Hammerstein-Wiener Model: A New Approach to the Estimation of Formal Neural Information

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ABSTRACT

A new approach is introduced to estimate the formal information of neurons. Formal Information, mainly discusses about the aspects of the response that is related to the stimulus. Estimation is based on introducing a mathematical nonlinear model with Hammerstein-Wiener system estimator. This method of system identification consists of three blocks to completely describe the nonlinearity of input and output and linear behaviour of the model. The introduced model is trained by 166 spikes of neurons and other 166 spikes are used to test and validate the model. The simulation results show the R-Value of 92.6 % between estimated and reference information rate. This shows improvement of 1.41 % in comparison with MLP neural network.

1. Introduction

As a brief definition, information methods are those that estimate the mutual information between an ensemble of spike trains and some other experimental variable (Goldberg, Victor and Gardner, 2009). As it was proposed by Reich, Mechler and Victor (2001), we could simply distinguish two categories for this concept: formal information and attribute-specific information. "Formal information" mainly discusses about the aspects of the response that is related to the stimulus. Difference between the entropy of responses to an ensemble of temporally rich stimuli and the entropy of responses to an ensemble of repeated stimuli has main effect on calculation of this kind of information. On the other hand, "Attribute-specific information" refers to the amount of information that responses have about a parameter which is obtained in a particular experiment. Category specific information is the case which the parameter describes one of several discrete categories (Victor, 2006).

Recently some complex information theory methods such as entropy method, Binless method and metric space method are presented to estimate the neural information, but studying this problem as a system identification problem, there will be more methods to reach such a result. The approach of the work is modelling a mathematical system to calculate the information of neuron. This model is based on designing a system with a particular type of neural network to simulate the calculated information by Goldberg et al. (2009). With this approach, we have used the presented model by Goldberg as a mother model and tried to fit a nonlinear system on it. This newly estimated model could easily calculate the output (Neural Information in words of Goldberg) without the calculation cost of the mother model.

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In system identification methods, nonlinear process identification has recently became one popular method in both research institutions and industry. Linear models can only achieve limited performance which is mainly because of the nonlinear nature of the real-world processes. As a consequence, nonlinear system identification using Hammerstein-Wiener model is proposed. Hammerstein-Wiener model belongs to the class of block-oriented models. They are described as a series or parallel combinations of linear dynamic and static nonlinear functions (Zhu, 1999). The interest in block-oriented model is increasing due to several factors, i.e. low cost in identification computation, easy to comprehend and easy to use in control (Patcharaprakiti et al., 2010).

Hammerstein-Wiener model could represent the nonlinearity through algebraic polynomial expressions, piecewise-linear, basis function, wavelets, neural networks, look-up tables and fuzzy models (Biagiola and Figueroa, 2009). Meanwhile, the linear dynamic is represented either by impulse response, pulse transfer models and state space models. Neural networks and estimation based on them could have a big part in neuroscience research. Recent publication of Lotfi-Noghabi et al. (2012) shows one of these applications in estimation of optimal dosage of sodium valproate in idiopathic generalized epilepsy.

Recently, Hammerstein-Wiener model have been used in other biomedical applications such as estimation of muscle force from electromyography signals (Abbasi-Asl et al., 2011)

In this paper we will introduce a non-parametric model based on Hammerstein-Wiener model with use of sigmoid network in nonlinear block of model which can be classified in neural network model category. Section II will discuss on different aspects of Neural Information. Structure of Hammerstein-Wiener model will be introduced in section III. In section IV, Model Output and Simulation Results will be described and finally a conclusion remark will be represented.

Information

Understanding the brain function in processing and representation of information is such a complex issue that there is no certain method to comprehend it. Part of brain function is involved with processing sensory and motor commands in different contexts. Neurons are basic components of the brain structure that process and convey information. In any context, neural activities represent the feature of stimulus and motor command. In neural coding problem which comprises the information transfer and the response function, information theory has a basic role (Goldberg et al., 2009). The construction of neural code has a fundamental role in neuroscience. Neural coding refers to this matter that what is being encoded and how? Achieving the response of these questions requires experimental research and computational methods. Computational neuroinformatics is a significant tool that collaborate these due to synthesize neural representation and information processing. Nonetheless not many researchers have used information theory method in neural coding problem. Some of them used only a linear decoding filter to model the stimulus–response function, and obtained only the corresponding lower-bound estimate of information (Borst and Theunissen, 1999).

