Spatial–Temporal Event Recognition and Metastable Oscillations in CNN Wave Computer

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Theses of the Ph.D. Dissertation

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1 Introduction and aim

In our everyday observations, a lot of recognition tasks are connected to the identification of spatial–temporal dynamics. Often it is not a characteristic figure that we consider familiar, but a specific movement, series of actions or views. Tennis game enthusiasts recognize their favourite player on the court from the backhand movement, horse fans recognize their favourite breed of horse from the posture and from the trot. Dance is also such an activity, whose type cannot be identified from one or more still picture; however, if we consider the whole transient of the movement, we can recognize without doubt which kind of folk or classical dance we see.

By signal processing tasks, the audio signal processing is a good example of one–dimensional temporal analysis. It can be either some kind of noise filtering, or the cut of some frequency range, or other signal processing issues. In the case of spatial (more precisely “planar”) analysis we can think of the simplest image processing tasks, like a two–dimensional image from which we want to extract some features, like edges, corners, specific kind of surfaces, big or small patches, or something else. If we take into consideration the combination of spatial and temporal analysis, we reach the classical frame–by–frame processing of video analysis. The “frameless” processing philosophy of Cellular Neural Networks (CNN) breaks with this approach: not only the real hardware which represents the time and the signal as continuous (not discrete) quantities, but the whole input flow processing is continuous, too. Although the consecutive, frame–by–frame (classical) processing of the input pictures gives answer to every question, this needs appropriately built processing unit and organized memory. In contrast to this, if some characteristics of the evolving dynamics (for example, an output pattern temporarily becoming stable) indicates some event taking place in time, then no further architecture–extension is necessary. The time evolution of the dynamics provides itself alone the recognition, which is significantly “cheaper” in computation complexity.

In one part of my doctoral work I dealt with the recognition of spatial–temporal dynamics. **I was looking for the answer to the**

following question: what kind of recognition issues exist and how can they be solved in those cases, when the continuity of the input flow is the quality difference (compared to the separate processing of the individual still pictures) that makes solvable a recognition problem.

In the case of engineering problems, stable solutions are welcome, which can be robust in spite of the small environmental effects / changes. It can be a stable constant value, or a regularly repeating change, a periodic oscillation. In general it is a must to be reliable, robustly resisting measurement- and environmental noise. Interesting and special case is the seemingly stable regular change in time (metastable periodic oscillation). For a long time it seems ordinary periodic oscillation, but after a point, through a short intermediate interval, it converges to a stable point, settling down to a constant value. Often this transient happens without any priori sign, just the last few cycles imply change in the behavior. As an example, specific waves in the brain activity show similar phenomenon. According to certain theories, these metastable periodic oscillations have functional role (for example, recognition, understanding, association).

In the other part of my doctoral work I dealt with metastable periodic oscillations. I have analyzed the phenomenon under specific architectural constraints (one–dimensional CNN array with periodic boundary condition). **I was looking for the answers to the following questions: what kind of oscillations exist in which region of some specific parameters? How do these parameters influence the length of the oscillation (strength of metastability)? If there exist more different waveforms, what kind of connections are there between them?**

2 Methods used in the experiments

The considered objectives are strongly connected to the CNN Wave Computer's computing model. My results are based on simulations, but some of them are relying on real measurements, where the input flow is served by an infrared sensor array. This array contains 8×8 distance measuring LED–phototransistor pairs, where the sensors measure the LEDs' reflected light from the environment / measured object. Every LED can be controlled separately, and the readout of the phototransistors can be in arbitrary order. There is a controlling and readout circuit connected to the sensor array, in this way we can realize high level communication (via serial line) with the simulator of the Wave Computer.

I have utilized morphological– and wave–operations in the frameless computation model. I have analyzed the effects of different wave propagating templates on the continuously changing input flow. Throughout the analysis I leaned on an earlier published template class, with fine–tuning of the elements I tried to achieve the appropriate behavior. This template class is sign–antisymmetric, coupled, and contains a few non–zero elements. Earlier it was considered due to its wave processing behavior and due to the emerging state–transitions (stable equilibrium point – periodic orbit – chaotic behavior). In the detailed analysis of the measurements I examined the behavior of the system's equilibrium points, the dependency between specific parameters and the evolving state, and the robustness of the whole phenomenon.

