

## Reference ID

### PULSED NEURAL NETWORKS FOR FEATURE DETECTION USING DYNAMIC SYNAPSES

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#### ABSTRACT

Technical applications where scene analysis is involved rely on a robust feature extraction. Feature extraction based on neural principles traditionally emphasize the analogue representation of information as well as analogue information processing at least to the level where simple cells are modeled. In contrast to this we will show in this paper how principles of correlation and detection of correlation can be used to extract features up to a level of complexity of at least that of simple cells. Using only two data-driven adaption rules for connection weights dependent on membrane potentials as well as on dendritic current simple networks can be implemented to detect gradients of intensity. By replicating of those detectors and defining density of connectivity to the receptors of the retina complex detector-profiles can be implemented.

#### INTRODUCTION

It is widely accepted that feature detection in visual scenes form the basis for robust scene analysis and image processing. Especially the so-called *simple cells* in the mammalian visual cortex were extensively studied with regard to their response to different types of visual stimulus. Summarizing an important result the receptive fields of simple cells can be modeled by gabor functions. This was originally proposed by Daugman [5], [6] and Marcelja [7] whereupon Jones and Palmer [3,4] verified this hypothesis by successfully fitting experimental results to parameters of the theoretical characteristics. With this findings simple cells respond to local visual input by firing patterns and are sensitive to orientation as well as to specific spatial frequencies. The spatial frequency as well as the angle of orientation is fixed for a given neuron just as the location of the receptive field.

The response of the simple cells is given by measuring the respective pulse rate of the cell. Since pulses are already used at that early stage of visual pre-processing it is commonly accepted to consider averaged rates to emphasize an analogue representation of information here.

While considering pulse rates only individual pulses of different neurons are to be considered to fire independently. In fact, in certain cases patterns generated by ensembles of neurons show ordered structures. Thus, the representation of information in such networks has to be assessed in a different way. While ordered structures within firing patterns may result on one hand from the external input (for example pixel information) and on the other hand from the network dynamics the underlying principles for pattern generation have to be examined in detail. More precisely, we are interested in utilizing additional principles that influence the order within certain firing patterns in a defined way to encode information using measurable quantities different from pulse rates.

One way to influence the pattern generation process is to introduce dynamic synapses to couple individual neurons [2]. We will show that simple feature detectors can be implemented using essentially two types of dynamic synapses only. Here, the features will be detected by generating and analyzing spatial-temporal structures of pulses using dedicated networks. Typical structures are correlated and decorrelated pulses as well as the order of incoming pulses. Then, more complex features are composed from replication, merging and spatial distribution of such simple feature detectors.

The adaption of the synapses depends either on the membrane potential of the receiving neuron or on the pre-synaptic current summed up on the dendrite. In both cases adaption is started by pre-synaptic pulses. Because of that, the dynamics of synapses is completely data-driven and depends on local quantities only.

The focus of the discussion here is the development of feature detectors similar in their behavior to those found in the visual cortex. Here, we present the architecture of an artificial simple cell. By repeating the experiments from Jones and Palmer [3,4] to sample the response profiles of biological simple cells we present the response profile of our artificial cell.

Starting the discussion by reviewing a special type of dynamic synapse an architecture for a gradient detector will be presented. Then, by building a network of such gradient detectors we show how detectors having arbitrary response profiles can be constructed.

## FEATURE DETECTION USING ADAPTIVE SYNAPSES

The simplest feature found in visual scenes is intensity of light received by receptors on the retina. If we attach a single neuron to each receptor which converts the incoming intensity into pulses, a very simple representation of information about local light intensity is given. Normally, the pulse rate of the attached neuron will be a monotonous function of the input.

For scene analysis information about single pixels is not useful in most cases. Instead, many pixels within a surrounding of a given position are included for analysis to gain information about the structure of the scene.

### Dynamic of the Spot-Detector

If for instance, several neighboring pixels have nearly the same light intensity those pixels can be bound to so-called *spots*. To bind several pixels to spots the principle of synchronization can be utilized [1]. Neurons belonging to the same spot should synchronize their pulses while neurons belonging to different spots are being desynchronized.

