

Spiking neural network with delay-adaption learning model for decision support in treating dental malocclusions

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This paper presents a supervised delay-adaptation Spiking Neural Network (SNN) model to support decision making in treating dental malocclusions, in particular for orthodontic extraction. This temporal coding spiking neural network model employs a Hebbian-based rule to shift the connection delays instead of previous approaches to delay selection. Here, the tuned delays compensate for differences in the input firing times of temporal patterns and enable them to coincide. The coincidence detection capability of the spiking neuron has been utilised for detecting and classifying patterns. The structure of the network is similar to that of an LVQ network except that the output layer neurons are coincidence-detecting spiking neurons. An input pattern is represented by the group of the neuron that is the first to fire among all the competing spiking neurons.

The proposed SNN has been implemented as a software tool and it was trained to predict whether an orthodontic extraction is necessary or not. Data for training and testing the SNN was collected from clinical examinations carried out on 150 patients treated at the

Department of Orthodontics of the University of Naples Federico II. The data considered here has 32 attributes belonging to two classes, whether an orthodontic extraction is necessary or not for treating Dental malocclusions. The trained network obtained an average classification accuracy of 89.8% on previously unseen test data. This was achieved with a network of 2x4 spiking neurons trained for 40 epochs using 100 training examples. The classification accuracy of the proposed model was found to be better than that of an MLP network trained with the same data using the error back-propagation algorithm.

Keywords: Spiking neural networks, pattern recognition, orthodontic extraction, dental malocclusions

1 Introduction

Artificial Neural Networks (ANNs) are a flexible computational tool for solving a wide range of problems such as modelling, time series analysis, pattern recognition, signal processing and control in many domains including manufacturing, banking, medical diagnosis, and robotics.

Although the development of ANNs was inspired by biological neural systems, ANNs are considered to be limited compared to their biological counterpart due to their simplistic structure and behaviour. Classical ANNs are based on the McCulloch and Pitts neuron which computes a linear sum of the inputs it receives from other neurons, weighted by the strengths of the synaptic connections, and then passes this sum through a static non-linearity. Experimentalists have recognised for long that a synapse is a dynamic element with complex non-linear behaviour instead of the general realisation as a passive device whose output is a linear function of its inputs [1, 2]. These considerations have led to increased interest in temporal

coding spiking neurons which are more biologically realistic artificial neurons and in Spiking Neural Networks (SNNs) which are made up of such neurons. Generally, in biological neural systems, information is conveyed to neurons through neural connections by electrical pulses or spikes. In other words, the information is coded in the frequency of the spikes [3] and the analogue variable representing the input and output of the classical neural networks correspond to this frequency of spikes, i.e. the firing rate of a neuron [2]. However, experimental evidence collected in recent years indicates that many biological neural systems use the timing of single spikes to encode and process information [2, 4]. This method, known as temporal coding, is regarded as the coding mechanism in biological neural systems for fast cortical events [4].

Networks of spiking neurons with temporal coding have become an important research area. Hopfield [5] introduced the idea of using the timing of action potentials to represent the values for computation within a network. Maass [2] showed that a network of spiking neurons can simulate arbitrary feed-forward sigmoidal networks (ANNs with sigmoidal activation) and can approximate any continuous functions. It has been proved that spiking neural networks which convey information by individual spike times are more computationally expressive than networks with sigmoidal activation [6]. Another feature of spiking neurons is that even with a seemingly increased structural complexity they are relatively easier to implement in large neural networks [7]. Different learning algorithms for SNNs with temporal coding were proposed in [7-16] and their efficiency was found to be comparable with that of popular sigmoidal neural network models.

It is understood that biological neurons operate in two modes, as integrators and as coincidence de-

