PREDICTION OF EPILEPTIC SEIZURES BY CNN WITH LINEAR WEIGHT FUNCTIONS

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In this contribution, a novel approach for the prediction of epileptic seizures is introduced using binary input-output patterns and boolean CNN [1,2] with linear weight functions.. Two different algorithms are introduced and verified on invasive recordings of different patients.

1 Introductions

In a focal epilepsy [4] a circumscribed area of the human brain initiates seizures. Invasive multichannel recordings of brain electrical activity will be often considered for diagnostical purposes, which may lead to a surgically removal of the seizure generating area. In a preceeding study [3] we study boolean CNN for the classification of a statistical measure in order to analyse brain electrical activity. The aim of this investigation is to detect the occurrence of certain patterns before a seizure onset leading to a boolean CNN for seizure prediction, which strongly reduce the desired CNN layout complexity for the realization of a portable seizure warning system. The networks considered in our investigation can be described by state equations of the form

$$C\frac{dx_i(t)}{dt} = -\frac{1}{R}x_i(t) + a_i y_i(t) + I_i + \sum_{j \in N_r(i)} B_{j-i} u_j, i = 1, \cdots, M, \tag{1}$$

where for each cell C_i of all cells M, the cell state $x_i(t)$ is influenced by the cell output $y_i(t)$ and the cell input u_j by the translation invariant template B_{i-j} and a_i, while I_i denotes the cell bias. The piecewise linear output function

$$y_j = f(x_j) = \frac{1}{2}(|x_j + 1| - |x_j - 1|) \tag{2}$$

and Neumann boundary conditions are considered in nearly all cases. Furthermore the investigation was focused on CNN with a neighborhood radius $r = 1$.

A CNN is said to be boolean, if with any given binary input pattern with the size M

$$U = \{u_i \in \{-1, 1\} : i = 1, 2, \cdots, M\} \tag{3}$$

the steady state output $y_i(\infty)$ of each cell C_i is also binary and can be here uniquely determined from the input pattern of only its direct neighbors. Each of this input-output combinations can be decoded by using boolean window pattern $\mathcal{B}(K)$ [1].

For $r = 1$, a cell C_i is only directly influenced by its input and the input values of the next 8 neighbor cells, thus $\mathcal{B}(K)$ is a 3×3 window pattern. The decoding of such a CNN can be successfully done if the desired binary output of all possible 512 window patterns is specified. In this investigation, the relative frequencies of all possible patterns were determined for different recordings of brain electrical activity. The time dependent distribution of such patterns can be used to find a linear template for a CNN to act as a seizure warning system.

2 Data base and pattern occurence analysis

Data segments $\tilde{V}_{m,k}$ $1 \leq m \leq 5184$ of normalized brain electrical activity with zero mean and $-1 \leq \tilde{V}_{m,k} \leq 1$ were taken as input values for a CNN. The following discussed results are based on 18 recordings of 5 different patients. In all treated

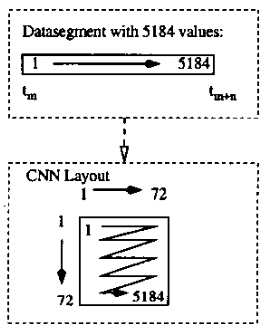

Figure 1. Ordering of a segment $V_{m,k}$ in a CNN using 72×72 cells.

cases, the data segments were firstly transformed into a binary representation by applying threshold values $l_{thresh} = \{-1, -0.9, -0.8, \cdots 0.9, 1\}$. Then each segment of brain electrical activity is ordered in a CNN with 72×72 cells, as shown in Fig.1. We consider in all cases the initial conditions given by the CNN Software Library[7] for the used templates. All calculations have been performed with the simulation system SCNN[5,6] on IBM pSeries Hardware. The flow of this calculation is depicted in Fig.2. The relative frequency $P(\mathcal{B}(\mathrm{i}))$ of all 512 different pattern have been determined for all segments of brain electrical activity taking the above given threshold values. Results obtained for certain pattern will be given in the following.