These simulators were realized both in C++ language and in MATLAB environment. It is easier to implement evaluating softwares in MATLAB environment; however, in some cases I used a function library which is available only in C++ language. The microcontroller of the sensor array was programmed in C language. The real measurement scenes were partially realized with an xyz table capable of moving with $10\mu m$ precision.

By the metastable periodic oscillations, firstly I examined the details of the phenomenon with the simulation of the dynamics; naively tried to discover the characteristics of the transients and their parameter–dependencies. With numerical evaluation of the data I predicted the results of the analytical eigenvalue–analysis made by *Professor Barnabás Garay*, where the latter one is the rigorous mathematical proof of the metastability in our example.

The simulations were realized both in C++ language and in MATLAB environment. The built-in solver *ode45* of MATLAB has stabilized unexpectedly the solution in some cases (symmetrical initial conditions); but the self-made solvers (MATLAB: Explicit Euler (EE) method; C++: EE, RK45) have shown the convergence to the stable point in every case. Some of the parameter–changes and the evoked bifurcations were analyzed with the AUTO bifurcation–analysis software.

Under the guidance of the italian cooperating research group (*Mauro Forti*, *Luca Pancioni*, *Mauro Di Marco*, *Massimo Grazzini*) I have prepared a one–dimensional, periodic CNN array from discrete components, on which platform I experimentally examined the existence of metastable periodic oscillations.

3 New scientific results

Thesis 1: *Recognition of a feature spanning frames (in space and/or in time) with a CNN Wave Computer interfaced with a two–dimensional, depth measuring sensor array equipped with own lightsources.*

Our measurement and processing differs from the input recording and processing method of the original CNN Wave Computer in two major points. In contrast to the ordinary, *passive* input recording, the picture of the measured object is produced *actively* by us: there is an LED next to every phototransistor, which measures the reflected light of the LED from the environment. This measurement method is novel in the sense that, the global solution evolving on the computing array can be influenced during the transient of the computation (an earlier, inspiring paper [14]). In the other hand, the process of the computation is continuous, not discrete from frame to frame (frame–by–frame). The individual pictures are not separately processed and evaluated, but a single, continuous processing flow exists, which gets from time to time the appropriate input picture, and produces a static or oscillating pattern at the output as the result of the computation. Another, frameless processing example is [15], and an analogous example is [16].

We have used both of the above mentioned measurement and processing specialities for solution of detection problems, but in this dissertation I will present only the results connected to the continuous processing method. We believe that these computation methods have a key role in time–critical object and event recognition tasks.

Published in: [3], [9], [10], [13].

1.1. Applying a specific coupled template class with few non–zero elements on a CNN Wave Computer interfaced with a two–dimensional, depth measuring sensor array equipped with own lightsources, I showed that, in contrast to the frame–by–frame input processing, the continuous input flow makes possible to the evolving dynamics of the computing array the unambiguous identification of object– or scene–properties spanning frames (in space

and/or in time). I provided a solution for detecting a given, oversized terrain feature; I have verified the applicability of my method with measurements.

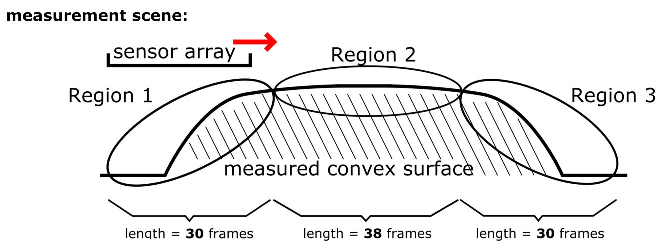

Figure 1: This figure depicts the schematic drawing of the key-measurement example. The sensor array passes over a terrain bump (horizontally from left to right, as the red arrow shows on the picture). The terrain bump consists of three different regions: the uphill-, the plateau- and the downhill-regions (Region1, Region2 and Region3, respectively).

