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A New Application of Recurrent Neural Networks for EMG-Based Diagnosis of Carpal Tunnel Syndrome

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1. Introduction

Carpal tunnel syndrome (CTS), an entrapment neuropathy of median nerve at the wrist, is one of the most common peripheral nerve disorders with an incidence of 99 per 100.000 population (Bland JDP, 2005., Sternbach G, 1999). CTS is more common in females than males, with a ratio of seven to three. Although it is more prevelent between the fourth and sixth decades, it occurs in all age groups (Kanaan N & Sawaya RA, 2001). The condition produces bilateral symptoms in approximately half of patients (von Schroeder HP & Motte MJ, 1996), but dominant hand usually is more severely affected, especially in idiopathic cases (Ilbay K et al.,2010, Preston DC & Shapiro BE, 2005).

CTS arises from compression of the median nerve between the transverse carpal ligament, also called the flexor retinaculum, superiorly, and the flexor tendons, and carpal bones inferiorly. Anatomically, the fibres of median nerve originate from the fifth, sixth, seventh, and eighth cervical roots, and the first thoracic root and pass through the lateral and medial cords of the brachial plexus. The motor branch innervates the abductor pollicis brevis, opponens pollicis, and the two lateral lumbricals in the hand. The sensory branch supplies sensation to the volar aspect of the radial three digits and the lateral half of the fourth digit extending to the palm and the distal dorsal aspects of these digits beyond the distal interphalangeal joints (Kanaan N & Sawaya RA, 2001).

There are two distinct varieties of CTS-acute and chronic. The acute form is relatively uncommon condition in which there is a rapid and sustained rise in interstitial pressure in the carpal tunnel. This most commonly occurs as the result of a distal radius fracture as described by Sir James Paget (Sternbach G, 1999). Other causes include burns, rheumatoid arthritis, infections, haemorrhage (caused by coagulopathy or trauma), repetitive and intensive manual work and injection injuries (Table 1) (Sternbach G, 1999., Aroori S & Spence RAJ, 2008., Luchetti R, 2007).

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Burns
Wrist fracture and dislocation
Haemorrhage
Infections
Injection injuries
Rheumatoid arthritis
Repetitive and intensive manual work

Table 1. Acute CTS causes

The chronic form is much more common and symptoms can persist for months to years. However, in only 50 % of cases are the cause identified (Aroori S & Spence RAJ, 2008). The causes of chronic CTS summarised in Table 2.

Any process that increases the volume of the contents of the carpal tunnel, such as tumour, inflammation, and edema, will elevate the pressure within the canal (Sternbach G, 1999). The pathophysiological mechanism of the nerve lesion is ischemic with the compression of the vasa nervosum secondary to the increased pressure (Sunderland S, 1976).

In most patients, the cause of CTS is not clear and it is defined as idiopathic. The idiopathic forms frequently show up as "non specific tenosynovitis" (Sternbach G, 1999., Luchetti R, 2007).

Patients with CTS may present with a variety of symptoms and signs. In early stages, patients usually complain of aching, burning, tingling or numb sensations in the distribution of median nerve distal to wrist. The portion of the hand involved is typically the thumb, index and middle fingers, and radial half of the ring finger. Symptoms are typically worse at night, are exaggerated by a flexed or extended wrist posture (Kanaan N & Sawaya RA, 2001., Preston DC & Shapiro BE, 2005). The pain may radiate to the forearm, arm, or rarely shoulder. Motor complaints include finger weakness and the disease may be mistaken for cervical radiculopathy, shoulder bursitis, thoracic outlet syndrome, transient ischemic attack, coronary artery ischemia, tendinitis, fibrositis or lateral epicondylitis. Long-term involvement leads to thenar muscle atrophy, with loss of thumb abduction and opposition strength (Sternbach G, 1999., Kanaan N & Sawaya RA, 2001).

The diagnosis of CTS based mainly on clinical symptoms and nerve conduction studies. Imaging studies have played a minimal role in evaluation of CTS. Magnetic resonance imaging (MRI) has recently been shown to help in establishing the diagnosis. But the application of MRI in CTS diagnosis has been limited and should remain so for reasons: 1) routine electrophysiologic studies are adequate and can be performed with confidence in both community and academic settings; 2) MRI remains expensive; 3) acquisition of high-quality peripheral nerve images and their expert interpretation is not widely available; and 4) the low specifity of MRI could complicate treatment decision (Fleckenstein JL & Wolfe GI, 2002).