In some studies of sensory and motor system it is assumed that the spike numbering of a neuron in an arbitrary time window is related to the stimulus features that are encoded. But in this point neurons are normally studied individually (Averbeck and Lee, 2004). Various information theory methods such as entropy method, Binless method, metric space method, etc. were developed. Many of these methods have high potential in understanding neural coding, information processing strategies, and mental disorders. Information theory utilizes statistical methods to identify how a neuron response changes with various stimulates. It means that these methods define what information about stimulus is included in spiking patterns. Another usage of information theory methods is calculation of maximum rate of information conveyance (Borst et al., 1999).

Neuroinformatic methods are used in estimating stimulus parameters from spike timing and spiking patterns. Spike timing decoding is used in sensory and motor system identification. For example, in auditory system, spike timing contains important information in sound source specification. Also, information estimated through neuroinformatic methods, are used in determining movement kinematics and object properties in grasping task (Goldberg et al., 2009).

There are some evidences that show another role of precise spiking patterns. In some cases that precise spiking patterns carry additional information that is not related to stimulus features, like information of temporal structure that is relevant within the spike trains of single neurons (Averbeck and Lee, 2004).

In this work, we proposed a new system of identification method based on Hammerstein-Wiener model to estimate the neural information from spikes.

2. Methods: Hammerstein-Wiener Model

A. Structure of Hammerstein-Wiener Models

Figure 1 illustrates the block diagram of a Hammerstein-Wiener model structure. We could study this model as a combination of three series blocks. To formulate the problem, we have equation (1) which is a nonlinear function transforming input data *u (t)* and *w (t)* has the same dimension as *u (t).*

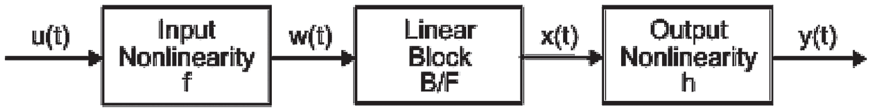

Figure 1. Block diagram of a Hammerstein-Wiener model NEUROSCIENCE

$$w(t) = f\big(u(t)\big) \tag{1}$$

For the second block:

$$x(t) = \frac{B}{F} w(t). \tag{2}$$

Equation (2) is a linear transfer function. has the same dimension as where B and F are similar to polynomials in the linear Output-Error model. For outputs and inputs, the linear block is a transfer function matrix containing entries:

$$\frac{B_{ji}(q)}{F_{ji}(q)} \tag{3}$$

where:

$$j = 1,2,\ldots, n_y$$
$$i = 1,2,\ldots,\ n_u\,. \tag{4}$$

Finally for the third block:

$$y(t) = h\big(x(t)\big) \tag{5}$$

which is a nonlinear function that maps the output of the linear block to the system output. and are internal variables that define the input and output of the linear block, respectively. Because f acts on the input port of the linear block, this function is called the input nonlinearity. Similarly, because h acts on the output port of the linear block, this function is called the output nonlinearity. If system contains several inputs and outputs, you must define the functions f and h for each input and output signal.

It is not necessary to include both the input and the output nonlinearity in the model structure. When a model contains only the input nonlinearity f, it is called a Hammerstein model. Similarly, when the model contains only the output nonlinearity h, it is called a Wiener model.

The nonlinearities f and h are scalar functions, one nonlinear function for each input and output channel.

The Hammerstein-Wiener model calculates the output y in three stages:

1. Calculates *w (t)= f (u(t))* from the input data. w(t) is an input to the linear transfer function B/F. The input nonlinearity is a static (memoryless) function, where the value of the output at given time t depends only on the input value at time t. The input nonlinearity can be set as a sigmoid network, wavelet network, saturation, dead zone, piecewise linear function, one-dimensional polynomial, or a custom network. It is possible to remove the input nonlinearity.