I was able to detect a property with frameless processing mode, which is far more difficult when we process the input frame–by–frame. The sensor array was passed over a terrain bump with size three and a half times larger, than the size of the array itself (for the measurement setup the Reader is kindly referred to Figure 1); the activation sources were constantly lighting. In the three main regions of the bump (uphill, plateau, downhill) three different output patterns became solely dominant, which were preserved till the end of the specific regions. By the frame–by–frame processing of the input flow (instead of a long–continuous computation, separate short ones), more different patterns (even oscillations) were able to emerge in the different regions. This means that, from one / a few separate input pictures we are unable to unambiguously decide over which region stands the array. Although with a statistics of more still input pictures we could overcome this problem, this needs additional memory and post processing routines.

On the other hand, in the case of frameless processing, the evolution and inner state of the dynamics itself stands for the solution, it needs comparably less processing, it is easier. The executing architecture “involves” this dynamics. If the inner state of the computing is easily readable from outside, then the result of the computation can be known without any special device during the computation itself.

$$A = \begin{bmatrix} 0 & 0 & 0 \\ s & p & q \\ 0 & r & 0 \end{bmatrix}, B = \begin{bmatrix} 0 & 0 & 0 \\ 0 & b & 0 \\ 0 & 0 & 0 \end{bmatrix}, z = z \tag{1}$$

$$s = 1.1,\ \ p = 1.0,\ \ q = -1.1,\ \ r = -0.7,\ \ b = 1.0,\ \ z = 0.0 \tag{2}$$

On the computing array we applied the template–family according to Equation (1), with the parameter values in Equation (2). In the literature, the templates contain generally more values which are different from zero, the filling rate of this template is sparse. The computing array had zero-flux boundary condition, the initial state was the first input picture. This template appeared in István Petrás’s PhD dissertation [17], where the Author processed only separate, still input pictures. He discovered the different template–value regions according to different output dynamics (stable equilibrium point, stable oscillation, chaotic behavior), which results I used as initial values during parameter–tuning.

Measuring the performance of detection with this phenomenon is difficult, there is no ready specific architecture which could run the computation in real time. But if we consider that no read-out and memory moduls are necessary, we can assume that this solution would outperform other, general systems in the context of time- and energy-management.

Thesis 2: *Measurement range tuning and complex movement detection with a CNN Wave Computer interfaced with a two–dimensional, depth measuring sensor array equipped with own lightsources.*

Published in: [1], [4], [5], [7], [11].

2.1. I presented a locally adaptive algorithm for the tuning of the range of depth dynamics, in the proposed architectural setup where a two–dimensional, depth measuring sensor array equipped with own lightsources is interfaced to a CNN Wave Computer.

Current imaging sensors are unable to take a picture of scenes with high light dynamic range. This is due to the linear relationship between the amount of the incoming light and the amount of the recorded light. In this way only two or three orders of magnitude can be covered. There are specific solutions, where either the sensitivity of the sensor is logarithmic, or the light capture process happens on an adaptive (or rather on a locally adaptive) way. These solutions can result in that, there will not be any part of the picture in saturation. In the case of CNN Wave Computer architecture, there exists already a locally adaptive solution in the doctoral dissertation of Róbert Wagner, which solution is based on the locally adaptive settings of the cells' integrating time on the whole array.

The architectural difference and the depth range are the novelties in my solution. I work with the cells' light activation strength of the depth measuring sensor array in a frame–by–frame iterative algorithm. The integrating time of the sensing cells is not varied. As an advantage, my method needs only the logical unit of the cell (thinking in the architecture of the CNN-UM) to the adaptive calibration of the light-conditions meaning that the analog unit has to take care of the "main" objective (CNN-algorithm) only. Because our sensor array supports binary activation patterns (On / Off), this algorithm was implemented only in simulation.

2.2. I presented CNN–algorithms for the detection of moving objects with constant speed but varying direction, and for the detection of tilting movement, in the

proposed architectural setup where a two–dimensional, depth measuring sensor array equipped with own light-sources is interfaced to a CNN Wave Computer.

