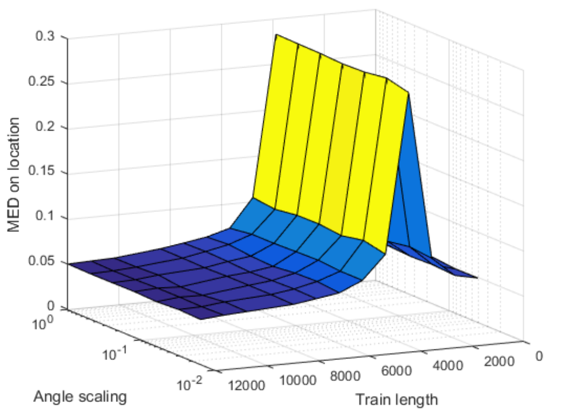

Figure 3.1: Parameter sweep on angle scaling and training size.

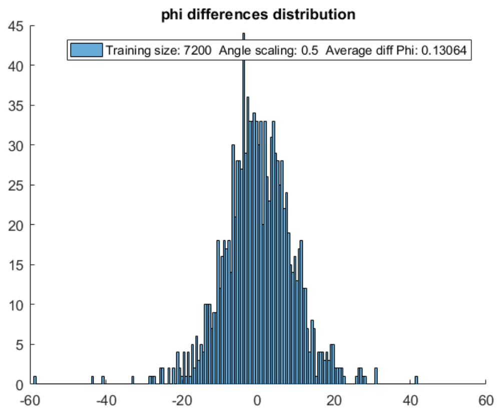

Figure 3.2: Error in the direction of a moving source.

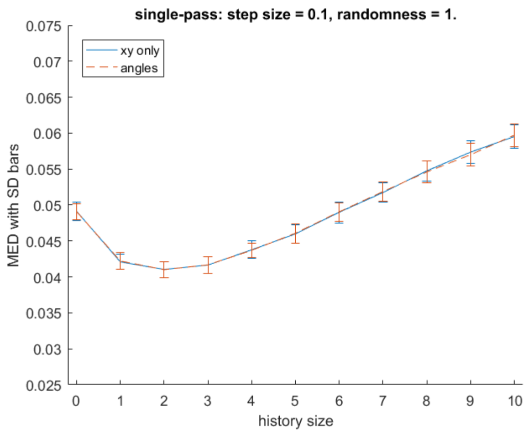

Figure 3.3: Implementation of history.

treme learning machine which originates from the hidden layer. The size of the hidden layer is the amount of hidden nodes. When the training size is as large as the size of the hidden layer, so when the matrix to be calculated becomes a square, the error rate goes up. It seems that there is no difference of the influence of angle scaling on the MED error. An angle scaling of 0.5 was used in the remainder of this research, as the *sin*- and *cos*-values would then be in the interval $[-0.5, 0.5]$, as are the x- and y-coordinates. A training size of 7200 samples was used in the remainder of this research, as there is no relevant improvement as compared to a training size of 12000 samples, while the training time nearly doubles. Therefore 7200 training samples was decided to be an optimal setting, as the network learned fast and accurately.

3.2 Direction of a moving source

The first research question was whether the direction of a moving source could be learned by the neural network. The distribution of the error of the angle of movement is shown in figure 3.2. It is a two-sided distribution to show that the error is distributed normally with a mean of 0.13 degrees and a standard deviation of 9.5 degrees. The Shapiro-Wilk test for normality yielded $W = 0.97942, p < 0.001$. The absolute average angular error is the error regardless of the direction of the error. This absolute average angular error is 6.7 degrees.

3.3 The effect of history

It was investigated whether adding history to the input of the network shows an improvement in localization performance when the network also learned the direction of a moving source over a network that did not. A history parameter was implemented on the interval $[0, 10]$ in the network that also learns the sine and the cosine, and in the network that only learns the location. The MED error in localization is shown in 3.3. The step size and maximum angular change inbetween samples are $[0.1, 1]$, corresponding to figure 2.2. The solid blue line corresponds to the network performance of the network that only learns the location. The dashed orange line corresponds to the network performance of the network that also learns the direction. The optimal performance is at the history size of 2. The results show no significant difference between the networks with and without angular information present in the output. It was then investigated if there was a difference between the networks on lower step sizes. Therefore the speed of the source was reduced. Two other parameter settings were used, namely $[0.025, 0.5]$ and $[0.0125, 0.25]$ for the step sizes inbetween samples and the maximum angular change respectively. The settings $[0.0125, 0.25]$ correspond to figure 2.3. Figure 3.4 depicts the results for both networks on the three different settings for the step size. It shows that a lower step size results in better performance at a larger history size. The solid lines correspond to the network that learned only the location. The

