On the Application of Feed-Forward Artificial Neural Networks to the Maritime Target Motion Analysis Problem

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Abstract. This work presents a novel approach for the fast prediction of future positions of marine vessels utilizing a simple feed-forward artificial neural network. It is shown that this simple network architecture with a single hidden layer, containing three hidden neurons is capable of predicting the future position of a maritime vessel with an accuracy of 99.26% . For this research a simulation was developed, in order to generate enough track data needed to train the network. The input data had to be converted from common polar coordinate system used by navigators into Cartesian coordinates in order to increase the accuracy of the predictions. The predictions are based on three previous observed positions and their corresponding observation times. It was shown that the accuracy decreased linearly with an increasing noise level of the observations. If the noise level exceeded a maximum noise level c of 20 m, the performance of the network degraded beyond its practical use.

Keywords: Feed-Forward Neural Network · Target Motion Analysis

1 Introduction

Target Motion Analysis (TMA) in the maritime context aims to make predictions about the state of a signal-emitting object, known as the target, by considering its location, bearing, and velocity based on past observations [1]. However, in practical applications, the accuracy of time delay measurements is affected by noise. This noise might be caused by various factors, such as the cross-correlation function used to find a common signal in a pair of sensors or environmental influences [2]. Another source of errors is false readings or clutter. This clutter is usually assumed to be uniformly distributed over an area *A*.

Figure 1 shows a typical scenario for the TMA problem, where Fig. 1a depicts the ideal scenario, while Fig. 1b shows a real-world scenario with clutter and noise.

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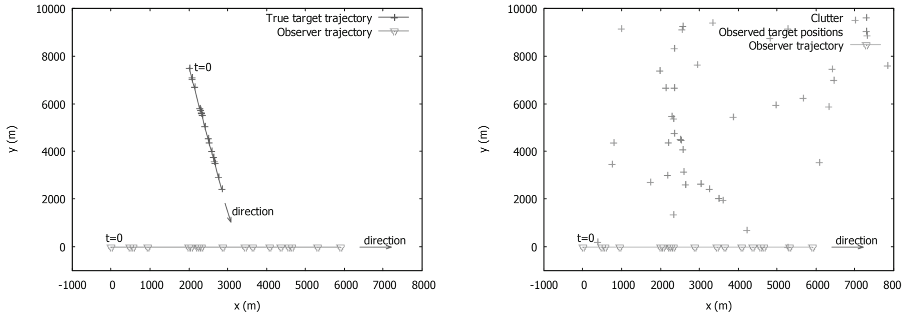

a) ideal scenario

b) real-world scenario with noise and clutter

Fig. 1. Scenario for the Target Motion Analysis problem

An observer and a target are moving with constant speed and the target is detected at unequally spaced time instances by the observer.

In the ideal scenario (Fig. 1a), Newtonian physics can be used to calculate the future position, based on the current bearing, speed and location of an object. However, due to the noise and clutter affected measurements, in a real-world scenario (Fig. 1b), the prediction of the future position, more robust methods, such as Kalman filters [3, 4] or Particle filters [5] are employed. More recently, artificial intelligence methods, like LSTM [6] or Ant Colony Optimisation [7] were successfully applied to the TMA problem achieving better accuracy than classical methods used for TMA [6]. Since it was proven by Hornik *et al.* [8, 9] that feed forward neural networks are capable of approximating any given function with any required level of accuracy, this study tries to answer the question, are simple feed-forward neural networks, in principle, capable of solving the TMA problem? Training a feed-forward neuronal network usually requires a large amount of linearly independent training examples. It is very difficult to acquire these amount of real-world training data. Therefore, a simulation was developed, that generates target tracks in a marine environment for training and evaluation.

2 Simulations

A simulation tool was developed, which generates target tracks in relation to the ownships position. The parameters of the simulated targets are based on the limitations of real-world targets like ships and boats.

