A neuronal model of the photic driving tremor influence

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Abstract—**This paper uses the physiological hand tremor signal as a window to observe and analyze the central nervous system's (CNS) organization. In this perspective we investigated the possibility to model and to explain the CNS's influence (central photic driving influence) in physiological hand tremor. An adaptive system was used to model this behavior already proved by us in a previous paper. The system receives stimuli of the visual stimulation frequency and it has to produce similar spectrum components with ones obtained for the real physiological hand tremor signal. The obtained neuronal model was then used to characterize the neuronal pathway and to explain the visual influence.**

I. Introduction

The understanding of the physiology of tremor movements has made significant progress in the last decade, but many hypotheses are not yet tested enough and are not supported on sufficient data. The neurology science needs to develop and validate such hypotheses, because this is the only way to develop appropriate medical and surgical therapies and to have a close understanding of the neurological system.

For a large variety of pathological tremor activities (like essential tremor and tremor that appears in Parkinson disease) it has been already proved the influence of the central oscillator in producing the rhythmic activation of the motoneurons that controls the extremities [1], [2], [3]. Moreover, multiple central oscillators are responsible for the tremor in different extremities of patients with Parkinson's disease and essential tremor [3], [4].

For the physiological hand tremor movements several basic mechanisms have been proposed and tested for such an oscillatory muscular activity: intrinsic muscle properties, mechanical oscillation resonances, oscillations based on reflexes, oscillations due to central neuronal influences and, not in the last, oscillations due to disturbed feed-forward or feedback loops.

There are different studies that concurrently support [5], [6] or invalidate [2] the central neuronal origins of the physiological hand tremor. Due to the contradictory results, to the different conditions of data recording and analyses, to the existence of different neurological pathologies of the investigated subjects, it was difficult to support without any doubts the central origins of some spectral components of the tremor signal.

In order to determine if the physiological hand tremor movements are originated in the central nervous system we have devised a number of experiments to evidence this influence [7], [8]. As a result, we demonstrated that the visual stimulation is reflected in the tremor signal by a spectral component situated at double the stimuli frequency [8]. The changes in the frequency characteristics of the tremor signal due to visual stimuli demonstrated a significant connection between visual regions in the CNS and the regions governing tremor (parts of the somatic motor system). Moreover, in this case the global complexity of the system that generates the tremor increases, fact that was revealed by the analysis of system's complexity in a study of the tremor signals recorded in a photic driving paradigm [9]. This confirms the emerging coupling strength that appears in the moment of stimuli presentation between the visual CNS pathways and the motor centers generating tremor.

The origins of these oscillations that are driving the physiological hand tremor are still unknown. They could be cortical and/or subcortical (e.g. thalamus, brainstem etc.). Also, from the experimental data there is no evidence for "pure" sensory pathways, figured as dashed line in Figure 1.

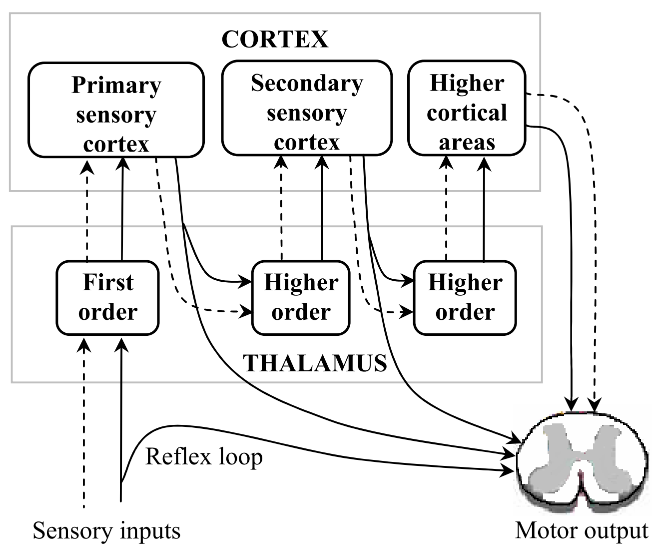

Fig. 1. Sensory processing pathways

Manuscript received June 30, 2006. This work was supported in part by the National University Research Council under CNCSIS Grant code 17, theme 26.