There are already known algorithms in the literature to detect movement, or to detect moving objects at a given speed. The basis of them essentially is the difference computation of two consecutive frames with a specific delay–distance in the input flow.

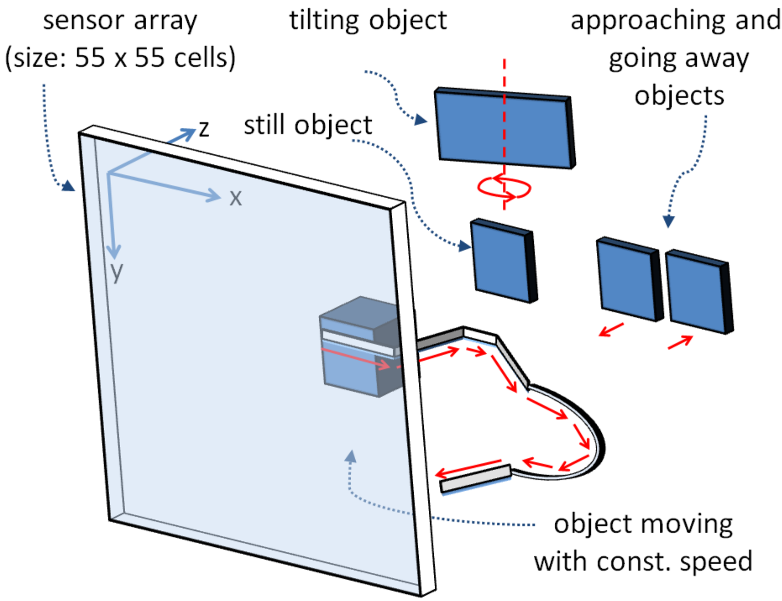

Figure 2: Simulation scene in connection with Thesis 2.2. In the scene we can see a standing object, a tilting object, a perpendicularly moving pair of objects (getting closer and going farther), and an object moving on a spatial trajectory at constant speed.

Due to the speciality of our system (depth measurement) we are able to observe the depth–displacement (getting closer or farther) of the moving object. In the case of the first algorithm (*detection of* *moving object at constant speed but varying direction*) we compute first the planar (in the plane of axes x–y) and the depth (axis z) components, then we take the resultant of them.

The second algorithm detects the objects with tilting movement, when a surface tilts around an axis. The plane of the axis and the surface of the sensor array must be parallel. The algorithm begins with a difference computation on two images of the input flow with specific delay between them. On the resulting image, a modified edge–detecting method is run, which results in bigger patches at those places, where the neighboring rows/columns are detected with continuously changing intensity (due to the tilting movement).

Figure 2 shows a complex simulation scene of objects with different locomotions. I tested the complex movement detection algorithms on this scene, analyzing the specificity with counterexamples, too.

Thesis 3: *Long transient, metastable periodic oscillations in simulations and in circuit experiments.*

In the literature we can see qualitatively similar phenomena with other systems, like those investigated in [18] and in [19].

In our case, the phenomenon is observed in a one–dimensional, autonomous CNN array with periodic boundary condition. The cells are regular, first order ones. The neighborhood connection is realized by the template according to Equation 3. The output function of the cells is the well known piecewise linear activation function, described by Equation (4).

$$A = [\alpha \; 0 \; \beta], \alpha > 0, \beta > 0, \;\; B = [0 \; 0 \; 0], \;\; z = 0 \tag{3}$$

$$y = f_{pwl}(x) = \frac{1}{2}(|x+1| - |x-1|) \tag{4}$$

According to [20] an eventually strongly monotone semiflow (ESM) converges to an equilibrium point, apart from a set of initial conditions with zero measure. Although our system is only a monotone semiflow (not an ESM) due to the squashing effect of the output function ([21]), the limit set dichotomy and most of the convergence properties of the ESM semiflows are still valid ([22][23][24][25]), in this way the "good" properties of the ESM semiflows are present here as well. This means that the system must converge to an asymptotically stable equilibrium point.

In contrast to this, both in simulations and in circuit measurements we were able to observe unexpectedly long oscillations (lasting even hundreds of cycles) on a wide set of the coupling parameters (α, β). But these periodic oscillations are not stable, I prove their metastability with the computation of their Floquet eigenvalues.

