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The Interductive Modification Model as a Neuromathematical Approach to Describe the Development of Neural Structures and their Interdependence with Environment

Waldemar Schwarzkopf

Abstract

This paper presents the elaboration of the Interductive Modification Model (IDM model) as an approach to understand the interdependence between neural systems and their environment. As a starting point, the Integrated Information Theory (IIT) as well as considerations in the field of neuroanatomy and the development of artificial consciousness are used as boundary conditions for an interaction model between neural structures and the environment via reciprocal affection. In order to formulate the processes of creation and destruction of neural connections, therefore their development, the Matrical Situarics (MS) is used, especially the *classification function of affects*. The construction of the IDM model results as a consequent formulation of successively appearing affections, called *ducti*, between the environment and the neural structure, as well as a separated mutation of the neural structure itself. Furthermore, succession functions are adapted to the ducti in order to complete the continuous description of interdependence processes. Subsequently, both functional and ductive cycles are embedded into a multidimensional space, in which multiple process cycles can occur simultaneously. However, the interdependencies within the environment are not discussed here yet. In fact, the model treats anything outside a neural structure as its environment, which includes the own body or even other neural structures as well. Hence, it has been formulated to leave space for further adjustment and elaboration. Summarizing, the IDM model is evolved from already sophisticated and accepted models, as well as an abstract approach. Therefore, it represents a quite distinct description of neural development, whereas the precision can be scaled arbitrarily, if necessary. Moreover, it explains that consciousness can solely evolve by perception and also provides an explanation for the well-known mirror test.

1. Introduction.

Based on and motivated by the Integrated Information Theory, hereinafter IIT [1,2], the content of this article is the development of the Interductive Modification Model, hereinafter IDM model, which describes the influence of the environment on neural networks and their development. The model is elaborated using the classification function, which has been already developed [3]. This work aims to provide a theoretical construct which allows the formulation of the development of consciousness on a basic, neural level. This goal arises from the assumption that consciousness develops by itself if a suitable system is exposed to according circumstances, providing wide implications for development strategies, for instance in the field of artificial consciousness [4,5]. In order to elaborate the IDM model, the classification function is adapted to boundary conditions that allow perception and interaction with the environment. Such conditions are fundamental for the formulation of models and experiences in the qualia space, which represent essential components of consciousness according to several researches [1,6,7]. The classifications depend on fundamental elements of the analysis of effects, thus properties as well. Subsequently, a detailed depiction of neural network development is sketched. In the course of this, the IDM model focuses not on the states of the neural networks, but on their changes. The depicted transformations ultimately lead, including further general considerations, to the development of neural networks. The IDM model describes this development both as interactive with the environment as well as isolated from it.

Before the development of the IDM model is depicted, the IIT [2] and the essential aspects of the matrical situation, hereinafter MS [3], are to be presented briefly.

2. The Integrated Information Theory.

The IIT has already been discussed and expanded in several articles. All important foundations of this theory can be found in [1]. According to the purpose of this article, only the basic aspects of the IIT are repeated and some innovations are mentioned in order to guarantee a sufficient level of knowledge. In [2] all important aspects of the developed theory are summarized, as well as the following summary of the IIT: The theory represents a connection between consciousness and the states of the physical substance on which it is based. For this purpose, fundamental properties of the experiences are first identified and formulated as axioms. Using postulates, their realization is associated with certain properties of physical substance, which are following : existence, composition, information, integration and exclusion. The presented mathematical framework allows the description of fundamental consciousness as a consequence of the formation of neural network complexes. The theory provides the possibility of a qualitative and quantitative description of consciousness and explains several phenomena concerning brain functions. In addition, some specific predictions are also discussed in this article.

3. Essential elements of the matrical situarics.

The basic principle of MS is the consistency of the syntax of descriptions in all possible cases. This language differentiates between *finalities* as property carriers (*Finx*), properties or *attributes* ($Sit\eta_x$) and effects or *affects* ($Sit\varepsilon_x$), which are contained within a *situation* ($Sit\sigma$), as shown in (3.1). With the help of this initially simple concept, a flexible and versatile language has been developed. The instruments used in this article are limited to the interaction between two finalities, which can be traced back to the affects. Since these are dictated by attributes, the corresponding properties of the described objects can be determined using the interaction analysis. The required instruments are provided by the classification function $\boldsymbol{K}$, which classifies the affects according to three aspects (3.2). In addition to the pure *range R* of the affects, the *activation T* and the *affection* Φ are considered. The range is expressed as the sum of all elements connected by the affect. Activation describes the ability of an affect to induce its object to arise affects of itself. As a special case, *deactivation* describes the case that no activation takes place. During *transactivation*, affects from the initial object aim other objects, subsequently. Finally, affects carried out by the object can have an effect on the subject as well, which is interpreted as *reactivation*. Furthermore, affection describes the ability of an affect to change its object. As mentioned above, the latter two functions, which are used explicitly in this work, can be described in terms of the *compatibility* C, which in turn depends on the *basic degree of similarity Æ* and the *relevance vector* $\boldsymbol{r}$. The fundamental character of the relevance vector, which reduces all possible changes of a property into the two dimensions of *destruction* and *construction*, allows a detailed description of any process. In addition, perception is also formulated as a function of compatibilities between the perceiving subject and the perceived object. It is also referred as the *copula potential*, which is, in this case, identical to reactivation and thus is not described in detail. It is important to note that their equivalence solely occurs if all incoming affects are in fact percepted by the finality. Indeed, this framework condition is applicable in the viewed case, since deactivation does not contribute to neural development. The equivalence of these terms is used to develop the IDM model. All MS terms important for the analysis are summarized in chart 3.1 a and chart 3.1. b.

Chart 3.1 a: Summary of important definitions in the MS with basic formulations and explanations of the terms. The information is extracted from [3].

Term	Formalism and formula	Explanation
Finality	$Finx$	Most basic simplification of a description and property carrier in the MS.
Attribute	$Sit\eta$	Property of a finality.
Affect	$Sit\varepsilon$	Effect of a finality that depends on its attribute.
Situation	$Sit\sigma$	A matricially represented event, which describes a finality with its attributes and affects in each column, while these are arranged in raws.
Composed finalities	$Finx: \begin{pmatrix} Finx_1 \\ \dots \\ Finx_n \end{pmatrix}$	If finalities consist of individual parts, these sub-finalities are to be written in brackets after the meta-finality. Sub-finalities are called situational elements, while meta-finalities are called situational elements.
Situant symmetry	$Finx: \begin{pmatrix} Finx_1 \\ \dots \\ Finx_n \end{pmatrix} \; Sit\eta: \begin{pmatrix} Sit\eta_1 \\ \dots \\ Sit\eta_n \end{pmatrix}$	Changes to situational elements are automatically transferred to their counterparts within the same column, represented by indices.
Basal similarity grade	$Æ_{A,B} = \frac{\lvert E_A \cap E_B \rvert}{\lvert E_A \rvert + \lvert E_B \rvert}$	Degree of similarity between two meta-finalities as a function of their sub-attributes. It is calculated by dividing the set of common sub-attributes by the sum of all sub-attributes of both meta-finalities. E_A is the set of all attributes of finality A and E_B is the set of all attributes of finality B.
Relevance vector	$r = \begin{pmatrix} \delta \\ \kappa \end{pmatrix}$	Represents the two-dimensionally described change of an attribute through an affect. The first dimension is the destruction of the sub-attributes, δ. The second dimension is the construction of new sub- attributes, κ.
Destruction	δ	Has negative values and can be expressed either in integers, representing destroyed sub-attributes or in negative percentages.
Construction	κ	Has positive, integer values, representing the amount of constructed sub-attributes.