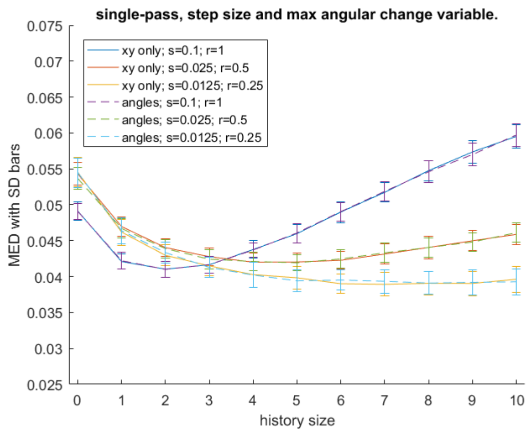

Figure 3.4: History with different step sizes and different maximum angular change settings.

dashed lines correspond to the network that learned the direction as well. The solid and dashed lines corresponding to the same settings for the step size within samples are very close together.

3.4 The effect of explicit history

It was investigated whether the two-pass model described in the previous section could show an improvement in the localization with a network that learns both the location and the direction of a source, compared to a network that learns only the location of a moving source. Figure 3.5 depicts the results in terms of MED error in localization on different history sizes for the three settings for the step size and maximum angular change. As before, the continous lines correspond to the network that only learned the location. The dashed lines correspond to the network that also learned the direction. It can be observed that there is an improvement of localization performance when the network learned both the location and the direction. The two-pass model was also compared to the single-pass ELM that incorporated history based on the concatenation of excitation profiles. Figure 3.6 depicts the different models on the lowest setting for the step size. For all settings improvements can be observed, however on this setting the improvement was visualized best. In both models there was a network that only learned the location and a network that learned both the location and the angle of movement. The solid

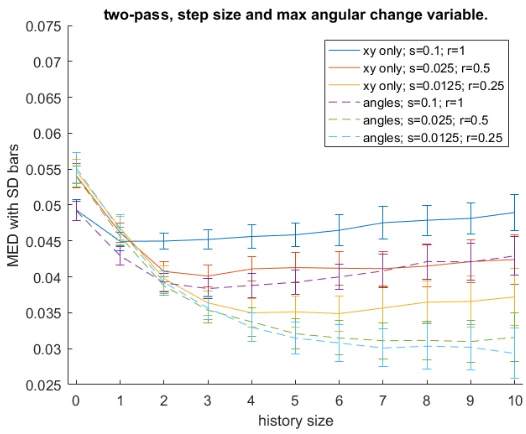

Figure 3.5: Two-pass model; history with different step sizes and different maximum angular change settings.

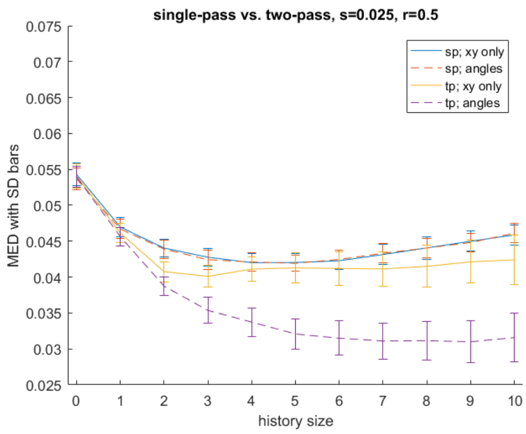

Figure 3.6: Single-pass model versus two-pass model with a step size of 0.025 and a maximum angular change of 0.5.

blue line and the dashed orange line correspond to the single-pass model in which the input consists of concatenations of excitation patterns, in which the blue line represents the network in which only the location is learned, and in which the orange line respresents the network that also learned the direction. These correspond to the orange and green line in figure 3.4 respectively. The yellow line is the MED error result for the two-pass model that only learned the direction. The MED error rates are lower than both networks of the single-pass model. The purple dashed line corresponds to the two-pass model in which the network also learned the direction of the moving source. Its MED error rates are lower than the two-pass network that only learned the location of the source.

It was tested per history setting whether the two-pass model in which the network only learned the location yielded no difference as compared to its single-pass counterpart. It was tested as well whether there is no difference in MED error between the two-pass model in which the network learns the direction and the network that only learns the location of the source. All tests yielded $p < 0.002$ and therefore all differences are significant.