The main parameter used for track generation is the speed of the target. The maximum speed is based on generally known speeds of ships, boats, and other water vehicles. These reach up to 90 km/h or 25 m/s. For each target a constant speed v was chosen randomly from the interval:

$$\left\{ v \in \mathbb{R} | 0\frac{\mathrm{m}}{\mathrm{s}} \leq v \leq 25\frac{\mathrm{m}}{\mathrm{s}} \right\}. \tag{1}$$

Due to the problem at hand, it cannot be guaranteed that observations are equidistant in the time domain. Therefore, the time between two observations t was selected randomly from the interval:

$$\{t \in \mathbb{R} | 1\text{s} \leq t \leq 10\,\text{s}\}. \tag{2}$$

In principal targets in different distances are of interest. However, due to physical limitations of passive sonar systems measurements up to 6 km are assumed to be sufficiently accurate under most conditions [10]. The initial distance r of the targets is chosen randomly from the interval:

$$\{r \in \mathbb{R} | 0\text{m} \leq r \leq 6000\,\text{m}\}. \tag{3}$$

The initial position of the targets are determined by the radius r and the bearing φ. The bearing was also chosen randomly from the interval:

$$\left\{\varphi \in \mathbb{R} | -180^\circ \leq \varphi \leq 180^\circ\right\}. \tag{4}$$

In order to test the reliability of the network, the simulation offers the possibility of adding noise to the track data generated. In order to generate realistic error curves, the added noise is randomly chosen from a Gaussian distribution with mean of zero and a distance depending standard deviation. The track data generated by the simulation was validated by human experts. Figure 2 shows a plot of 1,000 simulated target tracks. For training the artificial feed-forward network, sets of 10,000 were used, as discussed in the next section.

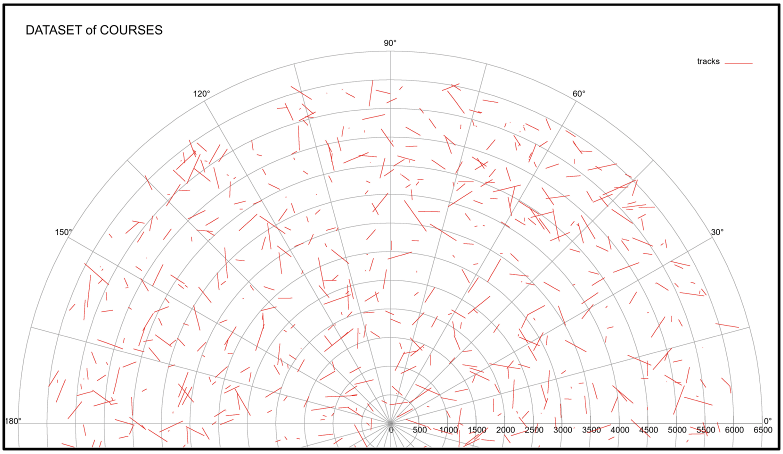

Fig. 2. Example of generated track data

3 Network Type and Architecture

It has been proved by Hornik, Stinchcombe and White that standard multilayer feedforward networks with one hidden layer using arbitrary squashing functions are capable of approximating any measurable function from one finite dimensional space to another to any desired degree of accuracy [8, 9]. Here, a multilayer perceptron network with one hidden layer, utilizing Sigmoid and ReLU activation functions were used and the topology was determined empirically (Fig. 3). The training of the network was undertaken with 70% of the data is for training while 30% of the data were used for testing.

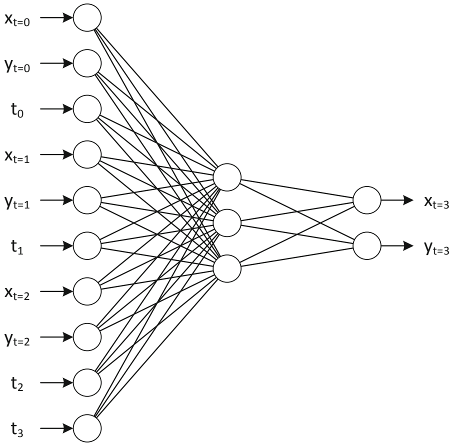

Fig. 3. Network topology

The three positions and the related observation times together with the prediction time *t3* is feed into the network in Cartesian coordinates. The output of the network is the predicted target position at time *t3* in Cartesian coordinates. In order to improve the accuracy of the predictions, it was necessary to convert the given polar coordinates into Cartesian coordinates. The number of hidden neurons was determined empirically. The best results were achieved by using as few as three hidden units. This topology was then used for the final evaluation as described in the next section.

