Autopoiesis and Image Processing I: Detection of image structures by using auto–projective operators

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Abstract

The theory of Autopoiesis attempts to give an integrated characterization of the nature of the living systems. This article explores the use of autopoietic concepts in the field of Image Processing. Two different approaches are used. The first approach assumes that the organization of an image is represented only by its grayvalue distribution. In order to identify autopoietic organization inside an images' pixel distribution, the *steady state Xor–operation* is identified as the only valid approach for an autopoietic processing of images. The effect of its application on images is explored. The second approach, presented in the related article *Autopoiesis and Image Processing II: Autopoietic–agents for Texture Analysis*, makes use of a second space, the A–space, as the autopoietic processing domain. This allows for the formulation of adaptable recognition tasks. Based on this second approach, the concept of autopoiesis as a tool for the analysis of textures is explored.

1 Introduction

The theory of *Autopoiesis*, developed by the Chilean biologists Humberto Maturana and Francisco Varela, attempts to give an integrated characterization of the nature of a living system, which is framed purely with respect to the system in and of itself. The term autopoiesis was coined some twenty five years ago by combining the Greek **auto** (self-) and **poiesis** (creation; production). The concept of autopoiesis is defined as ([1], p. 13):

> *'An autopoietic system is organized (defined as a unity) as a network of processes of production (transformation and destruction) of components that produce the components that:*
>
> *1. through their interactions and transformations continuously regenerate and realize the network of processes (relations) that produced them; and*

2. constitute it (the machine) as a concrete unity in the space in which they (the components) exist by specifying the topological domain of its realization as such a network.'

In other words an autopoietic system produces its own components in addition to conserving its organization. A network of local transformations produce elements, which maintain a boundary. This boundary captures the domain, in which the local transformations take place. In this context, *life* can be defined as autopoietic organization realized in a physical space. The autopoietic theory describes what the living systems are and not what they do. Instead of investigating the behaviour of systems exhibiting autonomy and the concrete implementation of this autonomy (i.e. the system structure), the study addresses the reason why such behaviour is exhibited (i.e. the abstract system organization). A complete material concerning the autopoietic theory (tutorials, study plan, bibliography, internet links, etc.) can be found in the Internet site *Autopoiesis and Enaction: The Observer Web* [2].

The autopoietic theory has been applied in diverse fields such as biology, sociology, psychology, epistemology, software engineering, artificial intelligence and artificial life. In this context, this article tries to explore the use of autopoietic concepts in the field of Image Processing.

Two different approaches will be used. These approaches differ in their interpretation of the domain of the processes. The first approach, presented in this article, assumes that the organization of an image is represented only by its grayvalue distribution. In order to identify autopoietic organization inside an images' pixel distribution, the *steady state Xor-operation* is identified as the only valid approach for an autopoietic processing of images. The effect of its application on images will be explored. The second approach, presented in the related article *Autopoiesis and Image Processing II: Autopoietic-agents for Texture Analysis*, makes use of a second space, the *A*-space, as an autopoietic processing domain. This allows the formulation of adaptable recognition tasks. Based on this second approach, the concept of autopoiesis as a tool for the analysis of textures is explored.

2 Recognition of image structures by using auto-projective perators

2.1 Autopoiesis and the Steady State Xor-Operator

At first, the question arises whether images by themselves preserve some kind of autopoietic organization. Because images generally are considered as static representations of real-world objects, but autopoiesis is constituted by a network of dynamic transformations, the image must be processed by suitable operators in order to reveal possible organizational principles. Thereby, the original image appears to be like a "frozen" state of its intrinsic dynamical processes. Two approaches are possible: the first approach assumes no relation between these dynamics and the real-world objects pictured in the image, in contrary to the second approach, which refers to the kind of features of real-world objects from which the dynamics are driven. As an example, textures are identified as such features for the second approach, which will be detailed in the related article *Autopoiesis and Image Processing II.*