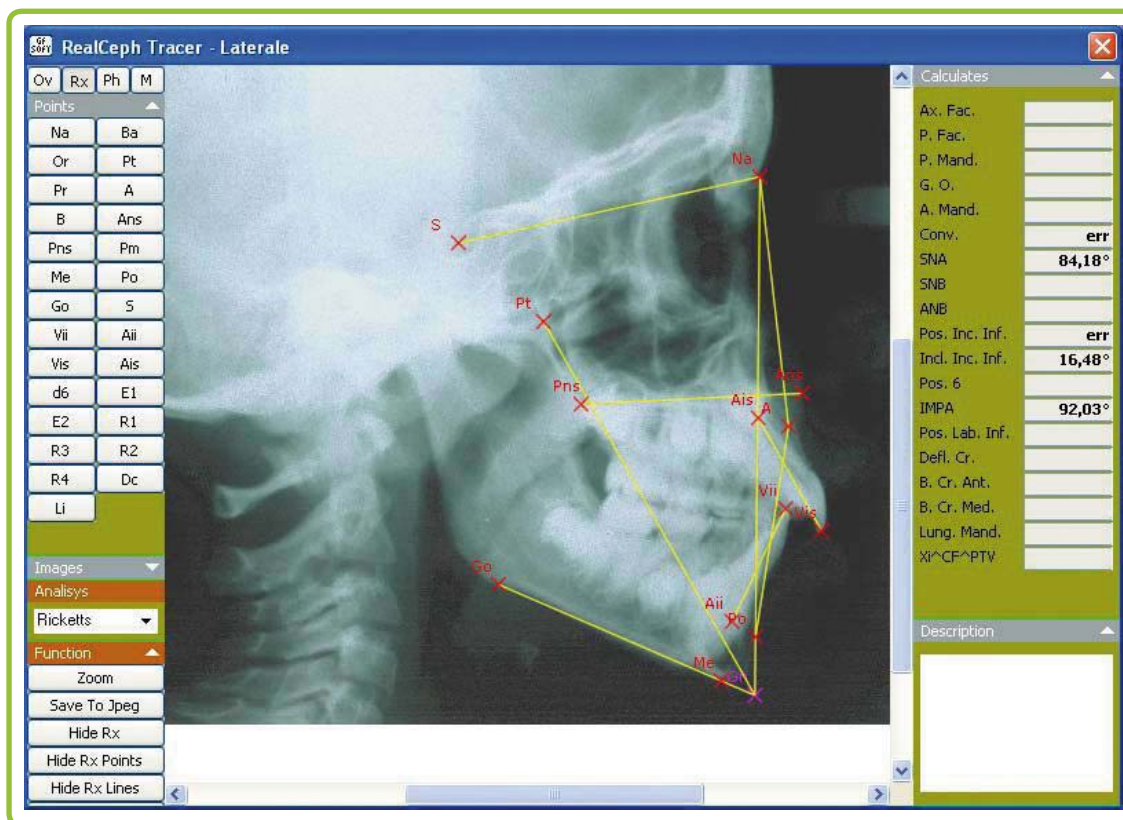


Fig. 1.

Example of orthodontic casts and radiographic measurements

tectors [17]. When acting as a coincidence detector, a neuron fires only when it receives coinciding input spikes. This special feature for artificial computation was first utilised in [5] and later in [7, 10, 11]. Here, the spiking neuron was identified to be functioning similarly to a Radial Basis Function (RBF) neuron. Through a delay selection process, these models choose a sub-set of suitably delayed connections from a broad set. This selected set of connections can compensate for timing differences between input spikes and make them coincide at some neuron. This selection is achieved through a weight adaptation technique in which the connection weights of suitable delays are enhanced while unwanted ones are pruned away. Another method of delay adaptation known as delay shifting can be found in the literature [18-21]. Here, instead of delay selection through weight adaptation, connection delays are shifted in order to achieve the objective of making certain input spikes to coincide at a given neuron. This technique which has been used in biological modelling

studies has never been employed in applications of SNNs.

This paper presents a clinical application of SNNs employing the coincidence detection property of spiking neurons and a Hebbian-based delay adapting rule. The clinical application considered here is the treatment of dental malocclusions, which is a highly prevalent pathology in the general population. The greater attention given to the aesthetic and functional problems have driven to a larger demand of orthodontic treatment. A critical step in the orthodontic therapy is diagnosing the problem correctly and devising an effective treatment plan. However, orthodontic diagnosis often found to be very difficult and influenced by subjective interpretation of the measured parameters. For this reason, Artificial Neural Network (ANN) based approaches have been considered to provide valid support for diagnosis in orthodontics [22].

The application considered here is of providing support in deciding whether a patient requires orthodontic extraction as a part

of the orthodontic treatment for dental malocclusions. Data for the application of SNN was collected from orthodontic casts and radiographic measurements as well as clinical examinations carried out on 150 patients treated at the Department of Orthodontics of the University of Naples Federico II. Out of the 150 patients, orthodontic extractions were performed as part of the treatment on 37 patients.

Cephalometric analysis was performed on lateral standardized cephalograms, taken by a single technician using the same x-ray device and a standardized procedure. The cephalograms were made with the mandible in the intercuspal position. The cephalometric analysis was performed by means of RealCeph® software and was addressed to define the subjects' facial typology and sagittal relationship. Fig. 1 shows an example of orthodontic casts and radiographic measurements used by the RealCeph® software to conduct the analysis.

A number of patients were excluded for data collection and the

exclusion criteria were: number or shape anomalies, previous extractions, necessity of extractions for parodontal or endodontic problems, orofacial surgical treatment.

The data collected consists of 32 features and Table 1 lists all the features, their type of measurement and range. The 32 features made up a 32-component input vector and the extraction therapeutic option represented the corresponding 1-component output vector classified as belonging to one of two categories: extraction (Od = 1) or not extraction (Od = 0).