In [1] synchronization is achieved by using dynamic synapses. To explain the dynamic of the proposed system we start with the dynamics of the neuron.

For the neuron a simple integrate-and-fire-neuron (IAF) will be given. The neuron has two states while the neuron can be either in the sending state or in the receiving state. If  $N_K$  is assumed to be a set of neurons connected to neuron K the membrane potential  $a_K$  of neuron K changes in the receiving state accordingly to:

$$\dot{a}_K = \sum_{L \in N_K} W_{KL} \cdot X_L + W_{K0} \cdot i_K \quad (1)$$

If  $a_K$  exceeds a given threshold  $\theta$  neuron K sends out a pulse  $X_K$  of a given duration  $t_d$ . While the pulse  $X_K$  is sent the membrane potential  $a_K$  is reset to an initial value and the integration of  $a_K$  starts again if the pulse has been decayed.

To achieve synchronization of neurons belonging to the same spot a so-called nearest-neighbor connection scheme was considered as architecture. If two neurons are connected through a synapse  $W_{KL}$  the connection weight

adapts if a pulse  $X_L$  from neuron L is arriving at the synapse:

$$\dot{W}_{KL} = -\gamma \cdot W_{KL} + \mu \cdot \left(a_K - \frac{\theta}{2}\right) \cdot \chi(X_L) \quad (2)$$

K is the index of the receiving neuron. After the pulse of neuron L has been decayed the weight relaxes to 0.

Consider the case where neuron L fires. If the membrane of the receiving neuron is close to  $\theta$  the weight rises as well as the membrane potential of neuron K due to eq. (1). While a significant positive feedback is revealing here, neuron K will be forced to fire within a short time.

Here, the quantity *correlation* can be used to quantify the pattern generation process. If we define the correlation  $C_{KL}$  between neuron K and neuron L to eq. (3)

$$C_{KL} = \frac{1}{T} \int_0^T X_L(\tau) \cdot X_K(\tau) d\tau, \quad (3)$$

the correlation will be maximized due to the dynamics of the synapse if the condition for positive feedback initially holds).

In the other case, where  $a_K$  is small  $W_{KL}$  will not rise at all or rise only up to small values. Here, the feedback is less significant or has no effect on neuron K. Consequently, the correlation appears to be diminished.

Effectively, neurons that are connected through these synapses and receive nearly the same input will be synchronized after a short period while neurons belonging to different spots appear to be desynchronized.

Synchronization has two meanings: (i) synchronized neurons fire with the same pulse rate, (ii) synchronized pulses of *connected* neurons have a small phase difference and correlation becomes significant. Because of that, the dynamic coupling leads to collective actions of neurons belonging to a spot. The collective action results in so-called *pulse-waves* running over the spot.

### Detection of gradients

Spots are defined as regions where the local intensity distribution can be considered to be homogeneous. Of course, also information about non-homogeneous structures, for example edges or lines, is of interest. Here, gradients of intensity come into play.

For now, the aim is the detection of intensity gradients between two pixels. If we consider two neurons receiving input from a light intensity sensor (figure 1) two cases are of interest.

First, if neuron 1 and neuron 2 receive the same input both pulse rates will be equal. Here it is assumed that neuron 1 and neuron 2 are not connected to each other. Thus, the relative phase is of arbitrary but fixed magnitude and depends on the initial condition. If for instance neuron 1 fires and we look back for foregoing pulses of both neurons, it is most likely that the last preceding pulse has

been sent out by neuron 2. This is independent from the relative phase since both neurons fire alternately.

Then, if intensity for neuron 1 is increased, the pulse rate of neuron 1 increases as well. If neuron 1 fires there is a certain probability that the last preceding pulse has also been sent out by neuron 1. This probability rises by the difference between the pulse rates of neuron 1 and neuron 2. Hence, if we find for certain pulses from neuron 1 that the preceding pulses are not generated from neuron 2 there must be a gradient of intensity from neuron 1 to neuron 2.