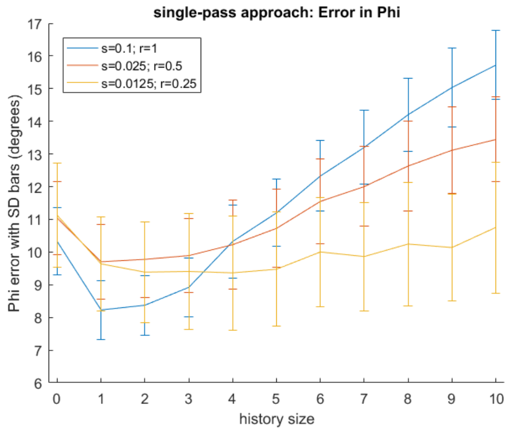

Figure 3.7: Single-pass model angle prediction for various step sizes and various maximum angular change settings.

3.5 Direction error

It was investigated whether the application of a two-pass network that learned the direction of movement yielded different result than a single-pass network in means of angular error. Besides the resulting standard deviation figures a p-value graph is presented as well to show significance. Figure 3.7 shows the error in phi of a single-pass network with different step sizes on different history sizes. Figure 3.8 depicts whether there is a significant difference in the distributions of angle measurement error. Between step sizes 0.1 and 0.025 there is no significant difference at a history size of 4. That is not a surprising observation as the lines representing these step sizes in figure 3.7 intersect closely to a history size of 4. At history sizes 0 and 1 there is no significant difference between the step sizes of 0.025 and 0.0125, as their corresponding lines are close together on lower history sizes in figure 3.7. Figure 3.9 shows the error in phi of a two-pass network with different step sizes on different history sizes.

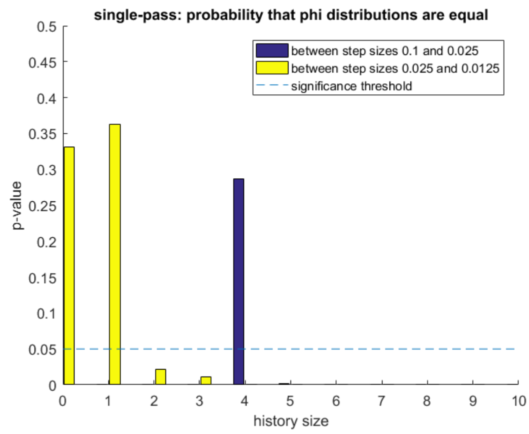

Figure 3.8: Single-pass model: probability of equality in distributions across the step size and maximal angular change settings.

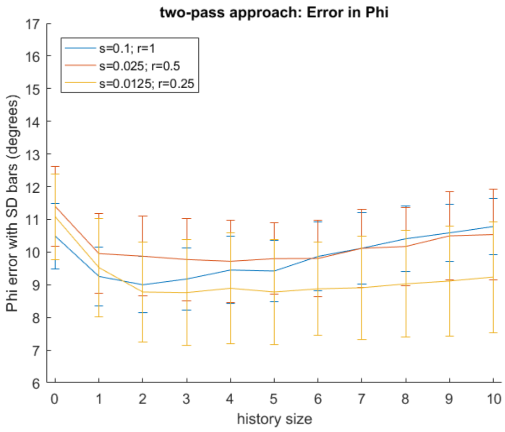

Figure 3.9: Two-pass model angle prediction for various step sizes and various maximum angular change settings.

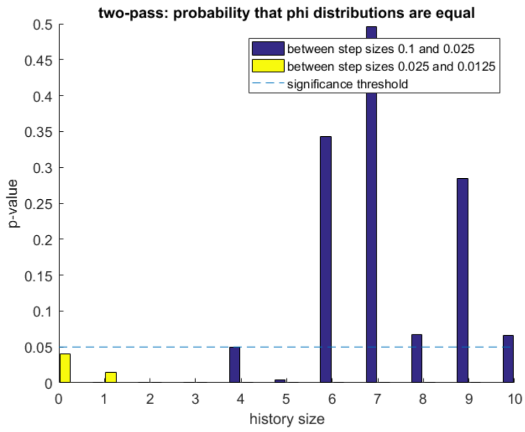

Figure 3.10: Two-pass model: probability of equality in distributions across the settings for step size and maximum angular change.

Figure 3.10 depicts whether there is a significant difference in the distributions of angle prediction error. The difference in angular error between step sizes 0.025 and 0.0125 seems to be significant at all the tested history sizes. At a history size of 6 and higher the difference is not significant between step sizes 0.1 and 0.025.