Chart 3.1 b: Summary of important analytical instruments in the MS with explanations of the terms. As in chart 3.1 b, the information is extracted from [3].

Term	Formalism and formula	Explanation
Relevance factor	$\|r\| = \sqrt{\delta^2 + \kappa^2}$	The absolute amount of the relevance vector.
Compatibility	$C_{A,\,B} = Æ_{A,\,B} \sum_{j=1}^{\alpha} \sum_{i=1}^{\beta} r_{Aj}(Sit\eta_{Bi})$	Degree for determining the “receptivity” of an affect through a finality, conditioned by its sub-attributes. This depends on the basic degree of similarity and the sum of the relevance factors of the sub-attributes of the object.
Range	$R(Sit\varepsilon_A) = \sum_{v=0}^{w} E_{U} \quad Kon\rho := \langle Sit\varepsilon_A; E_{U} \rangle$	The set of all elements on which the affect acts, i.e. with which he enters into a non-nonvial relation (a relation which can be described).
Activation	$T(Sit\varepsilon_{AB}) = C_{A,B} \cdot \left(C_{B,A} + \sum_{k=C}^{n} C_{B,k} \right)$	The ability of one affect to induce the execution of another affect through the object’s finality.
Transactivation	$T(Sit\varepsilon_A) = C_{A,\,B} \left(C_{B,\,C} + \sum_{k=C}^{n} C_{B,\,k} \right)$	The activation of an affect of the object finality on other finalities.
Reactivation	$T(Sit\varepsilon_{AB}) = C_{A,B} \cdot C_{B,A}$	Special case of reactivation, in which the affect of the object finality reacts back to the original subject finality.
Deactivation	$T(Sit\varepsilon_{AB}) = 0$	De facto non-activation. For numerical and analytical reasons, it is advantageous to include this as an activation type.
Affection	$\Phi(Sit\varepsilon_A) = \sum_{\varkappa=B}^{y} \sum_{i=0}^{\varkappa} \lvert Sit\eta_{\varkappa l} \rvert + \delta_{C,\,i} + \kappa_{C,\,i}$	The ability of an affect to change the object finality’s attributes.
Concertation	$C\left(\sum_{j=0}^{\alpha} \varkappa_{j,\,A} \right) = \varkappa_A \;\Big\vert\; \varkappa \in \{\delta, \kappa\}$	Adjustment of the δ and κ values. If e.g. a certain attribute is already destroyed by a sub- affect, this cannot be done again. All other δ values for this attribute are to be disregarded.
Classification	$K(Sit\varepsilon_A) = \begin{pmatrix} T \\ \Phi \\ R \end{pmatrix}$	Three-dimensional classification of affects. The first dimension is activation, the second is affection and the third is reach.

(3.1)

$$Sit\sigma := \left\{ \begin{array}{|c|} Sit\varepsilon_x \\ Sit\eta_x \\ Fin x \end{array} \right\}$$

(3.2)

$$K\left(Sit\varepsilon_A\right) = \begin{pmatrix} T \\ \Phi \\ R \end{pmatrix} = \begin{pmatrix} \sum_{\varkappa = B}^{y} C_{A\varkappa} \cdot \left(C_{\varkappa A} + \sum_{k=\varkappa}^{n} C_{\varkappa k} \right) \\ \sum_{\varkappa = B}^{y} \sum_{i=0}^{\varkappa} \left| Sit\eta_{\varkappa I} \right| + \delta_{C,i} + \kappa_{C,i} \\ \sum_{v=0}^{w} E_{Ц} \middle| Kon\rho := \left\langle Sit\varepsilon_A ; E_{Ц} \right\rangle \end{pmatrix}$$

4. Elaboration of the interductive modification model.

Basic considerations.

The basis of the interductive modification model is the consideration that consciousness cannot exist without perception. That is, because the agent must distinguish itself from its environment in order to define itself. Without this contrast, it would have no orientation for defining itself as a closed system. As already explained in [1], the IIT is based on the essential role of qualia spaces as a representation of the phenomenology of consciousness. In addition, axioms for the minimal consciousness of agents were discussed in [6], the realization of which would either be completely unrealistic or not possible at all without a perception of the environment. The role of perception has been also discussed by [8] with regard to robotic self-awareness. Therefore, the modeling of a neural network capable of consciousness is based on perceptual ability. As already mentioned, I have described perception [3] as a form of interaction, which in turn can be traced back to the compatibilities of the affects of the objects in question. Under the mentioned circumstances, the equations for the copula potential (4.1) and reactivation (4.2) are equivalent. Since reactivation is a special case of activation, perception can be linked to the classification function, thus creating an initial framework for calculating the mutual influence between agent and environment. In addition, the affection is limited to the affects' range, as mentioned in 3. This is the second framework condition for the formulation of the three-dimensional classification.

(4.1)

$$Þ_{A,B} = C_{A,B} \cdot C_{B,A}$$

(4.2)

$$T\left(Sit\varepsilon_{AB}\right) = C_{A,B} \cdot C_{B,A}$$

In order to specifically apply the classification function on the affects, the situation must first be described in terms of the matrical situation. The corresponding situational matrix is formulated in (4.3). Fin_A*:(*Fin_a*)* describes the neural network Fin_A, consisting of the links Fin_a, where the variable a runs from 1 to e. e is the total number of neural connections. Following the principles of situant symmetry , the attributes of this finality are accordingly designated as $Sit\eta_A:(Sit\eta_a)$ and the affects as $Sit\varepsilon_A:(Sit\varepsilon_a)$, respectively. In this approximation, the environment is divided into two levels. The first level contains composite objects, represented by the finalities Fin_o. The second level contains the individual parts that make up the objects on the first level, Fin_i. The variable o runs from 1 to u, the variable i runs from 1 to $j(o)$, or simply j. The environment can thus be summarized as $Fin_o:(Fin_i)$. According to the finalities of the environment, its properties and affects, as described above, are also contained in the matrix. In this article, the expression *(o,i)* is used for the environment hereinafter. All variables are considered to change over time, which will later be essential for description of neural development. In the matrix, the affects of the two columns are aimed at one another, resulting in interdependence.