Application of neural networks for decision making on orthodontic extraction was originally addressed using the above mentioned data by Martina et. Al. [22] using a Multi-Layer Perceptron (MLP) network trained using the error back-propagation algorithm.

The remainder of this paper is organised as follows. Section II introduces SNNs and explains their pattern detection capability. Section III details the proposed supervised delay adapting SNN learning model. Section IV outlines the decision making process in orthodontic extraction and previous work conducted by four of the authors. Section V presents the classification results obtained using the proposed SNN model. Section VI concludes the paper.

2 Spiking Neural Networks and temporal pattern detection

Spiking neuron models are simple phenomenological models which describe the biophysical mechanisms responsible for generating the activity of a neuron by means of its membrane potential. A SNN is a network of spiking neurons where the neurons are usually placed in layers and connected through weighted connections. In addition to a weight, a connection in a spiking neural network could have a delay mechanism which postpones the arrival of an input spike at the other end of the connection.

This study is based on the spiking neural network model introduced in [23]. The model employed in this study can be defined as follows.

Let Γ_j be the set of neurons presynaptic to neuron j and \mathfrak{T} the set of firing times of the neurons $i \in \Gamma_j$. The state of neuron j at time t is specified by its potential $u_j(t)$ which can be computed using equation 1.

$$u_j(t) = \sum_{i \in \Gamma_j} w_{ji} \varepsilon(t - (t_i + d_{ji})) \quad (1)$$

Where $t_i \in \mathfrak{T}$ and $t_i + d_{ji} \leq t$. w_{ji} is the connection weight and d_{ji} is the connection delay between neurons i and j . $\varepsilon(t)$ is the spike response function which specifies the effect of an input spike at time t . A typical spike response function is given by equation 2 and shown graphically in Fig. 2.

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$$\varepsilon(t) = (t/\tau) e^{-(t-\tau)/\tau} \quad (2)$$

where τ is a time constant. In the above defined model, information is coded with the timing of the first spike of a neuron and therefore it is sufficient for a neuron to fire only once during a particular activity [8, 9]. Hence in this model the inputs to the network and the outputs are coded by the timing of spikes. The collective effect of all the input spikes at a neuron is specified by its potential which can be computed by equation (1). The effect of an input spike at some time t is specified by equation (2). According to the cumulative effect of all the inputs a neuron will fire whenever its potential exceeds the firing threshold Θ . The output of the network is taken as the timing of these spikes.

As mentioned earlier, an interesting feature of a spiking neuron is that it can act as a coincidence detector for the incoming pulses. Spiking neurons can detect coincidence of the input signals with ease unlike for classical neural networks where this is computationally expensive to realise [24, 25].

A neuron fires only when its potential due to the incoming spikes exceeds the threshold value. Due to the non-linear nature of the connections of a SNN, the effect of an input spike will increase with time to reach a maximum value and then dissipate over time. The total potential of a neuron will not exceed the threshold value if there are significant differences between the arrival times of the input spikes. In reality the timing of the input spikes will differ and this difference can be compensated for by correctly tuned delays. Hence, when similar input patterns are temporally coded, a spiking neuron can detect them with a finely tuned set of delayed connections. Fig 3. shows a simple scenario where

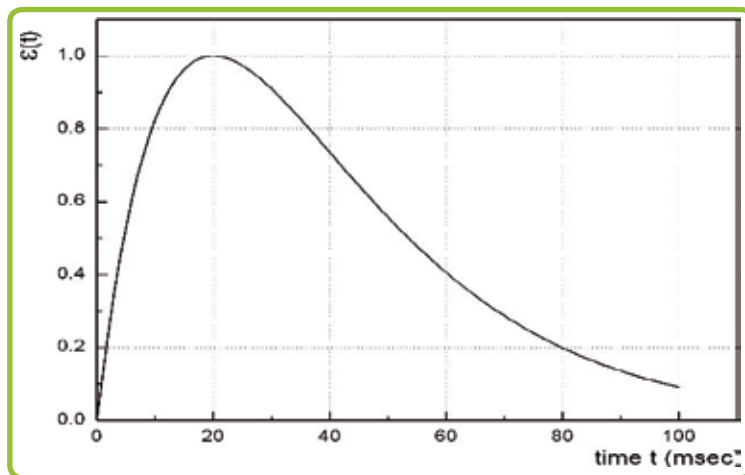


Fig. 2: Spike response function, here the time constant $\tau=20$ msec.

Table 1.