Published in: [2], [3], [6], [8], [12].

3.1. I have numerically proven the existence of long transient metastable periodic oscillations in the dynamics of a one–dimensional, coupled, autonomous CNN Wave Computer with periodic boundary condition (ring). With the numerical eigenvalue computations I have defined the

region of the strongest metastability on the parameter plane, where the phenomenon is certainly reproducible even with an electrical circuit by means of higher tolerance components.

In the case of the periodic oscillations with stronger metastability, I determined the Floquet eigenvalues and eigenvectors on the basis of the Poincaré return map.

Table 1: The exponential convergence of the dominant Floquet eigenvalue in the function of the size of the array. The coupling parameters are $\alpha = 3.5$, $\beta = 2.5$, the initial condition is consecutively $N/2$–times $\{+1\}$ and $N/2$–times $\{-1\}$ (where N is even). The main message of this table is the eigenvalue being slightly bigger than one, resulting in the periodic oscillation does not change significantly in the time–frame of the order of $1/(\lambda_1 - 1)$.

N	λ_1
6	2.5883
8	1.0985
10	1.00917
12	1.00089
14	1.00014
16	1.000097
18	1.000044

Fixing the parameter values, the metastability (in Floquet–sense) of the periodic orbit increases in exponential order with the size of the array, as we can see this in Table 1. *Professor Barnabás Garay* has analytically proved both the real metastability and the asymptotical behavior of the metastability in the function of the number of the cells.

Figure 3 depicts the parameter space of α and β from the feedback template A, where certain negative values of β ($|\beta| \leq \alpha$) are defined as well, in this way – according to the author's best knowledge – extending the cooperative region analysed in the literature so far. The waves evolving on the cells can differently connect to each other. These dif-

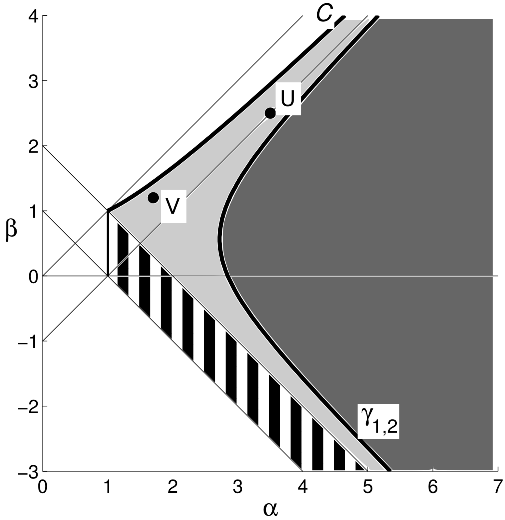

Figure 3: The existence of metastable periodic rotating waves on the parameter plane α, β of the feedback template A (in the region $\alpha \geq 1,\ -\alpha+1 \leq \beta \leq \alpha$); where the different shades of gray and the striped region indicate different types of metastable rotating waves. There is no metastable periodic oscillation in the white region.

ferent forms are indicated on the figure with different shades of gray, $\gamma_{1,2}$ is the borderline between them (the exact location of it depends on the number of the cells (N), in the function of N it exponentially converges to the curve indicated on the figure). The relationship between the neighboring cells' waves has further transformations in the striped region, approaching the line $\beta = -\alpha + 1$ (the exact borderlines are known, this figure has only illustrative purposes). In the close vicinity of curve $\mathcal{C}$ the oscillation gets slower and slower, on the curve it dies with a heteroclinic bifurcation. The circuit measurements of the phenomenon are done in points $U = (3.5; 2.5)$ and $V = (1.7; 1.2)$ of the parameter plane (see subthesis 3.2), in whose vicinity the metastability can be observed by means of an electrical circuit.

3.2. I built a paradigmatic experimental electrical circuit with the use of discrete components, which can realize the functionality of a one–dimensional, autonomous CNN Wave Computer. Appropriately connecting the cells I realized an electrical implementation, which is applicable to reproduce the phenomenon of long transient metastable oscillations. In this way I measured the phenomenon in the electrical circuit as well, experimentally demonstrating its robustness.

