The Kinetic Basis of Morphogenesis

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Abstract

It has been shown recently (Shalygo, 2014) that stationary and dynamic patterns can arise in the proposed one-component model of the analog (continuous state) kinetic automaton, or a kinon for short, defined as a reflexive dynamical system with active transport. This paper presents the extensions of the model, which increase further its complexity and tunability, and shows that the extended kinon model can produce spatio-temporal patterns pertaining not only to pattern formation but also to morphogenesis in real physical and biological systems. It indicates the possible applicability of the model to morphogenetic engineering and robotics.

Introduction

In his seminal paper on morphogenesis, Alan Turing demonstrated (Turing, 1952) that different spatio-temporal patterns can arise due to instability of the homogeneous state in reaction-diffusion systems, but at least two species are necessary to produce even the simplest stationary patterns.

It has been shown recently (Shalygo, 2014) that stationary and dynamic patterns can arise in the proposed one-component model of the analog (continuous state) kinetic automaton, or a kinon for short, defined as a reflexive dynamical system with active transport. The proposed model stems from a number of existing models of complex dynamical systems, and the following in particular:

- **Cellular Automata (CA)** conceived in 1950's by John von Neumann and Stanislaw Ulam.
- **Coupled Map Lattices (CML)** proposed in 1985 by Kunihiko Kaneko as a paradigm for the study of spatio-temporal complexity.
- **Lattice Gas Automata (LGA)** introduced in 1986 by Frisch et al and Stephen Wolfram independently for the modeling of fluid dynamics.
- **Lattice Boltzmann Model (LBM)** evolved from LGA and attracting growing popularity in Computational Fluid Dynamics (CFD) and other fields (Chopard et al, 2002).

Nevertheless, a decisive impetus for the kinon model was given by Konrad Zuse’s *net automaton* (Zuse, 1969) and Gordon Pask’s *diffusion network* (Pask, 1961) [Fig.1]. The central idea behind these networks is that nodes of the network are connected reciprocally with the lines that have transport and storage functions. This is in sharp contrast to the conventional view on network links as passive elements.

None of the existing models can be applied to Pask’s diffusion networks; therefore a new generation of topology and state space invariant models with active links is needed.

![Fig.1 Dynamic systems with active transport](image)

The kinon model, introduced in the previous paper and outlined in the next paragraph, was a trial step in this direction. This paper presents the extensions of this model, increasing further its complexity and tunability, and shows that the extended kinon model can produce spatio-temporal patterns pertaining not only to pattern formation but also to the process of morphogenesis in real physical and biological systems.

Background

The majority of the existing models are discrete time networks, in which values assigned to nodes and representing their current state are updated synchronously by some transformation. According to the type of transformation, they can be divided in two main groups: functional and relational.

**Functional transformation** maps a set of input values onto a single (scalar) output value - a new state of the node, which is relayed or fanned out to all output links. Formally, functional transformation is a many-to-one map \( F: Q^{\times 1} \rightarrow Q \), where \( Q \) is a set of states of the node and its \( k \) neighbors [Fig.2a].

**Relational transformation** maps a set of input values onto a set (vector) of output values of the same dimension, therefore it is homomorphism or a structure preserving (one-to-one) map of the form \( R: Q^{\times 1} \rightarrow Q^{\times 1} \) [Fig.2b].

![Fig.2 Feynman diagrams of state transformation](image)
The difference stems from different model structures. In functional models, the state of a cell is represented by a scalar value \( q_0 \) [Fig.3a]. In relational models, it is a vector \( \{q_0, q_1, \ldots, q_k\} \) associating the first component with a cell and the other ones with its \( k \) neighbors [Fig.3b]. Contrary to functional models, the value \( q_0 \) is not observable to the neighbors of the cell. The values \( q_1, \ldots, q_k \) represent the feedback (observables) of the cell and reside in the links responsible both for information propagation and storage. It implies the dualism of relational models, reincarnating as autonomous cells during collision or autonomous links during propagation.

The model represented in Fig.4 was elaborated with having in mind Rosen’s Modeling Relation (Rosen, 1991) as well as Kauffman’s autonomous agent doing its own work-constraint cycle (Kauffman, 2000).