To detect the gradient of intensity we propose an architecture showing a behavior described in the following. First, we mark individual pulses of neuron 1 if a particular preceding pulse was sent from neuron 2. This is done by a third neuron connected to neuron 1 and to neuron 2 by two adaptive synapses. If this neuron sends out a pulse synchronously to neuron 1 the pulse of neuron 1 is labeled as *marked*. In a second step we detect all those pulses of neuron 1 that are not marked and let these pulses pass the network to an output layer. The remaining pulses will be strongly attenuated with respect to the effect on the receiving neuron. Both, marking of pulses as well as attenuating of pulses will be realized by a network of dynamic synapses described next below.

### Detection of preceding pulses

The network used for marking individual pulses is shown in figure 1. Neuron 1 as well as neuron 2 build up the input-stage receiving input from intensity sensors. Pulses from neuron 3 are used to mark pulses from neuron 1, as described above. The connection from neuron 1 to neuron 3 ( $W_{31}$ ) as well as from neuron 2 to neuron 3 ( $W_{32}$ ) is adaptive having the dynamics eq. (1) while the sign of  $\mu_{32}$  is negative and the sign of  $\mu_{31}$  is positive. Thus, we expect  $W_{31}$  to increase correlation between neuron 1 and neuron 3 under certain circumstances, while the negative sign of  $\mu_{32}$  indicates that the correlation between neuron 2 and neuron 3 can be neglected in most cases.

In detail we assume that the membrane  $a_3$  of neuron 3 is reset initially and  $W_{31}$  is relaxed to 0 due to  $\gamma$ . Pulses from neuron 1 will not affect  $W_{31}$  since  $a_3$  is less than  $\Theta/2$  (we limit all weights  $W$  to be positive or zero) and  $a_3$  remains unaffected. On the other hand if neuron 2 fires at least once (at  $t=t_2$ ) the weight  $W_{32}$  rises as well as  $a_3$  due to the positive synaptic current through  $W_{32}$ . The characteristics of  $a_3$  can be approximated by eq. (5) as long as neuron 2 fires and  $W_{32}$  is positive:

$$a_3(t) \approx \frac{\theta}{2} \cdot \left(1 - e^{-\gamma/2 \cdot (t-t_2)} \cdot \cos \omega_0(t-t_2)\right) \quad (4)$$

$$\omega_0 = \sqrt{|\mu_{32}| - \frac{\gamma^2}{4}} \quad (5)$$

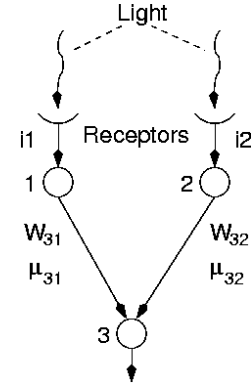


Figure 1: Detector for preceding pulses of neuron 2

From eq. (5) it can be shown that  $a_3$  never reaches  $\theta$  for all cases but can be larger than  $\theta/2$  if  $\mu$  has been chosen large enough. Additional pulses from neuron 2 in turn will not affect  $a_3$  any further since it is necessary to have  $a_3 < \theta/2$  initially for adaption of  $W_{32}$ . Note that  $W_{32}$  relaxes very quickly to 0 after the pulse  $X_2$  of neuron 2 has been decayed.

If  $a_3$  is precharged to  $a_3(t_2+t_d)$  and  $a_3(t_2+t_d) > \theta/2$  holds, a pulse of neuron 1 (at  $t=t_1$ ) causes  $W_{31}$  to adapt causing the membrane  $a_3$  to rise very quickly. As long as  $a_3(t_2+t_d) > \theta/2$  holds,  $a_3(t)$  can be approximated by eq. (7):

$$a_3(t) \approx \frac{\theta}{2} + \frac{1}{2} \cdot \left(a_3(t_2 + t_d) - \frac{\theta}{2}\right) \cdot e^{\sqrt{\mu_{31}}(t-t_1)} \quad (6)$$

If  $\mu$  is chosen sufficiently large  $a_3$  reaches  $\theta$  while neuron 1 is still sending whereby neuron 3 fires. As a result, the correlation is maximized here.