The features included in the collected Orthodontic data

	Features	Type	Range
1.	age	Years	9 - 26
2.	sex	Binary (Male = 1, Female = 0)	0, 1
3.	dentobasal discrepancy (DDB)	Degree	72.9 - 86.2
4.	37/47 impact (37-47)	Degree	71.9 - 86.4
5.	intercanine diameter difference (3 diameter)	Degree	0.06 - 7.6
6.	intermolar diameter difference (6 diameter)	Degree	0.1 - 16.2
7.	distance from canine Angle's I class dx (3 dx Class)	Degree	19.4 - 42.8
8.	distance from canine Angle's I class sx (3 sx Class)	Degree	9.4 - 34.0
9.	distance from molar Angle's I class dx (6 dx Class)	Degree	89.0 - 125.6
10.	distance from molar Angle's I class sx (6 sx Class)	Degree	73.2 - 107.4
11.	Lee Way Space (LWS)	Millimetres	0.02 - 8.3
12.	Overjet (OVJ)	Millimetres	-3.5 - 11
13.	Overbite (OVB)	Millimetres	0 - 8
14.	median line agreement (Med.line)	Degree	42.5 - 166.9
15.	Ricketts' line (Rck line)	Millimetres	-9,1 - 4.7
16.	superior lip thickness (Sup lip)	Millimetres	-5 - 4
17.	maxillar position (SN\A)	Millimetres	-11 - 14
18.	mandibular position (SN/Pg)	Millimetres	-4 - 8
19.	sagittal intermaxillar relationship (AN/Pg)	Millimetres	-5 - 7
20.	maxillar inclination (SN\ASN.PNS)	Millimetres	-2 - 7
21.	mandibular inclination (SN\Go.Gn)	Millimetres	-6 - 7
22.	vertical intermaxillar relationship (ANS.PNS\Go.Gn)	Millimetres	-4 - 8
23.	upper incisive inclination (+1/ANS.PNS)	Millimetres	0 - 4.4
24.	lower incisive inclination (-1/Go.Gn)	Millimetres	-2.5 - 2.5
25.	lower incive compensation (-1/A.Pg)	Binary	0 - 1
26.	interincisive's angle (Ang Inter)	Ord Scale	0 - 1
27.	inferior sulcus position (Inf S pos)	Ord Scale	0 - 1
28.	gingival tipology (Geng Tip)	Ord Scale	0 - 1
29.	gingival recessions' presence (Rec)	Nom Scale	0 - 1
30.	labial incompetence (Lab incomp)	Ord Scale	0 - 1
31.	labiomental (Labm Contr)	Ord Scale	0 - 1
32.	orbicular (Orb Contr) muscles' contraction	Ord Scale	0 - 1

connections with tuned delays enabling the inputs to coincide. This figure shows a simple SNN with three input neurons and two output neurons. Here the inputs to the network are spikes at 7th msec (from input neuron 1), 3rd msec (from input neuron 2) and

at 5th msec (from input neuron 3). The top output neuron's connection delays are tuned to detect patterns similar to the input pattern. Due to the connection delays the effect of each input spike from 1st, 2nd and 3rd input neurons will begin to be realised at the top

output neuron at 11, 10 and 11th msec respectively. Since the inputs are nearly coinciding at the top output neuron there is a better chance for that neuron to generate an output spike. The chance is much less for the lower output neuron since the inputs are real-

ised at different times. Hence patterns similar to the one given in this example can be detected by the network by the firing of the top output neuron.

3 Proposed model

A novel supervised delay adaptation learning model has been developed for training spiking neural networks where the spiking neurons are realised as coincidence detectors. A network structure similar to that of an LVQ network [26] is utilised. The structure comprises an input layer, a hidden layer with spiking neurons and a linear output layer (see Fig. 4). The

input neurons and the computing spiking neurons are fully connected with feed-forward connections in which input information is encoded. Each connection is characterised by a weight value and a delay value. Each class in the data set is represented by a group of spiking neurons connected to a single linear neuron in the output layer. This neuron will produce an output of 1 if one of the neurons connected to it fires first during a specified time window. This indicates that the presented input data has been recognised as belonging to the class represented by the spiking neuron group connected to that output neuron. Otherwise the output will be 0.

In each cycle of activity, the network is presented with temporally coded inputs. In a practical situation, more than one neuron will fire for an input pattern. A highly activated neuron will tend to fire earlier [3]. The neuron which fires first (the winning neuron) will have a high degree of coincidence among its inputs, thus having the most accurate delay pattern to compensate for differences in input timings. Therefore, the winning neuron is more likely to represent the input vector [7, 10, 11].

