THE NEURAL-NETWORK ANALYSIS
DATA FILTERS
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Content:

1. Introduction to neural networks

1.1 What is a Neural Network?

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurones. This is true for ANNs as well.

1.2 Historical background

Neural network simulations appear to be a recent development. However, this field was established before the advent of computers, and has survived at least one major setback and several eras.

Many important advances have been boosted by the use of inexpensive computer emulations. Following an initial period of enthusiasm, the field survived a period of frustration and disrepute. During this period when funding and professional support was minimal, important advances were made by relatively few researchers. These pioneers were able to develop convincing technology which surpassed the limitations identified by Minsky and Papert. Minsky and Papert, published a book (in 1969) in which they summed up a general feeling of frustration (against neural networks) among researchers, and was thus accepted by most without further analysis. Currently, the neural network field enjoys a resurgence of interest and a corresponding increase in funding.

The first artificial neuron was produced in 1943 by the neurophysiologist Warren McCulloch and the logician Walter Pits. But the technology available at that time did not allow them to do too much.

1.3 Why use neural networks?

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyze. This expert can then be used to provide projections given new situations of interest and answer "what if" questions.
Other advantages include:

1. Adaptive learning: An ability to learn how to do tasks based on the data given for training or initial experience.
2. Self-Organization: An ANN can create its own organization or representation of the information it receives during learning time.
3. Real Time Operation: ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.
4. Fault Tolerance via Redundant Information Coding: Partial destruction of a network leads to the corresponding degradation of performance. However, some network capabilities may be retained even with major network damage.

1.4 Neural networks versus conventional computers

Neural networks take a different approach to problem solving than that of conventional computers. Conventional computers use an algorithmic approach i.e. the computer follows a set of instructions in order to solve a problem. Unless the specific steps that the computer needs to follow are known the

computer cannot solve the problem. That restricts the problem solving capability of conventional computers to problems that we already understand and know how to solve. But computers would be so much more useful if they could do things that we don't exactly know how to do.

Neural networks process information in a similar way the human brain does. The network is composed of a large number of highly interconnected processing elements (neurones) working in parallel to solve a specific problem. Neural networks learn by example. They cannot be programmed to perform a specific task. The examples must be selected carefully otherwise useful time is wasted or even worse the network might be functioning incorrectly. The disadvantage is that because the network finds out how to solve the problem by itself, its operation can be unpredictable.

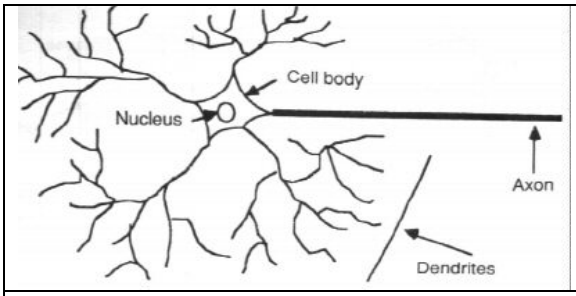
On the other hand, conventional computers use a cognitive approach to problem solving; the way the problem is to solved must be known and stated in small unambiguous instructions. These instructions are then converted to a high level language program and then into machine code that the computer can understand. These machines are totally predictable; if anything goes wrong is due to a software or hardware fault.

Neural networks and conventional algorithmic computers are not in competition but complement each other. There are tasks are more suited to an algorithmic approach like arithmetic operations and tasks that are more suited to neural networks. Even more, a large number of tasks, require systems that use a combination of the two approaches (normally a conventional computer is used to supervise the neural network) in order to perform at maximum efficiency.

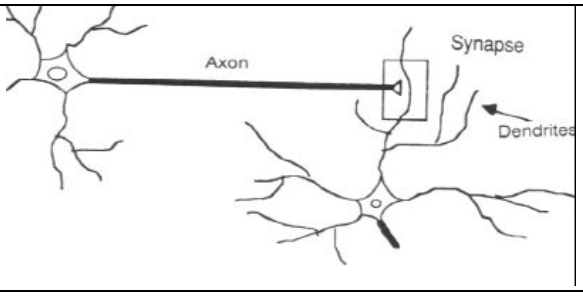
2. Human and Artificial Neurones - investigating the similarities

2.1 How the Human Brain Learns?

Much is still unknown about how the brain trains itself to process information, so theories abound. In the human brain, a typical neuron collects signals from others through a host of fine structures called *dendrites*. The neuron sends out spikes of electrical activity through a long, thin stand known as an *axon*, which splits into thousands of branches. At the end of each branch, a structure called a *synapse* converts the activity from the axon into electrical effects that inhibit or excite activity from the axon into electrical effects that inhibit or excite activity in the connected neurones. When a neuron receives excitatory input that is sufficiently large compared with its inhibitory input, it sends a spike of electrical activity down its axon. Learning occurs by changing the effectiveness of the synapses so that the influence of one neuron on another changes.



Components of a neuron



The synapse

2.2 From Human Neurones to Artificial Neurones

We conduct these neural networks by first trying to deduce the essential features of neurones and their interconnections. We then typically program a computer to simulate these features. However because our

knowledge of neurones is incomplete and our computing power is limited, our models are necessarily gross idealizations of real networks of neurones.