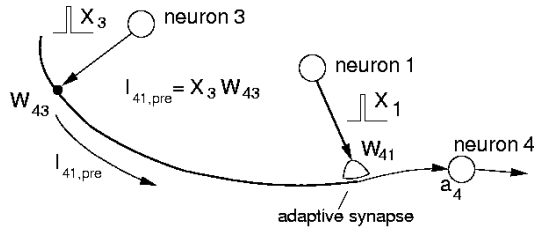
Here, we can specify the role of neuron 3. Pulses from neuron 3 result from specific pulse actions of neuron 1 and neuron 2 whereas the order of incoming pulses to neuron 3 play a crucial role. In fact, neuron 3 acts as a detector which is sensitive to specific incoming pulse pattern. It encodes the detected pattern by sending out a pulse if and only if the input pattern matches exactly the *intrinsic* pattern of the detector.

### Detection of decorrelation

Considering the pulse pattern from neuron 1 and neuron 3 a specific pattern is of interest to detect a gradient of intensity between the input of neuron 1 and neuron 2. The more pulses of neuron 1 appear to be correlated to pulses from neuron 3 the higher the probability is that there is no gradient of intensity between the input of neuron 1 and neuron 2. As a conclusion, we can say that the more pulses of neuron 1 have *no* correlated pulses of neuron 3 the larger the gradient must be.

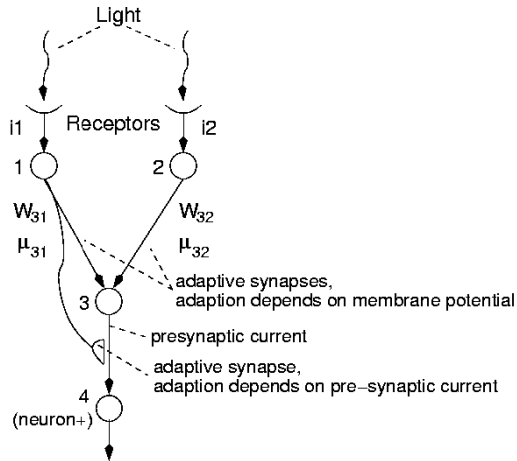
Here, the desired detector must be sensitive towards non-concurrency of pulses if uncorrelated pulses have to be detected. For this purpose a fourth neuron connected to neuron 1 and neuron 3 is introduced which encodes that a pulse of neuron 1 is *not* correlated to neuron 3 by sending out a pulse. The detection of non-concurrency will also be based on dynamic synapses but of different type as given by eq. (1). We consider the case where neuron 3 fires and charges the membrane  $a_4$  of neuron 4. We try to conclude a concurrent action of neuron 3 from observing  $a_4$ . While the membrane potential  $a_4$  appears to be non-leaky in our model the magnitude of  $a_4$  represents the accumulated sum of previous *and* concurrent action at any time. Exactly, concurrent action can be detected if  $a_4$  *changes* while the change in  $a_4$  is caused by a synaptic current.

Here, we propose a second type of dynamic synapse where the adaption depends on a synaptic current instead of a membrane potential. Consider the network shown in figure 2.



**Figure 2: Dendrite and adaptive synapse**

If neuron 3 is sending a pulse a synaptic current  $I_{41,pre}$  is induced through  $W_{43}$  on the dendrite travelling to the receiving neuron 4. While  $W_{43}$  is kept small the membrane  $a_4$  charges only slowly and many pulses from neuron 3 are necessary to excite neuron 4.



**Figure 3: Architecture of the gradient detector**

Now presume synapse  $W_{41}$  to be adaptive in the following way: the adaption of synapse  $W_{41}$  will be initialized by a pulse from neuron 1 and should be

dependent from activity of neuron 3 to detect non-concurrency between pulses from neuron 1 and neuron 3.