4 Experimental Results and Discussion

Once the network was trained using 10,000 generated tracks, experiments were carried out using noisy inputs in order to reflect the limitations of real-world sonar systems.

Due to the nature of the sonar system, the motion data of the targets is given in polar coordinates. When using polar coordinates, a deviation in the angle has a higher impact on the error than a similar deviation in the radius. Therefore, an accuracy metric, based on the absolute distance *d* between two points given in polar coordinates is used in this research:

$$d = \sqrt{\left(r_t^2 + r_p^2 - \left(2 \cdot r_t \cdot r_p \cdot \cos\left(\varphi_t - \varphi_p\right)\right)\right)}. \tag{5}$$

where *d* represents the absolute distance between the true position and the predicted position represented in polar coordinates. Here r_i represents the radius while φ_i represents the angle of the polar coordinate *i*. The index *t* represents the true position, while the index *p* represents the predicted position.

The accuracy *acc* is calculated using the maximum distance of 6,000 m as follows:

$$acc = 1 - \frac{d}{6,000\,m}. \tag{6}$$

A distance *d* above 30 m, reflecting in an accuracy smaller than 0.995, is deemed insufficient for practical applications.

The noisy inputs $\hat{x}$ were calculated according to:

$$\hat{x} = x + \min(r(\sigma(d)), c). \tag{7}$$

where $\hat{x}$ represents the noise affected positon, x denotes the real position, $r(c)$ represents the Gaussian random number with a standard deviation of $r(\sigma(d))$ depending on the distance d. The constant c is used to limit the maximum noise level and is chosen from the interval:

$$\{c \in \mathbb{N} | 0, 20, \ldots, 120\}. \tag{8}$$

- Experiments for all seven values of *c,* were carried out using 10,000 new generated tracks each. The mean accuracy following Eq. (6) for the different noise levels *c* are depicted in Fig. 4.

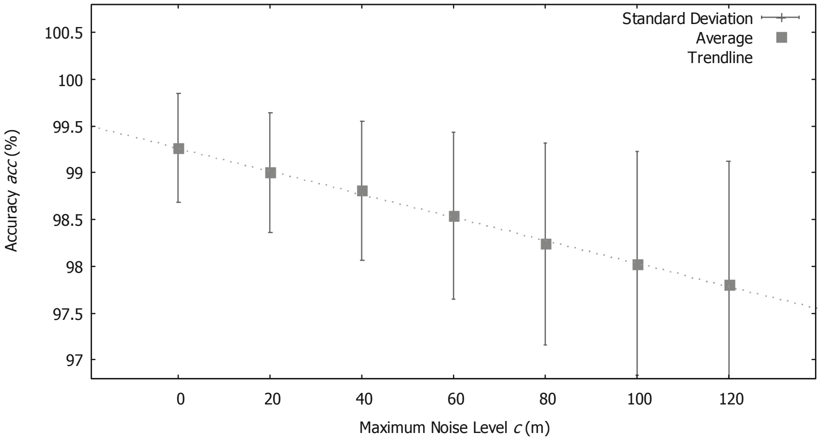

Fig. 4. Experimental results

It can be seen from the figure that the average accuracy of the predictions without noise was 99.26%. This is slightly worse than the target accuracy of 99.5% given for practical applications. In addition, it can be seen that the accuracy decreases linearly with increasing noise with an R^2 value of 0.9979, whereas the standard deviation increases following an exponential equation with an R^2 value of 0.9888.

5 Conclusions and Future Work

It was shown that a simple feed-forward network with a single hidden layer, containing three hidden neurons is capable of predicting the future position of a maritime vessel. The prediction for a variable chosen point in the future is based on three previous observed positions and their corresponding observation times. The accuracy achieved in these early experiments was near the accuracy required for real-world applications. It was shown that the accuracy decreased linearly with an increasing noise level of the observations. If the noise level exceeded a maximum noise level c of 20 m, the performance of the network degraded beyond its practical use.

Also, the experiments did not include clutter, i.e. observations that do not originate from the target. In future work the influence of clutter on the predictions will be examined. In addition, the network will be fine-tuned using real-world data based on Automatic Identification System (AIS) tracks of seagoing vessels. This will potentially increase the accuracy of the network.

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