Some interesting numbers

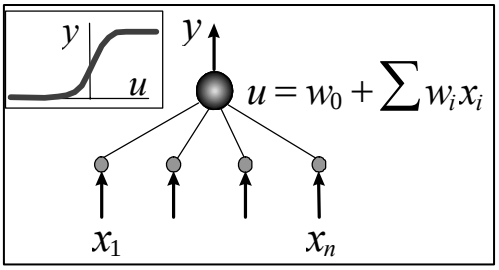
BRAIN	PC
Vprop=100m/s	Vprop=$3*10^8$ m/s
$\omega_N = 100hz$	$\omega_N = 10^9 hz$
N=10^{10}-10^{11} neurons	N=10^9
The parallelism degree ~10^{14} like 10^{14}processors with 100 Hz frequency. 10^4 connected at the same time.	

3. An engineering approach

3.1 A neuron

A more sophisticated neuron is the McCulloch and Pitts model (MCP). The difference from the previous model is that the inputs are 'weighted'; the effect that each input has at decision making is dependent on the weight of the particular input. The weight of an input is a number which when multiplied with the input gives the weighted input. These weighted inputs are then added together and if they exceed a pre-set threshold value, the neuron fires. In any other case the neuron does not fire.

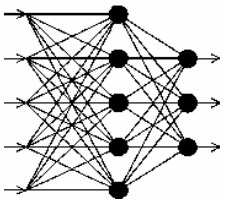
In mathematical terms, the neuron fires if and only if; the addition of input weights and of the threshold makes this neuron a very flexible and powerful one. The MCP neuron has the ability to adapt to a particular situation by changing its weights and/or threshold. Various algorithms exist that cause the neuron to 'adapt'; the most used ones are the Delta rule and the back error propagation. The former is used in feed-forward networks and the latter in feedback networks.



$$y = f\left(\sum_{j=1}^{d} w_j x_j + w_0\right) \equiv f\left(\sum_{j=0}^{d} w_j x_j\right)$$

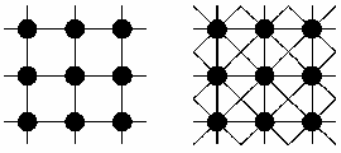
4 Architecture of neural networks

4.1 Feed-forward networks



Feed-forward ANNs allow signals to travel one way only; from input to output. There is no feedback (loops) i.e. the output of any layer does not affect that same layer. Feed-forward ANNs tend to be straight forward networks that associate inputs with outputs. They are extensively used in pattern recognition. This type of organization is also referred to as bottom-up or top-down.

4.2 Feedback networks



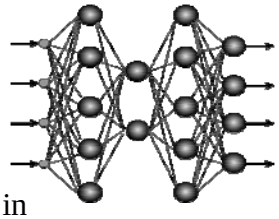
Feedback networks (figure 1) can have signals traveling in both directions by introducing loops in the network. Feedback networks are very powerful and can get extremely complicated. Feedback networks are dynamic; their 'state' is changing continuously until they reach an equilibrium point. They remain at the equilibrium point until the input changes and a new equilibrium needs to be found. Feedback architectures are also referred to as

interactive or recurrent, although the latter term is often used to denote feedback connections in single-layer organizations.

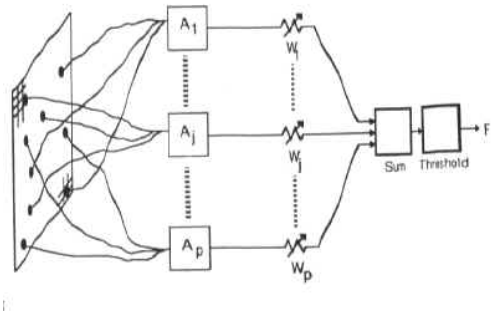
4.3 Network layers

The commonest type of artificial neural network consists of three groups, or layers, of units: a layer of "**input**" units is connected to a layer of "**hidden**" units, which is connected to a layer of "**output**" units.
The activity of the input units represents the raw information that is fed into the network.
The activity of each hidden unit is determined by the activities of the input units and the weights on the connections between the input and the hidden units.
The behavior of the output units depends on the activity of the hidden units and the weights between the hidden and output units.
This simple type of network is interesting because the hidden units are free to construct their own representations of the input. The weights between the input and hidden units determine when each hidden unit is active, and so by modifying these weights, a hidden unit can choose what it represents.
We also distinguish single-layer and multi-layer architectures. The single-layer organization, in which all units are connected to one another, constitutes the most general case and is of more potential computational power than hierarchically structured multi-layer organizations. In multi-layer networks, units are often numbered by layer, instead of following a global numbering.