![Fig.3 Structure of functional (a) and relational (b) models](image)

![Fig.4 Kinon State-Transition Structure](image)

![Fig.5. Schematic diagram of the basic kinon model](image)
Since all operators are relational transformations or morphisms, a kinon cycle can be also represented using a category theory notation. The diagram in Fig.6 gives a concise overview of the transformation sequence and usage of storage in encoding (ε) and decoding (δ). Categorical system theory (Louie, 1983) and Robert Rosen’s fiber space approach to pattern generation (Rosen, 1981) provide a very promising mathematical language for further formalization of the kinon model and its applications.

![Categorical kinon cycle diagram](image)

An isolated kinon, in which respective input and output buffers are looped, is possible but the collective behavior of kinons organized in networks is far more interesting. Formally, a kinon network is a balanced digraph, i.e. a directed graph in which the in-degree and out-degree of every vertex vᵢ representing one kinon, are equal: \(d^+(v_i) = d^-(v_i)\). A balanced digraph is said to be regular if all nodes have the same in-degree and out-degree. Zuse’s net automaton and Pask’s diffusion network, shown in Fig.1, exemplify regular and irregular kinon networks. Regular kinon networks, considered further, can be described by a node degree \(d\) and lattice width \(w\) (or a number of nodes \(N\)).

**Model extension incentives**

It was shown in the previous paper that relational approach and innate tunability of the model, i.e. the ability to be controlled by a smooth variation of one or more real-valued parameters, dramatically increase the complexity of its behaviour in comparison to continuous cellular automata. Nevertheless, the only tunable block in the basic model is the modulator, while other blocks are firmly hardwired. Encoding and decoding blocks, performing although trivial but very important transformations, also can be made tunable via the elaboration of their circuitry, and these enhancements may have crucial consequences for the model’s dynamics.

According to Robert Rosen, encoding is closely related to the problem of measurement and can be stated by the following propositions (Rosen, 1978):

- **The only meaningful physical events which occur in the world are represented by the evaluation of observables on states.**
- **Every observable can be regarded as a mapping (or encoding) from states to real numbers.**

This view is in line with the approach to measurement of the American psychophysicist Stanley Stevens who defined measurement as ‘the assignment of numerals to objects according to a rule’ (Stevens, 1946). Initially, he identified four levels of measurement defined by groups of scale invariant mathematical transformations: nominal, ordinal, interval and ratio, but later added another scale type, log-interval (Stevens, 1959). Following Stevens invariance scheme to its conclusion, ratio is not the highest level of measurement. The ratio scale has one fixed point (‘zero’) and the choice of the value of ‘one’ is essentially arbitrary. An absolute level of measurement can be obtained if the value of ‘one’ is fixed as well. One example of an absolute scale is probability, where the axioms fix the meaning of ‘zero’ and ‘one’ simultaneously.

The kinon model was derived from LBM model based on statistical mechanics, nevertheless it is fully deterministic. It equates the value of ‘one’ to the total amount of storage and inflow in the kinon, but it is invariant only during the current cycle; therefore a scaling step of encoding is related to a ratio scale. On the other hand, a scaling block transforms absolute (raw) input values corresponding to a nominal scale. The usage of other scales or evaluation methods in encoding may contribute to the overall complexity of the model’s behaviour.

For that purpose, additional structural elements corresponding to electronic analog filters can be added to the encoder, which will process raw input values (observables) before scaling. Such filter can be treated as a meter evaluating input values via some nonlinear map, e.g. logarithmic or other function with a domain and codomain in \(\mathbb{R}^+\). It will be a direct implementation of the Rosen’s treatment of measurement as ‘a mapping from states to real numbers’, or formally \(f : S \rightarrow \mathbb{R}\).

Another interesting option is the usage of a low-pass filter with memory known as a leaky integrator. A physical example of a leaky integrator is a bucket of water with a hole in the bottom. The rate of leakage is proportional to the depth of water depending on the difference between input and “leak” rates (hence the name). A very simple discrete time implementation of a leaky integrator is shown in Fig.7, where \(I'\) stands for an input and \(P\) for a potential, which depends on the output in the previous time step and plays the role of water in a leaky bucket or short-term memory, which fades without reinforcement. This is akin to a moving average but does not require data buffering, which is very costly in computational and memory usage terms.