High-resolution ultrasound has advantages over MRI in terms of cost and provides dynamic images. It has been shown to produce accurate measurements of carpal tunnel and nerve diameters (Kamolz LP et al, 2001).

This chapter presents the use of recurrent neural networks (RNNs) for diagnosis of CTS. In different disciplines for modelling complex real-world problems, artificial neural networks (ANNs) have many applications. ANNs have been used for solution of different problems, such as pattern classification, time series prediction, nonlinear control, function approximation, and biomedical signals analysis. ANNs can produce nonlinear models

A.Local and regional causes	B.Systemic causes
Tumours	Diabetes
	Alcohol
Ganglion	Obesity
Haemangioma	Hypothyroidism
Cyst	Pregnancy
Lipoma	Menopause
Neuroma	Systemic lupus erythematosus
	Dermatomyositis
Anatomical anomalies	Scleroderma
Bony abnormalities	Renal failure
Abnormal muscle bellies	Long-term haemodialysis
Persistent median artery	Acromegaly
Aneurysm or arterio-venous malformation	Multiple myeloma
	Sarcoidosis
Inflammatory	
Tenosynovitis	
Hypertrophic synovium	
Histoplasma fungal infection	
Gout	
Amyloidosis	

Table 2. Causes of chronic form of CTS

relating the inputs (the independent variables of a system) to the outputs (the dependent predictive variables). ANNs are desirable because learning and adaptivity allow the system to modify its internal structure in response to changing environment and the model can be applied to the unlearned data. RNNs have a wide application field among the ANNs architectures. One of the most important applications of pattern recognition is automated diagnostic systems and they have role at assisting doctors in making diagnostic decisions (Haykin S, 1994; Basheer I.A. & Hajmeer M., 2000; Chaudhuri B.B. & Bhattacharya U., 2000; Miller A.S. et al., 1992).

The recurrent neural networks (RNNs) (Elman J.L., 1990; Thissen U. et al., 2003; Übeyli E.D., 2008a; 2008b; 2009a; 2009b; Übeyli E.D. & Übeyli M., 2008; Ilbay K et al., 2010) have been studied extensively for classification, regression and density estimation. The results of the existing studies (Elman J.L., 1990; Thissen U. et al., 2003; Übeyli E.D., 2008a; 2008b; 2009a; 2009b; Übeyli E.D. & Übeyli M., 2008; Ilbay K et al., 2010) showed that the RNNs have high accuracy in classification of the biomedical data, therefore we used the RNNs in the diagnosis of CTS. In this study, in order to diagnose CTS, the RNNs and multilayer perceptron neural network (MLPNN) trained with the Levenberg-Marquardt algorithm are implemented (Figure 1). A significant contribution of the present chapter is to examine the performance of the RNNs on the diagnosis of CTS (normal, right CTS, left CTS, bilateral CTS).

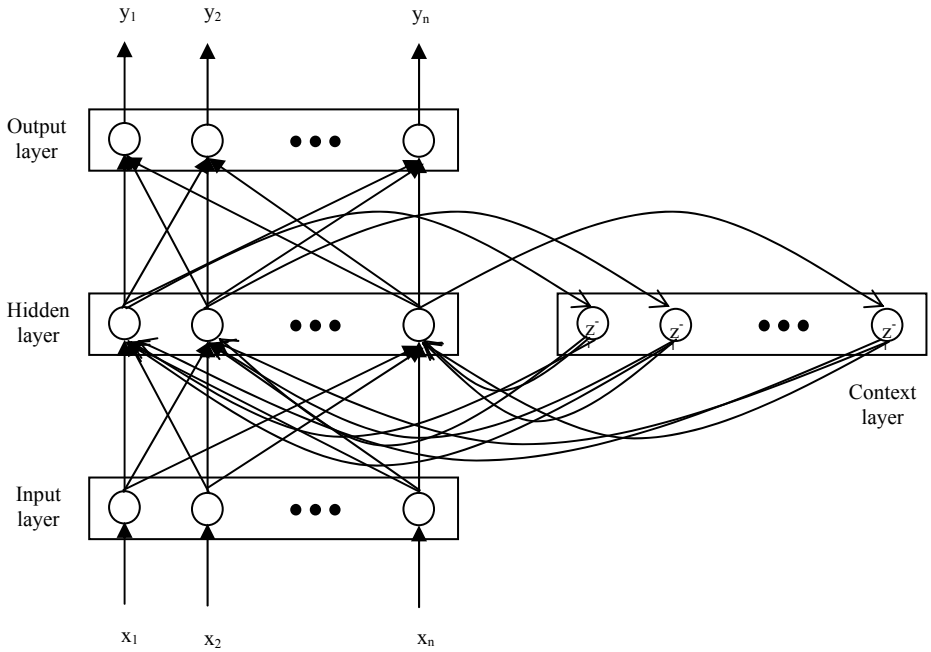

Fig. 1. A schematic representation of an Elman recurrent neural network. z^{-1} represents a one time step delay unit (Thissen U. et al., 2003).

