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A new method of detection of coded signals in additive chaos on the example of Barker code

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Abstract

The paper presents a concept of model-based detection of coded signals on the example of 13-element Barker code signal, embedded in additive chaos. The process of signal detection consists of two stages: approximation of chaotic dynamics and decision making. Dynamic models of chaotic signals, considered in this paper, were created in the form of linear autoregressive models as well as in the form of non-linear feedforward neural networks (of several types). The accuracy of models in one step ahead prediction of chaotic signals is satisfactory, even for chaotic signals with fast changes of their values. The error between an observed signal and its model is passed as the input to the decision-making (detection) module.

When the signal received is a composite of Barker code and chaos, its dynamic properties change rapidly in the periods of Barker code appearance. Thus the error between the signal and its model becomes significant, and that allows for successful detection of Barker code. In this paper the detection module is based on a neural network; various architectures of neural net-based detectors have been proposed and tested in numerical experiments. Numerical simulations presented in this paper show good performance of detection of Barker code embedded in chaos.

Robustness of such a detection scheme was also examined: the neural detectors, trained for a specific energy ratio between Barker code and chaos (SNR ratio), turned out capable detecting Barker code in a relatively wide range of SNR ratios. Also the comparison between neural detection and a detection structure, using matched filter, has been presented. Experiments have shown superiority of neural detection over detection with a matched filter, especially for low SNR ratios. It should be also noted that very simple neural network architectures were proposed as the models of signal dynamics and for the detection module.

Keywords: Signal classification; Signal detection; Neural networks; Dynamic modelling

1. Introduction

Detection of signals embedded in noise is one of the most important problems in signal processing.

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Nomenclature

$w(t)$	additive model of observation
$s(t)$	useful signal
$n(t)$	noise
t	time
MLP	Multilayer Perceptron
RBF	Radial Basis Function
AR	Linear Autoregressive Model
x, y, z	continuous state variables in state equations of chaotic models
x_k, p_k, y_k	discrete state variables in state equations of a presented chaotic models
$\boldsymbol{x}(n)$	vector of discrete state variables of a chaotic dynamic model
$y(n)$	output signal of a chaotic dynamic model
D	number of historical output samples of a discrete chaotic model
D_0	fractal dimension
$\boldsymbol{r}(n)$	vector of an output sample and historical output samples up to order D in a chaotic model
$\mathrm{f}(\cdot)$	function of state variables used in a discrete state equation
$\mathrm{g}(\cdot)$	function of state variables used in a output signal
$\mathrm{F}(\cdot)$	approximation of chaotic dynamics as a predictive model
(t7-t7-l1)	architecture of a neural network (seven neurons with tangensoidal activation functions in the input layer, seven neurons with tangensoidal activation functions in the hidden layer, one linear neuron in the output layer)
SNR	signal to noise ratio calculated as $\frac{\text{normalized energy per one sample of the Barker code}}{\text{normalized energy per one sample of chaos}}$
NPE	normalised prediction error calculated as $\frac{\sqrt{\text{sum of squares of prediction errors}}}{\text{length of an error vector}}$
NTRE	normalised training error calculated as $\frac{\sqrt{\text{sum of squares of training errors}}}{\text{length of an errors vector}}$
NTEE	normalised testing error calculated as $\frac{\sqrt{\text{sum of squares of testing errors}}}{\text{length of an errors vector}}$
NDE	normalised detection error calculated as $\frac{\sqrt{\text{sum of squares of detection errors}}}{\text{length of an error vector}}$
H_0	null hypothesis in a binary test of hypotheses
H_1	alternative hypothesis in a binary test of hypotheses

The additive model of observation $w(t)$, which consists of the useful signal $s(t)$ and additive noise $n(t)$ or only noise alone, is often assumed in detection algorithms. Noise is modelled as a stochastic process with known statistics and unknown parameters. The receiver used in the detection process should be optimal for given class of signals and noises, to allow making a proper decision about presence or absence of a useful signal in observations. The value of likelihood ratio is computed and compared with a threshold for a given optimality criterion (e.g. Neyman–Pearson criterion, Bayes risk criterion) [1,2]. The quality of detection depends significantly on the signal-to-noise (SNR) ratio. The classical detection task can be formulated as binary classification or binary testing of hypotheses.

Depending on a particular application, the useful signal $s(t)$ can be taken in a specific form. For example, in telecommunication systems the