A. The learning rule

Learning is achieved through adapting the delays in the network connections to encode the input information. The Hebbian-based delay shifting rule proposed in [21] is employed for this purpose. The rule is specified in equation 3 and described graphically in Fig. 5. In this figure, the spike response function, which is shown in dotted lines, specifies the effect of the learning rule relative to that of an input spike.

$$d_{ji} = \eta \quad cm_j \quad g(\delta t) \tag{3}$$

where

$$g(\delta t) = \delta t \left(\frac{e^{-\delta t^2 / \tau_{stdp}^2}}{\tau_{stdp}} \right) - b \tag{4}$$

here d_{ji} is the change in delay value for the connection between spiking neuron j and input neuron i . τ_{stdp} is the time constant for the learning rule and η is the learning rate parameter. cm_j is a measure of coincidence and b is a positive bias value. δt is the time difference between the delayed input spike and the output spike, which is given by equation 5.

$$\delta(t) = t'_j - (t + d_{ji}) - s \tag{5}$$

where t_i is the firing time of input neuron i and t_j is the firing time of

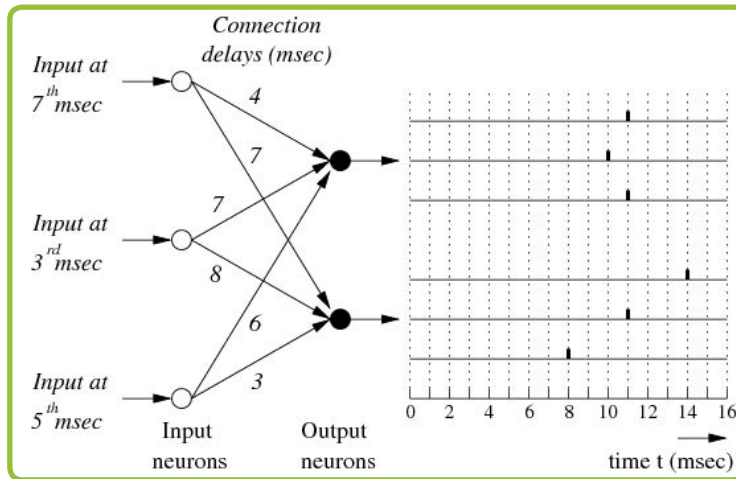


Fig. 3:

Pattern detection by a spiking neural network

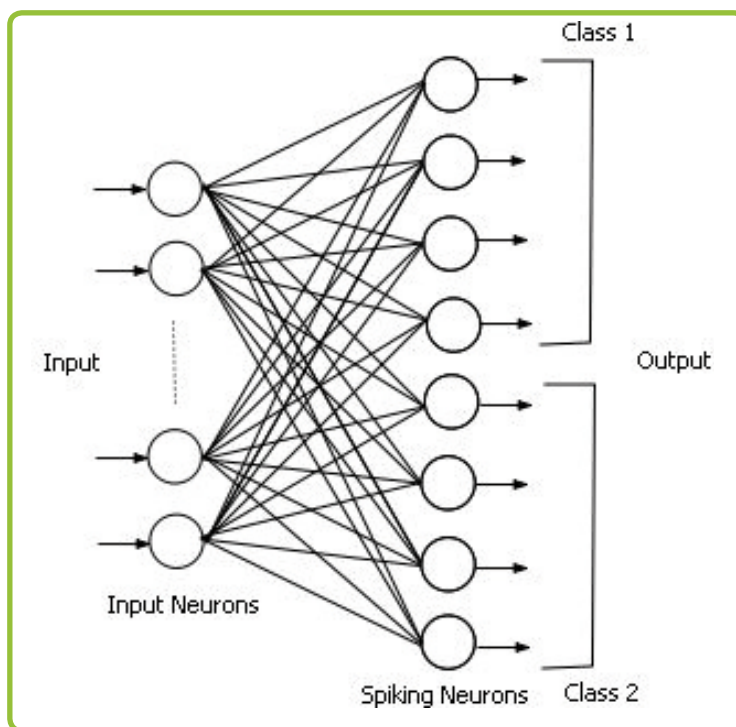


Fig. 4.

Structure of the proposed network

spiking neuron j . d_{ij} is the delay of the connection between neurons i and j . s is a positive term, the effect of which is to shift the origin of the time axis in the positive direction. Both b and s are control parameters used in the learning process.

B. Delay change estimation

The objective of the learning process is to tune the connection delays of a single neuron in such a way that the delayed inputs coincide with each other. The training of the network is conducted in a supervised mode using the learning rule specified in equation 3 to modify the connection delays. This rule estimates the amount of modification for each connection delay in order to achieve the objective of the training. There is a need to select appropriate values for the learning rule parameters τ , τ_{stdp} , b and s . It was found experimentally that better learning could be achieved if the values for the time constants τ and τ_{stdp} are set to allow the learning function to reach its maximum when the spike response function begins to saturate as shown in Fig. 5.