Firstly results are discussed which are obtained by considering 4 recordings of a certain patient, where three of them have been recorded during a seizure free period. Two different behaviours were observed.

1. A pattern occurs only once before a seizure and never occurs in any other recording. We call this a type 1 behaviour.

2. A pattern occurs frequently in all recordings never exceeding a maximum distance of N segments between two occurances. This distance is much smaller

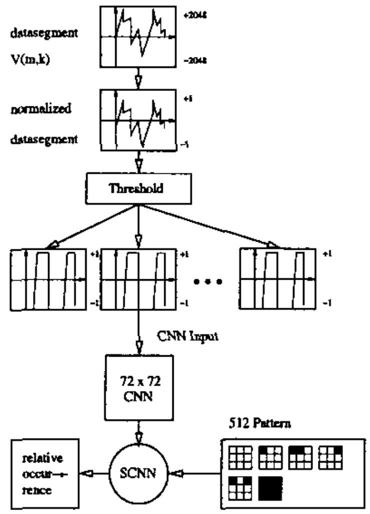

Figure 2. Pattern analysis by binary CNN.

than the distance between the last occurance of the window pattern and the seizure onset. We call this a type 2 behaviour.

For the realization of a warning system detecting such distinct changes, it would be enough to reliable show this behaviour for only one electrode of a patient, but as our investigations reveal, this behaviour can be found in many different electrodes for different patterns. The number of patterns that satisfy the criteria defined above is given in Table 1 for different electrodes.

This table shows a rather typical behaviour, so for all other investigations it is sufficient to consider thresholds of $l_{thresh} = \{-0,1,0,0,1\}$ only.

3 CNN algorithms for pattern detection

The type 1 behaviour can be detected using a CNN algorithm with only two linear Templates as introduced in Fig. 3. By taking the **PatternMatching-Finder-Template**[7]

$$\mathbf{A} = \begin{pmatrix} 0,0,0 \\ 0,1,0 \\ 0,0,0 \end{pmatrix}, \mathbf{B} = \begin{pmatrix} b_1, b_2, b_3 \\ b_4, b_5, b_6 \\ b_7, b_8, b_9 \end{pmatrix}, \mathbf{I} = -N + 0.5 \tag{4}$$

the desired pattern can be isolated, all boundary cells must be held at 0. Depending on the considered window pattern, the values b_i in the feedforward template were set to 1 if the corresponding point in the $3x3$ pattern is black, -1 if white and 0 if it does not matter. N denotes the entries different from 0. The **PatchMaker-**

l_{thresh}	k	No.	Type 1	Type 2	k	No.	Type 1	Type 2
-0.9	TL01	0	0	0	TL02	9	9	0
-0.8		3	0	3		3	0	0
-0.7		6	6	0		27	24	0
-0.6		14	14	0		45	45	0
-0.5		80	80	0		57	52	0
-0.4		67	65	2		54	54	0
-0.3		54	43	11		52	38	2
-0.2		66	31	35		63	32	2
-0.1		73	12	47		73	16	9
0.0		191	22	85		202	40	19
0.1		80	21	56		82	24	3
0.2		63	37	26		84	45	2
0.3		60	42	18		70	44	0
0.4		15	9	6		46	38	0
0.5		3	0	3		28	28	0
0.6		3	0	3		4	1	0
0.7		6	2	4		12	0	0
0.8		12	0	12		0	0	0
0.9		12	0	12		0	0	0

Table 1. Frequency of occurance of type 1 and type 2 patterns for two different electrodes of all recordings of a patient. TL01 and TL02 denote two implanted depth electrodes.

