Oscillations in an ANN Convert Competing Inputs into a Temporal Code

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**Abstract:**

Deep convolutional neural networks show strong similarities to the architecture of the ventral stream; but they typically disregard the temporal dynamics experimentally observed in the visual system. For instance, alpha oscillations dominate the dynamics of the human visual cortex; yet oscillations are rarely considered in ANNs. We propose a neural network that embraces oscillatory dynamics, to convert spatial information into a temporal code. The network was trained to classify three letters in four quadrants. Post-training, we added semi-realistic temporal dynamics to the hidden layer, introducing relaxation and pulsed inhibition mimicking neuronal alpha oscillations. The relaxation ensured non-sustained activation, that could be entrained to the rhythmic inhibition. The trained network correctly classified individual letters but showed high uncertainty when presented with two stimuli, indicating the bottleneck problem. When introducing pulsed inhibition, the output nodes activated sequentially, generating a temporal code. Our model provides a novel approach for implementing multiplexing in ANNs. Future work will expand to larger networks and constraining the dynamics based on neural recordings.

Keywords: Neural networks; Neuronal oscillations; Temporal dynamics; Inhibition; Multiplexing

Deep convolutional neural networks have had enormous success in solving a wide range of computer vision problems (Krizhevsky et al., 2012; LeCun and Bengio, 1995; Voulodimos et al., 2018). Originally inspired by the receptive fields of neurons in visual cortex, the activations in these networks have been repeatedly shown to correspond strongly to MEG and fMRI recordings of the visual ventral stream of the human brain (Cichy et al., 2017, 2016; Guclu and van Gerven, 2015) and the non-human primate brain (Kriegeskorte, 2015; Marques et al., 2021; Schrimpf et al., 2020; Yamins et al., 2014; Yamins and DiCarlo, 2016). While alpha oscillations (8-12 Hz) are strongly modulated in visual tasks, the dynamics observed in electrophysiological recordings are typically related to static networks, and often collapse over time (Kuzovkin et al., 2018; Reddy et al., 2021).

Here, we propose a network that embraces oscillatory dynamics in the hidden layer activations. Using relaxation dynamics and pulsed inhibition, the networks segments simultaneously presented inputs in time, reading out the inputs as a temporal code.

# Methods

## Network architecture

We present a neural network with one hidden layer (68 units), fully connected to the three units in the output layer (Fig. 1). The input (56x56 pixels) presented one of three letters (“A”, “E”, “T”) in one quadrant per image. To implement competition between the quadrants, the input was filtered by a convolutional kernel of size 28x28 with stride = 28, and the resulting 2x2 output was summed up at each hidden unit. The hidden activations were calculated as:

( 1 )

With being the activation at hidden unit , and the result of the convolution and summation. Note that the sigmoid activation was steepened and shifted to ensure that the activations were sparse and outside the linear part of the sigmoid, i.e., close to 0 or 1. This was relevant for the imposed dynamics described below. Output activations were calculated using the (arg)-softmax function. The weights were learned using

stochastic gradient descent.

A picture containing diagram

Description automatically generated

Fig. 1 The architecture of the one-layer fully connected network. Competition between quadrants was implemented using a convolutional kernel. The dynamics were added post-training to the hidden layers, using a relaxation term R and pulsed inhibition .

## Oscillatory dynamics

After the training, we added semi-realistic temporal dynamics to each node in the hidden layer, based on differential equations, solved using the explicit Euler method. Dynamics in each hidden unit j were defined as:

( 2 )

The relaxation term was added to ensure a non-sustained activation, and followed the activation in according to:

( 3 )

The pulsed inhibition was implemented as a 10Hz sine wave. The adjustable parameters and , defining the temporal properties of the hidden activations and relaxation, were selected to generate oscillations in the 8-14 Hz frequency band (). was set to a small number to push the sigmoid activations to 1 (). The increase of at each time step, defined by was set to a multiple of the maximum pre-activation in the hidden unit, ensuring that opposed the hidden activations.

# Results

## Pulsed inhibition generates a temporal code

Fig. 2a shows the activation of the output node to a single letter T, presented for 300ms at luminance 1. The activation in the output unit corresponding to the T builds up following . The activations in the “E” and “A” units approach 0 (Fig. 2a, top right).

When presenting two inputs simultaneously, we modulated their gain such that all values corresponding to the attended letter (here T) were set o 1.1 and pixel values in the unattended letter (here E) were set to 0.9 (Fig. 2b, top left). As expected, the softmax function divided the activation between the output units of the two letters but favored the T (Fig. 2b, top right). When adding relaxation dynamics, the activations in the output nodes oscillate in antiphase. However, E eventually loses the competition against the stronger input T, and never reaches activations above 0.5 (Fig. 2b, bottom left). Adding the 10Hz pulsed inhibition to the network results in a temporal code, with T being read out at an earlier phase of the oscillation than E, approaching an activation of 0.9. As the activation of the T reduces to due the relaxation dynamics, the unit corresponding to the letter E starts to activate and reaches an activation of about 0.75. Unlike the dynamics without inhibition, this code is stable over time, and the weaker input E wins the competition against T in every cycle (Fig. 2b, bottom right).

A picture containing graphical user interface

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Fig. 2 Dynamics in the output units. **A** Activations in the output node corresponding to T increase following . **B** Presentation of two letters indicates the bottleneck problem. The weaker input (here E) loses the competition against the stronger T. When imposing relaxation dynamics and inhibition, the network generates a temporal code.

# Discussion

We here present a dynamical neural network that solves the competition between simultaneously presented inputs using relaxation dynamics and pulsed inhibition. Without having been explicitly trained to disentangle simultaneously presented inputs, the network dynamics separate the hidden activations of the individual inputs in time. The strongest input overcomes the inhibition first and is read out at an earlier phase of the rhythmic inhibition than the weaker input. These results are in line with a gating mechanism suggested to be implemented by alpha oscillations in visual cortex (Jensen et al., 2021, 2014); and the hippocampal phase code implemented by phase-coupling between theta and gamma oscillations (Lisman and Idiart, 1995). Our work provides a proof-of-principle for the use of dynamical networks as models of the visual system. Future work will focus on building deeper dynamical networks that can be related to electrophysiological recordings of the human and non-human primate visual cortex.

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