Connection delays are updated based on the difference between the time when an input spike arrives and the time when an output spike is generated. If an input spike arrives at a neuron through a delayed connection before there is an output spike then the delay associated with that connection is increased so that the time difference can be reduced. If the input spike arrives after the generation of an output spike, then the connection delay is decreased. If the output spike follows an input spike within a very short time then the delay change is set to zero or negative in order to control the adaptation of the connection delays. This is achieved through the term s in the learning rule. A similar situation applies when an input spike reaches the neuron much after the output spike is generated. In this case

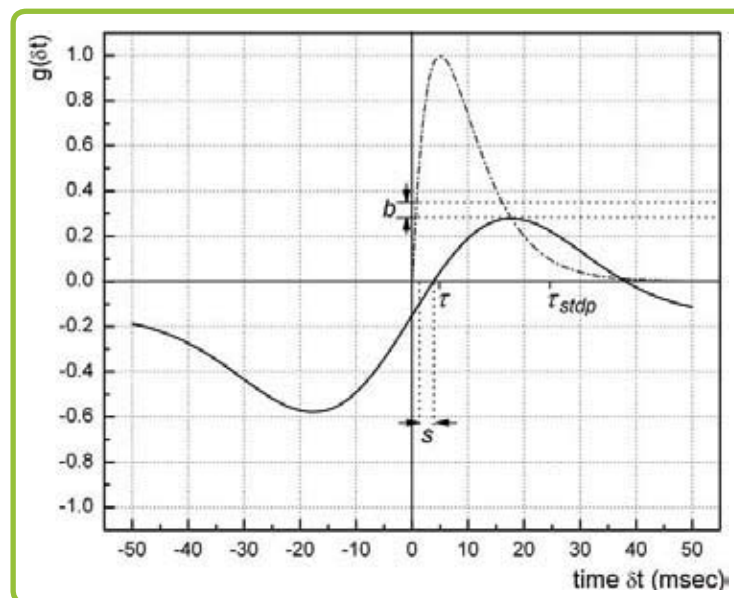


Fig. 5:
Learning rule for delay adaptation.

the change in connection delay is dominated by parameter b . Thus b and s specify the range of spike time differences where the connection delays are increased or decreased.

C. Implementation and training

The proposed model has been implemented as a discrete model [27] and implemented in software.

Continuous input values are coded using small temporal differences, where a high input value is represented by an early input spike and a low value by a late spike with reference to an input time window [7]. The input time window is the part of the activation period where the inputs are presented to the network. Binary and ordinal values are represented with spikes at some specific time in accordance to the above mentioned representation. For ease of implementation, temporal differences are calculated in discrete unit intervals. It has been reported that coincidence detection can be achieved when the activation period is less than the inter spike interval [14]. Hence the spiking neurons are made to act as coincidence detectors by assigning a relatively low value for the time constant of the spike response function, with respect to

the input time window. This will reduce the effective summing up period and enables the neuron to be sensitive to the arrival time of input spikes.

During the training process, temporally coded input vectors are presented to the network and the outputs from all the neurons are found. The training process is conducted in two phases. In the first phase, the connections to all the neurons in the desired group are updated. In the second phase, only the neuron which was the first to fire in the desired group of neurons is updated. In both phases the change in delay is computed using equation 3. In order to keep relevant neurons active, a low threshold value is assigned initially and increased after each training epoch in small equal steps to a preset value. Number of training cycles and the maximum threshold values for each phase are found by trial and error.

D. Control of the learning task

This is also achieved in two distinct phases. One is to control learning in the group of neurons which represent a particular class and the other is to control learning in the network as a whole. Training of the network should be controlled properly in order to achieve good classification and generali-

sation. As a class is represented by a group of neurons, a measure based on the coincidence of inputs is incorporated to train each neuron in that group. The simple linear measure given by equation 6 has been adopted to control neuron learning based on the time between the first and last delayed input spikes to the neuron.

$$cm_j = \frac{\max[\hat{t}_i] - \min[\hat{t}_i]}{t_{input_window}} \quad (6)$$

where \hat{t}_i , for $i = 1..n$ is the time of arrival of input spike generated at t_i at neuron j . Here \hat{t}_i is equivalent to $t_i + d_{ji}$; d_{ji} is the delay of the connection between neuron i and j . t_{input_window} is the input time window. If the delays had been tuned to enable the input spikes to coincide then further modification is not necessary. Hence the amount of change for a particular connection delay could be decreased with the achieved degree of coincidence. Therefore, if the total change of connection delays falls below a minimum value or the change remains constant, then the training process is terminated. To control the learning of the whole network, a global error value is utilised. This error value is calculated based on the desired outputs and the actual outputs. Training continues until the error value falls below an acceptable value or when no change is observed.

4. Decision support in orthodontic extraction

Dental malocclusions are common anomalies found in the general population. Due to the aesthetic and functional problems associated with these anomalies, there is a demand for orthodontic treatment. Correct diagnosis and careful planning, especially in the case of orthodontic extractions, which are a non-reversible procedure, are essential for efficient treatment. The large number of diagnostic parameters and the lack of agreement in interpreting these parameter values make the planning of treatment for individuals difficult. Neural networks can be utilised as a tool for decision support in orthodontic treatment. Neural networks can be trained with data extracted from known cases and the trained network can be utilised to predict whether or not a new patient needs orthodontic extraction [22].