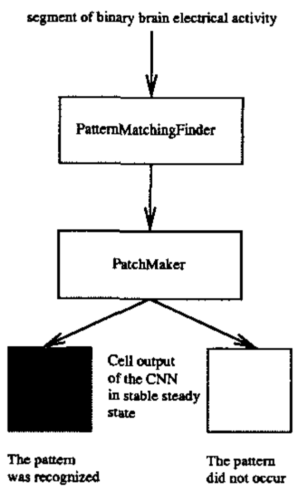

Figure 3. Algorithm for detecting a type 1 behaviour. The binary data of brain electrical activity is used as input to a CNN. By applying the **PatternMatchingFinder**-Template, the pattern can be identified. Seccondly the **PatchMaker**-Template assures a homogeneous cell output. If a single occurrence of a pattern is detected before the onset of an epileptic seizure, the whole CNN in its stable state is characterised by $y_i(t) = 1 \; \forall \; \mathbf{i}$ (black), otherwise $y_i(t) = -1 \; \forall \; \mathbf{i}$ (white).

Template

$$\mathbf{A} = \begin{pmatrix} 0,1,0 \\ 1,2,1 \\ 0,1,0 \end{pmatrix}, \mathbf{B} = \begin{pmatrix} 0,0,0 \\ 0,1,0 \\ 0,0,0 \end{pmatrix}, \mathbf{I} = 4.5 \qquad (5)$$

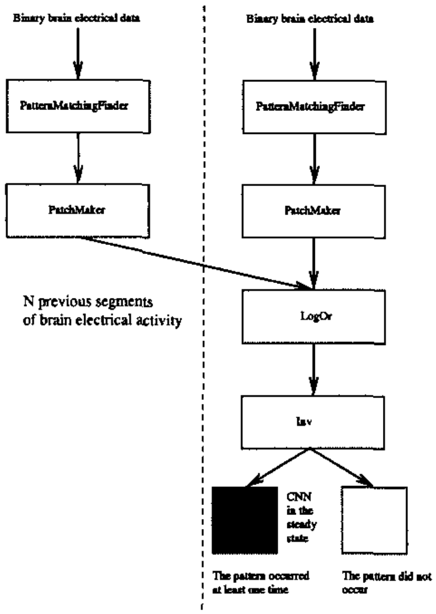

Figure 4. Algorithm to detect a type 2 behaviour.

assures a homogenous output of all cells by considering Neumann boundary conditions. If the pattern is detected, the whole CNN is in its steady state $y_i(t) = 1 \; \forall \; \mathbf{i}$ (black), otherwise $y_i(t) = -1 \; \forall \; \mathbf{i}$ (white). The second algorithm discussed here detects a type 2 behaviour. Firstly the maximum distance N has to be determined. For a detection of a type 2 behaviour the previous N segments of brain electrical data segments were pre-processed with the above mentioned method. Then by using simply the **LogOr**-Template a logical or of all pre-processed patterns leads to a result $y_i(t) = 1 \; \forall \; \mathbf{i}$ if the considered window pattern occurs again in the pattern sequence, otherwise $y_i(t) = -1 \; \forall \; \mathbf{i}$ which is a type 2 behaviour. Because the output of the LogOr CNN is inverted compared to the output of type 1 algorithm, finally the **Inv**-Template is applied. This algorithm is depicted in Fig. 4.

4 Results

Both algorithms have been applied to all recordings of our data base. For all patients, the type 1 and 2 behaviour can often be found allowing a prediction of a seizure. Table 2 shows some results. The following discussed example in the TL01 electrode illustrates these findings for one patient. The pattern $K = 42$ exhibits a type 1 behaviour for a certain patient shortly called patient 1 by using $l_{thresh} = 0$, which is shown in Fig. 5 and Fig.6. A type 2 behaviour can for example be seen for the same electrode and threshold level for pattern $K = 29$, which is illustrated in Fig. 7, two recordings without a seizure are given in Fig. 8. To assure that the

Patient	Electrode	Type 1	Type 2
1	TL01	22	85
	TL02	40	19
	TL03	33	27
2	TL01	23	8
	TL02	2	0
	TL04	0	0
	TL05	23	0
3	TL01	32	0
	TL03	0	0
4	TBAL	0	7
	TBAR1	0	0
	TL10	0	4
5	TBAR2	0	0
	TBAR4	64	56
	TL02	17	32

Table 2. Number of type 1 and 2 behaviour for all patients for some example electrodes and $l_{thresh} = 0$.