4.4 Perceptrons



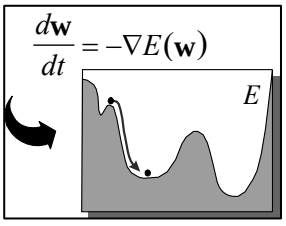
The most influential work on neural nets in the 60's went under the heading of 'perceptrons' a term coined by Frank Rosenblatt. The perceptron turns out to be an MCP model (neuron with weighted inputs) with some additional, fixed, pre--processing. Units labeled A1, A2, Aj, Ap are called association units and their task is to extract specific, localized featured from the input images. Perceptrons mimic the basic idea behind the mammalian visual system. They were mainly used in pattern recognition even though their capabilities extended a lot more.



In 1969 Minsky and Papert wrote a book in which they described the limitations of single layer Perceptrons. The impact that the book had was tremendous and caused a lot of neural network researchers to loose their interest. The book was very well written and showed mathematically that *single layer* perceptrons could not do some basic pattern recognition operations like determining the parity of a shape or determining whether a shape is connected or not. What they did not realize, until the 80's, is that given the appropriate training, multilevel perceptrons can do these operations.

5. The Learning Process

5.1 Types of learning



All learning methods used for adaptive neural networks can be classified into two major categories:
Supervised learning which incorporates an external teacher, so that each output unit is told what its desired response to input signals ought to be. During the learning process global information may be required. Paradigms of supervised learning include error-correction learning, reinforcement learning and stochastic learning.

$$E(\mathbf{w}) = E\left\{\mathbf{x}^{\alpha}, \mathbf{y}^{\alpha}, \mathbf{y}\left(\mathbf{x}^{\alpha}, \mathbf{w}\right)\right\}$$

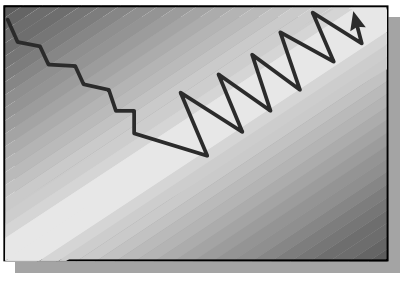
An important issue concerning supervised learning is the problem of error convergence, i.e. the minimization of error between the desired and computed unit values. The aim is to determine a set of

weights which minimizes the error. One well-known method, which is common to many learning paradigms, is the least mean square (LMS) convergence.
Unsupervised learning uses no external teacher and is based upon only local information. It is also referred to as self-organization, in the sense that it self-organizes data presented to the network and detects their emergent collective properties. Paradigms of unsupervised learning are Hebbian learning and competitive learning.
from Human Neurones to Artificial Neuron Esther aspect of learning concerns the distinction or not of a separate phase, during which the network is trained, and a subsequent operation phase. We say that a neural network learns off-line if the learning phase and the operation phase are distinct. A neural network learns on-line if it learns and operates at the same time. Usually, supervised learning is performed off-line, whereas unsupervised learning is performed on-line.

5.2 Transfer Function

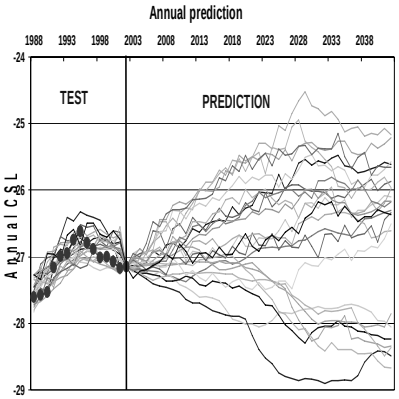
The behavior of an ANN (Artificial Neural Network) depends on both the weights and the input-output function (transfer function) that is specified for the units. This function typically falls into one of three categories:
-linear (or ramp)
-threshold
-sigmoid $f(a) = 1/\left(1+\exp(-a)\right)$
For **linear units**, the output activity is proportional to the total weighted output.
For **threshold units**, the output are set at one of two levels, depending on whether the total input is greater than or less than some threshold value.
For **sigmoid units**, the output varies continuously but not linearly as the input changes. Sigmoid units bear a greater resemblance to real neurones than do linear or threshold units, but all three must be considered rough approximations.
We can teach a three-layer network to perform a particular task by using the following procedure:
We present the network with training examples, which consist of a pattern of activities for the input units together with the desired pattern of activities for the output units.
We determine how closely the actual output of the network matches the desired output.
We change the weight of each connection so that the network produces a better approximation of the desired output.

In order to train a neural network to perform some task, we must adjust the weights of each unit in such a way that the error between the desired output and the actual output is reduced. This process requires that the neural network compute the error derivative of the weights (**EW**). In other words, it must calculate how the error changes as each weight is increased or decreased slightly. The back propagation algorithm is the most widely used method for determining the **EW**.



The back-propagation algorithm is easiest to understand if all the units in the network are linear. The algorithm computes each **EW** by first computing the **EA**, the rate at which the error changes as the activity level of a unit is changed. For output units, the **EA** is simply the difference between the actual and the desired output. To compute the **EA** for a hidden unit in the layer just before the output layer, we first identify all the weights between that hidden unit and the output units to which it is connected. We then multiply those weights by the **EA**s of those output units and add the products. This sum equals the **EA** for the chosen hidden unit. After calculating all the **EA**s in the hidden layer just before the output layer, we can compute in like fashion the **EA**s for other layers, moving from layer to layer in a direction opposite to the way activities propagate through the network. This is what gives back propagation its name. Once the **EA** has been computed for a unit, it is straight forward to compute the **EW** for each incoming connection of the unit. The **EW** is the product of the EA and the activity through the incoming connection.