For predicting whether a patient needs orthodontic extraction or not a SNN was designed and implemented as a software tool. The orthodontic data needed to train and test the SNN was collected from 150 patients who were treated at the Department of Orthodontics of the University of Naples Federico II. These patients were treated by human experts and all the decisions were made manually. The collected data included the detail whether an orthodontic extraction was carried out or not for each patient.

The SNN software model was trained and tested to establish its

applicability for clinical decision making. The collected data was used for training and testing the proposed model. Once the SNN was fully trained on the available data and was able to classify the output with acceptable accuracy, it can be used to predict whether a new patient needs an orthodontic extraction or not. For a new patient, values of the 32 features specified in Table 1 have to be collected and presented as input to the trained SNN. The output of the SNN, i.e. the decision regarding extraction can be included in the treatment plan for that new patient.

5. Results and discussion

The collected orthodontic data belongs to two classes, whether an extraction is necessary or not. The SNN designed for classifying orthodontic data to support decision making in treating dental malocclusions, in particular for orthodontic extraction is described below.

The SNN with 2 neuron groups, each consisting of 4 spiking neurons, was constructed. The number of spiking neurons was chosen empirically to achieve a balance between accurate classification and rapid learning. The connections were assigned approximately equal weight values and random delay values in the mid range of the input time window. The input time window was 30 time units in width and each training cycle was activated over 65 time units. The time constants for the spike response function and the learning equation were 5 and 25 respectively. The values for s and b were chosen to be 2 and 0.15 respectively. Initial threshold values were set to $60 \times 0.5 \times 0.55$ and increased up to $60 \times 0.5 \times 0.7$ for the first phase and increased further up to $60 \times 0.5 \times 0.78$ for the second phase of training. Here 60 is the number of input neurons and 0.5 is the average connection weight.

Trial No.	Classification Accuracy %		
	SNN		MLP
	Training	Testing	Testing
1	90.5	89.4	n/a
2	89.8	90.1	n/a
3	89.9	89.9	n/a
Average	90.1	89.8	87.5

Table 2. Experimental results of the proposed SNN compared to a MLP network.

The SNN described above was implemented as a software tool. The collected orthodontic data was divided into three equal parts of which two portions were used for training the SNN and the third for testing it. This process was repeated three times with different portions of the data set for training and testing and the average classification accuracies were noted. The network training consisted of 40 epochs, with 20 epochs in the first phase and 20 epochs in the second phase. The results are shown in Table 2. The SNN achieved an average classification accuracy of 90.1% at the end of training and 89.8% during testing.

The performance of the SNN was compared with the MLP results reported in [22]. The MLP network obtained a test accuracy of 87.5 %. This was achieved using a MLP network with 12 hidden nodes. A leave-one-out method was used for training and testing where the network required between 10,000 and 100,000 learning steps for training.

The results show that the SNN achieved a higher classification accuracy compared to the MLP with a significantly smaller number of training epochs and computing neurons. The number of network connections required for the SNN is significantly less than the MLP.

6 Conclusions

A supervised learning model with a network of temporal coding spiking neurons for classifying orthodontic data to support decision making in treating dental malocclusions, in particular for orthodontic extraction has been proposed. The proposed SNN based approach will not only assist the dentists in their decision making but also minimise the errors introduced during orthodontic diagnosis often found to be very difficult and influenced by subjective interpretation of the measured parameters. The correct diagnosis, achieved by

the SNN based decision support, in treating dental malocclusions which is a critical step in the orthodontic therapy, will lead to devising an effective treatment plan for the patients.

The model which realises the spiking neurons as coincidence detectors encodes the training input information in the connection delays. A Hebbian-based learning rule was utilised to adapt the connection delays according to the differences between the input and output spike timings. The proposed model was able to achieve better classification accuracy in comparison with an MLP trained using the error back-propagation algorithm, with fewer computing neurons and training epochs. In this work, the values of the connection weights were fixed. The classification accuracy could be further improved by adaptation of both connection weights and delays, as this would enable better tuning of the SNN.

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8 REFERENCES

- [1] A.M. Zador, "The basic unit of computation," *Nature Neuroscience supplement*, 3, 2000, p. 1167.
- [2] W. Maass, "Fast sigmoidal networks via spiking neurons," *Neural Computation*, 9(2), 1999, pp. 279-304.
- [3] S.J. Thorpe, A. Delorme and R. van Rullen, "Spike-based strategies for rapid processing," *Neural Networks*, 14(6-7), 2001, pp. 715-726.
- [4] W. Gerstner, R. Kempter, J.L. van Hemmen and H. Wagner, "Neuronal learning rule for sub-millisecond temporal coding," *Nature*, 383(6595), 1996, pp. 76-81.

- [5] J.J. Hopfield, "Pattern recognition computation using action potential timing for stimulus representation," *Nature*, 376, 1995, pp. 33-36.