(4.3)
$$Sit\sigma_R := \left\{ \begin{matrix} Sit\varepsilon_A : (Sit\varepsilon_a) & Sit\varepsilon_o : (Sit\varepsilon_i) \\ Sit\eta_A : (Sit\eta_a) & Sit\eta_o : (Sit\eta_i) \\ Fin\,A : (Fin\,a) & Fin\,o : (Fin\,o) \end{matrix} \right\}$$

If the definitions for compatibility and the relevance vector or the relevance factor are used as shown in (4.4). The classification function (4.5) classifies the affect of the agent on the environment, whereas the function (4.6) classifies the affect of the environment on the agent. The first is formulated in such a way that the agent first acts on the composite environmental elements, which in turn have an effect on the individual components. This assumption grounds on the consideration that if individual elements are put together, their properties interact and therefore the combined element must first be viewed as a whole before the affect is passed on to the individual elements. In (4.4), the first summation $C_{A,a,(o,i)}$ is called the *from-term*, as the compatibility refers to the effect ranging from the subject to the object. The second summation $C_{(o,i),a}$ is called the *to-term*, accordingly.

(4.4)
$$C_{A,a,(o,i)} + C_{(o,i),a} =$$
$$\sum_{a=1}^{e} \sum_{o=1}^{u} \sum_{i=1}^{j} \sqrt{\left(\delta_{a,o}(o,i)\right)^2 + \left(\kappa_{a,o}(o,i)\right)^2} + \sum_{o=1}^{u} \sum_{i=1}^{j} \sum_{a=1}^{e} \sqrt{\left(\delta_{(o,i),a}(o)\right)^2 + \left(\kappa_{(o,i),a}(o)\right)^2}$$

(4.5)
$$K\left(Sit\varepsilon_{A,a}\right) = \begin{pmatrix} \left(T_{A,a}\right)R \\ \left(\Phi_{A,a}\right)R \\ \left(R_{A,a}\right)R \end{pmatrix} = \begin{pmatrix} Æ^2_{A,a,(o,i)}\left[C_{A,a,(o,i)} + C_{(o,i),a}\right] \\ \sum_{a=1}^{e} \sum_{o=1}^{u} \sum_{i=1}^{j} \left|Sit\eta_{(o,i)}\right| + \left(\delta_{a,o}(o,i)\right)_C + \left(\kappa_{a,o}(o,i)\right)_C \\ \sum_{o=1}^{u} \sum_{i=1}^{j} Sit\eta_{(o,i)} \Big| Sit\eta_{(o,i)} \subset Kon\rho\left(\left(\Phi_{A,a}\right)_R\right) \end{pmatrix}$$

(4.6)
$$K\left(Sit\varepsilon_{(o,i)}\right) = \begin{pmatrix} \left(T_{(o,i)}\right)R \\ \left(\Phi_{(o,i)}\right)R \\ \left(R_{(o,i)}\right)R \end{pmatrix} = \begin{pmatrix} Æ^2_{(o,i),A,a}\left[C_{(o,i),a} + C_{A,a,(o,i)}\right] \\ \sum_{o=1}^{u} \sum_{i=1}^{j} \sum_{a=1}^{e} \left|Sit\eta_{A,a}\right| + \left(\delta_{(o,i),a}(a)\right)_C + \left(\kappa_{(o,i),a}(a)\right)_C \\ \sum_{a=1}^{e} Sit_{A,a} \Big| Sit_{A,a} \subset Kon\rho\left(\left(\Phi_{(o,i)}\right)R\right) \end{pmatrix}$$

Since the activation of an element is preceded by the affection, the latter is regarded as the core of the affect classification. Furthermore, it is advantageous to consider solely affects, which in fact have an effect on the objects, in which case the range is defined by the affection as well. Given considerations lead to the conclusion that both activation and range depend on the affection. This means that there must be two functions τ and ρ assigning activation and range to the affection. These functions can be derived from the concrete formulations (4.5) and (4.6).

Several steps are required to formulate the τ-function. First, the sum term of the properties of the target element must be subtracted. In case (4.5) these are the properties of the environment, in case (4.6) those of the agent. In the second step, the δ and κ values have to be de-concerted, which is done with the C^{-1} function. In addition, the amounts of the respective relevance vectors must be formed, since only the relevance factors appear in the activation function. The next step is to mirror the relevance factors. For this purpose, a reflection factor μ is introduced. Since both the original and the mirrored relevance factors are required, the factor $(1+\mu)$ is used. Finally, the product obtained is multiplied by the square of the basal similarity. Overall, one obtains the expressions (4.7) for the effect of the agent and (4.8) for the effect of the environment. However, derivation of the ρ-function is much simpler. For its formulation, solely the sum of the concerted δ and κ values is subtracted from the affection term. This leads to the expressions (4.9) for the affect of the agent and (4.10) for the affect of the environment, respectively. Both the τ-function and the ρ-function are referred to as *intraductive functions.*

(4.7)
$$\left(T_{A,a}\right)_R - \tau\left(\left(\Phi_{A,a}\right)_R\right) - Æ^2_{A,a,(o,i)}(1+\mu)\left\|\left[C^{-1}\left[\left(\Phi_{A,a}\right)_R - \sum_{o=1}^{u}\sum_{i=1}^{j}\left|Sim_{(o,i)}\right|\right]\right]\right\|$$

(4.8)
$$\left(T_{(o,i)}\right)_R = \tau\left(\left(\Phi_{(o,i)}\right)_R\right) = Æ^2_{A,a,(o,i)}(1+\mu)\left\|\left[C^{-1}\left[\left(\Phi_{(o,i)}\right)_R - \sum_{a=1}^{e}\left|Sim_{A,a}\right|\right]\right]\right\|$$

(4.9)
$$\left(R_{A,a}\right)_R = \rho\left(\left(\Phi_{A,a}\right)_R\right) = \left(\Phi_{A,a}\right)_R - \left[\sum_{a=1}^{e}\sum_{o=1}^{u}\sum_{i=1}^{j}\left(\delta_{a,o}(o,i)\right)_C + \left(\kappa_{a,o}(o,i)\right)_C\right]$$

(4.10)
$$\left(R_{(o,i)}\right)_R = \rho\left(\left(\Phi_{(o,i)}\right)_R\right) = \left(\Phi_{(o,i)}\right)_R - \left[\sum_{o=1}^{u}\sum_{i=1}^{j}\sum_{a=1}^{e}\left(\delta_{(o,i),a}(a)\right)_C + \left(\kappa_{(o,i),a}(a)\right)_C\right]$$

Since reactivation contributes to affection in the respective next step of a temporal sequence, which, in turn, determines the reactivation through the τ-function, this results in a change between Φ-functions and T-functions with regard to time-developed interactions.

Presentation of the IDM model.