6. Data filters



That is all we need to know about Neural Nets, if we want to make forecasts. The next problem with which you will have to fight - is noise in real signals. And the biggest trouble, that nobody knows what is noise and what is pure signal. For example, how to choose the right variant for the problem in the right?

6.1 Adaptive filters

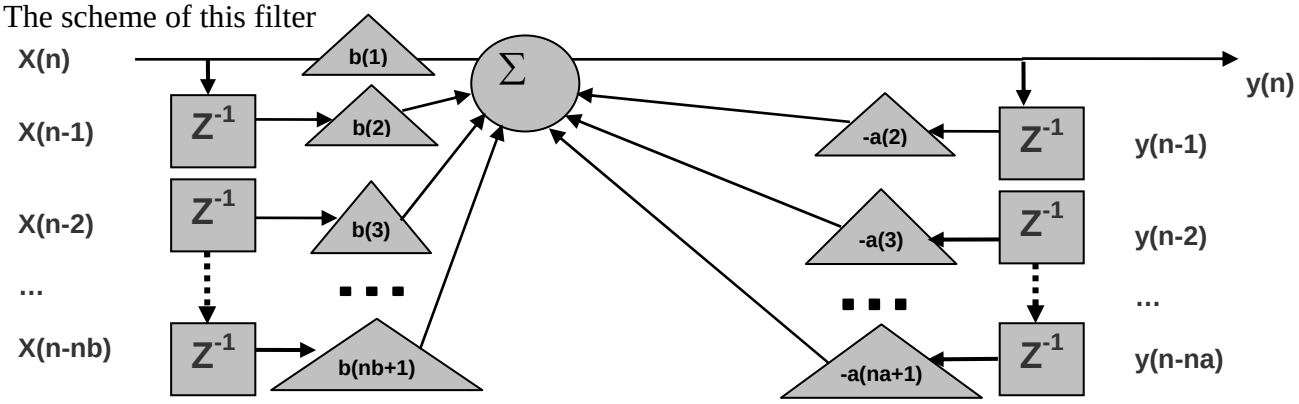
Main features, which we must obtain:
1) Zero-phase distortion (because we are going to make forecasts and we shouldn't influence on the data's phase we have.
2) We don't know what real signal is and what is noise, especially in case of share values or smth like that. So one have to decide apriori what is the signal we want to obtain.
In this chapter I'm going to make an overview of 3 types of adaptive filters: Zero-phase filter (smoothing filter), Kalman filter (error estimator), and Empirical mode decomposition.

6.2 Zero-phase filter

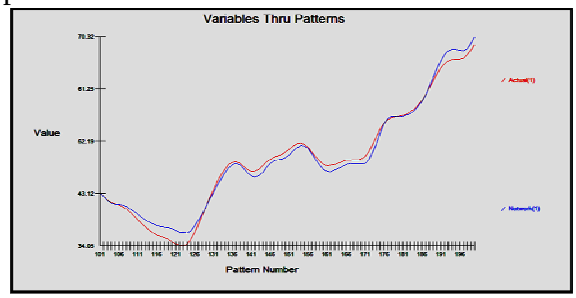
The main equation of this filter:

$$y(n) = b(1)x(n) + b(2)x(n-1) + ... + b(nb+1)x(n-nb) - a(2)y(n-1) - ... - a(na+1)y(n-na)$$

The scheme of this filter



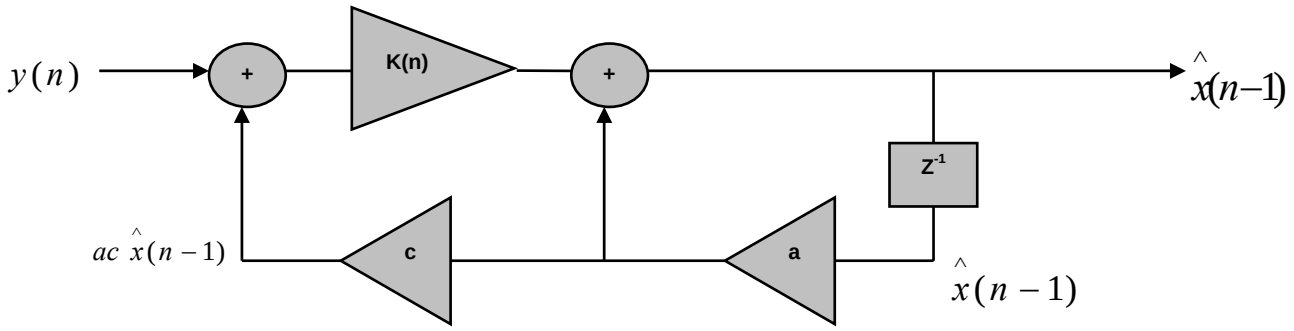
Where $x(n)$ is the signal we have at the moment n. Z^{-1} – means that we take the previous value of the signal (moment (n-1)). b, a - are the filter coefficients.
Filter performs zero-phase digital filtering by processing the input data in both the forward and reverse directions. After filtering in the forward direction, it reverses the filtered sequence and runs it back through the filter. The resulting sequence has precisely zero-phase distortion and double the filter order. filter minimizes start-up and ending transients by matching initial conditions, and works for both real and complex inputs. Note that filter should not be used with differentiator and Hilbert FIR filters, since the operation of these filters depends heavily on their phase response.