- [6] W. Maass, "Noisy spiking neurons with temporal coding have more computational power than sigmoidal neurons," in *Advances in Neural Information Processing Systems*, volume 9, M. Mozer, M. I. Jordan, and T. Petsche, Eds, MIT Press, Cambridge, 1997, pp. 211-217.

- [7] S.M. Bohte, J.N. Kok and H. La Poutre, "Error-back propagation in temporally encoded networks of spiking neurons," *Neurocomputing*, 48, 2002, pp. 17-37.

- [8] B. Ruf and M. Schmitt, "Learning temporally encoded patterns in networks of spiking neurons," *Neural Processing Letters*, 5(1), 1997, pp. 9-18.

- [9] B. Ruf and M. Schmitt, "Self-organisation of spiking neurons using action potential timing," *IEEE Transactions on Neural Networks*, 9(3), 1998, pp. 575-578.

- [10] T. Natschläger and B. Ruf, "Spatial and temporal pattern analysis via spiking neurons," *Network: Computational Neural Systems*, 9(3), 1998, pp. 319-332.

- [11] S.M. Bohte, H. La Poutre, and J.N. Kok, "Unsupervised clustering with spiking neurons by sparse temporal coding and multilayer RBF networks," *IEEE Transactions on Neural Networks*, 13(2), 2002, pp. 426-435.

- [12] X. Tao and H.E Michel, "Data clustering via spiking neural networks through spike timing dependent plasticity," *IC-AI*, 2004, pp. 168-173.

- [13] D.T. Pham, M.S. Packianather, E.Y.A. Charles, "A novel self-organised learning model with temporal coding for spiking neural networks," *Intelligent Production Machines and Systems 2006*, D.T. Pham, E.E. Eldukhri, A.J. Soroka, editors, Elsevier, Amsterdam, Netherlands, 2006, pp. 307-312.

[14] D.T. Pham, M.S. Packianather, E.Y.A. Charles, "A self-organising spiking neural network trained using delay adaptation," Proceedings of the IEEE International Symposium on Industrial Electronics, Vigo Spain, 2007, pp. 3441-3446.

[15] D.T. Pham, M.S. Packianather, E.Y.A. Charles, "Spiking neural network for control chart pattern recognition", Proceedings of the European Control Conference, Kos, Greece, 2007, pp. 1392-1397.

[16] D.T. Pham, M.S. Packianather, E.Y.A. Charles, "Control chart pattern clustering using a new self-organizing spiking neural network", IMeche Part B, 222(10), 2008, pp. 1201 – 1211.

[17] P. Konig, A.K. Engel and W. Singer, "Integrator or coincidence detector? The role of the cortical neuron revisited," Trends in Neurosciences, 19(4), 1996, pp. 130-137.

[18] S.P. Day and M.R. Davenport, "Continuous-time temporal back-propagation with adaptable time delays," IEEE Transactions on Neural Networks, 4(2), 1993, pp. 348-354.

[19] P. Baldi and A.F. Atiya, "How Delays Affect Neural Dynamics and Learning," IEEE Transactions on Neural Networks, 5(4), 1994, pp. 612-621.

[20] C.W. Eurich, K. Pawelzik, U. Ernst, J.D. Cowan and J.G. Milton, "Dynamics of Self-Organized Delay Adaptation," Physical Review Letters, 82, 1999, pp. 1594-1597.

[21] T. Tversky and R. Miiikkulainen, "Modeling Directional Selectivity Using Self-Organizing Delay-Adaptation Maps," Neurocomputing, 44-46, 2002, pp. 679-684.

[22] R. Martina, R.Teti, D. D' Adona, and G. Iodice, "Neural network based system for decision making support in orthodontic extractions," Intelligent Production Machines and Systems 2006, D.T. Pham, E.E. Eldukhri, A.J. Soroka, editors, Elsevier, Amsterdam, Netherlands, 2006, pp. 235-240.



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[23] W. Maass, "Lower bounds for the computational power of networks of spiking neurons," Neural Computation, 8(1), 1996, pp. 1-40.

[24] W. Maass, "Computing with Spiking Neurons," in Pulsed Neural Networks, W. Maass and C.M. Bishop, Eds, The MIT Press, Cambridge, 2001, pp. 55-85.

[25] C. Panchev and S. Wermter, "Hebbian spike-timing dependent self-organisation in pulsed neural networks," Proceedings of the world congress on Neuroinformatics, 2001.

[26] S. Haykin, Neural Networks - A comprehensive foundation (2nd edn). Prentice hall, New Jersey, 1999.

[27] A. Jahnke, U. Roth and T. Schönauer, "Digital simulation of Spiking Neural Networks," in Pulsed Neural Networks, W. Maass and C.M. Bishop, Eds, The MIT Press, Cambridge, 2001, pp. 237-257.



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