If the situation shown in (4.3) is included in a chronological sequence, several “currents”, hereinafter *ducti*, of affects can be distinguished: The *ductus interior* D_i describes the affect of the environment on the neural network. The *ductus exterior* D_e represents the affect of the neural network on the environment. Based on the IIT and its elaboration in [2], the influence of the neural networks on themselves must also be considered, which represents their development without external stimuli taking place in between the mentioned ducti. These interactions are summarized in the *ductus modificator* D_m. The ***K***-function is formulated concretely in (4.11) for all ducti, including the formulation of the τ-functions and the ρ-functions. Since the environment is obviously present before the formation of neural networks and thus exerts the first influence, D_i is regarded as the initial affect ductus. Afterwards, D_m takes place as a sequence of effects of the neural network on itself, which includes a total of ν steps. The corresponding running variable is n. This is followed by the affect on the environment, D_e, which belongs to the subsequent process. Any depicted process is referred to as *ductive cycle*. All ductive cycles are identified by the run variable f which ranges from 1 to ϕ. The first cycle contains only two ducti, the $(D_i)_1$ and the $(D_m)_{n(1)}$. All other cycles begin with $(D_e)_f$ and therefore contain three different ducti. The background is that the environment changes during the neural modifications and can therefore has a different constellation than at the time, when the initial stimulus of the cycle occurs. Fig. 4.1 shows an abbreviated compilation of a ductive cycle. From this initial, one- dimensional sequence of ductive cycles, further functions are derived in order to connect the ducti to their respective successors. In each case, a reactivation term of a ductus is connected to the affection term of the successor ductus. These functions are referred to as *interductive functions*.

(4.11)

$$\left(\mathrm{D}_i\right)_f=\begin{pmatrix} \text{Æ}^2_{A,a(f),(o,i)(f)}(1+\mu)\left\|\left[C^{-1}\left[\left(\Phi_{(o,i)(f)}\right)_R-\sum_{a(f)=1}^{e(f)}\left|Sim\eta_{A,a(f)}\right|\right]\right]\right\| \\ \sum_{o(f)=1}^{u(f)}\sum_{i(f)=1}^{j(f)}\sum_{a(f)=1}^{e(f)}\left|Sim\eta_{A,a(f)}\right|+\left(\delta_{(o,i)(f),a(f)}(a(f))\right)_C+\left(\kappa_{(o,i)(f),a(f)}(a(f))\right)_C \\ \left(\Phi_{(o,i)(f)}\right)_R-\left[\sum_{o(f)=1}^{u(f)}\sum_{i(f)=1}^{j(f)}\sum_{a(f)=1}^{e(f)}\left(\delta_{(o,i)(f),a(f)}(a(f))\right)_C+\left(\kappa_{(o,i)(f),a(f)}(a(f))\right)_C\right] \end{pmatrix}$$

$$\left(\mathrm{D}_e\right)_f=\begin{pmatrix} \text{Æ}^2_{A,a(f),(o,i)(f)}(1+\mu)\left\|\left[C^{-1}\left[\left(\Phi_{A,a(f)}\right)_R-\sum_{o(f)=1}^{u(f)}\sum_{i(f)=1}^{j(f)}\left|Sim\eta_{(o,i)(f)}\right|\right]\right]\right\| \\ \sum_{a(f)=1}^{e(f)}\sum_{o(f)=1}^{u(f)}\sum_{i(f)=1}^{j(f)}\left|Sim\eta_{(o,i)(f)}\right|+\left(\delta_{a(f),(o,i)(f)}(a(f))\right)_C+\left(\kappa_{a(f),(o,i)(f)}(a(f))\right)_C \\ \left(\Phi_{A,a(f)}\right)_R-\left[\sum_{a(f)=1}^{e(f)}\sum_{o(f)=1}^{u(f)}\sum_{i(f)=1}^{j(f)}\left(\delta_{a(f),o(j)}((o,i)(f))\right)_C+\left(\kappa_{a(f),(o,i)(f)}(a(f))\right)_C\right] \end{pmatrix}$$

$$\left(\mathrm{D}_m\right)_{n(f)}=\begin{pmatrix} \text{Æ}^2_{A,a,n(f)-1,A,a,n(f)}(1+\mu)\left\|\left[C^{-1}\left[\left(\Phi_{A,a,n(f)-1}\right)_R-\sum_{a_{n(f)}=1}^{e_{n(f)}}\left|Sim\eta_{A,a,n(f)}\right|\right]\right]\right\| \\ \sum_{a_{n(f)-1}=1}^{e_{n(f)-1}}\sum_{a_{n(f)}=1}^{e_{n(f)}}\left|Sim\eta_{A,a,n(f)}\right|+\left(\delta_{a,n(f)-1,a,n(f)}\left(a_{n(f)}\right)\right)_C+\left(\kappa_{a,n(f)-1,a,n(f)}\left(a_{n(f)}\right)\right)_C \\ \left(\Phi_{A,a,n(f)-1}\right)_R-\left[\sum_{a_{n(f)-1}=1}^{e_{n(f)-1}}\sum_{a_{n(f)}=1}^{e_{n(f)}}\left(\delta_{a,n(f)-1,a,n(f)}\left(a_{n(f)}\right)\right)_C+\left(\kappa_{a,n(f)-1,a,n(f)}\left(a_{n(f)}\right)\right)_C\right] \end{pmatrix}$$

The corresponding functions are written in square brackets and are summarized in (4.13), showing their arguments and outputs. The explicit formulations of the function terms are derived below. It is important to note that this is solely a simplification of actual processes. Possible interactions within the environment can be summarized with the functions [x], which are not dealt with explicitly in the model yet, since this would overstrain the content of this work. Accordingly, they are implicitly included in the [i]-functions.

Fig. 4.1: Scheme of ductive succession. The indices refer to an arbitrary cycle *f*, which is followed by the cycle *f+1*. The red arrows show the logical dependency which are explained by the intra- and interductive functions.

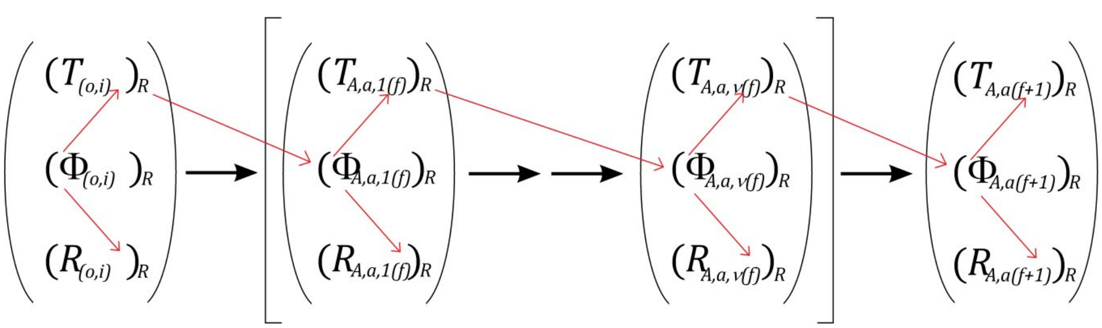


Chart 4.1: Summary of relevance vectors for the state changes **S1**, **S2** and **S3** in fig. 4.2. The left column includes the number of subject neurons. The first raw, accordingly, includes the numbers of object neurons. Since the connection of a neuron to itself is not included, the relevance vectors of symmetrical relations are not shown. In the indices, the subjects are enlisted first, followed by the objects. The last raw shows the summation of all vectors aiming the same neurons, while the last column shows the summations of vectors originating from the same subjects. For each step, the summations of all vectors are enlisted in the right bottom corner. Their absolute values show the amount of change for each step.