![Discrete time leaky integrator (λ-filter)](image)

Leaky integrators find their use in the neural and cognitive modeling (Graben et al, 2008) and modeling of systems with anticipation property (Makarenko et al, 2007). An anticipatory system is a system that contains an internal predictive model of itself and its environment, which allows it to change the current instant state in accordance with the model’s predictions pertaining to a later instant (Rosen, 1985).
A leaky integrator is, perhaps, the simplest model capable of predicting the future state of a system and the easiest way to introduce a field approach in the kinon model. It can be implemented by linking additional values to input buffers and storage, which will represent the channel potentials and play the role of local curvature or space. In this case, potentials will be influenced by input flow and, in their turn, influence output flow, representing matter. This is analogous to the famous quote by John Wheeler, the Nobel physicist: “Matter tells space how to curve and curved space tells matter where to move”.

The usage of cut-off (threshold) filters for the elimination of unwanted marginal values or simulation of surface tension would be also beneficial for the overall model nonlinearity.

**Extended model**

A gathering block of the encoder was augmented by the embedding of λ-filters in all input and storage channels. They are leaky integrators with a common tunable real-valued control parameter λ in a unit range, representing a memory “leak” rate. Scaling block was enhanced by the incorporating of ψ-filters which transform input absolute values via a nonlinear function. The nonlinearity is vital here because modulation is scale invariant. This operation is similar to gamma-correction used in image processing for the adjustment of pixel intensity values according to human visual perception. The letter ψ is frequently used as a symbol of psychology and perception, and therefore was chosen for the name of the filter. The introduced filters are shown in Fig.8 and highlighted by a peach color.

![Fig.8 Schematic of the tunable encoder](image)

Similarly, a decoding module, consisting of the rescaler and scatterer, was enhanced by adding two new kinds of analog filters shown in Fig.9. θ-filters truncate rescaled absolute output values below a threshold before scattering them into output buffers. They are tuned by a common real-valued control parameter θ in the range [0, Θ], where Θ is much less than the total quantity of the network. It is used for the simplistic simulation of fluid cohesion due to surface tension.

![Fig.9 Schematic of the tunable decoder](image)

Another novel filter, shown in Fig.10 in more detail, is analogous to λ-filter, i.e. a leaky integrator, but is a little different. Similar to a conventional leaky integrator, it integrates values obtained on different time steps, but in this case, both time steps take place during the same cycle. A tunable parameter η defines here not a storage ‘leak’ rate but a share of the input storage value not participating in distribution (decoding) and remaining in the storage. In medicine, a small passage which allows movement of fluid from one part of the body to another is called a shunt, so a shunting integrator is a more proper name for such a filter. It is used for the simplistic simulation of fluid viscosity, a quantitative measure of fluid resistance to flow drag, generally denoted by η. Its influence is similar to damping in mechanical systems, although it is not based on energy loss. Nevertheless, a damper might be another “telling” name for the η-filter.

![Fig.10. Shunting integrator (η-filter)](image)

It will be demonstrated further that these quite numerous but seemingly marginal schematic extensions have far more influential and diverse ramifications on the model’s dynamics than it might be expected.
Results

All results presented further are obtained using the simplest kinetic map: \( y = \text{Max}[0, 1 - \kappa x] \). It was demonstrated in the previous paper that this map, despite its simplicity, exhibits highly complex behaviour with phase transitions. It has a single real-valued control parameter \( \kappa \), which substantially simplifies the description of the parameter space and clarifies the influence of other parameters on the morphology of generated patterns.

Since this paper is aimed to show the applicability of the kinon model to morphogenesis, the evolution of the kinon network always starts from a ‘singularity’ state, corresponding to a zygote state in biological morphogenesis. It means that only one kinon has a non-zero storage equal to the total quantity (energy) of the network. This value is set to 20 000 for a 200 x 200 square grid, which is equivalent to 0.5 average value per a kinon visualized as a grey color in a greyscale image. It never changes during the evolution of the kinon network because quantity conservation is a staple feature of the model.

Apart from kinetic map parameters in the basic model, the extended model has a set of additional parameters \( \{\lambda, \psi, \eta, \theta\} \) controlling the introduced filters. The parameters \( \lambda, \eta, \theta \) are real-valued non-negative numbers equal to a zero by default, while \( \psi \) is a function with characteristic parameters. The latter parameter is equal to the identity map \( \text{Id} \): \( y = x \) if another is not specified.