2. Electrophysiological tests for the diagnosis of CTS: nerve conduction study and electromyography

The combination of clinical symptoms and signs with electrodiagnostic findings allows possible prognostic validation for the neurosurgeon. Neurophysiology is a method that solely expresses the functional state of the median nerve alone with carpal tunnel (Haase J, 2001).

The usual electrophysiological procedures start with nerve conduction studies (NCS), sensory followed by motor NCS. Next, electromyography (EMG) is performed (Cornblath DR & Chaudry V, 2001).

NCS are based on the principle of nerve stimulation across the area of interest. For median nerve, the nerve is stimulated proximal to the carpal ligament and compound muscle action potential (CMAP) is picked up by skin electrodes placed over the thenar eminence. The CMAP reflects the status of the motor fibres in the median nerve. The amplitude of the CMAP reveals stimulation of the whole population of motor nerve fibres. The duration reflects the conduction velocities across the different fibres. The latency, between the point of nerve stimulation and the onset of the CMAP, reveals the fastest velocity of the motor fibres across the carpal tunnel (Kanaan N & Sawaya RA, 2001).

The sensory component of the median nerve is affected much earlier than the motor component and in early stages of CTS there is usually a delay in the sensory nerve

conduction study. Stimulation of sensory fibres is done at the same location as for motor stimulation and the sensory nerve action potential is recorded from the distal phalange of the second or third digits. The study of the sensory fibres can be performed orthodromically or anti-dromically (Kanaan N & Sawaya RA, 2001., Aroori S & Spence RAJ, 2008).
Those studies usually involve a comparison of the median nerve to another nerve in the same hand. The ulnar nerve is the nerve most commonly used for comparison (Preston DC & Shapiro BE, 2005).
Needle electromyography (EMG) is a complementary rather than a compulsory test in addition to NCS. EMG describes the functional state of the muscle fibres that are dependent on innervation by motor axons. In CTS, it is usually performed on the median nerve – innervated muscles of the hand and forearm. Denervation activity in the EMG reflects recent nerve damage. Neurogenic changes and reinnervation potentials indicate chronic nerve pathology (Kanaan N & Sawaya RA, 2001). Following of nerve decompression, a typical reiinervation pattern is found often earlier than that by clinical examination (Haase J, 2007).
EMG is also used to reveal other nerve lesions in the involved arm when the findings of NCS are not consistent with CTS. These include nerve entrapment in the forearm, plexus lesions or cervical root disease (Kanaan N & Sawaya RA, 2001).

3. Database description and evaluation of electrophysiologic recordings

We retrospectively considered 350 patients (289 females and 61 males) with various CTS symptoms and signs who underwent nerve conduction studies. Of these patients, 121 had no electrophysiologic evidence of CTS, and were accepted as normal group (103 females and 18 males). 229 of the patients were suffered from right CTS (32 females and 15 males), left CTS (22 females and 14 males) and bilateral CTS (132 females and 14 males). Patients with generalized peripheral neuropathy caused by diabetes or other medical illness and those who had undergone prior carpal tunnel surgery were not included in the study. Each subject completed a self-administered questionnaire. The questionnaire focused on hand symptoms that are commonly associated with CTS.
All the studies were performed with the subjects at supine position in a warm room with the temperature maintained at 26 to 28°C. Skin temperatures were checked over the forearm. Nerve conduction studies were performed using standard techniques of supramaximal percutaneous stimulation with a constant current stimulator and surface electrode recording on both hands of each subject. Sensory responses were obtained antidromically stimulating at the wrist and recording from the index finger (median nerve) or little finger (ulnar nerve), with ring electrodes at a distance of 14 cm. The results of the median motor nerve obtained by stimulating the median motor nerve at the wrist and elbow and the recording was done over the abductor pollicis brevis muscle. The results of the ulnar motor nerve were performed by stimulating the ulnar nerve at the wrist, below the elbow, and above the elbow and the recording was done over the abductor digiti minimi muscle, with the arm flexed 135°. In the present study, the following median nerve and ulnar nerve measures were used: (1) distal onset latency of the sensory nerve action potential (DL-S); (2) distal onset latency of the compound muscle action potential (DL-M). Median sensory latency greater than 3.5 ms, median motor latency greater than 4.2 ms was used as the criteria for abnormal median nerve conduction (Budak F et al., 2001).