Problem: After the neural net the forecast will have 1 day delay if we tried to make forecast for one day. It looks like the picture on the right. But I should mention that all statistical values e.g. correlation coefficient are very good. It means that it's is possible to use this filter, but with some kind of error estimator.

6.3 Kalman filter (error estimator)

Consider a linear, discrete-time dynamical system. The concept of state is fundamental to this description. The state vector or simply state, denoted by x, is defined as the minimal set of data that is sufficient to uniquely describe the unforced dynamical behavior of the system; the subscript n denotes discrete time. In other words, the state is the least amount of data on the past behavior of the system that is needed to predict its future behavior. Typically, the state x_k is unknown. To estimate it, we use a set of observed data, denoted by the vector y_k. In mathematical terms, the block diagram embodies the following pair of equations:



The equation of this filter is given below:

$\hat{x}(n) = a\hat{x}(n-1) + k(n)[y(n) - ac\hat{x}(n-1)]$, where $x(n) = ax(n-1) + w(n-1)$ model of generating signal,

$w(n)$ – white noise and $y(n) = cx(n) + \nu(n)$ signal after *neural net*, $\nu(n)$ – white noise

Problem: After Kalman filter the error became less, but there is still a day delay. The solution is Empirical Mode Decomposition.

6.4 Empirical Mode Decomposition

A new nonlinear technique, referred to as *Empirical Mode Decomposition* (EMD), has recently been pioneered by N.E. Huang *et al.* for adaptively representing nonstationary signals as sums of zero-mean AMFM components [2]. Although it often proved remarkably effective [1, 2, 5, 6, 8], the technique is faced with the difficulty of being essentially defined by an algorithm, and therefore of not admitting an analytical formulation which would allow for a theoretical analysis and performance evaluation. The purpose of this paper is therefore to contribute experimentally to a better understanding of the method and to propose various improvements upon the original formulation. Some preliminary elements of experimental performance evaluation will also be provided for giving a flavor of the efficiency of the decomposition, as well as of the difficulty of its interpretation.

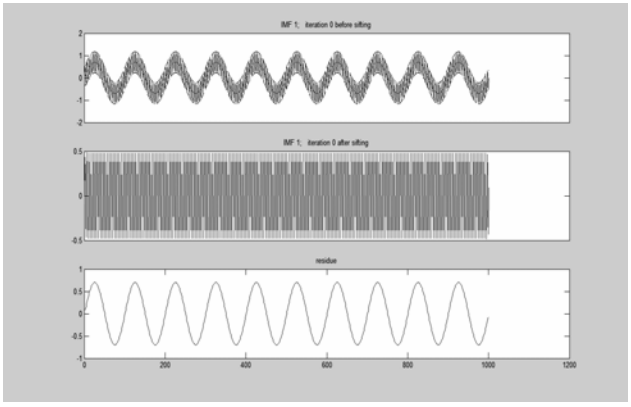
The starting point of the Empirical Mode Decomposition (EMD) is to consider oscillations in signals at a very local level. In fact, if we look at the evolution of a signal $x(t)$ between two consecutive extrema (say, two minima occurring at times t_- and t_+), we can heuristically define a (local) high-frequency part $\{d(t),\ t_- \le t \le t_+\}$, or local *detail*, which corresponds to the oscillation terminating at the two minima and passing through the maximum which necessarily exists in between them. For the picture to be complete, one still has to identify the corresponding (local) low-frequency part $m(t)$, or local *trend*, so that we have $x(t) = m(t) + d(t)$ for $t_- \le t \le t_+$. Assuming that this is done in some proper way for all the oscillations composing the entire signal, the procedure can then be applied on the residual consisting of all local trends, and constitutive components of a signal can therefore be iteratively extracted. Given a signal $x(t)$, the effective algorithm of EMD can be summarized as follows:

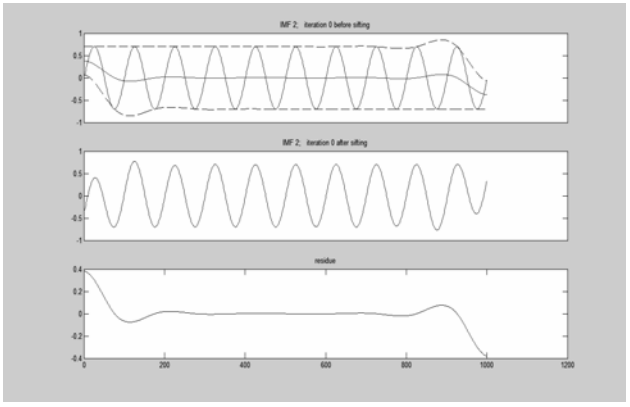
1. Identity all extrema of $x(t)$
2. Interpolate between minima (resp. maxima),
ending up with some envelope $e_{\min}(t)$ (resp. $e_{\max}(t)$)
3. Compute the mean $m(t) = (e_{\min}(t)+e_{\max}(t))/2$
4. Extract the detail $d(t) = x(t) - m(t)$
5. Iterate on the residual $m(t)$