S1	**1**	**2**	**3**	**4**	**5**	$\sum_{k=1}^{5}\begin{pmatrix}\delta\\\kappa\end{pmatrix}_{i,k}$
1		$\begin{pmatrix}0\\1\end{pmatrix}_{1,2}$	$\begin{pmatrix}0\\1\end{pmatrix}_{1,3}$	$\begin{pmatrix}0\\0\end{pmatrix}_{1,4}$	$\begin{pmatrix}0\\0\end{pmatrix}_{1,5}$	$\begin{pmatrix}0\\2\end{pmatrix}_{1}$
2	$\begin{pmatrix}0\\1\end{pmatrix}_{2,1}$		$\begin{pmatrix}0\\0\end{pmatrix}_{2,3}$	$\begin{pmatrix}0\\0\end{pmatrix}_{2,4}$	$\begin{pmatrix}0\\0\end{pmatrix}_{2,5}$	$\begin{pmatrix}0\\1\end{pmatrix}_{2}$
3	$\begin{pmatrix}0\\0\end{pmatrix}_{3,1}$	$\begin{pmatrix}0\\0\end{pmatrix}_{3,2}$		$\begin{pmatrix}0\\1\end{pmatrix}_{3,4}$	$\begin{pmatrix}0\\0\end{pmatrix}_{3,5}$	$\begin{pmatrix}0\\1\end{pmatrix}_{3}$
4	$\begin{pmatrix}0\\0\end{pmatrix}_{4,1}$	$\begin{pmatrix}0\\0\end{pmatrix}_{4,2}$	$\begin{pmatrix}0\\0\end{pmatrix}_{4,3}$		$\begin{pmatrix}0\\0\end{pmatrix}_{4,5}$	$\begin{pmatrix}0\\0\end{pmatrix}_{4}$
5	$\begin{pmatrix}0\\1\end{pmatrix}_{5,1}$	$\begin{pmatrix}0\\1\end{pmatrix}_{5,2}$	$\begin{pmatrix}0\\0\end{pmatrix}_{5,3}$	$\begin{pmatrix}0\\0\end{pmatrix}_{5,4}$		$\begin{pmatrix}0\\2\end{pmatrix}_{5}$
$\sum_{i=1}^{5}\begin{pmatrix}\delta\\\kappa\end{pmatrix}_{i,k}$	$\begin{pmatrix}0\\2\end{pmatrix}_{,1}$	$\begin{pmatrix}0\\2\end{pmatrix}_{,2}$	$\begin{pmatrix}0\\1\end{pmatrix}_{,3}$	$\begin{pmatrix}0\\1\end{pmatrix}_{,4}$	$\begin{pmatrix}0\\0\end{pmatrix}_{,5}$	$\begin{pmatrix}0\\6\end{pmatrix}_{total}$
S2	**1**	**2**	**3**	**4**	**5**	
1		$\begin{pmatrix}0\\0\end{pmatrix}_{1,2}$	$\begin{pmatrix}0\\0\end{pmatrix}_{1,3}$	$\begin{pmatrix}0\\0\end{pmatrix}_{1,4}$	$\begin{pmatrix}0\\0\end{pmatrix}_{1,5}$	$\begin{pmatrix}0\\0\end{pmatrix}_{1}$
2	$\begin{pmatrix}-1\\0\end{pmatrix}_{2,1}$		$\begin{pmatrix}0\\1\end{pmatrix}_{2,3}$	$\begin{pmatrix}0\\0\end{pmatrix}_{2,4}$	$\begin{pmatrix}0\\0\end{pmatrix}_{2,5}$	$\begin{pmatrix}-1\\1\end{pmatrix}_{2}$
3	$\begin{pmatrix}0\\0\end{pmatrix}_{3,1}$	$\begin{pmatrix}0\\1\end{pmatrix}_{3,2}$		$\begin{pmatrix}0\\0\end{pmatrix}_{3,4}$	$\begin{pmatrix}0\\0\end{pmatrix}_{3,5}$	$\begin{pmatrix}0\\1\end{pmatrix}_{3}$
4	$\begin{pmatrix}0\\0\end{pmatrix}_{4,1}$	$\begin{pmatrix}0\\0\end{pmatrix}_{4,2}$	$\begin{pmatrix}0\\0\end{pmatrix}_{4,3}$		$\begin{pmatrix}0\\0\end{pmatrix}_{4,5}$	$\begin{pmatrix}0\\0\end{pmatrix}_{4}$
5	$\begin{pmatrix}0\\0\end{pmatrix}_{5,1}$	$\begin{pmatrix}0\\0\end{pmatrix}_{5,2}$	$\begin{pmatrix}0\\0\end{pmatrix}_{5,3}$	$\begin{pmatrix}0\\0\end{pmatrix}_{5,4}$		$\begin{pmatrix}0\\1\end{pmatrix}_{5}$
$\sum_{i=1}^{5}\begin{pmatrix}\delta\\\kappa\end{pmatrix}_{i,k}$	$\begin{pmatrix}-1\\0\end{pmatrix}_{,1}$	$\begin{pmatrix}0\\1\end{pmatrix}_{,2}$	$\begin{pmatrix}0\\1\end{pmatrix}_{,3}$	$\begin{pmatrix}0\\0\end{pmatrix}_{,4}$	$\begin{pmatrix}0\\0\end{pmatrix}_{,5}$	$\begin{pmatrix}-1\\2\end{pmatrix}_{total}$
S3	**1**	**2**	**3**	**4**	**5**	
1		$\begin{pmatrix}0\\0\end{pmatrix}_{1,2}$	$\begin{pmatrix}0\\1\end{pmatrix}_{1,3}$	$\begin{pmatrix}0\\0\end{pmatrix}_{1,4}$	$\begin{pmatrix}0\\1\end{pmatrix}_{1,5}$	$\begin{pmatrix}0\\2\end{pmatrix}_{1}$
2	$\begin{pmatrix}0\\0\end{pmatrix}_{2,1}$		$\begin{pmatrix}0\\0\end{pmatrix}_{2,3}$	$\begin{pmatrix}0\\1\end{pmatrix}_{2,4}$	$\begin{pmatrix}0\\0\end{pmatrix}_{2,5}$	$\begin{pmatrix}0\\1\end{pmatrix}_{2}$
3	$\begin{pmatrix}0\\0\end{pmatrix}_{3,1}$	$\begin{pmatrix}0\\0\end{pmatrix}_{3,2}$		$\begin{pmatrix}0\\0\end{pmatrix}_{3,4}$	$\begin{pmatrix}0\\0\end{pmatrix}_{3,5}$	$\begin{pmatrix}0\\0\end{pmatrix}_{3}$
4	$\begin{pmatrix}0\\0\end{pmatrix}_{4,1}$	$\begin{pmatrix}0\\0\end{pmatrix}_{4,2}$	$\begin{pmatrix}0\\0\end{pmatrix}_{4,3}$		$\begin{pmatrix}0\\1\end{pmatrix}_{4,5}$	$\begin{pmatrix}0\\1\end{pmatrix}_{4}$
5	$\begin{pmatrix}-1\\0\end{pmatrix}_{5,1}$	$\begin{pmatrix}0\\0\end{pmatrix}_{5,2}$	$\begin{pmatrix}0\\0\end{pmatrix}_{5,3}$	$\begin{pmatrix}0\\0\end{pmatrix}_{5,4}$		$\begin{pmatrix}-1\\1\end{pmatrix}_{5}$
$\sum_{i=1}^{5}\begin{pmatrix}\delta\\\kappa\end{pmatrix}_{i,k}$	$\begin{pmatrix}-1\\0\end{pmatrix}_{,1}$	$\begin{pmatrix}0\\0\end{pmatrix}_{,2}$	$\begin{pmatrix}0\\1\end{pmatrix}_{,3}$	$\begin{pmatrix}0\\2\end{pmatrix}_{,4}$	$\begin{pmatrix}0\\2\end{pmatrix}_{,5}$	$\begin{pmatrix}-1\\5\end{pmatrix}_{total}$