4. Recurrent Neural Networks

In the diagnosis applications, Elman RNNs were used and therefore the Elman RNN is presented in this chapter. In principle, the set up of an Elman RNN is formed as a regular feedforward network. In the architecture of the network, all neurons in one layer are connected with all neurons in the next layer. The only difference in the architecture of the Elman RNN is the context layer which is a special case of a hidden layer. The neurons in the context layer, which are called as context neurons, hold a copy of the output of the hidden neurons. The output of each hidden neuron is copied into a specific neuron in the context layer. The value of the context neuron is used as an extra input signal for all the neurons in the hidden layer one time step later. Therefore, the Elman network has an explicit memory of one time lag (Elman J.L., 1990; Thissen U. et al., 2003).

The strength of all connections between neurons are denoted with a weight. Initially, all weight values are chosen randomly and are optimized during the stage of training. In an Elman network, the weights from the hidden layer to the context layer are set to one and are fixed because the values of the context neurons have to be copied exactly. After this stage, the initial output weights of the context neurons are equal to half the output range of the other neurons in the network. The training algorithms of the Elman network are similar to the training algorithms of the regular feedforward neural networks. So, the Elman network can be trained with gradient descent backpropagation and optimization methods (Thissen U. et al., 2003; Pineda F.J., 1987). In the many applications, the backpropagation has some problems. The algorithm cannot find the global minimum of the error function, because gradient descent can probably get stuck in local minima, where it may remain indefinitely. Therefore, in order to improve the convergence of the backpropagation a lot of variations were proposed (Haykin S., 1994). In the training of neural networks optimization methods such as second-order methods (conjugate gradient, quasi-Newton, Levenberg-Marquardt) have also been used. The Levenberg-Marquardt algorithm combines the best features of the Gauss-Newton technique and the steepest-descent algorithm and omitted their limitations. The algorithm suffers from the problem of slow convergence (Battiti R., 1992; Hagan M.T. & Menhaj M.B., 1994) and can obtain a good cost function compared with the other training algorithms.

The Levenberg-Marquardt algorithm is a least-squares estimation algorithm based on the maximum neighborhood. $E(\mathbf{w})$ be an objective error function composed of m individual error terms $e_i^2(\mathbf{w})$ as follows:

$$E(\mathbf{w}) = \sum_{i=1}^{m} e_i^2(\mathbf{w}) = \left\| f(\mathbf{w}) \right\|^2, \tag{1}$$

where $e_i^2(\mathbf{w}) = \left(\mathbf{y}_{di} - \mathbf{y}_i\right)^2$ and $\mathbf{y}_{di}$ is the desired value of output neuron i, $\mathbf{y}_i$ is the actual output of that neuron.

It is assumed that function $f(\cdot)$ and its Jacobian J are known at point $\mathbf{w}$. The Levenberg-Marquardt algorithm is trying to compute the weight vector $\mathbf{w}$ such that $E(\mathbf{w})$ is minimum. Then by the Levenberg-Marquardt algorithm, a new weight vector $\mathbf{w}_{k+1}$ can be computed from the previous weight vector $\mathbf{w}_k$ as follows:

$$\mathbf{w}_{k+1} = \mathbf{w}_k + \delta \mathbf{w}_k, \tag{2}$$

where $\delta \mathbf{w}_k$ is defined as

$$\delta \mathbf{w}_k = -(J_k{}^T f(\mathbf{w}_k))(J_k{}^T J_k + \lambda \mathbf{I})^{-1}. \quad (3)$$

In equation (3), J_k is the Jacobian of f computed at $\mathbf{w}_k$, λ is the Marquardt parameter, $\mathbf{I}$ is the identity matrix (Battiti R., 1992; Hagan M.T. & Menhaj M.B., 1994). The Levenberg-Marquardt algorithm can be explained as in the following:

i. compute $E(\mathbf{w}_k)$,
ii. start with a small value of λ ($\lambda = 0.01$),
iii. solve equation (3) for $\delta \mathbf{w}_k$ and compute $E(\mathbf{w}_k + \delta \mathbf{w}_k)$,
iv. if $E(\mathbf{w}_k + \delta \mathbf{w}_k) \geq E(\mathbf{w}_k)$, increase λ by a factor of 10 and go to (iii),
v. if $E(\mathbf{w}_k + \delta \mathbf{w}_k) < E(\mathbf{w}_k)$, decrease λ by a factor of 10, update $\mathbf{w}_k : \mathbf{w}_k \leftarrow \mathbf{w}_k + \delta \mathbf{w}_k$ and go to (iii).