4 Discussion

4.1 Angular scaling and training size

There is no clear optimal setting for the angular scaling. The network finds no impairment in learning two extra parameters of which there is clear evidence in the input patterns. This is because the ELM utilized in this research has only one hidden layer. There is no influence by extra output nodes in the weights from the input layer to the hidden layer because they are fixed. The hidden layer has connections to each output node, but the output nodes do not interfere with each other, and the calculations are not affected. Therefore there is no influence of angular scaling on the localization of the source. After the parameter sweep, the best training size was concluded to be fixed at 7200, to have a good balance between the speed of training and accuracy of the network.

4.2 Direction estimation

The error in direction is 0.13 degrees with a standard deviation of 9.5 degrees. These results can be interpreted as a positive answer to the first research question. The distribution of the error in direction is normal because the Shapiro-Wilk test yielded a p value below 0.001.

4.3 Effect of learning the direction

The absence of an effect of learning the direction as depicted in figure 3.4 was surprising at first. It can however be explained by examining the structure of the ELM more closely. As described in subsection 3.1, there is no interference of the parameters to be learned. There is also no feedback of the output nodes back into the network. When presented the exact same excitation patterns as input, localization is not aided by also learning the angle of direction, because the angle of direction is calculated separately from the coordinates, and does not contribute to the calculation of the coordinates. There is no back-propagation in the ELM, and therefore the extra learned information can not be utilized to increase localization performance. The balance between training time and accuracy of an ELM is preferable as compared to that balance in other types of networks. The ELM can however not utilize additionally learned information. This inability explains the absence of improvement in the localization of a moving source when incorporating angular information in the output.

4.4 Effect of explicit feedback

The second network in the two-pass model can utilize transformations of previous excitation patterns to improve localization. The two-pass model as described does provide a significant and relevant advantage when the direction is present in the output as compared to the situation where only the location is concatenated with the excitation pattern and presented to the second network. There is also a significant but smaller improvement when merely providing feedback on the location as to no feedback at all, as in the single-pass model. Because said improvement is smaller it is less relevant. The effects are more severe as the history size increases. It can be concluded that the two-pass model with angular feedback outperforms the two-pass model in which only the location is used as feedback, and therefore there is an improvement in localization when the direction is learned.

4.5 Effect of direction estimation on localization

The overall observation can be made that in the two-pass model, with increasing history size the error of the direction is more consistent than in the single-pass environment. The differences in error for different settings of the step size are not always significant. Although trends are visible, and they are significant at times, it can not be concluded that the results of differences between the step size settings are relevant. When translating these values back to the original problem, if the error in direction measurement is 10 or 16 degrees, that does not cause large problems. The network still has a sense of the direction in which the source is moving. And this can still be used to make a better prediction on the next location than if there was no extra information about the direction.

5 Conclusions

5.1 Plausibility and practicality

Although the extreme learning machine provides a fast and accurate means to localize a moving source, applying a two-pass model is perhaps not a very plausible construction in biology, but challenges are also faced in a laboratory setting. The training time is multiplied by two as compared to a single-pass ELM model because two networks have to be trained and tested instead of one. The training time is however insignificant since training a network is only done once. After training thet network is ready to be utilized for a much longer time than the training time itself. Since the two-pass model yields results that are significantly better and are relevant, the extra training time is worth it. Future research may involve finding a more plausible and practical substitute for the two-pass model described in the current research.

5.2 Sample size

The sample size for training the network should have been increased on lower step sizes, to compensate for the lower spread in both training and testing data. It is highly likely that the conclusions would have been the same, but the evidence would be even more convincing. On the other hand taking more samples would have increased the calculation time for these settings, but the more convincing evidence, or better prediction, would be worth it.

5.3 Angular change

Different settings for the maximum angular change could have been used. At a step size of 0.1 the maximum angular change per time-step was 1 rad. At a step size of 0.025 the angular change was set to 0.5 rad. This means that in the latter case the source is forced to make its turns twice as sharp. For future research it may for example be interesting to investigate what the result is of allowing the source to make its turns twice as wide.

5.4 About the ELM

The ELM has been shown to be a powerful tool in localization research. Depending on the purpose of the research, it is a useful network as the calculations for the different parameters do not interfere with eachother. It is therefore a very good network to use for testing and tweaking. When adding a parameter that might not be learned properly based on the input pattern, this does not influence the other parameters. If it were not possible to learn the direction, the error in the according output nodes would be of large proportion. The error in the location of the source would not be affected. This network allows attempts to learn additional information without blurring the already incorporated capabilities. On the other hand, this means that additionally learned information can not lead to improvement of the previously present capabilities in the single-pass environment. It would require back-propagation, a feature that the ELM lacks, but other networks posess (Huang et al, 2006).

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