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The role of the majority of the thalamic relays regions are not yet understand, but it is recognized the evidence of [10]: the connectivity patterns shown in Figure 1, the related motor thalamic connections and the motor function of the associated thalamic relays. This connectivity pattern is also true for the axons that arise in the layer five of the cortex that branch to the: "higher-order" thalamic relays and to the lower motor centers. Moreover, the main motor neurons for voluntary movement, called Betz cells, are placed in the fifth cortical layer of the primary motor cortex (a possible generator for physiological hand tremor).

This paper presents a computational model of the central photic driving influence, based on real physiological hand tremor signals. Its main goal is to analyze the neuronal pathways able to exhibit the real spectral behavior observed in the real life hand tremor. This behavior is one characterized by a spectral component on the hand tremor signal situated at the double of the visual stimuli frequency.

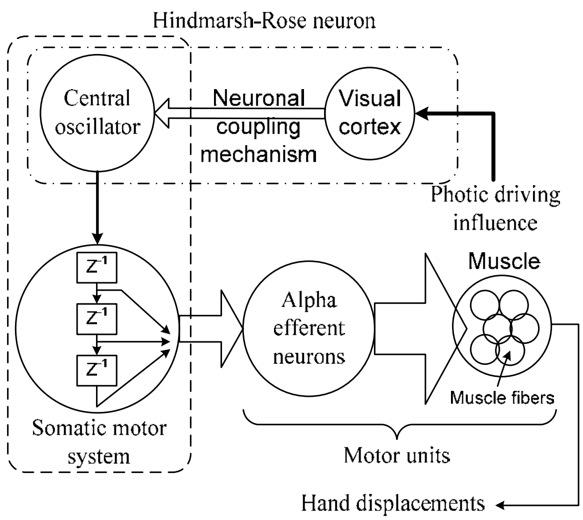


Fig. 2. The implementation of the neuronal model for the first analysis

II. METHODS

Two different paradigms of model analysis type will be implemented. In the first neuronal model the pathway formed by: (1) the visual cortex (more general, visual system), (2) higher centers of the somatic motor system and (3) motor neurons of the spinal cord (motor units) will be analyzed. For this we used the demonstrated results of the existence of direct or, maybe, indirect efferent pathways (through activator ascendent reticular system, thalamic relays etc.) between the visual system's specific pathways and those of the somatic motor system [8]. In the second analyze, a higher order thalamic relay will be additionally modeled, Figure 1, in order to address the relationship between the visual stimulation frequency and the spectral component reflected in the tremor signal.

The cortical (subcortical)-motor coupling mechanism is modeled by a system consisting of an adaptive network modeling the neuronal pathways. The adaptive system led by an external driving force is a Hindmarsh-Rose (HR) neuronal model coupled with a virtual signal generator. The reference signal in the adaptation process was a real physiological hand tremor signal acquired previously with a special multimodal virtual reality device named Virtual Joystick [7], [11]. The system was trained based on the adaptation error between the output of the adaptive structure (the hand displacement, Figure 2) and the desired signal – a real physiological hand tremor.

In both model analyses the ability of the adaptive neural network was tested in order to address their ability to model the characteristics of the real physiological hand tremor displacements, in two different situations: with and, respectively, without photic driving external influence.

The choice of the HR neuronal model for these analyses was motivated by the ability of this model to exhibit all of the neurocomputational properties that mimics the living cortical neurons: regular spiking excitatory neurons, low-threshold spiking neurons and fast spiking neurons [12]. Moreover, the HR model, equation (1), is one with minimal complexity (i.e., three variables only), and with a very good biological plausibility [12].

$$\begin{cases} \dot{x} = y - a \cdot x^3 + b \cdot x^2 - z + I_0 + \xi + I_1 \cos(\omega t) \\ \dot{y}_i = c - d \cdot x^2 - y \\ \dot{z} = r \cdot [s \cdot (x - x_0) - z] \end{cases} \quad (1)$$

This neuron model is used to mimics the regular spiking and chaotic spiking-bursting activity of the central pattern generator.