In practice, the above procedure has to be refined by a *sifting* process which amounts to first iterating steps 1 to 4 upon the detail signal $d(t)$, until this latter can be considered as zero-mean according to some stopping criterion. Once this is achieved, the detail is referred to as an *Intrinsic Mode Function* (IMF), the corresponding residual is computed and step 5 applies. By construction, the number of extrema is decreased when going from one residual to the next, and the whole decomposition is guaranteed to be completed with a finite number of modes. Modes and residuals have been heuristically introduced on "spectral" arguments, but this must not be considered from a too narrow perspective. First, it is worth stressing the fact that, even in the case of harmonic oscillations, the high vs. low frequency discrimination mentioned above applies only *locally* and corresponds by no way to a pre-determined sub band filtering (as, e.g., in a wavelet transform). Selection of modes rather corresponds to an automatic and adaptive (signal-dependent) time-variant filtering.

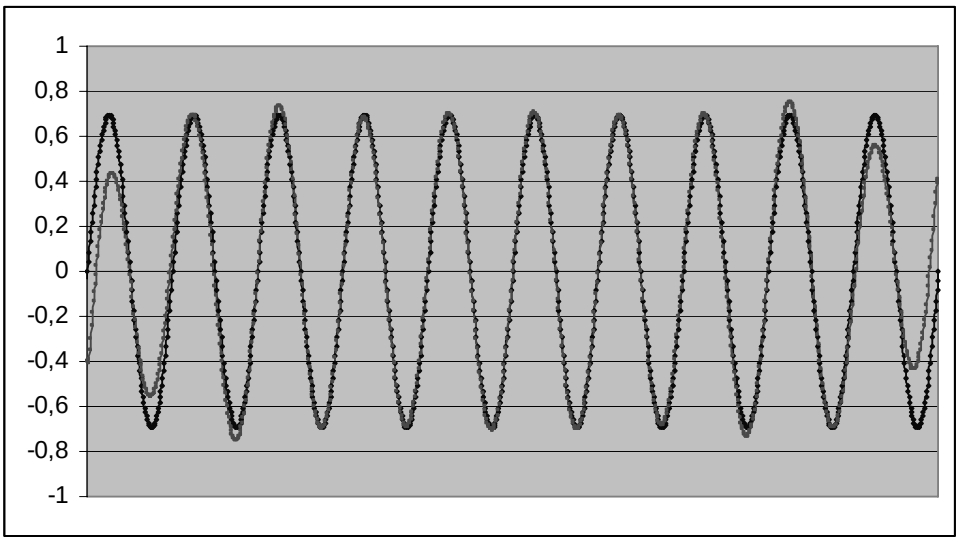
Let's try to do this procedure with next signal $x = 0{,}7\sin(20\pi t) + 0{,}5\sin(400\pi t), t \in [01]$

IMF#1 IMF#2





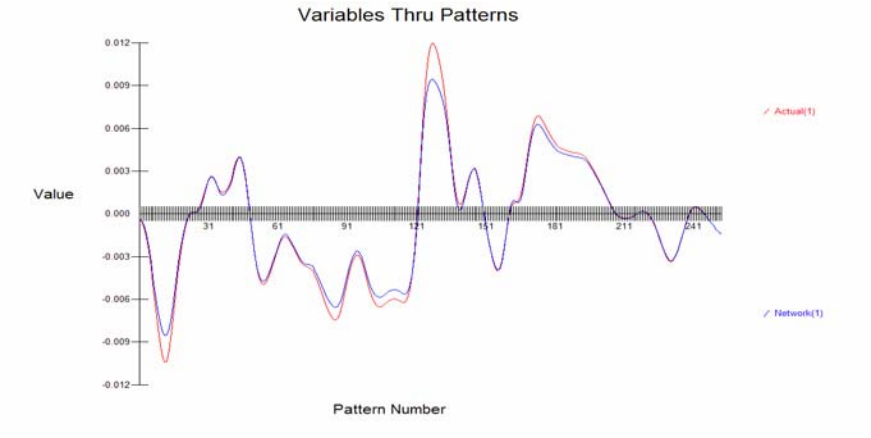
Let's try to filter from high frequency part (light gray – EMD, dark gray – zero phase filters)