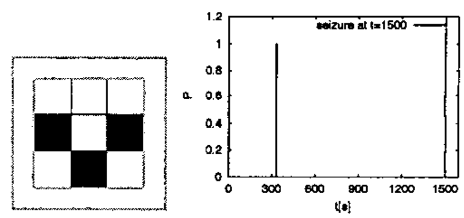

Figure 5. Pattern $K = 42$ (left) shows a type 1 behaviour. It occurs only before the seizure onset at $t = 1500$.

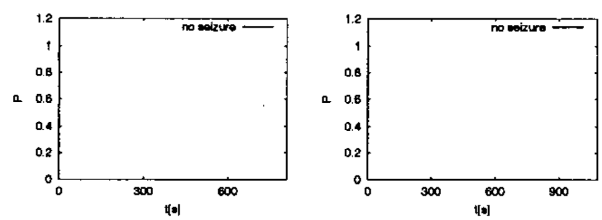

Figure 6. Pattern $K = 42$ shows a type 1 behaviour. Two recordings without a seizure onset where this pattern does not occur.

pattern is not caused by a certain shape of brain electrical activity like failure of a measurement or spike activity, an example for the type 1 result is given. Fig. 9

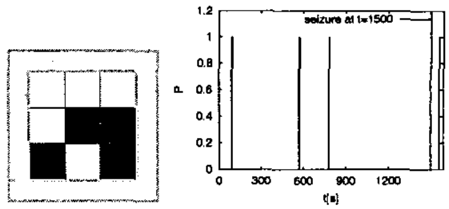

Figure 7. Pattern $K = 29$ (left) shows a type 2 behaviour. Before the onset at $t = 1500$ the pattern $\mathcal{B}(K)$ does not occur.

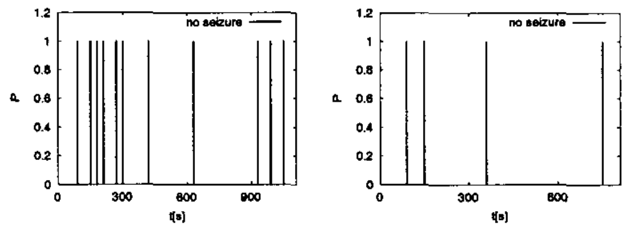

Figure 8. Pattern $K = 29$ shows a type 2 behaviour for two recordings without a seizure.

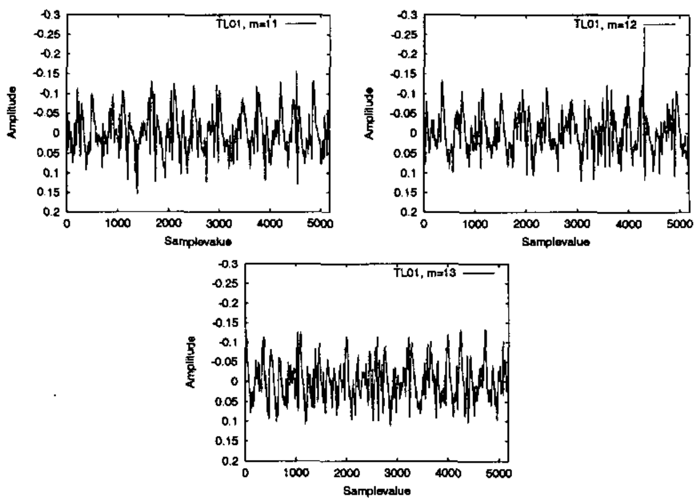

Figure 9. Segment of brain electrical activity before,during and after the occurance of pattern $K = 42$ for patient 1.

shows the segment of brain electrical activity where the pattern occurs only once with the previous and following segment.

5 Conclusion

A new method was introduced which may allow the prediction of epileptic seizures, distinct changes of the occurrence of certain binary $3x3$ patterns can be observed in all treated cases. This approach is based on CNN with linear templates, thus allowing a fast processing with current CNN hardware. The algorithms were verified in simulations on a broad data basis possibly enabling a basis for the realization of a portable seizure warning system.

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