Research Paper Engineering

Neural Network Based Hemoglobin State Classifier

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ABSTRACT

Hemoglobin (Hb) is an indispensable and vital integrant of red blood cells (RBC). Appraisement of a human being's biological well-being is actualized by gauging Hb concentration from their blood samples. The precincts connected with invasive methods are anguish and pain in the course of sample acquisition, longer exploration duration and debility to deliver real time precise observing. These restrictions were effectively managed by a diapason of non-invasive schemes. The resolute assessment methodology for different blood samples associated with non-invasive schemes demonstrates inherent complexities. This paper proposes a classification scheme for dissimilar blood samples by norm based assimilation and connotation to a prevailing data set. The structure was executed and established on multiple samples with different testing conditions

KEYWORDS Hemoglobin classifier, Neural network, Noninvasive optical measurement

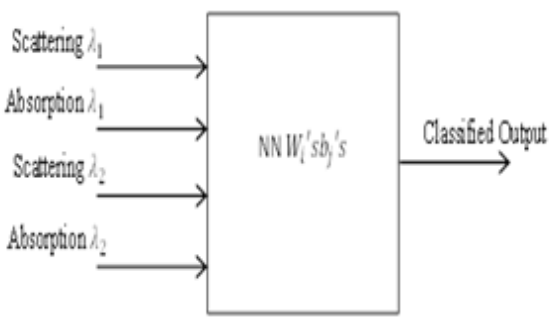
INTRODUCTION

Approaches based on recurrent neural networks for solving optimization problems, which use analog computation implemented on electronic devices to replace numerical computation realized by mathematical algorithms, have attracted considerable attention [1-10]. However, due to the existence of many equilibrium points of recurrent neural networks, spurious suboptimal responses are likely to be present [11-14], which limit the applications of recurrent neural networks. Thus, the global asymptotic/exponential stability of a unique equilibrium point for the concerned recurrent neural networks is of great importance from a theoretical and application point of view [15-21].

Research on the stability of recurrent neural networks in the early days was for symmetric recurrent neural networks with or without delays. Cohen and Grossberg [1] presented the analytical results on the global stability of symmetric recurrent neural networks. A brief review on the dynamics and stability of symmetrically connected networks is presented in [2], in which the effects of time delay, the eigenvalue of the interconnection matrix, and the gain of the activation function on the local dynamics or stability of symmetric Hopfield neural networks were discussed in detail. Both in practice and theory, the symmetric restriction on the connection matrix of recurrent neural networks is too strong, while asymmetric connection structures are more general [8], [9], [12]. For instance, a non-symmetric interconnection matrix may originate from slight perturbations in the electronic implementation of a symmetric matrix. Asymmetries of the interconnection matrix may also be deliberately introduced to accomplish special tasks [13] or may be related to the attempt to consider a more realistic model of some classes of neural circuits composed of the interconnection of two different sets of amplifiers (e.g., neural networks for nonlinear programming [16]). Therefore, the local and global stabilities of asymmetrically connected neural networks have been widely studied [17-19]. As pointed out in [20], the topic on global stability of neural networks was more significant than that of local stability in applications, such as signal processing and optimization problems. These important applications motivated researchers to investigate the dynamical behaviors of neural networks and global stability conditions of neural networks [5], [4], [2], [3]. Reference [4] applied the contraction mapping theory to obtain some sufficient conditions for global stability. Reference [3] generalized some results in [103] and [130] using a new Lyapunov function. Reference [9] proved that diagonal stability of the interconnection matrix implied the existence and uniqueness of an equilibrium point and the global stability at the equilibrium point. References [2], [6], and [6] pointed out that the negative semi definiteness of the interconnection matrix guaranteed the global stability of the Hopfield networks, which generalized the results in [4], [9], [6], and [11]. Reference [8] applied the matrix measure theory to get some sufficient conditions for global and local stability. References [5] and [12] discussed the stability of a delayed neural network using Lyapunov function and established a Lyapunov diagonal stability (LDS) condition on the interconnection matrixfences [7]–[13], [8], and [6] introduced a direct approach to address the stability of delayed neural networks, in which the existence of equilibrium point and its stability were proved simultaneously without using complicated theory, such as degree theory and homeomorphism theory. Note that the above references provided the global stability criteria of recurrent neural networks using different algebraic methods, which reflected the different measure scales on the stability property due to different sufficient conditions. These expressions of global stability criteria can generally be divided into two categories: 1) LDS condition and 2) matrix measure stability condition, which had been sufficiently developed in parallel. The former condition considered the effects of the positive and negative signs, that is, excitatory ($a>0$) and inhibitory ($a<0$) influences, of the interconnection strengths between neurons, while the latter only considered the positive sign effects of the interconnection strengths between neurons, which made the main differences between these two stability conditions. It is well known that symmetrically connected analog neural networks without delays operating in continuous time will not oscillate [13]–[16], in which it is assumed that neurons communicate and respond instantaneously. In electronic neural networks, time delays will occur due to the finite switching speed of amplifiers [9], [2], [21], [18]. Designing a network to operate more quickly will increase the relative size of the intrinsic delay and can eventually lead to oscillation [14]. In biological neural networks, it is well known that time delay can cause a stable system to oscillate [6]. Time delay has become one of the main sources to lead to instability. Therefore, the study of effects of time delay on stability and convergence of neural networks has attracted considerable attentions in neural network community [14-19]. Under certain symmetric connectivity assumptions, neural networks with time delay will be stable when the magnitude of time delay does not exceed certain bounds [12-16]. For asymmetric neural networks with delays,