This section is concerned with the first approach, i.e. image dynamics are restricted to the distribution of colors or grayvalues in the image. No reference is given to the pictured real-world objects. In order to ”melt” the image due to a possible intrinsic dynamic, an operator is searched with the following two essential properties:

1. The operator should be applied pointwise. Normally, image operators like the LAPLACE-Operator, the SOBEL-Operator or the median operator are applied to all image pixels, at once. But, as it was mentioned in the introduction, autopoietic systems constitute the domain of its realization. For an effective search of these domains, the size of them can not be predicted. Hence, the application domain of the operator must be balanced between pure local analysis (a pixel and its neighbourhood) and global analysis (all image pixels). Pre-defined image operators do not offer such a choice. By applying the local operation of the operator pointwise and repeating this, the effect of a local operation is spread out over the image, and more complicated patterns of interaction are possible. As a reminder for a similar procedure in genetic algorithms, we refer to this manner of image operator application as *steady state image processing*.

2. The requirements of autopoietic organization detection include the requirements for rejecting this hypothesis as well. The operators we are interested in, must be able to recover the original image, at least to some degree, or with a probability remarkable greater than zero. If the image dynamics appears to be not autopoietic, the process must be able to fail, i.e. to leave the image as it was at the beginning of the processing.

Speaking more formally, let $\oplus$ be the image operation, which is applied pointwise. A sequence of points $p(T)$ is generated randomly, where $p(T)$ is the point choosen at timestep T. Also, $g(p)$ is the grayvalue of point p in the image. In this article, all points are equally possible in the random sequence. Non-adjacent points in the sequence could be neighbours in the image. Assume $p(T_1)$ and $p(T_2)$ are such a pair of points with $T_1 < T_2$. Then, while applying the operator $\oplus$ to the point $p(T_1)$ and its neighbours, $p(T_2)$ is also affected. But later, at step T_2, the application of the operator onto the modified $p(T_2)$ also affects $p(T_1)$. Our demand is to have a non-zero probability of reproducing $p(T_1)$'s original value by this procedure. This demand can be fulfilled by using the Xor-operation. This can be verified by considering the following three properties of the Xor-operation, if it is used as such an operation $\oplus$:

Commutativity:	$a \oplus b = b \oplus a$
Associativity:	$(a \oplus b) \oplus c = a \oplus (b \oplus c)$
Auto-projectivity:	$(a \oplus b) \oplus b = a$

The third property explains the fundamental role of the Xor-operation in data coding, as well as for sprite algorithms in computer animations. It can be easily shown that the Xor-operation and its negate (Not-Xor) are the only binary operations fulfilling all of these three properties[1]. Hence, for detecting autopoietic organized structures in an images' grayvalue distribution, it is necessary to apply the Xor-operation in a steady

[1] From group theory, each finite ABEL-ian group is the product of cyclic groups Z_{r_i}, hence its order the product of the r_i. For the group given by $\oplus$, all r_i are 2, what refers to the Xor operation. But consider the appendix for a more elementary proof.

(a) (b) (c)

Figure 1: A face image (a), the result of the repetitive application of the above algorithm after 1000 ”generations” (b), and a dilated version of the second image (c).

state manner. The resulting algorithm is as simple as follows:

Repeat for a given number of times:

