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An Optimized Learning Algorithm Based on Linear Filters Suitable for Hardware implemented Self-Organizing Maps

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Abstract. In this study, we present a fast and energy efficient learning algorithm suitable for Self-Organizing Maps (SOMs) realized in hardware. The proposed algorithm is an extension of the classical algorithm used in Kohonen SOM. It is based on the observation that the quantization error that is a typical quality measure of the learning process, does not decrease linearly along the learning process. One can observe the phases of the increased 'activity', during which the quantization error rapidly decreases, followed by 'stagnation' phases, during which its values are almost the same. The activity phases occur just after decreasing the neighborhood radius, R. A set of finite impulse response (FIR) filters is used to detect both phases. This enables an automatic switching the radius R to a smaller value that shorts a given stagnation phase and starts a new activity phase. Comprehensive investigations carried out by means of the software model of the SOM show that the learning process can be shorten even by 80-95% that allows for reduction of energy consumption even by 70-90%.

1 Introduction

The motivation behind the work presented in this paper was to develop a simple and simultaneously fast learning algorithm suitable for Self-Organizing Maps (SOMs) realized at the transistor level in the CMOS technology. In such applications energy consumption is one of the main parameters and thus any shortening of the learning process is desired. The proposed solution can be viewed as an extension of the algorithm proposed by Kohonen in [2], which is relatively simple and thus suitable for low power hardware implementation [3].

The competitive unsupervised learning in Kohonen SOM relies on presenting the network with learning patterns $X(k)$ in order to make the neurons' weight vectors $W(k)$ resemble presented data. At each learning cycle, k, the SOM computes a distance between a given learning pattern $X(k)$ and the weight vectors $W_j(k)$ of particular neurons in the map. The neuron, whose weights

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resemble a given input pattern to the highest extent becomes a winner. As a result, this neuron as well as it's neighbors obtain the permission to adapt their weights. The adaptation is performed in accordance with the following formula:

$$W_j(k+1) = W_j(k) + \eta(k)G(R, d(i,j))[X(k) - W_j(k)], \tag{1}$$

where $\eta(k)$ is the learning rate, while $d(i,j)$ is a distance between the winning neuron and a given neighbor. Particular neurons that belong to the winner's neighborhood are adapted with different intensities, whose values strongly depend on the neighborhood function $G(\cdot)$ [3]. One of the main parameters is in this case the topology of the map. The topology identified with grid of interconnections between particular neurons in the map, determines which neurons belong to the winner's neighborhood for a given value of the neighborhood radius R [2]. The commonly used topologies include a hexagonal one (Hex) in which particular neurons have maximum six neighbors as well as rectangular topologies with four (Rect4) and eight (Rect8) neighbors [3].

In the SOM the quality of the learning process is typically evaluated by means of the, so called, quantization error (Q_{err}) as well as the topographic error (E_{T1}), which are defined as follows:

$$Q_{\mathrm{err}} = \frac{1}{m}\sum_{j=1}^{m}\sqrt{\sum_{\kappa=1}^{n}(x_{j,\kappa} - w_{i,\kappa})^2} \tag{2}$$

and

$$E_{\mathrm{T1}} = 1 - \frac{1}{m}\sum_{h=1}^{m}\lambda\left(X_h\right) \tag{3}$$

where m is the number of the learning patterns in a given data set, n is the number of the inputs of the map, while i denotes the winning neuron.

The first criterion illustrates how the map fits a given input data set [5]. The second criterion – the quality of the topographic mapping – is one of the measures proposed by Kohonen [2, 5]. The value of $\lambda(X_h)$ is equal to one when for a given pattern X two neurons whose weight vectors to the highest extent resemble this pattern are also direct neighbors in the map. Otherwise the value of $\lambda(X_h)$ is equal to zero. The lower the value of E_{T1} is, the better the SOM preserves topology of the map [1, 5]. The optimal value of E_{T1} is equal to zero.

The proposed addition to the classical learning algorithm of the Kohonen SOM involves filtering and analysis of these errors.

2 The proposed learning algorithm

2.1 Q_{err} and E_{T1} error waveforms

In the classical learning algorithm of the SOM the neighborhood function $G(\cdot)$ (see Eq. 1) depends on the radius R, that linearly decreases along the learning