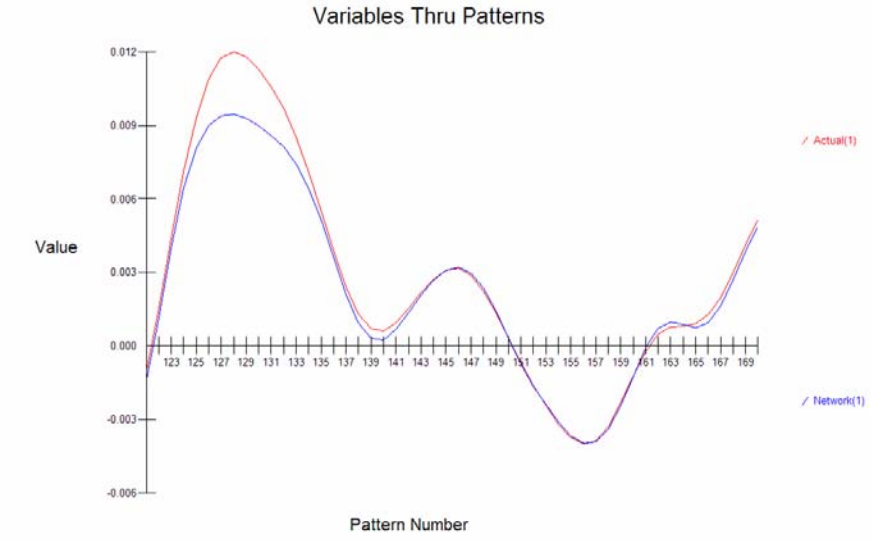
Problem: Using this method we have strong boundary effects. Sifting process can minimize this effect, but not at all.

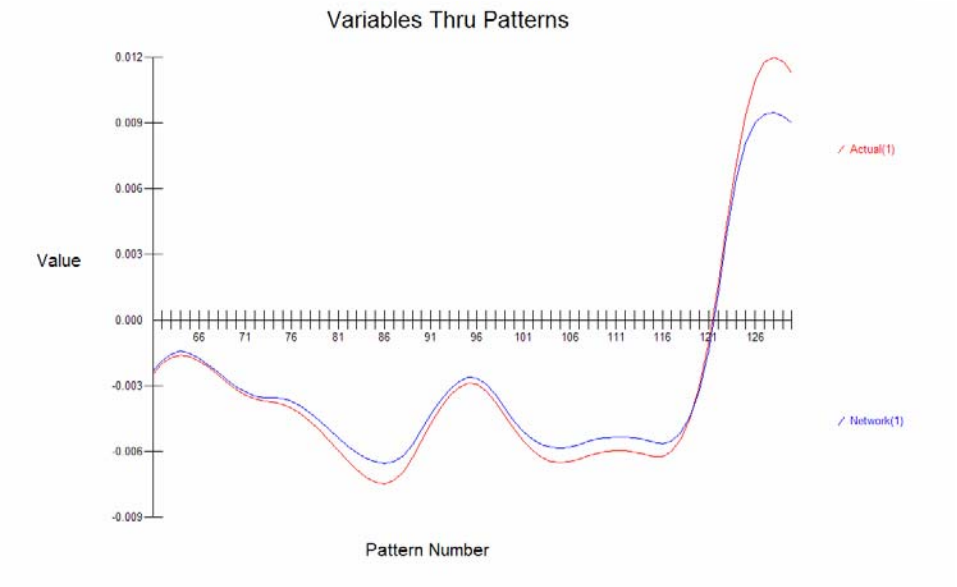
6.5 Zero-phase filter +Kalman filter +EMD = Solution

The so called solution is next. We should use data, obtained from zero-phase filter on the boundaries, we should use linear weighed sum of zero-phase and some IMF's in the middle. And after the forecast is done, we should apply Kalman filter to the forecast. Let's try to do that. The figure on the bottom is the forecast of siemens value. There is no delay.