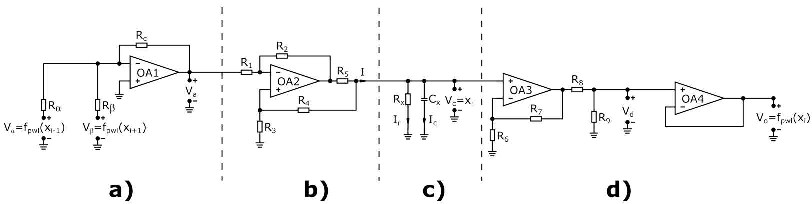

Figure 4: The schematic of a CNN cell built with the use of discrete components. The cell's functionality can be divided into four stages: summing amplifier (a), voltage controlled current source (b), inner state (c), and the realization of the piecewise linear output function (d) with a unity follower.

The circuit is built up by means of resistors, operational amplifiers and capacitances, the original version of the schematic was published in the Appendix of [26]. Figure 4 depicts the structure of a cell. Altogether 16 cells were built on a prototyping board, in this way we measured the phenomenon at different sizes of the ring with the reconfiguration of the inter–cell lines. The initial states were set with a switching circuit at every cell's V_c node; the switching circuits were uniformly controlled by a function generator. The resulting oscillation was recorded at node V_c (inner state) and V_o (output) of the cell numbered one.

4 Application of the results

The scope of the first and the second thesis group (object and event recognition, detection of complex movement) covers a wide range of possible applications. Inside mobile robotics, numerous unsolved (or just partially solved) problems exist, where a more efficient solution (compared to classical image processing) could be advantageous. Good examples are the tasks of the recent DARPA Challenge. In the case of walking on a rough surface, if we could tell some critical features of the ground just before putting the foot down, then we can stabilize the balance of the robot itself. In the case of climbing up a ladder in an industrial environment, a sensor array mounted on the foot can measure the outlines and characteristics of the rungs (surface, slope, accurate position) just before the step, resulting the reliable realization of the planned movement.

I have analyzed different situations in simulation as well as in real hardware measurement, when a sensor array supposedly mounted on the foot of a robot detects an unexpected salient object, or an unexpectedly steep slope, or an other moving object. In these cases the system has notified the central movement controlling unit with a "STOP" command. I have created a simulation environment, in which an autonomous mobile robot tries to get a predefined point in the changing environment with other moving objects. On the basis of the measurements of the distance measuring infrared sensor array mounted on the front, the agent tries to avoid adaptively the other objects in order to get the end point without collision.

In the case of the third thesis group (metastable periodic oscillation), beyond the detailed analysis of the oscillation we can expect information representation and processing (due to the biological motivation, for example [27], [28], [29]). Series of different waveforms and/or frequencies could identify a (quasi-)periodic series of phenomena/events; or a metastable oscillation could encode an engram in the memory with appropriate architecture. These examples try to mimic the information processing and representation observed or supposed in biology.

I have done other simulations with a slight modification of the computing architecture presented in Thesis 3. The objective was the detection of periodic oscillations with different patterns and speed (frequency): if the system got the desired signal-sequence on its input terminal, then the metastable oscillation became stabilized; however in the case of other sequences the waveform went wrong or the inner state of the system converged to a stable equilibrium point.

5 Acknowledgements

I have to say “thank you”. I could not have realized my studies during the years without the encouragement and help from others.

First of all I would like to thank *Professor Tamás Roska*, for his guidance and support during my studies, who quickened me with his honest enthusiasm hearing the news about the working circuit from Siena. I am thankful for the emphasizing of the intense work’s necessity. He encouraged us to devote time countlessly to the research.

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During the third year, I spent four months at the circuit-theory group of the University of Siena, where the circuit measuring metastable oscillations was prepared, and I was absorbed in the details of the equilibria's computation. I am grateful to *Professor Mauro Forti*, *Assistant Professors Mauro Di Marco*, *Massimo Grazzini* and *Luca Pancioni*.