5. Results and discussion

In this application example, the inputs of the RNNs are the features of CTS (right median motor latency, left median motor latency, right median sensory latency, left median sensory latency). Tables 3 and 4 (Ilbay K et al., 2010) show the values including right median motor latency, left median motor latency, right median sensory latency, left median sensory latency (four features used as inputs of the classifiers) of sample records of two classes (bilateral CTS and normal) which are presented in reports of the subjects.

Motor Nerve Conduction Study

Site	Latency (ms)	Amplitude	Area	Segment	Distance (mm)	Interval (ms)	NCV (m/s)
Median, L							
Wrist	4,74ms	7,83mV	16,09mVms	Wrist		4,74ms	
Elbow	8,25ms	6,68mV	13,43mVms	Wrist- Elbow	170mm	3,51ms	48,4m/s
Median,R							
Wrist	6,42ms	6,77mV	15,66mVms	Wrist		6,42ms	
Elbow	10,26ms	5,24mV	11,94mVms	Wrist- Elbow	170mm	3,84ms	44,3m/s
Ulnar, R							
Wrist	2,85ms	18,22mV	29,78mVms	Wrist		2,85ms	
Elbow	5,91ms	17,77mV	29,36mVms	Wrist- Elbow	180mm	3,06ms	58,8m/s

Sensory Nerve Conduction Study

Site	Latency (ms)	Amplitude	Area	Segment	Distance (mm)	Interval (ms)	NCV (m/s)
Median, L							
Wrist	4,32ms	19,60uV	1,24uVms	Wrist		4,32ms	
Median,R							
Wrist	4,72ms	7,20uV	1,00uVms	Wrist		4,72ms	
Ulnar, R							
Wrist	2,58ms	31,60uV	1,28uVms	Wrist		2,58ms	

Table 3. Values of median motor and sensory latency of the conduction study of the patient with bilateral CTS (Ilbay K et al., 2010).

The samples of the electromyogram (EMG) records of the patient with bilateral CTS and the normal subject are shown in Figures 2 and 3 (Ilbay K et al., 2010). MATLAB software package (MATLAB version 7.0 with neural networks toolbox) was used for implementation of the RNN and the MLPNN. The determination of architecture and training are important for the neural networks used in classification. The sizes of the training set and test set are determining the efficiency of neural networks. In order to determine the sizes of the training and testing sets of the CTS database, various experiments were performed. In the developed classifiers, 100 of 350 records were used for training and the rest for testing. The training set consisted of 40 normal, 17 right CTS, 12 left CTS and 31 bilateral CTS. The testing set consisted of 81 normal, 30 right CTS, 24 left CTS and 115 bilateral CTS (Ilbay K et al., 2010).

Motor Nerve Conduction Study

Site	Latency (ms)	Amplitude	Area	Segment	Distance (mm)	Interval (ms)	NCV (m/s)
Median, L							
Wrist	3,92ms	10,91mV	17,95mVms	Wrist		3,92ms	
Elbow	7,76ms	12,32mV	20,40mVms	Wrist- Elbow	220mm	3,81ms	57,7m/s
Median,R							
Wrist	3,72ms	2,70mV	64,21mVms	Wrist		3,72ms	
Elbow	8,04ms	3,38mV	51,41mVms	Wrist- Elbow	250mm	4,32ms	57,9m/s
Ulnar, R							
Wrist	2,58ms	4,07mV	3,51mVms	Wrist		2,85ms	
Elbow	6,72ms	3,31mV	2,64mVms	Wrist- Elbow	240mm	4,14ms	58,0m/s

Sensory Nerve Conduction Study

Site	Latency (ms)	Amplitude	Area	Segment	Distance (mm)	Interval (ms)	NCV (m/s)
Median, L							
Wrist	2,64ms	36,60uV	3,25uVms	Wrist		2,64ms	
Median,R							
Wrist	2,76ms	11,60uV	1,82uVms	Wrist		2,66ms	
Ulnar, R							
Wrist	2,58ms	25,90uV	1,28uVms	Wrist		2,36ms	

Table 4. Values of median motor and sensory latency of the conduction study of the normal subject (Ilbay K et al., 2010).