(4.13)

$$[e]_f := T_{(o,i)(f)}\left(\left(D_i\right)_f\right) \rightarrow \Phi_{A,a(f)}\left(\left(D_m\right)_{f,1(f)}\right)$$

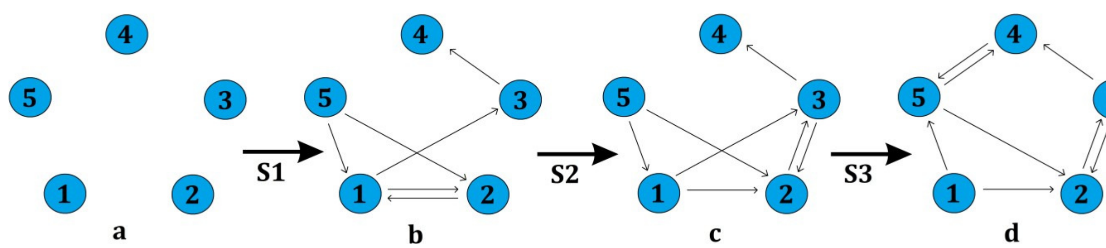
$$[m]_{n(f)} := T_{A,a,n(f)-1}\left(\left(D_m\right)_{f,n-1(f)}\right) \rightarrow \Phi_{A,a,n(f)}\left(\left(D_m\right)_{f,n(f)}\right)$$

$$[n]_{f+1} := T_{A,a,\text{v}(f)-1}\left(\left(D_m\right)_{f,\text{v}(f)}\right) \rightarrow \Phi_{A,a,\text{v}(f)}\left(\left(D_e\right)_{f+1}\right)$$

$$[i]_{f+1} := T_{A,a,\text{v}(f)}\left(\left(D_e\right)_{f+1}\right) \rightarrow \Phi_{(o,i)(f+1)}\left(\left(D_i\right)_{f+1}\right)$$

In order to illustrate the meaning of the respective δ and κ values, five neurons are shown in Fig.4.2, which connections are changed throughout the shown process of three steps S1 to S3. The initial situation in Fig. 4.2 a contains no connections. After every transformation up to Fig.
4.2 d, connections are either established or deleted. An introduction of any given connection is to be interpreted with a κ value equal to one, its deletion with a δ value equal to minus one, respectively. Chart 4.1 shows the corresponding values for the relevance vectors for each change. It should be noted here that the connections as assignment of neurons to themselves are not dealt with. Such a system, as shown in [2], would form a complex, which, however, leads to low Φ^{Max} values in terms of the IIT.

Fig. 4.2: An example of changing neural connections between a set of five neurons. Each step **Sx** includes a various number of both construction and destruction values which are summed up in relevance vectors shown in chart 4.1. The steps can be interpreted by interaction with other neural systems or the environment. The trivial type of steps is not shown, since in this case no changes are undergone and thus the amounts of all vectors are zero. As an example for construction, step **S1** can be explained. First, the system does not show any connections between the neurons in state
a. After **S1**, state **b** occurs to include constructed connections. This can be shown by relevance vectors, which have positive values for the dimension of construction. As an example for destruction, in step **S2**, the connection from 2 to 1 is deleted, which is shown in the according relevance vector with negative values in the destruction dimension.



Derivation of the interductive functions.

In contrast to the ductive cycles, the cycles of the interductive functions, hereinafter *functional cycles*, throughout have the same length and contain the function sequence $S_{function}$ as shown in (4.14). According to the indices, the functional cycles are offset over the ductive cycles. In the following elaboration, the concrete formulations of the functions are derived from the explicit expressions for the ducti.

(4.14)

$$S_{function} = \left\langle [e]_f ; [m]_{n(f)} ; [n]_{f+1} ; [i]_{f+1} \right\rangle$$

In the first step, the square of the basic similarity is shortened as an inverse function to the corresponding τ-function. Afterwards, the to-terms, which contain the δ and κ values from the object back to the subject, are also truncated. Their counterparts, the from-terms, are retained when the interductive functions are transformed. They are used to extract the corresponding δ and κ values using the following operation, called the $(\delta,\kappa)_{ex}$-function, and to determine the next δ and κ values using the attributes of the corresponding successor object. Since this is an essential step in ductive development, it will be discussed explicitly later.

After the new δ and κ values have been determined, the concertation function C is carried out, which acts as the inverse function of the de-concertation used for the τ-functions. For the $[e]_f$- function, the sum function $s^2{}_{a0(f),a1(f)}$ is used, which performs a double summation of the concerted δ and κ values according to the shown indices. In the last step, the amounts of the $Sit\eta_{A,a1(f)}$ are added up via the variable $a_{1(f)}$ to $e_{1(f)}$. They are added to the intermediate result. With the $[e]_f$-function, the expression for $\Phi_{A,a}((D_m)_{a(f)})$ results from the expression of the previous ductus, $T_{(o,i)}((D_i)_{a(f)})$. The first four steps are, in general, identical for all interductive functions. For the $[m]_{n(f)}$-function, the sum function appears as $s^2{}_{an(f)-1,an(f)}$, accordingly. Furthermore, the new attributes, $Sit\eta_{A,an(f)}$, are added in the last step. Thus, the $[m]_{n(f)}$-function converts the expression $T_{A,a}((D_m)_{n(f)\ -1})$ into the term $\Phi_{A,a}((D_m)_{n(f)})$. Since the $[n]_{f+1}$-function must form a three-fold sum, the sum function is written as $s^3{}_{a\nu(f),o(f+1),i(f+1)}$. Accordingly, the amounts of the attributes $Sit\eta_{(o,i)(f+1)}$ are added up at the end. Therefore, the $[n]_{f+1}$-function converts the expression $T_{A,a}((D_m)_{\nu(f)})$ into $\Phi_{A,a}((D_e)_{f+1})$. In the case of the $[i]_{f+1}$-function, the sum function is $s^3{}_{o(f+1),i(f+1),a0(f+1)}$. Moreover, the attributes $Sit\eta_{A,a0(f+1)}$ are added. The $[i]_{f+1}$ function converts $T_{A,a}((D_e)_{f+1})$ to $\Phi_{(o,i)}((D_i)_{f+1})$, so the functional cycle can start again. The presented functions are summarized with (4.15).