sufficient stability conditions independent of or depending on the magnitude of delays were also established [9-13]. These results are mostly based on linearization analysis and energy and/or Lyapunov function method. Recently, most of the stability results are for recurrent neural networks with delays, such as discrete delays, distributed delays, neutral-type delays, and other types of delays, and many different analysis methods were proposed. Since 2002 [19-20], the linear matrix inequality (LMI) method has been used in the stability analysis of recurrent neural networks, and then many different LMI-based stability results have been developed. Up to date, LMI-based stability analysis of recurrent neural networks is still one of the most commonly used methods in the neural network community. More recently, lots of efforts have been made on various stability analyses of recurrent neural networks [7-15], [19, 20]. A detailed survey and summary of stability results are necessary for understanding the development of stability theory of recurrent neural networks. Although there are some literature surveys available on the stability of recurrent neural networks exhaustive/cohesive reviews on stability of recurrent neural networks are still lacking, which motivates us to present a comprehensive review on this specific topic. Although there are many different types of recurrent neural networks, including complex-valued neural networks [6-8] and fractional-order neural networks [4], this paper is mainly concerned with the real-valued continuous-time recurrent neural networks described by ordinary differential equations in the time domain.

PROPOSED NEURAL NETWORK ARCHITECTURE



The type of Network used is a classifier network and once trained produces an output which is to be compared during runtime with the actual noisy patterns. The algorithm is given in figure 1.

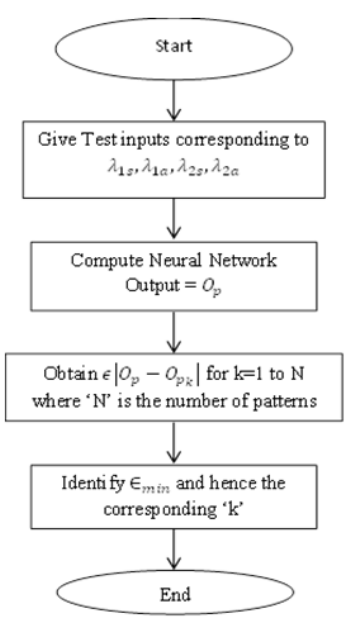


Figure 1 Flowchart showing state identification

As given in figure 1, the minimum value of '' corresponding to the difference between the trained output and the classified output is used to identify the Hb state.

TRAINING NETWORK DETAILS

The network architecture chosen in this work is input-5-1 i.e. '5' neurons in hidden layer and 1 neuron in output layer. A batch update learning rule is used to train the networks and this ensures that the network converges faster.

COMPARISON OF NEURAL NETWORK BASED CLASSIFIER

The features of Neural Network based classifier as compared with conventional classifier is listed in Table 1

Table 1: Features of Neural Network Classifier

S.No	NeuralNetwork Classifier	Conventional Classifier
1	Training time is slow	Training time is fast
2	Classification time is fast	Classification time

The limitations of (1) listed in table 2 is removed in this method using batch update method.

IMPLEMENTATION DETAILS AND RESULTS

The implementation result (using python program in Linux kernel) corresponding to Hb state 4 and state 5 is captured online and shown in figure 2 and figure 3. The trained neural output for the five different states is listed in Table 4. The value of '' (classification error) is listed in table 2. The error plot with is drawn in Figure 2.

Table 2: Error Value for the classified states (diagonal elements)

Hg state	Value of				
1	0.1445	45.485	43.993	46.659	23.127
2	+4.8754	0.5018	1.72198	2.94572	6.595
3	64.47	53.35	0.1648	56.309	99.592
4	15.0989	61.0564	9.022	3.555	69.054
5	41.183	131.605	27.263	42.844	1.619

The error plot is given in Figure 4
ϵ_{min} for the specific state

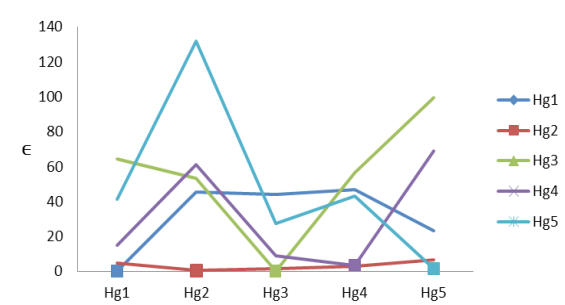


Figure 2: Error Plot from Table 3 for the different Hb States

Table 3: Misclassification Rate

	State1	State2	State3	State4	State5	PPV
State1	100	0	0	0	0	100%
State2	0	100	0	0	0	100%
State3	4	0	96	0	0	96/100%
State4	0	3	0	97	0	97/100%
State5	0	0	0	2	98	98/100%