In the equation 1 the $x(t)$ variable represents the membrane potential, $y(t)$ describes the dynamics of the resetting mechanism that restores the polarity of the membrane – being a recovery variable, $z(t)$ is the internal mechanism which regulates the patterns of discharges allowing the control of the interspike interval and ξ represents the background Gaussian white noise (synaptic, dendritic, axonic noise etc.) that is important in the stochastic resonance phenomena. The I_0 parameter denotes the intensity of a constant (tonic) signal that is delivered to the neuron from the external world. In order to compare our HR neuronal behavior with the one obtained in other studies [13] the parameters of the HR neuronal model were fixed to: $a = 1$, $b = 3$, $c = 1$, $d = 5$, $r = 0.006$, $s = 4$ and $x_0 = -1.6$. The variance of the noise was set equal to 1 and I_0 took value 5. In the final stage the values of the $x(t)$ spiking process were normalized in the range of [-0.9, 0.9] in order to avoid the saturation of the neuronal adaptive elements.

In Figure 3 there are presented the Hindmarsh-Rose neuronal model characteristics for an artificial neuron driven externally by a virtual signal generator having the amplitude equal to 8 and a frequency of 10 Hz. The results were obtained having the rest of the model parameters identical with the ones presented previously.

In both model paradigms only one central oscillator was

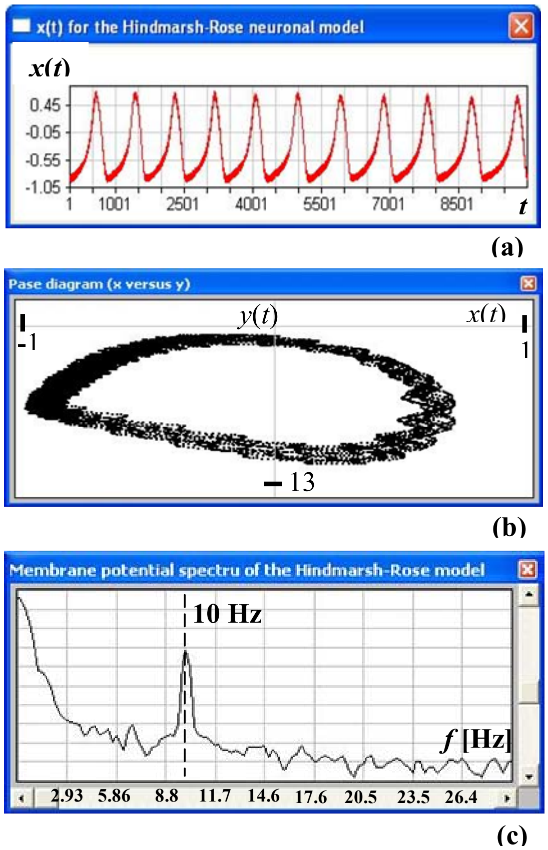


Fig. 3. Hindmarsh-Rose neuronal model analysis: (a) the spiking pattern (b) phase diagram *x*(*t*) versus *y*(*t*) and (c) x(t) spectrum – membrane potential spectrum

used to produce a rhythmic activation of the limb motoneurons. The output of the HR central oscillator, *x*(*t*), stimulates simultaneously different motor units at different time delays. The stimulation time delays were obtained using several delay units, Figure 2. There are two motivations of using these delay units:

- First - in the real case the motor units are recruited in a fixed order from the weakest to the strongest ones, based on the Henneman size principle: first are recruited the slow units which generate the smallest force but are the most resistant to fatigue, followed by the fast fatigue-resistant elements that are recruited next and, at the end are recruited the fast fatigable motor units which generate the strongest force.
- Second - one synchronization pattern encountered at the motor units' level is the "broad-peak" synchronization that is due and depends on the number of synapses separating the motor neurons from their shared inputs [14].

In order to model these two behaviors, several delays elements were used. In this mode not all the motor units are "fired" in the same time.

In both analyses the numbers of the processing units placed on the neural network layer associated with the real motor units, were varied from 10 units up to 150 units. In a real situation the innervation's ratio (the number of muscle fibers innervated by one motor neuron) can vary between 10 and 2000. A low innervation's ratio indicates a greater capacity for finely adjustment of the muscle force.

At the last element of the neuronal network all the outputs of the motor units are added in order to model the global effect generated by all the muscle fibers innervated by different α-efferent neurons.

