# Gravitational Wave Signal Detection with Neural Networks for the VIRGO Antenna

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**Abstract.** In this paper we describe a neural network-based acoustic noise identification procedure. In particular, we have performed some experimental tests on a classic Michelson interferometer used as a microphone, that although different from the VIRGO[1] antenna provides us with global information on the performance of neural networks. The preliminary results appear to be very promising for the analysis of real VIRGO outputs.

## INTRODUCTION

Gravitational Wave (GW) detection is a very complex problem [2]. Due to the interferometer sensitivity to environmental and internally generated noises, the not well known shapes of GW signals and their intrinsic weakness, the resulting s/n ratio is very poor, so it is important to develop robust models for the detection of GW signals in high noise environments. The GW signal can actually be considered as an anomaly in the signal output of the interferometer.

## ANOMALY DETECTION BY NEURAL NETWORKS

In the performed experiments we used a multi-layer perceptron (MLP) neural network (NN) [3] to build a model of the dynamics of the acoustic noise process. The experiment we performed had the following purposes:

1. Show that it is possible to identify the acoustic noise contribution to the output of the interferometer using a NN trained on the acoustic noise.
2. The presence of an anomaly in the noise sequence can be detected analysing the prediction residuals, which show how the model fails in reproducing the dynamics of the modelled system (if we are confident that the model is capable of reproducing the system dynamics).

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The approach we followed to build the model is based on sound theoretical foundations. First, we reconstructed the state space vector $\mathbf{x}(t)$ from the observed data s(t) via a *phase space reconstruction*[4] method. The vectors so obtained were then used to create a model by following a probabilistic Bayesian approach[3,4]; this allowed the exploration of a model space, rather than a single "optimal" model as usually happens in practice. By using Bayes' theorem and marginalizing the posterior distribution of model parameters to integrate out the hyperparameters[1] $\alpha$ and $\beta$ (which are used only to determine the form of the distributions) we have:

$$p(\mathbf{w} \mid D) = \frac{1}{p(D)} \iint p(\mathbf{w} \mid \boldsymbol{\alpha}) p(D \mid \mathbf{w}, \beta) p(\boldsymbol{\alpha}) p(\beta) \mathrm{d}\boldsymbol{\alpha} \mathrm{d}\beta. \quad (1)$$

The Bayesian learning framework has several advantages over traditional ones: *the model cannot overfit the data* also if it is very complex, and we can obtain *error bars* to assess the uncertainty in the predictions of the model.

## RESULTS

The trained model had 23 hidden units with tanh activation function, 11 input units (corresponding to the embedding dimension of the system) and 1 output unit with linear activation function. Fourteen regularization parameters have been used: one for each group of connections from each input units, one for each layer's bias connections and one for the group of connections to the output unit. The model was trained for 200 epochs. The residuals show that the model can achieve good predictive performances, also if it not very complex. To test the detection capability of the model a synthetic anomaly has been added to the interferometer signal. This anomaly is a segment of a chaotic time series, namely the solution of the Mackey-Glass time-delay differential equation. The signal has been chosen because it mixes well with the interferometer output. At a glance, it is not possible to see the anomaly. However, since its amplitude is greater than the residuals, we expect the network to detect it, which indeed it does. The Bayesian error bars are useful to see how well our model can detect anomalies; if we do not trust the model enough, we could simply detect as anomalies those spikes which are greater than, say, 2 or 3 times the error bars. Note that the model could be made more reliable by using a greater training set, using more units and training for more epochs. Further experiments need to be done with more complex models and signals to verify the applicability of the procedure to VIRGO data analysis.

## REFERENCES


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[1] The *alphas* are also termed *regularization coefficients*, since their use favours smooth mappings to be generated. We allow different *alphas* for different groups of parameters to give the model wider flexibility. The *beta* is the *precision* with which we realize the mapping.