It is not surprising that the most significant parameter is \( \lambda \) because it controls internal potentials relating to kinon ‘memory’ or ‘anticipation’ properties. Just two parameters, \( \kappa \) and \( \lambda = 1 \), are sufficient for the appearance of circular or square waves not observed in the basic model. The increment of the parameter \( \kappa \) results in the change of shape and length of the wave and the speed of its final fission into four solitons [Fig.11]:

\[
\begin{align*}
\kappa = 2 & \quad \bullet \quad \bullet \quad \bullet \quad \bullet \\
\kappa = 3 & \quad \bullet \quad \bullet \quad \bullet \quad \bullet \\
\kappa = 4 & \quad \bullet \quad \bullet \quad \bullet \quad \bullet
\end{align*}
\]

Fig.11 Two-dimensional kinetic waves (\( \lambda = 1 \))

The adjustment of scattering \( \theta \)-filters, which can be related to the change of surface tension, induces the appearance and development of manifold shapes. Using the same parameters \( \kappa \) and \( \lambda \) as above and the parameter \( \theta = 2 \), one can obtain dynamical patterns reminding the embryonic development of a ‘tetrapod star fish’ or a growth of a four-fold crystal [Fig.12]. The increments of the parameter \( \kappa \) result here in dramatic changes of the final morphology of the creature.

\[
\begin{align*}
\kappa = 2 & \quad \bullet \quad \bullet \quad \bullet \\
\kappa = 3 & \quad \bullet \quad \bullet \quad \bullet \\
\kappa = 4 & \quad \bullet \quad \bullet \quad \bullet
\end{align*}
\]

Fig.12 Kinetic morphogenesis (\( \lambda = 1 \ \theta = 2 \))

In all these examples, development starts from a single cell and goes through the stages which can be related to the oocyte, blastula, gastrulation and organogenesis stages in real biological morphogenesis. Due to the parameter \( \theta \), the developmental process finally stops at the state of a stable kinetic equilibrium corresponding to a mature full-fledged stage or stasis, which will be examined in the next paragraph in more detail.

For brevity, further demonstrations will show only the final stable state accompanied by a drawing of contour lines (isolines) after every 20 time steps. The results shown in Fig.13 demonstrate the influence of \( \eta \)-filter on the size and shape. According to a ‘damping’ nature of the \( \eta \)-filter, the final shape becomes more and more compact after the increment of this parameter.

\[
\begin{align*}
\eta = 0 & \quad \bullet \quad \bullet \quad \bullet \\
\eta = 0.1 & \quad \bullet \quad \bullet \quad \bullet \\
\eta = 0.2 & \quad \bullet \quad \bullet \quad \bullet \\
\eta = 0.3 & \quad \bullet \quad \bullet \quad \bullet \\
\eta = 0.4 & \quad \bullet \quad \bullet \quad \bullet \\
\eta = 0.5 & \quad \bullet \quad \bullet \quad \bullet
\end{align*}
\]

Fig.13 \( \eta \)-patterns (\( \kappa = 3 \ \lambda = 0.5 \ \theta = 1 \))

The influence of \( \psi \)-filter, which is closely related to the earlier discussed measurement problem and perception, cannot be so easily estimated. Similar to a kinetic map, it is a functor rather than function, i.e., it maps functions but not values. The outcomes of the application of some \( \psi \)-filters under the same other parameters are shown in Fig.14.

\[
\begin{align*}
y = x & \quad \sqrt{x} \\
\sqrt[3]{x} & \quad \log_2 x + 1 \\
\log_4 x + 1 & \quad \arctan x
\end{align*}
\]

Fig.14 \( \psi \)-patterns (\( \kappa = 3 \ \lambda = 1 \ \theta = 1.5 \ \eta = 0.1 \))

It is evident that this filter affects not only the size but also the morphology of the resultant shape. Due to increasing nonlinearity of the function, the growing nucleus develops a branching structure that becomes more stretched and pointed.
The shown patterns were obtained using a square grid with four nearest orthogonal neighbors, i.e. a four-degree \((d=4)\) network. They have a distinct four-fold symmetry imposed by the underlying grid but preferential directions are aligned along the diagonals of the axes. This phenomenon is related to the kinetic fission demonstrated in Fig.11, but is yet unexplained and requires further investigation.

The kinon model is topology invariant and allows arbitrary network structure including meshes and random networks. A \(d=4\) network was chosen only for the ease of computation and visualization. A square grid with eight nearest neighbors \((d=8)\) requires extra computation per a cycle but is also readily visualized by a greyscale image.