The first analysis (that takes into account the visual system, the cortical centers of the somatic motor system and the lower motor neurons) can represent a model for:

- the central photic driving influence (the neuronal coupling mechanism between the visual CNS pathways and the pathways of the somatic motor system),
- the motor centers generating tremor (including here, as an hypothesis, the large Betz cells which synapse directly on spinal motor neurons [15], Figure 2).

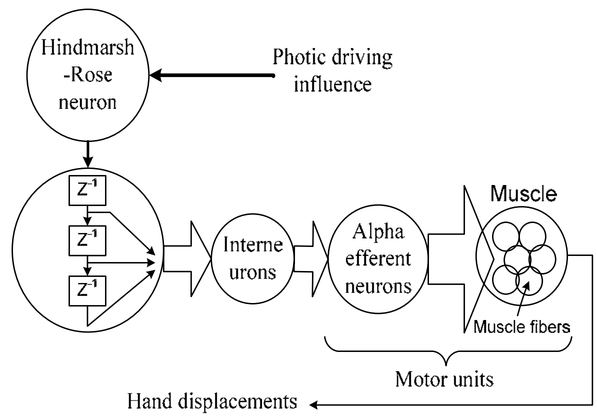


Fig. 4. The implementation of the neuronal adaptive model for the neuronal pathways going through a thalamic relays

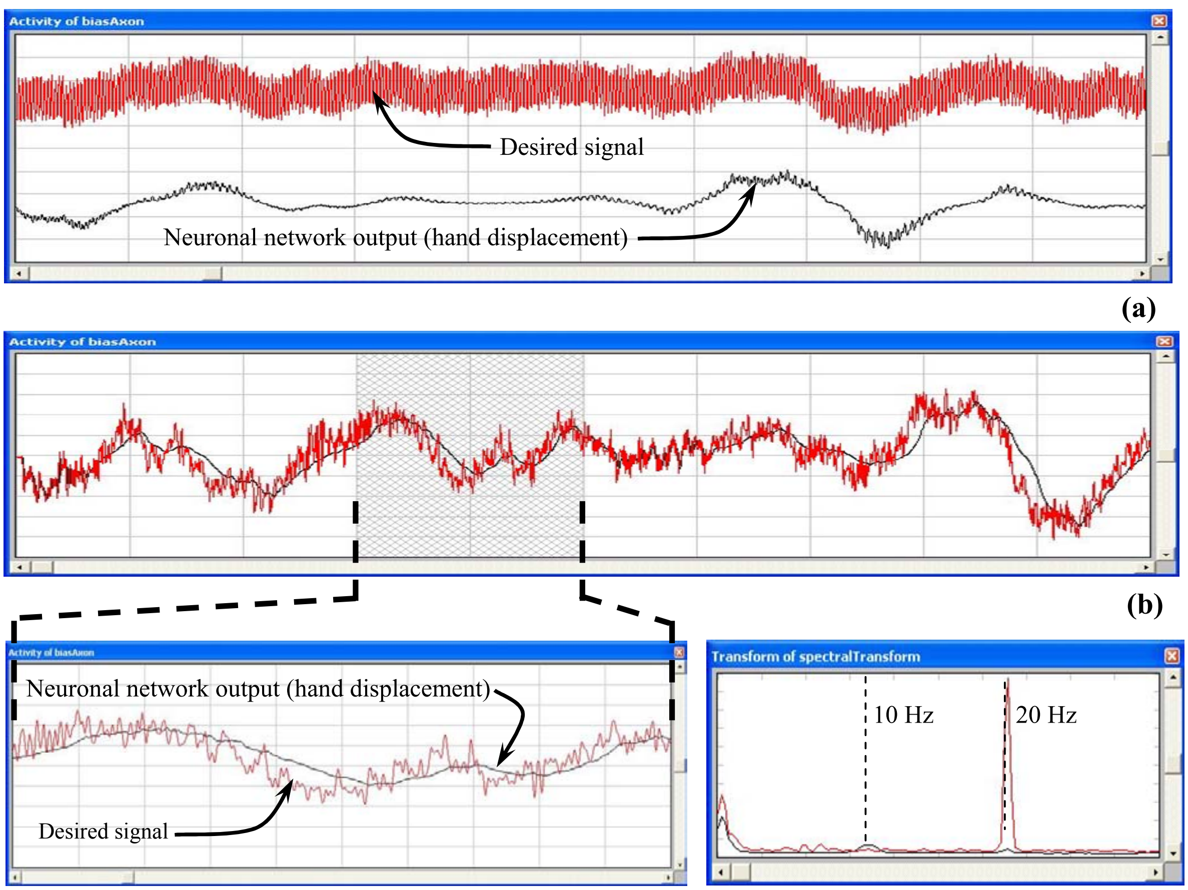
The second analysis models additionally a high order thalamic relay. The model for the high order thalamic relay is implemented through an additionally layer of neurons that represent the inter-neurons, Figure 4. For this last model the adaptive structure is shaped by an artificial neural network (ANN) with two hidden layers (first hidden layer models the inter-neurons and the second hidden layer models the motor units) excited by HR neuron that represents the central oscillator pattern generator.