2. Computes the output of the linear block using w(t) and initial conditions by (2). Configuration of the linear block will be done by specifying the numerator B and denominator F orders.

3. Compute the model output by transforming the output of the linear block using the nonlinear function h (as it mentioned in (5)).

The input-output relationship will be decomposed into two or more interconnected elements, when the output of a system depends nonlinearly on its inputs. So, we can describe the relationship by a linear transfer function and a nonlinear function of inputs. The Hammerstein-Wiener model uses this configuration as a series connection of static nonlinear blocks with a dynamic linear block.

Applications of Hammerstein-Wiener model are in wide areas, for example we can mention modelling electro-mechanical system and radio frequency components, audio and speech processing and predictive control of chemical processes. These models have a useful block representation, transparent relationship to linear systems, and are easier to implement than heavy-duty nonlinear. Therefore, they are very useful.

The Hammerstein-Wiener model can be used as a black-box model structure since it prepares a flexible parameterization for nonlinear models. It is possible to estimate a linear model and try to improve its quality by adding an input or output nonlinearity to this model (Wingerden and Verhaegen, 2009).

Also, we can use Hammerstein-Wiener model as a grey box structure to take in physical knowledge about process characteristics. For instance, the input nonlinearity might represent typical physical transformations in actuators and the output nonlinearity might describe common sensor characteristics (Wang, Chen and Wang, 2009).

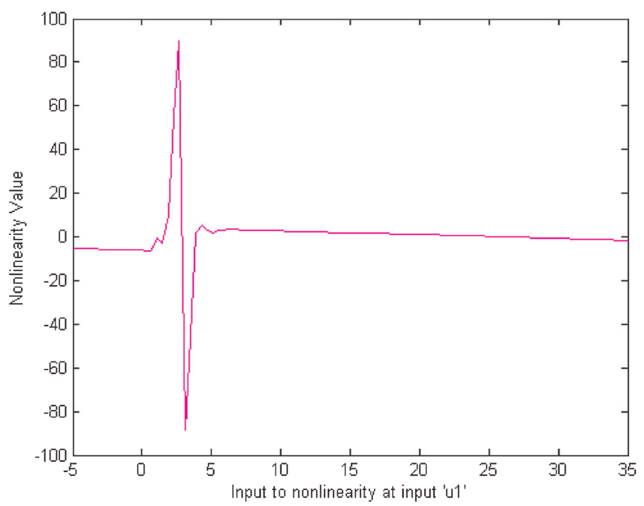

Figure 2. The input nonlinearity NEUROSCIENCE

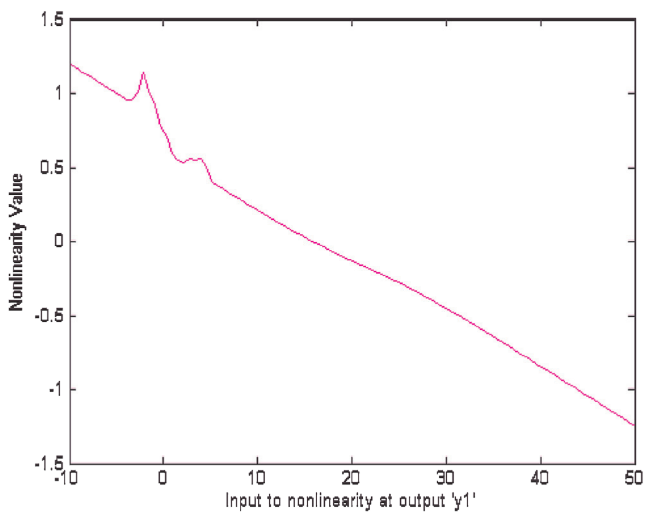

Figure 3. The output nonlinearity NEUROSCIENCE

B. Selected Parameters for Hammerstein-Wiener Model

In this work, the sigmoid network is chosen to represent the input and output nonlinearity. This network can model the system smoother and more dynamic than the others. Other networks have been simulated too, but the results were satisfactory when sigmoid network is used. Number of units for the sigmoid network has been set to 20. This amount of units, estimate the model very precisely, on the other hand, the simulations time are not too much in this case.