Fig.15 demonstrates \(\psi\)-patterns in a \(d=8\) network. The main difference from the previous experiment is the change of the preferred growth directions from diagonal to orthogonal. Besides, some new features of the body plan have appeared. Branches now may have not only pointed tips but also cleft and undulating ones.

![Fig.15 d=8 ψ-patterns (κ=8 λ=0.8 θ=0.3 η=0.4)](image)

The increased network connectivity makes kinon dynamics less predictable and parameter changes usually affect both the size and shape. Fig.16 demonstrates the susceptibility of the shape to minor variations of a single parameter, which indicates possible amenability of the extended kinon model to genetic and other evolutionary algorithms.

![Fig.16 Kinetic metamorphosis (d=8 λ=1 θ=0.6)](image)

The collections of some characteristic kinon morphogenetic patterns obtained using \(d=4\) and \(d=8\) grids are shown in Fig.17.

![Fig.17 Panopticon of d=4 (left) and d=8 (right) kinon creatures](image)

Speaking about a network structure, it is essential to define its boundary conditions. In practice, one cannot deal with an infinite lattice, so a common approach is to assume periodic (or cyclic) boundary conditions, i.e. to embed a lattice in a torus. However for morphogenetic studies, a better solution is the correct choice of the grid size and model parameters sufficient for a full-fledged state. Another option is the imposing of artificial boundaries (borders) on the network for the study of bounded growth. Due to topological invariance, the kinon model allows simple implementation of boundary conditions by the permanent elimination of respective links in boundary kinons. The examples of bounded growth with different borders are shown in Fig.18.

![Fig.18 Bounded growth (d=4 κ=6 λ=0.8 θ=0.4 η=0.5)](image)

**Macrodynamic analysis**

The total quantity of the kinetic network, which can be considered as energy or mass, is always the same because the model is conservative by definition. However, the total amount of all kinon output buffers (related to external or kinetic energy) and the total amount of kinon storage (related to internal or potential energy) interchangeably fluctuate. This feature can be used in the quantitative analysis of the kinon network macrodynamics.

The simplest macrodynamic index termed as an exchange rate \(K_e\) is the ratio of the total value of all kinon output buffers to the total quantity of the network. It also can be interpreted as the ratio of the kinetic energy to the total energy of the network and is calculated as follows [Eq.1]:

\[
K_e = \frac{\sum_i^n \sum_j^k O_{ij}}{\Omega} \in [0, 1],
\]

where: 
- \(n\) - the number of kinons in the network;
- \(k\) - the number of neighbors of the \(i\)-th-kinon;
- \(O_{ij}\) - the \(j\)-th-output buffer value of the \(i\)-th-kinon;
- \(\Omega\) - the total quantity of the network.

Another macrodynamic index, also having a unit range and termed as a turnover rate \(K_t\), is a half of the ratio of the absolute change of all kinon buffers during the current cycle to the total quantity of the network [Eq.2]:

\[
K_t = \frac{\sum_i^n (|\Delta S_{ij}| + \sum_{j=1}^k |\Delta E_{ij}|)}{2\Omega} \in [0, 1],
\]

where:
- \(\Delta E_{ij}\) - the difference of respective exchange buffers \((i|j) - O_{ij}\) of the \(i\)-th-kinon;
- \(\Delta S_{ij}\) - the change of the \(i\)-th-kinon storage.
Even such simple macrodynamic indices can tell a lot about the current state and dynamics of the whole network [Fig.19]:

![Fig.19 Macrodymanics of one-dimensional kinon networks](image)

The exchange rate $K_e$ is depicted in a red color and turnover rate $K_t$ in blue. Fig.19a shows the dynamics in a chaotic state. Fig.19b demonstrates the transition from a nearly equilibrium state to a stable non-uniform one. Fig.19c displays an almost still picture after the collision of solitons, sharply contrasting to the macrodynamic indices, oscillating in a nearly full range. Fig.19d illustrates the spiking behaviour of these indices during the fission of the standing wave in two solitons after the change of the kinetic map, marked by a red vertical line, and the collisions of these solitons.

Macrodymanics of some morphogenetic patterns is represented in Fig.20. A green line marks the beginning of stasis and an orange line marks the time step when dendrite tips hitted the border.