Both adaptive neuronal models were trained with the backpropagation learning rule, with momentum term [16]. The parameters of the model were estimated from the available data in order to produce the smallest possible error between the network output and the desired signal, using for this the least mean squared (L2) error criterion. All the neurons from the hidden layers used the tangent hyperbolic function as nonlinear activation function.

The desired signal for the training phase of the neuronal network was composed by two different sets of data. Each set of data was provided to the artificial neuronal network for one training epoch – named stage; the learning process consisted of a repetitive sequence formed by the two data sets. The learning process ended when the error was sufficiently small. In all odd training epochs (**corresponding to the first data set/stage**) the desired signal was represented by the tremor signal acquired without any visual stimulation. In this stage of the training the HR neuronal model parameter I_1 took 0 value; in this mode the forcing term of the model, $I_1\cos(\omega t)$, was eliminated. In the **second stage** (represented by all even training epochs) the desired signal was given by the tremor signal acquired when a repetitive visual stimulus were delivered to the subject. In this stage the frequency of the forcing term for the HR model was chosen to be identical with the one used in the real photic driving data acquisition paradigm and the I_1 parameter was set to 8.

The tremor signals were acquired from two subjects, one male and one female. They were healthy, with no known neurological or endocrine pathology and with no known Ca^{2+} or Mg^{2+} deficiency. The visual stimulation was done at 5 Hz and 10 Hz and the tremor movements were acquired using a sensor without any physical contact with the subject's hand [7], [11]. The subject's elbow was fixed in order to preserve the tremor characteristic unaffected by the hand fatigue influence. All the recordings took place in a quiet room, without any source of light. The stimuli consisted in a circle of 2 cm radius, placed in the middle of the display, changing its luminosity between a black background followed by a white flash. The stimuli changes pattern was a symmetric rectangular wave. The subjects had no visual control of their hands position. After the first time segment of 32.8 seconds, a visual stimulus of specified frequency was presented to the subject. Each recording had 98.4 s, but only the first 32.8 s and the last 32.8 s of hand tremor were kept. The sampling rate was 250 samples per second and they had been 8.200 samples per each acquired segment of a recording – this is also the number of exemplars on each training epoch of the ANN. In order to obtain accurate estimators we pre-filtered the signals with a low pas filter having the cutoff frequency 40 Hz and attenuation in the stop band of -60 dB.

In a previous analysis, significant (upper than 95% confidence limit) coherence values occurs in the tremor



(a) (b) (c) (d)

Fig 5. The results obtained for the first paradigm model: (a) the results obtained for the photic driving (second) stage of the learning process, (b) the result obtained for the first stage of the learning process, (c) a short region of the learning process (the network output and the desired signal) – for the first stage of the learning process and (d) the spectrum of the network output signal and the desired signal for the second stage.

signal at the double of the frequency stimuli [8]. In order to obtain these results the pooled coherence estimated was computed [8]. Unlike these results, in the power spectrum the amplitude of the induced spectral components is one comparable with both, the amplitude of the observational noise and that of the hand tremor signal itself; moreover, they overlap the tremor signal both in time and in frequency domain, making difficult for the neural network to learn these components. However, in order to get a conclusive result the desired signal used in the second stage of the training process was artificially obtained from the tremor signal used in the first stage of the learning process on which it was added a sinusoidal component with an amplitude of 50 mV.