For the linear block, the selected dimensions for the poles and zeros are 3 and 2, respectively. Simulations showed that this is enough to model the linear behaviour of the system.

3. Results

As it mentioned in previous system, the model needs to be trained by some input-output data, i.e. we should train the model by some computed information as the output for some neural spikes which are as our input. After training the model, the validation will be done by some other spikes. In this work, we used the spikes and computed information presented by Goldberg et al. (2009). 166 spikes are used to train the model and 166 spikes are used to test it.

As a pre-processing approach, we up-sampled both spikes and computed information presented by Goldberg et al. (2009), by 100 samples. In this case, the model could be trained into a more dynamic nature.

The nonlinearity value of the input and output of the system, which is obtained after training of the model, is shown in figures 2 and 3.

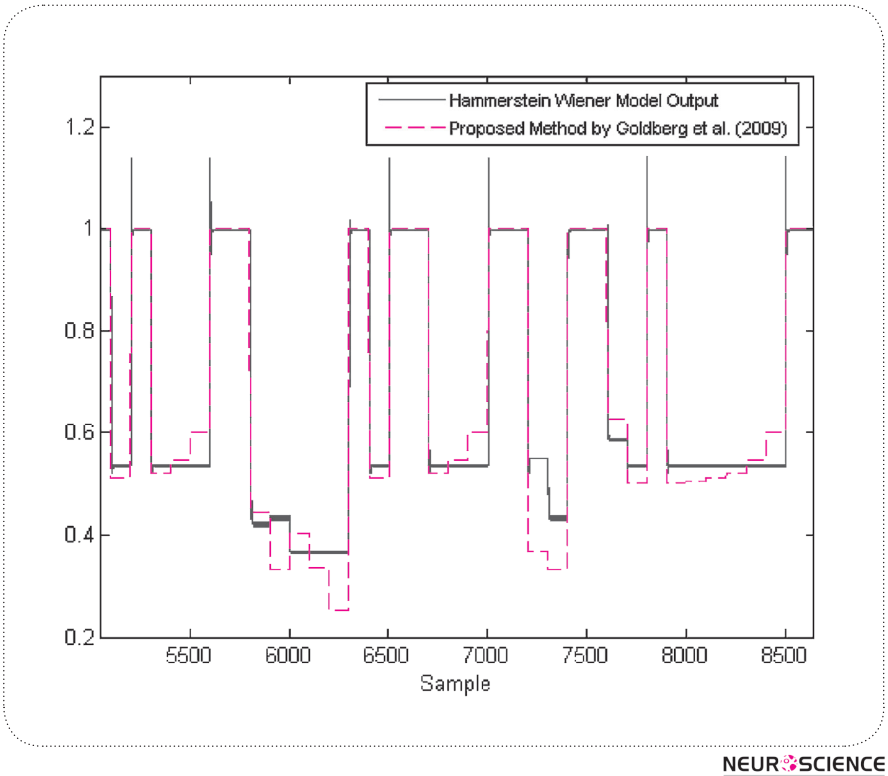

Figure 4. Our Model estimated information and computed information in [1] for 30 test spikes

Model output for 30 up-sampled test spikes has been depicted in figure 4 (solid curve). The computed information by Goldberg et al. (2009) is also shown in this figure (dashed curve). As it could be realized from these figures, Hammerstein-Wiener model could successfully estimate the information. For the 100 sample-intervals which we have a constant information, our model output has a stable value. Figure 5 shows how the model tries to keep the output in a constant value.