(4.15)

$$[e]_f\left(T_{(o,i)(f)}\left(\left(\mathrm{D}_i\right)_f\right)\right) = s^2_{a,0(f),a,1(f)}\left[C\left[(\delta,\kappa)_{ex}\left[\frac{T_{(o,i)(f)}\left(\left(\mathrm{D}_i\right)_f\right)}{\text{Æ}^2_{A,a(f),(o,i)(f)}\,C_{A,a(f),(o,i)(f)}}\right]\right]\right] + \sum_{a_{1(f)}=1}^{e_{1(f)}}\left|Sit\eta_{A,a,1(f)}\right|$$

$$[m]_{n(f)}\left(T_{A,a,n(f)-1}\left(\left(\mathrm{D}_m\right)_{f,n(f)-1}\right)\right) = s^2_{a,n(f)-1,a,n(f)}\left[C\left[(\delta,\kappa)_{ex}\left[\frac{T_{A,a,n(f)-1}\left(\left(\mathrm{D}_m\right)_{f,n(f)-1}\right)}{\text{Æ}^2_{A,a,n(f)-1,A,a,n(f)}\,C_{A,a,n(f),A,a,n(f)-1}}\right]\right]\right]$$
$$+ \sum_{a_{n(f)+1}=1}^{e_{n(f)+1}}\left|Sit\eta_{A,a,n(f)+1}\right|$$

$$[n]_{f+1}\left(T_{A,a,\nu(f)-1}\left(\left(\mathrm{D}_m\right)_{f,\nu(f)}\right)\right) = s^3_{a,\nu(f),(o,i)(f+1)}\left[C\left[(\delta,\kappa)_{ex}\left[\frac{T_{A,a,\nu(f)-1}\left(\left(\mathrm{D}_m\right)_{f,\nu(f)}\right)}{\text{Æ}^2_{A,a,\nu(f)-1,A,a,\nu(f)}\,C_{A,a,\nu(f),A,a,\nu(f)-1}}\right]\right]\right]$$
$$+ \sum_{o(f+1)=1}^{u(f+1)}\ \sum_{i(f+1)=1}^{j(f+1)}\left|Sit\eta_{(o,i)(f+1)}\right|$$

$$[i]_{f+1}\left(T_{A,a,\nu(f)}\left(\left(\mathrm{D}_e\right)_{f+1}\right)\right) = s^3_{(o,i)(f+1),a,0(f+1)}\left[C\left[(\delta,\kappa)_{ex}\left[\frac{T_{A,a,\nu(f)}\left(\left(\mathrm{D}_e\right)_{f+1}\right)}{\text{Æ}^2_{A,a,\nu(f),(o,i)(f+1)}\,C_{(o,i)(f+1)A,a,\nu(f)}}\right]\right]\right]$$
$$+ \sum_{a_{0(f+1)}=1}^{e_{0(f-1)}}\left|Sit\eta_{A,a,0(f+1)}\right|$$

The $(\delta,\kappa)_{ex}$-functions' argument contains both the corresponding from terms and the attributes of the consecutive objects. First, the δ and κ values are applied to the attributes of the previous objects, which are then viewed as subjects. Between them and the attributes of the new objects, the δ and κ values are subsequently determined and occur as output values of the function. Since the argument role of the δ and κ values is clear from the reactivation expressions, only the indices of the new objects are added to the $(\delta,\kappa)_{ex}$-functions in the interductive function terms.

The assignment of the indices and the resulting $(\delta,\kappa)_{ex}$-function notation are summarized in (4.16). Fig. 4.3 illustrates the relationship between the ductive and functional cycles.

(4.16)

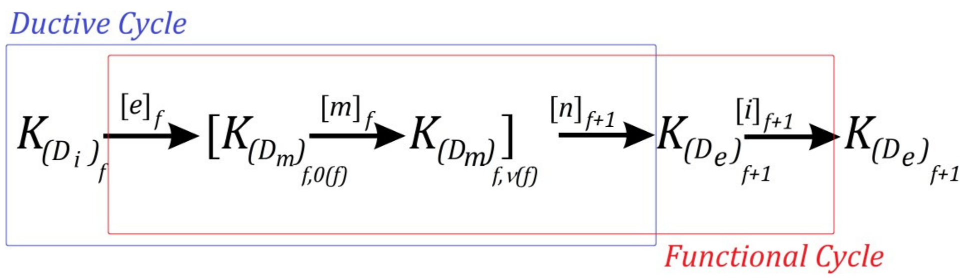
$$(\delta,\kappa)_{ex}^{a,1(f)} := (o,i)(f); a, 0(f) \quad \rightarrow a, 0(f); a1(f)$$

$$(\delta,\kappa)_{ex}^{a,n(f)} := a, n(f)-1; a, n(f) \rightarrow a, n(f); a, n(f)+1$$

$$(\delta,\kappa)_{ex}^{(o,i)(f+1)} := a, \nu(f)-1; a, \nu(f) \rightarrow a, \nu(f); o(f+1)$$

$$(\delta,\kappa)_{ex}^{a,0(f+1)} := a, \nu(f); o(f+1) \rightarrow (o,i)(f-1) : a, 0(f+1)$$

Fig. 4.3: Juxtaposition of the functional and the ductive cycle with respect to an arbitrary ductive cycle *f* as reference. The ductive cycle is shown with blue curved brackets, while the functional cycle is shown with red curved brackets. Additionally, the interductive functions [e], [m], [n] and [i] are explicitly shown for the marked functional cycle.