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6 Publications

6.1 The author's journal publications

[1] **M. Koller** and Gy. Cserey, "Spatial-temporal active wave computing using infrared proximity array," *International Journal of Circuit Theory and Applications*, vol. 40, no. 12, pp. 1209–1218, 2012.

[2] M. Forti, B. Garay, **M. Koller**, and L. Pancioni, "Long transient oscillations in a class of cooperative cellular neural networks," *International Journal of Circuit Theory and Applications*, 2014.

[3] A. Horváth, **M. Koller**, A. Stubendek, and T. Roska, "Spatial-temporal event detection via frameless cellular wave computing – a review," *Nonlinear Theory and Its Applications*, 2014. accepted.

6.2 The author's international conference publications

[4] A. Tar, **M. Koller**, and Gy. Cserey, "3D geometry reconstruction using large infrared proximity array for robotic application," in *Proceedings of IEEE International Conference on Mechatronics, ICM 2009*, (Malaga, Spain), 2009.

[5] **M. Koller** and Gy. Cserey, "CNN computational abilities of large infrared proximity arrays," in *Proceedings of the 12th IEEE International Workshop on Cellular Neural Networks and their Applications, CNNA 2010*, (Berkeley, CA), 2010.

[6] M. Forti, B. Garay, **M. Koller**, and L. Pancioni, "An experimental study on long transient oscillations in cooperative CNN rings,"

in *Proceedings of the 13th IEEE International Workshop on Cellular Neural Networks and their Applications, CNNA 2012*, (Torino, Italy), 2012.

[7] **M. Koller**, "3D spatio-temporal movement detection with adaptively tuned 2D active sensorarray," in *Proceedings of the IRUN Winter School on Nonlinear Dynamics in Cellular Wave Computing*, (Budapest, Hungary), 2013.

[8] M. D. Marco, M. Forti, B. Garay, **M. Koller**, and L. Pancioni, "Multiple metastable rotating waves and long transients in cooperative CNN rings," in *Proceedings of the European Conference on Circuit Theory and Design, ECCTD 2013*, (Dresden, Germany), 2013.

[9] **M. Koller**, A. Horváth, and T. Roska, "Frameless computing for spatial-temporal events," in *Proceedings of the European Conference on Circuit Theory and Design, ECCTD 2013*, (Dresden, Germany), 2013.

[10] **M. Koller** and T. Roska, "Activation light pattern helps detection," in *Proceedings of the 14th IEEE International Workshop on Cellular Neural Networks and their Applications, CNNA 2014*, (Notre Dame, IN), 2014.

[11] **M. Koller** and Gy. Cserey, "Uncertain ground detection by CNN based infrared proximity arrays," in *Proceedings of the 14th IEEE International Workshop on Cellular Neural Networks and their Applications, CNNA 2014*, (Notre Dame, IN), 2014.

6.3 The author's other publications

[12] M. Forti, B. Garay, **M. Koller**, and L. Pancioni, "Floquet multipliers of a metastable rotating wave," Tech. Rep. 2013-2, Department of Information Engineering and Mathematical Sciences, University of Siena, 2013.

[13] **M. Koller** and T. Roska, "Frameless spatial–temporal event detection via lighting activation," Tech. Rep. JLR – 4 / 2013, The Jedlik Laboratories, Faculty of Information Technology and Bionics, Pázmány Péter Catholic University, 2013.

6.4 Essentially connected publications to the dissertation

[14] T. Roska and Á. Zarándy, "Proactive, adaptive, cellular sensory-computer architecture via extending the CNN univesal machine," in *Proceedings of the European Conference on Circuit Theory and Design, ECCTD 2003*, (Krakow, Poland), 2003.

[15] A. Horváth and T. Roska, "Frameless spatial-temporal event detection via delay-templates," Tech. Rep. JLR – 2 / 2013, The Jedlik Laboratories, Faculty of Information Technology and Bionics, Pázmány Péter Catholic University, 2013.

[16] B. Molnár and M. Ercsey-Ravasz, "Asymmetric continuous-time neural networks without local traps for solving constraint satisfaction problems," *PLoS ONE*, vol. 8, 2013.

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