1. Take an arbitrary pixel p_1 and choose one of its neighbours p_2.
2. Replace $g(p_2)$ with $g(p_1) \oplus g(p_2)$.

2.2 Discussion

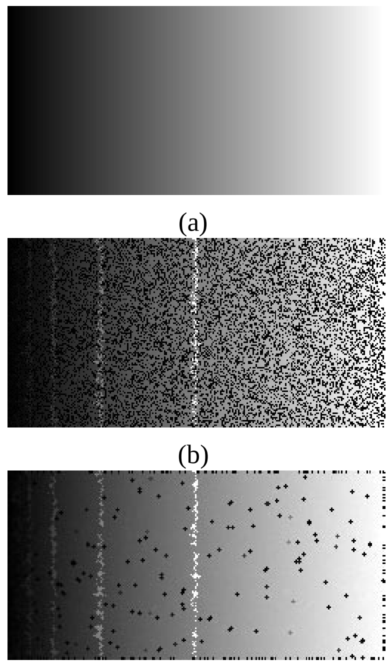
For a further understanding of the effect of this operation consider figure 1. There, a face image (a), the result of the repetitive application of the above algorithm after 1000 ”generations” (b), and a dilated version of the second image (c), are shown. A white circular contour around the phong on the forehead can be seen[2]. This phong is a result of the lighting conditions during image acquisition. Phongs are a major problem for facial recognition tasks. By using the Xor-operator, they can be easily detected. But where does this circle around the phong come from?

To understand this, consider the effect of the same procedure onto a gradient image (figure 2). Also, the original image, the image after 1000 steps and its dilated version are shown. A white line appears in the middle of the image, around the grayvalue 128, but not exactly in this position. The explanation of this effect reminds one of another famous role of the Xor-operation as a benchmark for neural networks. The Xor-operation is not linearly separable. A neural network needs a hidden layer to learn the Xor-operation. The gradient image helps to illustrate this fact. If p_1 has a grayvalue of 0, then $g(p_1) \oplus g(p_2)$ equals $g(p_2)$, i.e. for low grayvalues, the Xor-operator tends to be the identity transformation. If $g(p_1)$ is the maximum grayvalue (255 in our case), $g(p_1) \oplus g(p_2)$ equals the inverse of $g(p_2)$, i.e. for high grayvalues it tends to be the inverting transformation. But it is not possible to go linearily from the identical transformation to the inverse transformation! Hence, we must have a non-linear anomaly between these two extremes. This anomaly is represented by the white line. Grayvalues around 128 tend to complete each other to the maximum grayvalue 255. The white line appears to be a boundary between a gradual descent from the maximum to the minimum grayvalue. Even boundary exchange processes can be identified this way, i.e. the boundary must be a closed one to prevent the Xor-operations from pocketing it. Hence, the Xor-operation is able to detect the gradient-descending organization

[2]For another “face example”, an animated QuickTime movie can be downloaded at http://vision.fhg.de/ipk/koeppen/xor.mov.

of grayvalue distributions in an image, no matter how this descent is structured (line-likely, circularily, linearily ascending or faster). But also, the white line is a boundary separating interior from outside.

To summarize the foregoing discussion: For the detection of the autopoietic organization of a grayvalue distribution, or better, the actual grayvalue distribution as a ”frozen” state of a possible autopoietic organization, the Xor-operator must be applied in a steady state manner, i.e. on a sequence of randomly chosen image points. Only the Xor-operator has the property of auto-projectivity, which ensures a non-zero probability of regenerating the original image. This is true as long as grayvalues are represented by binary numbers. The application of the Xor-operator onto images yields phong-like structures, which prove to be the only organizational issues of intensity ordering in an autopoietic manner.



(c)

Figure 2: A gradient image (a), the result of the repetitive application of the above algorithm after 1000 ”generations” (b), and a dilated version of the second image (c).

3 Conclusions

The use of autopoietic concepts in the field of Image Processing was explored. The approach, which is presented in this article, assumes that the organization of an image is represented only by its grayvalue distribution. In order to identify autopoietic organization inside an images’ pixel distribution, the steady state Xor-operation was named as the only valid approach for an autopoietic processing of images. The application of the Xor-operator onto images yields phong-like structures, which prove to be the only organizational issues of intensity ordering in an autopoietic manner. These first results are encouraging enough to continue this work. It was shown, that the search for autopoietic organization in grayvalue distributions of images reveals new structural properties of them, which are hardly to find by means of other image processing operations. Further research on the Xor-operator should explore the role of the probability distribution for the random sequence of pixel positions. Also, other ordering relations in the image than the conventional intensity ordering should offer new application tasks for the Xor-operator.