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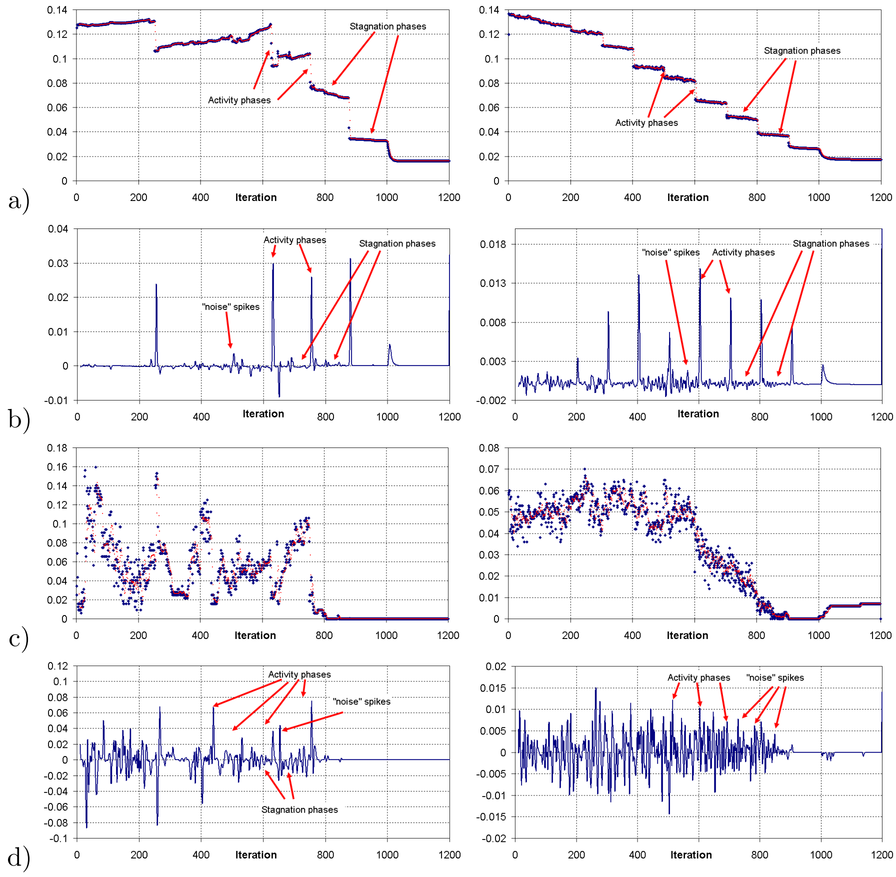

Fig. 1: Error waveforms vs. iteration of the learning process: a) the original Q_{err} waveform and its LP filtering, b) the HP filtering of the Q_{err}, c) E_{T1} error and its LP filtering d) the HP filtering of the E_{T1}. The left and the right waveforms are showed for the map with 8x8 and 16x16 neurons, respectively.

process starting from $R_{\max}$ to 0, thus shrinking the neighborhood. $R_{\max}$ is the initial and simultaneously the maximal value of the radius R. In the classical approach it is usually assumed that $R_{\max}$ covers at least half of the map [2].

In a typical learning process the number of epochs, $L_{\max}$, is much larger than $R_{\max}$, and therefore radius R varies by a fraction from epoch to epoch. Since the radius has to be an integer number, therefore it is always rounded to the closest integer value, so that for a given number of iterations, l (constant in the classical approach), the value of the neighborhood radius is fixed:

$$l = \textbf{round\_to\_integer}(L_{\max}/R_{\max}) \tag{4}$$

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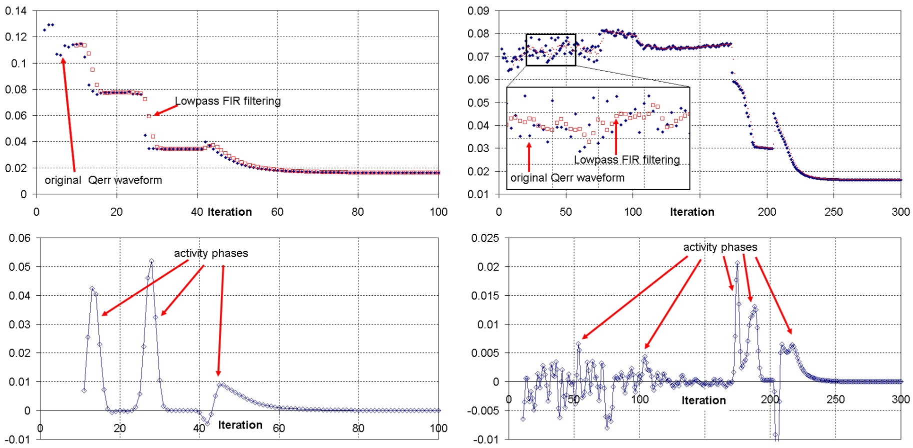

Fig. 2: Learning process after the proposed optimization for an example map with (left) 8x8 (right) 16x16 neurons: (top) original $Q_{\rm err}$ waveform and the output of the FIR lowpass filter, (bottom) output of the highpass FIR filter.