The bottom figures are zoomed pictures of previous figure





6.7 Holder-function behavior is important

The main idea is next. Consider $f(t) \in D_f$ Holder derived, that

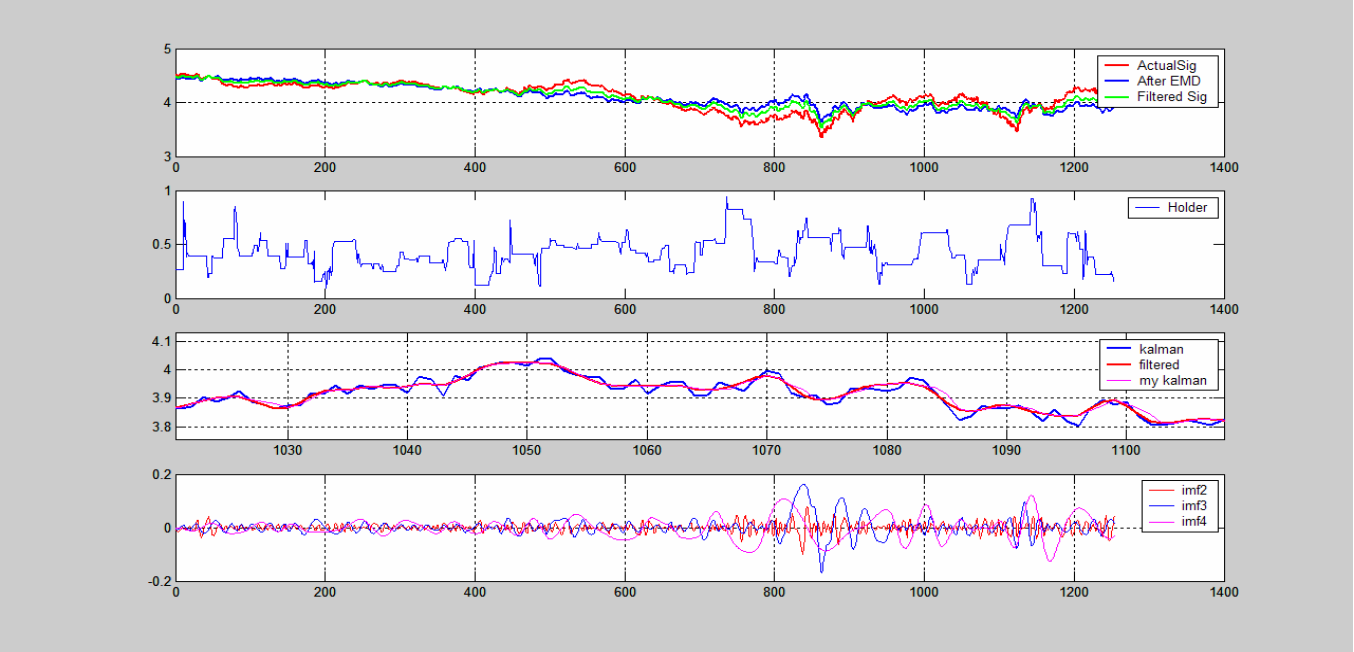
$| f(t+\Delta t) - f(t) | \leq const(\Delta t)^{\alpha(t)}, \alpha(t) \in [0,1]$

$\alpha = 0$ means that we have break of second order

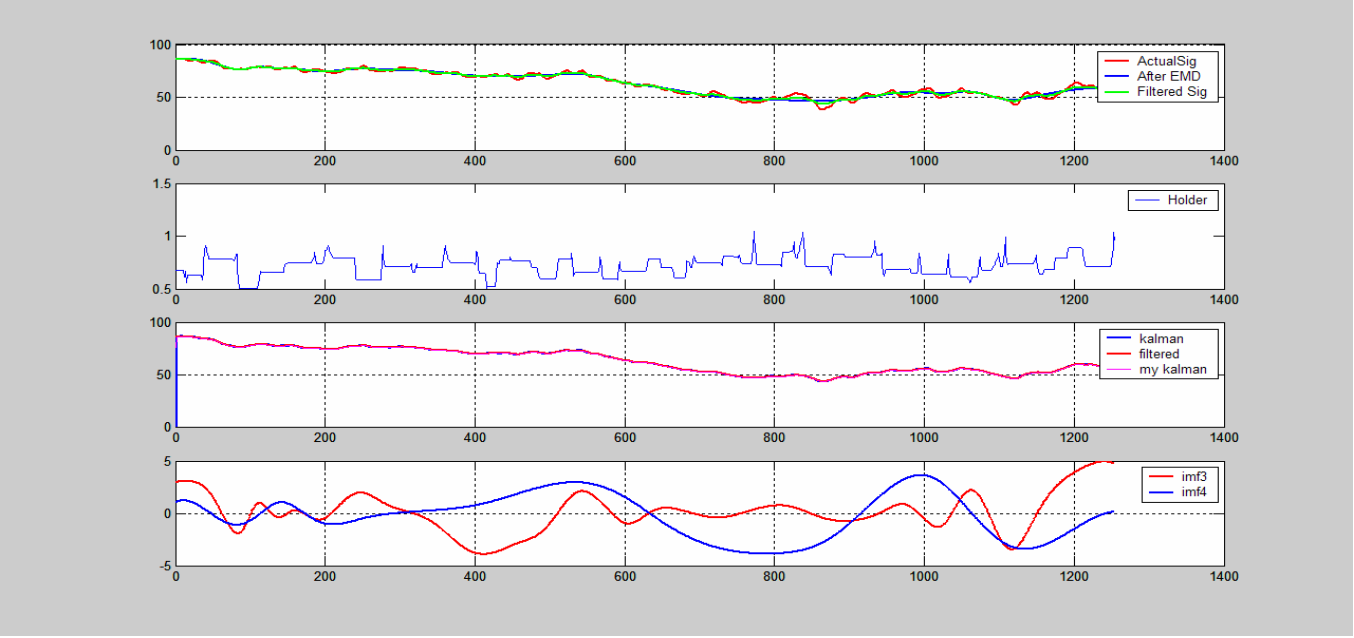
$\alpha = 1$ means that we have $O(\Delta t)$

So this formula is a somewhat connection between “bad” functions and “good” functions. If we will look on this formula with more precise we will notice, that we can catch moments in time, when our function knows, that it’s going to change it’s behavior from one to another. It means that today we can make a forecast on tomorrow behavior. But one should mention that we don’t know the sigh on what behavior is going to change.

The figure on the bottom is the result of mat lab program which shows all results in one window.



And pay attention to field Holder after filtration was done



So we can make forecasts without delay and we know Horst behavior. (In case of IMF filtering Holder function is more smooth)

7 Reference

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