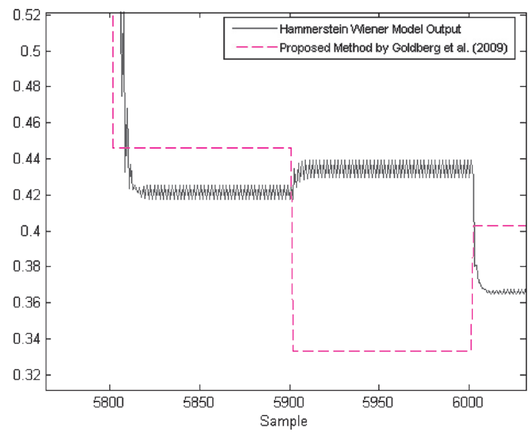

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Figure 5. Stable answer for the constant 100 sample-intervals

Table 1. R-Value and NRMSE of the 166 Test spikes information calculated by Hammerstein-Wiener and MLP method

	R-Value	NRMSE
MLP Neural Network	90.65 %	0.129
Hammerstein-Wiener	92.06 %	0.147

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Table 2. R-Value & NRMSE of the 166 Train spikes information calculated by Hammerstein-Wiener and MLP method

	R-Value	NRMSE
MLP Neural Network	95.39 %	0.112
Hammerstein-Wiener	96.46 %	0.100

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4. Discussion: Model Validation

To validate the introduced model, we have estimated the information using MLP neural network. MLP network is designed with two layers and 10 neurons in each layer. Sigmoid network, which is used in training process of first layer and the second one, have been designed in a linear manner. The correlation coefficient (R-Value) between designed models output and computed information by Goldberg et al. (2009) is calculated and is listed in table 1. We also run the model for the training data (Figure 7). The validation parameters for the train spikes are listed in table 2. All These values are archived from up-sampled data. As we can see, the R-Value is high and acceptable and has improvement in comparison with MLP neural network. The normal

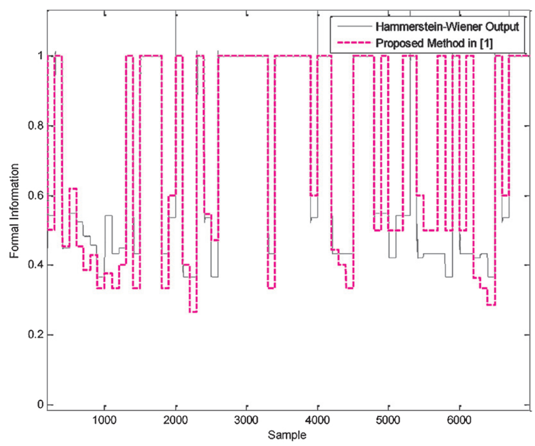

Figure 6. Model output for train data

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root mean square error is listed in next column for both models which shows that the Hammerstein-Wiener has improvement in estimation of the neural information. It should be mentioned that the results are related to conformity rate of the estimated output via calculated information by Goldberg et al (2009).

The scatter plot for the estimated information of test data set is depicted in figure 9. An acceptable correlation is achieved by the introduced model.

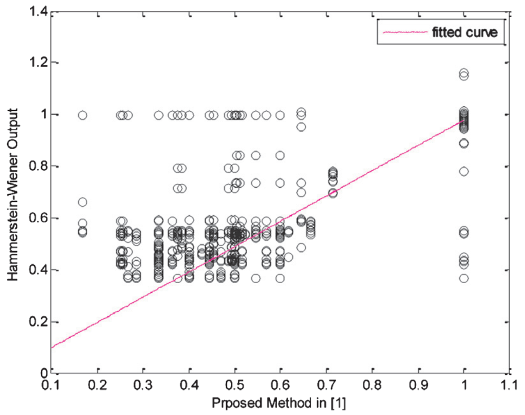

Figure 7. Scatter plot of the test spikes information

5. Conclusions

A new method is introduced to estimate the information of the neural spikes. The estimation is based on Hammerstein-Wiener model. This mathematical model could be replaced by the model presented by Goldberg et al (2009) and will save time and calculation cost in comparison with it. The nonlinear block in this model is based on sigmoid network which can smoothly estimate the output values. Simulations results shows that this model have low error rate. In further works we will add more complex pre-processing and post-processing approaches to our signal processing aspect of our work and also will try to reduce the NRMSE value for simulation results.

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