In the determination of efficient neural network architecture, experiments were done for different network architectures and the results of the architecture studies confirmed that networks with one hidden layer consisting of 25 recurrent neurons results in higher classification accuracy. In order to compare performance of the different classifiers, for the same classification problem MLPNN which is the most commonly used feedforward neural networks was implemented. The single hidden layered (20 hidden neurons) MLPNN was used to classify the CTS. The sigmoidal function was used as the activation function in the hidden layer and the output layer.

The confusion matrices are used to display the classification results of the classifiers. In a confusion matrix, each cell contains the raw number of exemplars classified for the corresponding combination of desired and actual network outputs. The confusion matrices showing the classification results of the classifiers used for classification of the CTS are given

in Table 5 (Ilbay K et al., 2010). From these matrices one can tell the frequency with which record is misclassified as another. The test performance of the classifiers can be determined by the computation of sensitivity, specificity and total classification accuracy. The sensitivity, specificity and total classification accuracy are defined as:
Sensitivity: number of true positive decisions / number of actually positive cases
Specificity: number of true negative decisions / number of actually negative cases
Total classification accuracy: number of correct decisions / total number of cases
A true negative decision occurs when both the classifier and the physician suggested the absence of a positive detection. A true positive decision occurs when the positive detection of the classifier coincided with a positive detection of the physician.

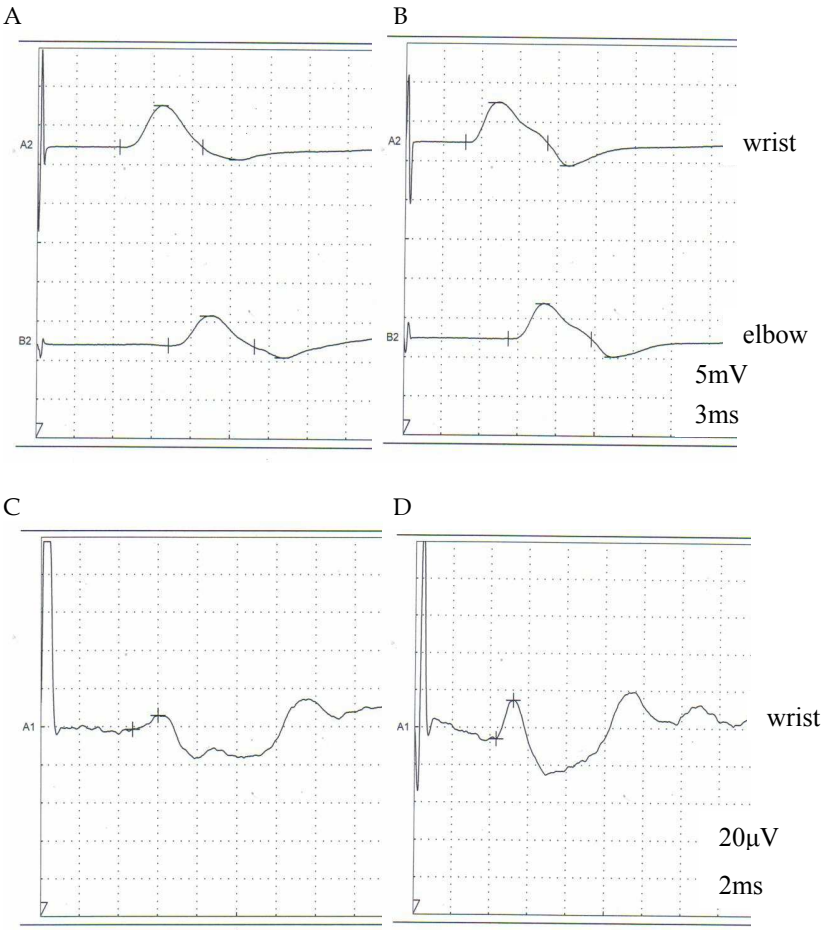

Fig. 2. The samples of EMG records of the patient with bilateral CTS; **A**. Image of motor nerve conduction study of right median nerve, **B**. Image of motor nerve conduction study of left median nerve, **C**. Image of sensory nerve conduction study of right median nerve, **D**. Image of sensory nerve conduction study of left median nerve (Ilbay K et al., 2010).