![Fig.20 Kinetic macrodynamics of morphogenesis](image)

These indices supplement visual representation of the kinon network dynamics and are indispensable in cases when visualization is intractable or automation of parameter space exploration is needed, e.g. for the search of viable stable shapes. All demonstrated morphogenetic examples come to a matured full-fledged stable state (stasis) in which both macrodynamic indices reach a zero value. This condition can be used for the automatic identification of stasis.

**Discussion**

The shown results demonstrate that the extended model, employing only trivial math, is capable of producing complex patterns, some of which resemble crystal dendrites (crystals with a typical multi-branching tree-like form). Dendritic crystal growth is very common and may be illustrated by snowflake formation and frost patterns on a window.

In metallurgy, a dendrite is a characteristic tree-like structure of crystals growing during molten metal solidification. This dendritic growth has large consequences in regard to material properties. That is why much research has been devoted to the simulation of crystal growth, and one of the most employed approaches is a phase-field model. This approach lets avoid the explicit tracking of sharp phase boundaries by introducing an order parameter, or a phase field, which varies smoothly from -1 in the liquid to +1 in the solid across a narrow diffuse zone. This field converts the problem into a system of partial differential equations that govern the evolution of the phase and diffusion fields. Despite enormous advance in computational terms, a phase-field model, based on the Ginzburg-Landau equation, requires much harder computation in comparison to a kinon model, although it generates similar shapes [Fig.21].

![Fig.21 Phase field simulation of dendritic growth](image)

The kinon model was not tailored to simulate dendritic growth in melts, although it captures this phenomenon rather closely. It hints that the same underlying self-organizing principle, namely kinetic instability hypothesized in the previous paper, may govern morphogenesis in real physical and biological systems.

Furthermore, the shown resemblance corroborates the main thesis of this paper that anisotropic diffusion, usually regarded as anomalous, in fact is quite ubiquitous and can be harnessd in morphogenetic engineering. The kinon model proved to be able to produce complex shapes using very simple local interactions by the exchange of real-valued numbers, which can be regarded as the quantities of the elusive long-sought substance called morphogen. A large collective of kinons embodied in a robot swarm would gradually aggregate into dendritic or more complex structures by the exchange of such morphogen with the nearest neighbors. Contrary to diffusion-limited aggregation (DLA), this model generates totally deterministic but not random shapes.
Future work

All figures demonstrating kinon network states and dynamics [Fig.11-20] were obtained using a framework called KinonLab, developed by the author. It is implemented in Wolfram Mathematica® and currently supports one-dimensional (d2) and two-dimensional regular networks with von Neumann (d4) and Moore (d8) neighborhood [Fig.22].

The framework offers rich functionality for the visualization of kinon network dynamics and the tools for the step-by-step exploration of the network state. Current parameter values and the results obtained at every time step are cached in RAM, so the experiment can be replayed back and forth at high speed. Besides, the results of the whole experiment, including the history of parameter values, can be saved in a file for the posterior analysis and demonstration.

The main directions of the ongoing improvement include the support of two-dimensional hexagonal (d6) and three-dimensional regular grids, implementation of microanalysis for the in-depth exploration of a single kinon dynamics, tools for comparative analysis, data exchange, etc. The future developments of the framework will be aimed at the study of multi-component and arbitrary topology kinon networks.

Conclusion

The presented here extended kinon model demonstrates its high potential for structural elaboration and improvement and the need for deeper exploration and validation. The given formal definition clarifies some ambiguities of the previous description and provides a common language and terminology to facilitate its further development. The schematic diagrams of the kinetic automaton not only illustrate its operational structure (‘modus operandi’) but also show the directions of the possible implementation of the model with analog circuits. The proposed macrodynamic indices provide the expressive measures for the quantitative analysis of kinon network dynamics and the criteria for the automation of parameter space exploration.

The main aim of this paper is to demonstrate the applicability of the model to the problem of morphogenesis. Kinetic automata proved to be able to generate complex spatio-temporal patterns pertaining to the process of morphogenesis in real-world phenomena, e.g. dendritic growth during solidification in melts and embryogenesis in biology. It gives an opportunity to harness anisotropic diffusion due to the instability of kinetic exchange in complex dynamical systems. In respect to Artificial Life research, the most promising directions of the kinon model application are rapidly emerging fields of morphogenetic engineering (Doursat et al, 2013) and swarm robotics (Brambilla et al, 2013).

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