III. Results

For the first paradigm analysis several different topologies were tested. The difference between all these analyses was given by the number of neurons placed on the hidden layer (in the tests the number of alpha neurons were varied between 10 elements and up to 150 elements), the number of delays elements (2 … 15) and the neuronal model was trained using 5 and 10 Hz frequency for the photic driving stimulus. Some of the results are presented in Figure 5. For this class of particular topologies, with only one hidden layer, the ANN model was unable to learn correctly the desired signals presented in the both learning stages, it being able to learn only the tendency of the signals (the coarse characteristics generated by the three components of the proposed model – the visual system, the cortical centers of the somatic motor system and the motor units). These results suggest that this first model has not enough power to model the real characteristics of the existing nervous pathways.

For the last paradigm the results are presented in Figure 5 and Figure 6. These results were obtained for the following neural network topology: 4 processing elements on the first hidden layer (inter-neurons), 70 neurons on the second hidden layer (equivalent with alpha neurons) and 4 input delay taps. In this case the cumulative mean square error (calculated for both learning stages) was 0.00048.

Using a new hidden layer (as a main difference compared with the first paradigm model) provides to the used ANN all the necessary power to correctly model the hand tremor signal in both learning stages, Figure 5(b) and Figure 6(b). In addition, what is more important for this type of artificial neuronal model is its capability to model the relationship that is established between the visual cortical projection and the central oscillator driving the physiological hand tremor (in particular, the frequency doubling mechanism).

In the Figure 5(c) and Figure 6(c) there are presented the Fourier transforms for both, the desired signal and the signal obtained at the output of the adaptive ANN model. The Fourier transform was the Fast Fourier Transform (FFT) computed on 1024 samples. The frequency resolution was 0.244 Hz. The analysis presented on Figure 5(c) and Figure 6(c) is based on 120 spectral lines. In this mode one horizontal division is equivalent with 2.9296 Hz. From the spectral information one can observe that the neuronal network is able to accurately reproduce the spectral components of the desired signal up to 24 Hz.

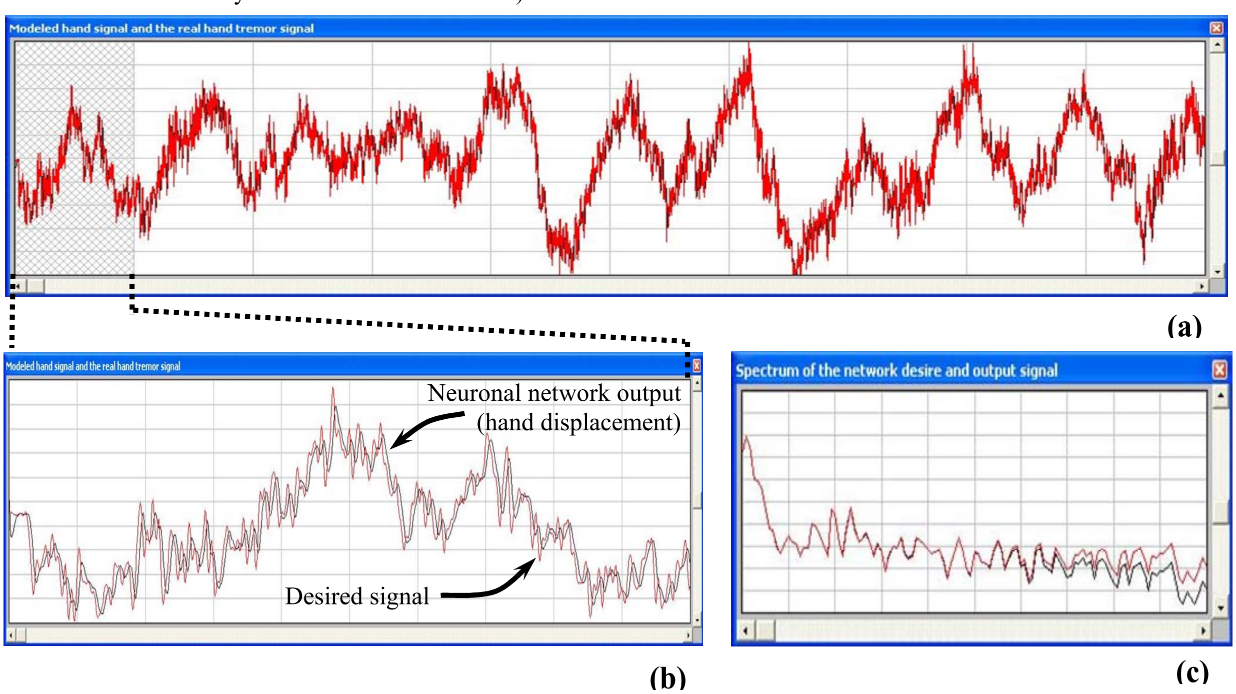


Fig 5. The results obtained for the second paradigm model in the first stage of the learning process: (a) the desired signal and the output of the neural network, (b) a detailed segment of the previously time series, and (c) the spectrum of the network output signal and of the desired signal.