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References

[1] Varela, F.J. (1979), *Principles of Biological Autonomy*, New York: Elsevier (North Holland).

[2] Whitaker, R. (1996), *Autopoiesis and Enaction: The Observer Web*, http://-www.informatik.umu.se/ rwhit/AT.html

Appendix

Proof for Xor being the only auto–projective operation

Be A a finite set with n elements, and $\oplus$ an operation: $\oplus : A \times A \to A$ with the following properties (a, b and $c \in A$):

1. Commutativity: $a \oplus b = b \oplus a$.
2. Associativity: $(a \oplus b) \oplus c = a \oplus (b \oplus c) = a \oplus b \oplus c$.
3. Auto–projectivity: $(a \oplus b) \oplus b = a$.

Theorem. The number n of elements of A is a power of 2.

Proof. The properties of $\oplus$ immediately imply the following two (simple) lemmas.

Lemma 1. There is a unique neutral element 0 in A, i.e. $a \oplus b = a$ iff $b = 0$. For all $a \in A$, $a \oplus a = 0$. In particular, $(A, \oplus)$ is a group.

Lemma 2. $a \oplus b = c$ implies $b \oplus c = a$ and $c \oplus a = b$.

We assume M to be a subset of A closed under $\oplus$, with $|M| < |A|$. An example for such a closed subset is the set $\{0, b\}$ with b an arbitrary element of A.
Be a an element of A, which is not in M. Then, we construct the set N by

$$N = \{n_i \mid n_i = m_i \oplus a, \ \ m_i \in M\}.$$

Note, that $a \in N$ because each closed subset M must contain the neutral element.
First, it follows $M \cap N = 0$. If there would be a $n_i = m_k$, then it would follow $n_i = m_i \oplus a = m_k$, and, by Lemma 2, $m_i \oplus m_k = a$, i.e. $a \in M$, because M is closed under $\oplus$. This is a contradiction, for $a \notin M$ was assumed.
Also, $|M| = |N|$, because from $n_i = n_j$ it easily follows that $m_i = m_j$ and vice versa.
Now, as essential part of the proof, we show, that the new set $M \cup N$ is closed under $\oplus$, i.e.

For any elements u, v in $M \cup N$ we have $u \oplus v \in M \cup N$.

There are four cases to consider (m_l assigns an element of M, n_l an element of N):

1. $u, v \in M$: Then, $m_i \oplus m_j \in M$ by M being closed under $\oplus$.
2. $u, v \in N$: Then, $n_i \oplus n_j = (m_i \oplus a) \oplus (m_j \oplus a) = (m_i \oplus m_j) \oplus (a \oplus a) = m_i \oplus m_j \in M$ by property 1, 2, Lemma 1 and M being closed under $\oplus$.
3. $u \in M, v \in N$: Then, $m_i \oplus n_j = m_i \oplus (m_j \oplus a) = (m_i \oplus m_j) \oplus a = m_k \oplus a \in N$ by definition of N, property 2 and M being closed under $\oplus$.
4. $u \in N, v \in M$: This equals case 3 by commutativity.

If there is a subset of A closed under $\oplus$ of size m, there is a closed subset of size $2m$, too. Because there is such a subset of size 2, there is also a maximum closed subset of size 2^k with $k \leq \log_2 |A| < k + 1$. If $k < \log_2 |A|$, then, there is an $a \in A$, which is not in the maximum closed subset of size 2^k. Hence, a closed subset of A can be constructed, with $2^{k+1} > |A|$ elements. Clearly, this is a contradiction, hence $k = \log_2 |A|$. The size of A has to be a power of 2.
The "bit–wise" Xor operation is an example for such an operation. By renumbering the elements of A, each other $\oplus$ can be identically mapped onto this variant of the Xor operation.

Hence, Xor and this variants are the only auto-projective operations.