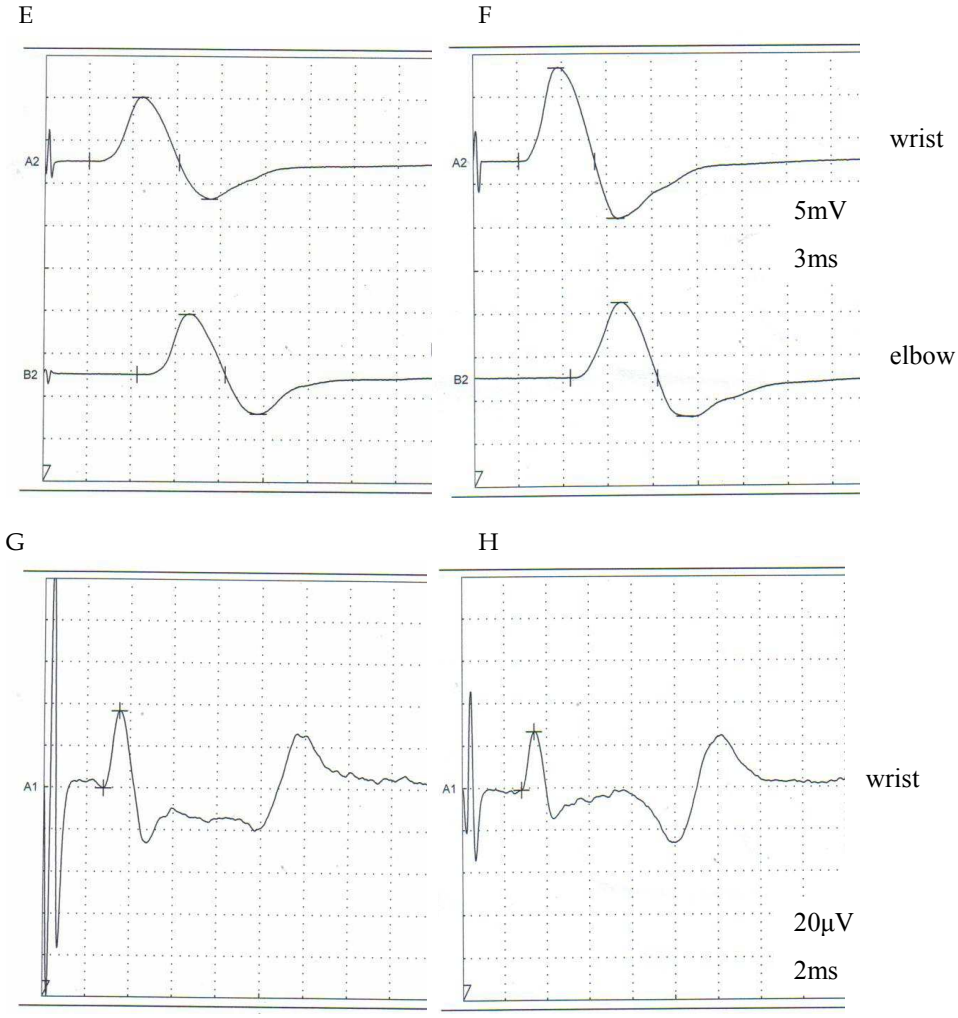

Fig. 3. The samples of EMG records of the normal subject; **E**. Image of motor nerve conduction study of right median nerve, **F**. Image of motor nerve conduction study of left median nerve, **G**. Image of sensory nerve conduction study of right median nerve, **H**. Image of sensory nerve conduction study of left median nerve (Ilbay K et al., 2010).

The classification accuracies (specificity, sensitivity, total classification accuracy) on the test sets of the classifiers are presented in Table 6 (Ilbay K et al., 2010), in order to show performance of the classifiers used for classification of the CTS.

All possible sensitivity/specificity pairs for a particular test can be graphed by receiver operating characteristic (ROC) curves. Therefore, the performance of a test can be evaluated by plotting a ROC curve for the test and ROC curves were used to describe the performances of the SVMs. Sensitivity rises rapidly and 1-specificity hardly increases at all until sensitivity becomes high for a good test.