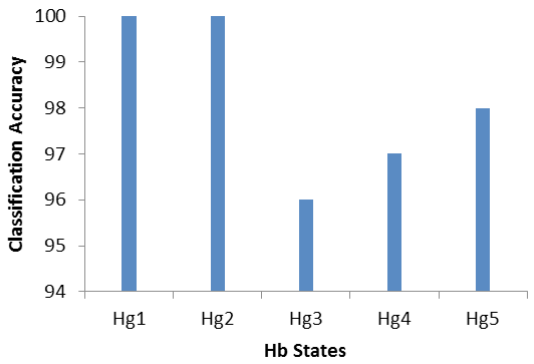
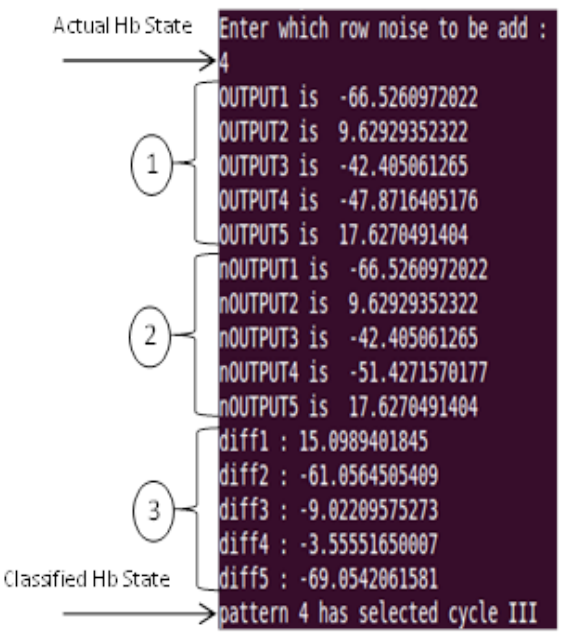


Figure 3: Classification efficiency against various States



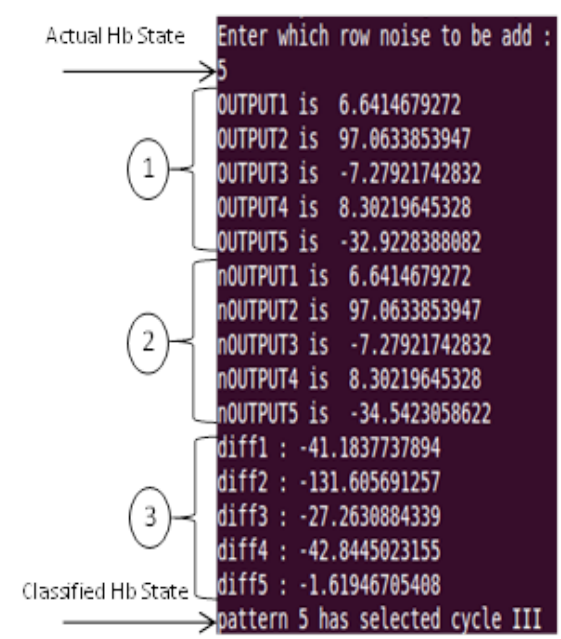


Figure 4: Classification efficiency for Various Hb states

Note:

1 → Trained Network output for the different Hb States (True Values)

2 → Classified output for the different Hb States (Noisy Values)

3 → The Computed error for the different Hb States i.e. ''

Hb state	Trained Output					Classified Output				
	0.1	0.2	0.3	0.4	0.5	0.1	0.2	0.3	0.4	0.5
State1	50.142	4.8	6.2924	3.627	27.158	50.286	4.8	6.29	3.627	27.15
State2	7.9861	2.608	4.832	0.1649	9.706	7.9861	3.11	4.832	0.1649	9.706
State3	-10.169	-21.289	-74.8	-18.3	24.95	-10.169	-21.289	-74.6	-18.3	24.95
State4	-66.25	9.629	-42.4	-47.87	17.627	-66.52	9.629	-42.4	-51.4	17.62
State5	6.641	97.06	-7.279	8.3	-32.92	6.641	97.06	-7.27	8.3	-34.5

Table 4: Trained output and Classified Output

CONCLUSIONS

This paper implemented a neural network based hemoglobin state classifier for noninvasive optical diagnostic technics and tested the error values for the classified states. The results obtained are utilized to minimize the error between clinically measured Hb value and optically measured value.

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