While the pulse of neuron 1 is active the synapse  $W_{41}$  is sensitive to the pre-synaptic current. If there is no pre-synaptic current because neuron 3 is inactive the weight  $W_{41}$  should rise very quickly to gain enough post-synaptic current to let neuron 4 fire.

On the other hand, if pre-synaptic current results from activity of neuron 3 the weight  $W_{41}$  should decay rapidly to attenuate the effect of a pulse from neuron 1 on  $a_4$  sufficiently. In general, this behavior can be achieved by using the following dynamic equation for the adaptive synapse assuming that neuron L is active, eq. (7):

$$\dot{W}_{KL} = -\gamma \cdot (W_{KL} - W_{\infty}) - \mu \cdot (I_{KL,pre} - I_{\Theta}) \cdot W_{KL} \quad (7)$$

$I_{\Theta}$  is a given threshold-current. If neuron L is inactive the synapse relaxes according to

$$\dot{W}_{KL} = -\gamma \cdot (W_{KL} - W_{\infty}) \quad (8)$$

The pre-synaptic current  $I_{KL,pre}$  results from summing up pulses from neurons attached to a sub-branch of the dendrite and represents the accumulated activity of the sub-branch that ends at synapse  $W_{KL}$ .

$$I_{KL,pre} = \sum_{\tilde{L} \in D_{KL}} W_{K\tilde{L}} \cdot X_{\tilde{L}} \quad (9)$$

### Characteristic of the gradient detector

The detector is given in figure 3. The network is arranged with two inputs and one output. While on the input side light intensity can be varied on the input, pulses occur on the output side. Since either neuron 1 or neuron 2 may have the larger input-intensity the output does not behave symmetrically. Neuron+ fires if the input of neuron 1 is larger than the input of neuron 2. Otherwise, there is no pulse activity on neuron+. To get the input-output characteristic the input for neuron 1 was fixed to 50% (input weight  $W_{K0} = 0.08$ ,  $\theta = 1$ ,  $t_d = 1\text{ms}$ ) while the input for neuron 2 was varied between 10% and 90%. For each input the system was simulated  $T = 500\text{ms}$ . Figure 4 shows the result. As long as the input of neuron 2 is larger than the input of neuron 1 the output neuron has no significant activity. While the input for neuron 2 is smaller than that for neuron 1 output activity for neuron+ can be observed. The larger the difference is the more pulses neuron+ sends. As an approximation the pulse rate of neuron+ can be seen as being equal to the difference to the pulse rates of neuron 1 and neuron 2.

The pulse rate of the output neuron varies within a certain range if we measure the rate using small time intervals. In figure 5 the results for three different cases for different initial conditions are shown. The initial condition is given by a difference of the membrane

potentials of neuron 1 and neuron 2. For each initial condition the system was simulated  $T=10s$  while for each  $T_m=600ms$  the pulse rate of the output neuron was measured. From that, an empirical variance and mean of the pulse rate can be determined. If we look at figure 5 we see, that the mean pulse rate and the variance is nearly independent from the initial condition. The variance was not larger than 2 pulses/s in any case. Additionally, for small differences, i.e. the input of neuron 2 is nearly as high as the input for neuron 1 the mean rate is quite larger than the expected rate (solid line). This can be explained considering figure 3. Remember, that neuron 3 pulses if neuron 2 and neuron 1 fire alternately. The higher the rate of neuron 2 is the higher the rate of neuron 3 will be. Since for every pulse of neuron 3 a small current flows to neuron 4 there is a certain probability that neuron 4 fires after a certain amount of incoming pulses.