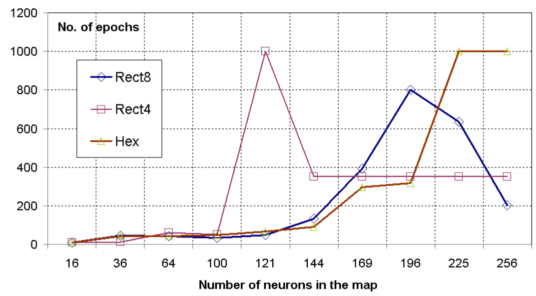

Fig. 3: Minimal number of the iterations obtained in case of using of the new algorithm for the map sizes varying in-between 4x4 and 16x16 neurons for map topologies: Hex, Rect4 and Rect8. The initial number of the iterations $L_{\max}$ was equal to 1000.

The value of l is usually in the range in-between 20 and 200, depending on the sizes of the map, learning data set and some other parameters.

The initial idea of the proposed algorithm has been proposed in [4]. It is based on the observation that the errors, given by Eqs. 2 and 3, do not decrease linearly along the learning process. In case of $Q_{\rm err}$ just after decreasing the neighborhood radius by 1 (after each l epochs), the error decreases rapidly, but this phase is relatively short, embracing only 2-10 epochs. Then the error waveform enters a “stagnation” phase, as shown in Fig. 1 (a). This process is visible more clearly

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in case of Q_{err} waveforms. In case of the E_{T1} error the analysis is much more difficult, as the corresponding waveforms are very noisy and often do not exhibit distinct 'stagnation' and 'activity' phases (see Fig. 1 (c)). To enhance the E_{T1} data, complex filters (e.g. FIR filters of high order) have to be applied to remove the noise. This is not a good direction, looking from the point of view of the hardware implementation of the SOM. For this reason the proposed algorithm, in it's current form, is based only on the analysis of the Q_{err} waveforms. Analysis of the E_{T1} errors requires further comprehensive investigations.

We have completed a series of more than 5000 simulations that showed that the phenomenon described above is typical. The simulations have been carried out for the Hex, Rect4 and Rect8 topologies, for the sizes of the map varying in-between 4x4 and 40x40 neurons and different values of the neighborhood range R_{max}. The network was trained with different data sets.

One of the interesting observations is that for the radius R larger than a critical value, the Q_{err} often does not decrease, so in this period of time the network does not make any progress in training. As a result, in practice the learning process can start with relatively small values of R_{max}.

2.2 The proposed algorithm

After the analysis of both errors we have focused only on the Q_{err} waveforms due to reasons described above. In this case two simple FIR filters connected in series have to be used to enable an automatic detection of the 'stagnation' phases. In the first stage a lowpass (LP) filter of order N=3 with the coefficients: $h_{\mathrm{LP}i}$ = 0.125, 0.375, 0.375, 0.125 (Butterworth filter with flat frequency response) has been used. The next step is the highpass (HP) filtering (coefficients: $h_{\mathrm{HP}i}$ = 1, 1, -1, -1)) that detects sudden changes in the output signal from the LP filter. The resultant waveforms are illustrated in Fig. 1 (b) for two example cases with different sizes of the map, different neighborhood functions and different data sets. The spikes in these waveforms indicate the "activity" phases.

Detection of the 'activity' as well as the 'stagnation' phases allows for the introduction of a mechanism that automatically switches over the radius R to smaller values once the learning process enters a 'stagnation' phase. As a result, the learning process can be shortened even by 95%, that in turn can reduce the energy consumed by the SOM even by 80-90% (some power will be consumed by the filters). Selected results illustrating shortening the learning process are shown in Fig. 2. Fig. 3 shows minimum numbers of iterations (after using the filters and the automatic switching of the radius R) for the sizes of the map varying in-between 4x4 and 16x16 neurons and particular topologies. The initial number of the iterations L_{max} was equal to 1000 in all cases, but similar results have been obtained even for L_{max} = 5000. For small maps (10x10 neurons or less) the learning process typically finishes after 40-60 epochs, while for larger maps (16x16 neurons in the presented case) after 200 epochs for the Rect8 topology. 1 epoch embraces 320 and 1280 patterns X, for the map with 8x8 and 16x16 neurons, respectively. The peak visible for 121 neurons needs more investigations to provide a thorough interpretation.

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Theoretically we could start learning the map with smaller values of $L_{\max}$, but we never know which value is optimal for a given combination of the parameters. The proposed method automatically search for this optimal value.

3 Conclusions

A simple extension of the learning algorithm of the Kohonen SOM suitable for low power neural networks realized at the transistor level has been proposed. The proposed solution is based on the observation that the quantization error does not decrease monotonically during the learning process. By the use of a set of linear FIR filters it is possible to control the moments in which the neighborhood radius R is switched to smaller values. This enables a substantial shortening of the overall learning process, even by 80-95%.

The intended application of the proposed algorithm is in ultra low power NNs used for data analysis in Wireless Sensor Networks. Such solutions are more and more frequently used in medical diagnostics [6, 7].

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