Classifiers	Desired Result	Output Result			
		Normal	Right CTS	Left CTS	Bilateral CTS
RNN	Normal	77	0	0	1
	Right CTS	2	28	0	2
	Left CTS	1	2	22	2
	Bilateral CTS	1	0	2	110
MLPNN	Normal	71	0	0	3
	Right CTS	5	26	1	4
	Left CTS	3	3	21	5
	Bilateral CTS	2	1	2	103

Table 5. Confusion matrix (Ilbay K et al., 2010)

Classifiers	Classification Accuracies (%)				
	Specificity	Sensitivity (Right CTS)	Sensitivity (Left CTS)	Sensitivity (Bilateral CTS)	Total classification accuracy
RNN	95.06	93.33	91.67	95.65	94.80
MLPNN	87.65	86.67	87.50	89.57	88.40

Table 6. The values of the statistical parameters (Ilbay K et al., 2010)

ROC curves which are shown in Figure 4 (Ilbay K et al., 2010) demonstrate the performances of the classifiers on the test files. From the classification results presented in Table 6 and Figure 4 (classification accuracies and ROC curves), one can see that the RNN trained on the features produce considerably high performance than that of the MLPNN.

6. Conclusions

The clinical symptoms and nerve conduction studies for the diagnosis of CTS are explained. The RNNs were used for automated diagnosis of CTS. The performance of the RNNs on the diagnosis of CTS (normal, right CTS, left CTS, bilateral CTS) was investigated. The accuracy of RNNs trained on the features of CTS (right median motor latency, left median motor latency, right median sensory latency, left median sensory latency) was analyzed. The classification accuracies and ROC curves of the classifiers were presented, in order to evaluate the used classifiers. The classification results and the values of statistical parameters indicated that the RNN had considerable success in discriminating the CTS (total classification accuracy was 94.80%). In the further studies, different neural network architectures and training algorithms can be used for obtaining more efficient results.

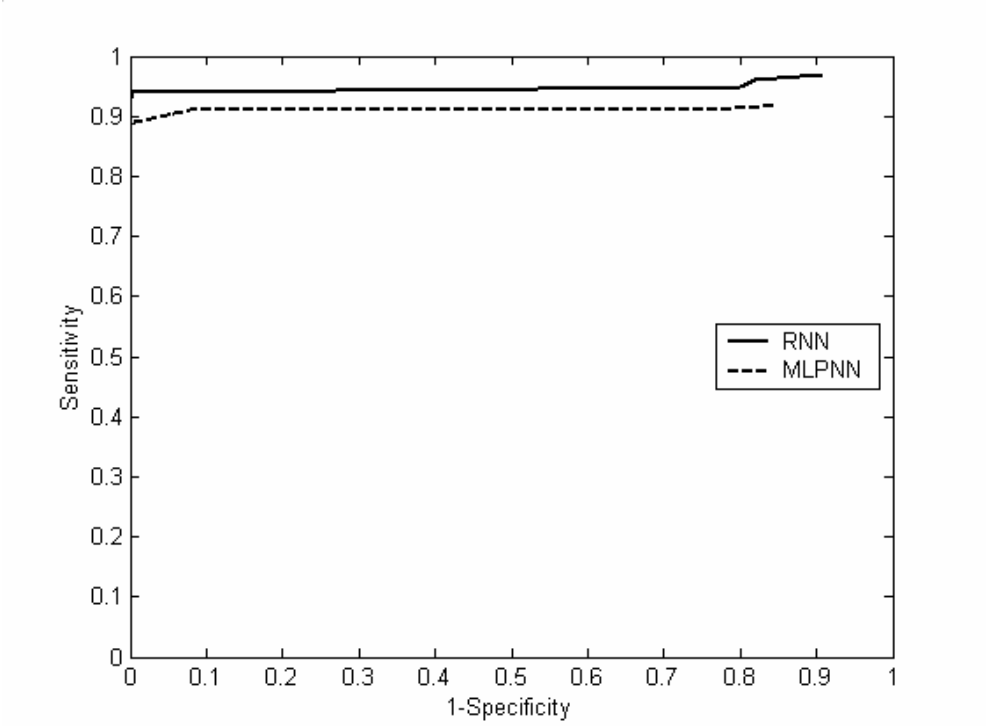

Fig. 4. ROC curves (Ilbay K et al., 2010)

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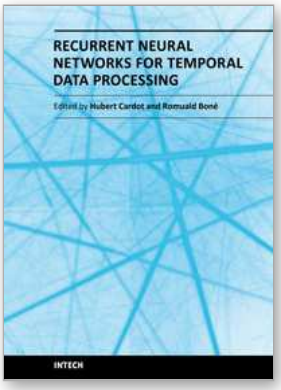

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The RNNs (Recurrent Neural Networks) are a general case of artificial neural networks where the connections are not feed-forward ones only. In RNNs, connections between units form directed cycles, providing an implicit internal memory. Those RNNs are adapted to problems dealing with signals evolving through time. Their internal memory gives them the ability to naturally take time into account. Valuable approximation results have been obtained for dynamical systems.

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