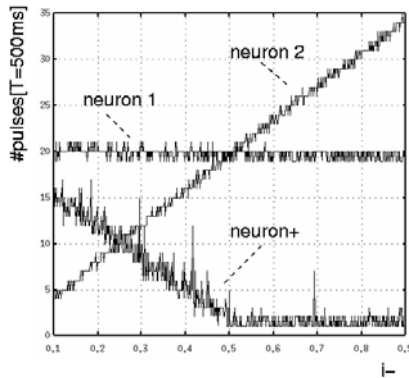


Figure 4: Characteristic of the gradient detector

### DETECTION OF PROFILES

Simple cells representing receptive fields show a specific behavior to a visual stimulus. If the shape of the local light intensity distribution is similar to the particular shape of the local receptive field of a simple cell this cell will respond to the stimulus with a noticeably higher pulse rate than for light intensity distributions that have a more dissimilar shape. The response is a function dependent on a specific shape. Specifically, simple cells respond to local edges of certain spatial wideness as well as to locally oriented lines. Those structures are given by sub-areas including a gradient of intensity along a particular direction and of characteristic length.

If we are interested in detecting specific intensity distributions within a receptive field we can start by detecting a gradient of intensity between two pixels which are located within the receptive field. If the detector sends out pulses we are assured that a gradient having a certain magnitude as well as a certain direction exists between the tested pixels at least. Since only two pixels are tested there is still a certain uncertainty about the surrounding of the pixels. To gain more confidence about the gradient we can test more pairs of pixels in the surrounding of the primarily chosen pair. The more detectors show pulse actions the more we are assured that a gradient spatially

expanded as well as of certain direction exists in a certain spatial domain within the receptive field which is defined by all the tested pixel-pairs.

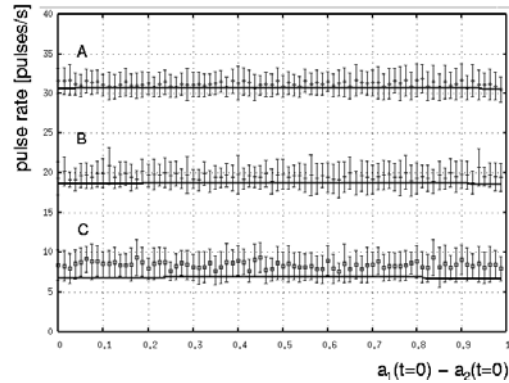


Figure 5: Measured pulse rates and variances.  $T = 10s$ ,  $T_m=600ms$ , neuron 2 has 90 % intensity,  $W_{k0}=0.08, \Theta=1$  A: neuron 1 has 20 % intensity, B: neuron 1 has 65 % intensity, C: neuron 1 has 80 % intensity

Because the detector response has to be encoded using pulses of a single neuron a very simple way to combine the individual pulse responses of several gradient detectors is to sum up all pulses on the dendrite connected to the output neuron. Here, the more gradient detectors respond to the stimulus the higher the pulse rate of the output neuron will be. Figure 6 shows the architecture resulting therefrom.

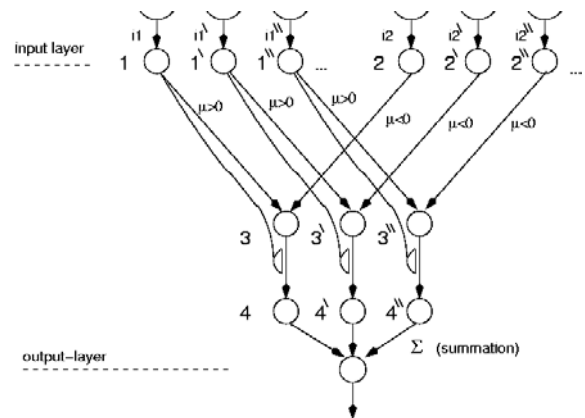
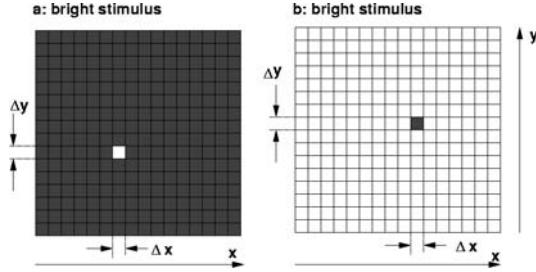


Figure 6: Architecture of the detector

While lines and edges can be detected with this architecture, there still has to be a correspondence to the experimental results from Jones and Palmer [3,4]. In [3,4] the assumption was made, that the response of a simple cell is due to a behavior similar to linear filters. The simple cell encodes the similarity between the attached filter kernel and the stimulus by taking a linear convolution between the input and the kernel.