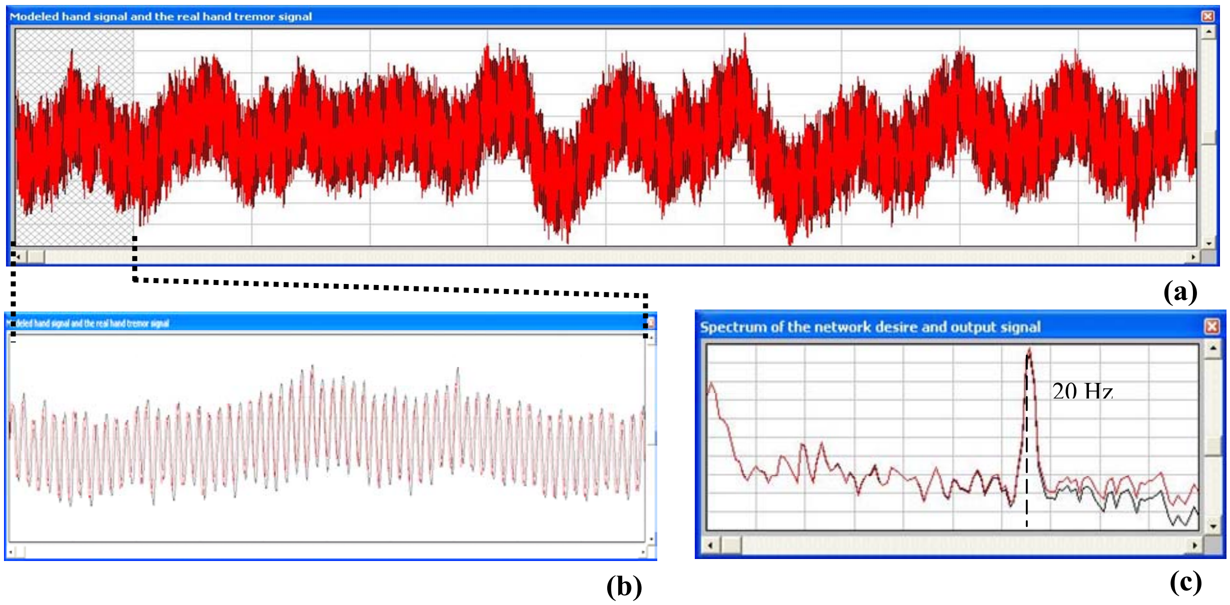


Fig. 6. The results obtained for the second paradigm model in the first stage of the learning process: (a) the desire signal and the output of the neural network, (b) a detail segment of the previously time series, and (c) the spectrum of the network output signal and of the desire signal.

IV. Discussion and Conclusion

While the second layer of the proposed adaptive system models the motor units (the motor neurons from the spinal cord level) and the HR neuron models the coupling mechanism between the visual and the central tremor generators, the necessity of the first hidden layer (needed in order to replicate the frequency doubling mechanism) supports the hypothesis of immixture of an intermediary cortical/sub-cortical relay area versus the hypothesis of "pure" sensory pathways.

The axons that innervate the thalamus and also give off branches to lower motor centres (see the first ANN model in the first paradigm context) are crucial for an immediate response; precisely, they will command – through the alpha neurons – the muscle to execute the coarse-fast movements like one presented in Figure 5 (a) and (b).

In this paper we presented and motivated the necessity of the existence of some cortical/sub-cortical relays in order to achieve a similar hand tremor behaviour with the one obtained in the real situation. Obviously, in order to get the very natural hand behaviour the two model paradigms, analysed in this paper, should be mixed and, in addition, the reflex arc should be taken into account as well.

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