Under this assumption the coefficients of the filter kernel can be obtained by sampling the receptive field

using small spots of certain contrast to stimulate the receptive field (figure 7). Those spots were exposed to different locations of the receptive field for a certain time while the response of the simple cell to the stimulus will be observed.



**Figure 7:** Stimulus to sample the receptive field

If we expose a spot frequently on a region  $dA$  within the receptive field of the simple cell, eq. (10):

$$dA = (x, x + \Delta x) \times (y, y + \Delta y) \quad (10)$$

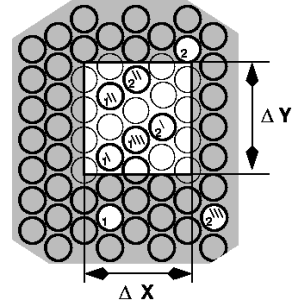
where  $x$  and  $y$  are coordinates and  $\Delta x$  and  $\Delta y$  the dimensions of the spot, respectively, we find that the total number of pulses sent out from the cell due to this stimulus is equivalent to the response of a linear gabor-filter.

From this we conclude that the response of the simple cell can be modeled by eq. (11):

$$\Pi^+ = (H - B) \cdot \iint_{dA} G(x, y) dx dy \quad (11)$$

In eq. (11)  $H$  is the intensity of the spot while  $B$  is the intensity of the background of the stimulus.  $\Pi^+$  is the pulse rate of the simple cell and  $G(x, y)$  models the gabor-function with its respective parameters. Note that two different types of stimulus are distinguished. The filter responds to the bright spot only when  $G(x, y)$  is mainly positive in the area activated by the spot. On the other hand, the filter responds to the dark spot only when  $G(x, y)$  is mainly negative in the respective area where the dark spot is located. Hence, the response from activation by a dark spot has to be counted with a negative sign. Note, that the stimulation with dark spots is necessary to get the negative portion of  $G$ .

In the following, we try to match this behavior to the behavior of the proposed architecture. As already mentioned, using the architecture shown in figure 6 we test at several locations of the receptive field if a gradient of intensity exists. While the output of the whole detector encodes the sum of all tests, we can predict the output if a certain stimulus as well as the distribution of the receptors used for the test is given .



**Figure 8:** Receptors of the retina and an example for an assignment to neurons to the input-layer

If we consider the region of the receptive field where the spot has been exposed (figure 8), certain receptors are used to test a gradient. While the gradient has a direction (neuron 1 has to have the higher intensity than neuron 2 to let the detector respond) some receptors are used to measure the gradient *to* the outside of the spot (pixels which are indexed “1”) and some receptors are used to measure the gradient *from* the outside to the spot (pixels that are indexed “2”).

If the distribution of receptors, labeled either by “2” or “1” is given by two density functions  $\rho^2(x, y)$  and  $\rho^1(x, y)$ , respectively, we can calculate the number of activated neurons on the input-layer of the detector. We obtain:

$$N^i_{(x, y)} = \iint_{dA} \rho^i(x, y) dx dy \quad i = 1, 2 \quad (12)$$

$N^2(x, y)$  gives the number of connected neurons labeled by “2” while  $N^1(x, y)$  gives the number of connected neurons labeled by “1” that are covered by the spot. Then, the output neuron has a pulse rate that is given by ( $W_0$  represents the input-weight  $W_{k0}$  to the IAF-neuron and has been chosen to be equal for all neurons):

$$\Pi^+ \approx \frac{W_0}{\Theta} \cdot (H - B) \cdot (N^1_{(x, y)} - N^2_{(x, y)}) \quad (14)$$

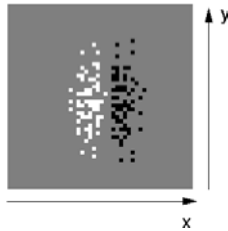
Note, that only neurons participate to the sum which are connected to receptors covered by the spot. Since the background is homogenous elsewhere, there is no response from those regions.

If we want to achieve a similar output behavior compared to eq. (11), we have to choose  $\rho^2(x, y)$  and  $\rho^1(x, y)$  appropriately. Given  $G(x, y)$  we obtain  $\rho^2(x, y)$  and  $\rho^1(x, y)$  to:

$$\rho^+(x, y) - \rho^-(x, y) = \frac{\Theta}{W_0} \cdot G(x, y) \quad (15)$$

This is the main result. Instead of using continuous weights representing filter coefficients we can realize a given filter kernel through a *spatial density distribution* of

connections that are used to test a gradient between each two pixels. Note, that  $G(x,y)$  has not necessarily to be a gabor-function.



**Figure 9:** Distribution of connected receptors to the input-layer of the detector. A bright spot indicates a connection to a  $1^{(n)}$ -neuron while a dark spot indicates a connection to a  $2^{(n)}$ -neuron.

As an example we tested an architecture that connects 128 pixel to the input-layer of the detector. In figure 9 the chosen distribution of connections is shown.

The profile of the detector was determined by sampling the receptive field using different stimuli shown in figure. The bright ones as well as the dark spots are as large as a region of  $3 \times 3$  receptors. The contrast was chosen to be  $C=60\%$ . While 256 different dark spots as well as 256 bright spots were exposed randomly on a  $16 \times 16$  grid which covered the receptive field, each stimulus was activated  $T_p=150\text{ms}$ .

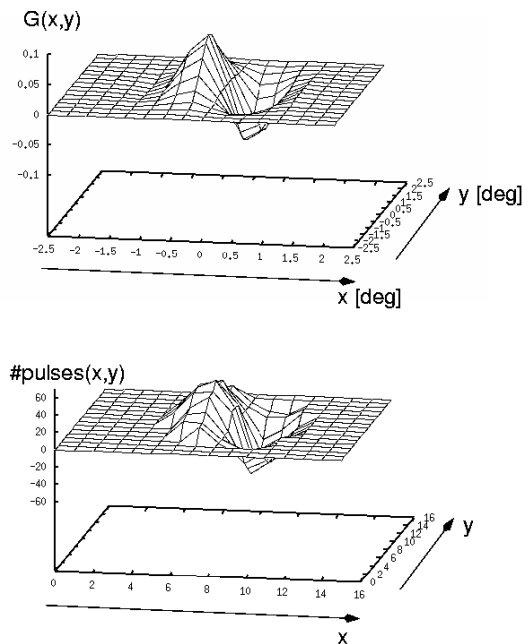
Figure 9 shows the results. The profile on the top represents the ideal profile from that the distribution shown in figure was derived. The bottom part of the figure shows the result from sampling.

## CONCLUSION

Technical applications where scene analysis is involved rely on a robust low-level feature extraction. So far, feature extraction based on neural principles emphasize the analogue representation of information at least to the level where simple cells are modeled.

In contrast to this in certain cases firing patterns generated by ensembles of neurons show ordered structures. Thus, the representation of information in such networks has to be assessed in a different way. We have shown how dynamic synapses can affect the pattern generation process of several neurons to encode additional information represented through high-order statistical quantities like correlation, for instance. It was shown that simple feature detectors can be implemented using essentially two types of dynamic synapses only. Here, the features will be detected by generating and analyzing spatial-temporal structures of pulses using dedicated networks. Typical structures are correlated and decorrelated pulses as well as the order of incoming pulses. Then, more complex features where orientation as well as spatial frequency is of interest are composed from replication, merging and spatial distribution of simple

feature detectors. Only connectivity and a distribution of connectivity to the retina has to be defined appropriately to get an arbitrary complex characteristic.



**Figure 10:** Top: ideal profile, Bottom: measured profile

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