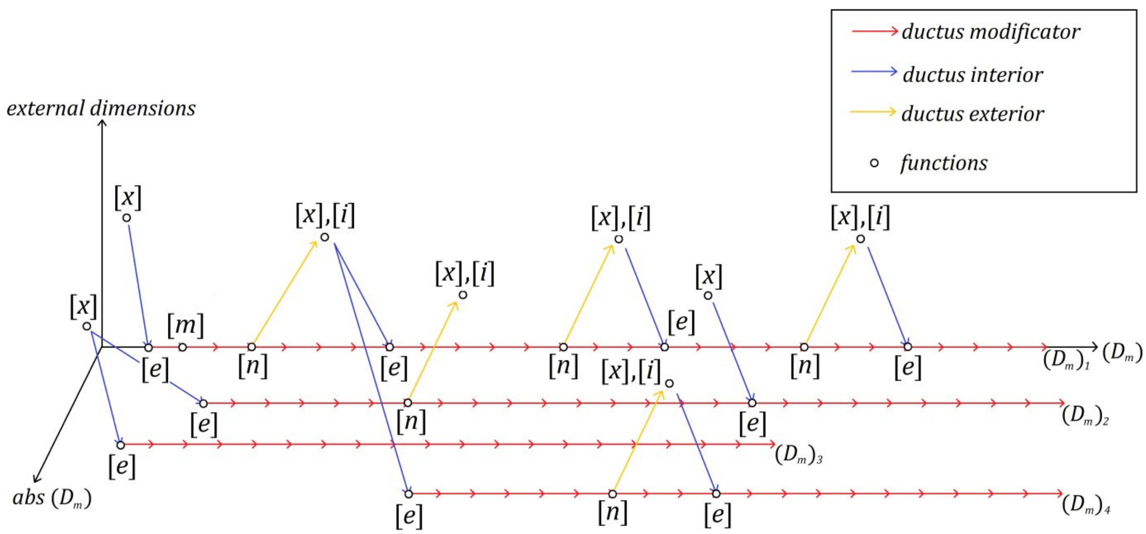
Multidimensional perspective.

The model described so far is one-dimensional and assumes that the neural changes only occur between the interactions of agent and environment. In fact, however, the neural networks are constantly changing, and the indirect effects of stimuli from the environment last longer than the time period the networks' respond occupy, especially in the context of sleep [9,10]. In addition, when describing a neural system in a global manner, it is also obvious that several ductive cycles, representing tasks, take place at the same time parallel to each other and, therefore, overlap [11]. Considering this level of complexity, it is important to adapt the elaborated theoretical framework. This adaptation is summarized in Fig. 4.4 as a multidimensional view. A *(D_m)* axis is introduced, which consists of the individual D_m vectors. The ducti are considered as vectors, since the classification function as a three-dimensional function connects states with each other, which, in turn, can be considered as points. Correspondingly, the interductive functions are punctual as well, since the assignments of ducti occur instantly. Everything outside the *(D_m)* axis can be understood as the environment and is shown in simplified form as a second dimension. Accordingly, D_e protrudes away from the *(D_m)* axis, while D_i protrudes back to it. D_i is entered as the first ductus, after which the D_m chain forms. The first cycle ends before the first D_e, then the next cycle starts, as mentioned above. However, since the *(D_m)* axis always continues uninterrupted (which corresponds to a development isolated from the environment), all D_m from D_e to the end of the cycle are to be included.

Since more than one external stimulus can act on the neural network, several cycles can be initiated accordingly. In order to distinguish them from one another, the variable *y* is introduced, which runs from 0 to υ. If another stimulus occurs, a new cycle begins with the initiating ductus D_i. If the development of the neural network has more than one response to the environment, a new cycle is started from the second response, the initiating ductus of which, however, is a D_e. The first functional cycles in each case are adapted accordingly to the initiating ducti: If D_i is the initiating ductus, the first functional cycle consists of the sequence as described in (4.14). If a cycle is initiated with D_e, the first cycle must begin with [i].

In a realistic view, it must be taken into account that the changes in the environment can be related to one another and, therefore, a kind of cross-reaction must be considered. Since this article concentrates on the neural network, these cross-reactions are summarized in the functions $[x]_{m(fy)}$ and "bridged" using the $[i]_{fy}$-function. As mentioned before, they can be analyzed in more detail in further research.

Fig. 4.4: Illustration of the multidimensional IDM model concept. The first dimension is represented by the (D_m) axis, the second dimension shows the amount of possible induced interductive cycles. The third dimension represents the environment. Since the environmental interdependencies have not been clarified yet, they are considered to be multidimensional, which allows to integrate complex structures yet. Blue arrows represent $D_{i,f}$, while yellow arrows depict $D_{e,f}$. $D_{m,f}$ are shown by red arrows. In this illustration, ducti are considered to be vectors, while functions are interpreted as punctual assignments. Summarizing, the external interactions are called [x], while the condensed counterpart is the discussed [i]-function. Furthermore, [n] and [e] functions are shown in each according change, while the usual [m] function is shown only once in $(D_m)_1$. It is clear to see, that the initiative grounds on external stimuli, while the system interacts casually, but not necessarily, with its environment. Furthermore, external effects can start more than one cycle, as the initiation of $(D_m)_2$ and $(D_m)_3$ shows, or lead to no effects back on the $(D_m)_2$ dimension at all, as to see in $(D_m)_2$. While the direct interaction between cycles has not been discussed yet, an indirect interaction through environmental interdependence can be sketched. This case is shown by the indirect interaction between $(D_m)_1$ and $(D_m)_4$.



If certain brain regions or functional regions are focused on, one intends to capture the overall changes in the system. In order to provide such calculations, the point in time t_0 and the associated interval T_0 are defined, while the length of T_0 corresponds to a change in the neural network. The time frame of changes can be adapted as precisely as required. In this context, the length can be set as equal to the time frame of a basic change in the neural network. The relation between point in time and time interval is given by (4.17).

(4.17) $$T_0 = \left(t_0 - dT_0 ; t_0\right], \quad dT_0 = var.$$

The number of existing cycles at a point in time t_0 or time interval T_0 is given as $\upsilon_{(t0)}$ and as $\upsilon_{(T0)}$, respectively. The run variable of a cycle run, y, can thus be written as $f_y(t_0)$ or $f_y(T_0)$ at time t_0 or a time interval T_0. Correspondingly, $n(f_y(T_0))$ is the running variable of $(D_m)_{fy(T0)}$ and $n(f_y(t_0))$ is the running variable of $(D_m)_{fy(t0)}$. This allows the ducti and the interductive functions [m] to be added up over a given time interval or a given point in time, given the according values of y. The result is presented in the equations (4.18) for the ductive functions and (4.19) for the interductive functions.

(4.18)
$$\left(D_m\right)_{T_0} = \sum_{y(T_0)=0}^{u(T_0)} \left(D_m\right)_{r\left(f_{y}(T_0)\right)}$$

(4.19)
$$[m]_{t_0} = \sum_{x(t_0)}^{u(t_0)} c\,[m]_{n\left(f\left(t_{x,0}\right)\right)}$$

It is important to mention that cycle runs can also end. This is the case when the δ and κ values all become zero. According to the definitions of reactivation function, it cannot be applied anymore, therefore the cycle ends. Hence, the possibility of a cycle termination is already implied by the definitions. This multidimensional perspective closes the first development of the IDM model and illustrates the manifold interactions within the neural networks and the environment, thereby leaving space for further theoretical development and adaptation to empirical data.

5. Discussion.

Explanatory capacity of the IDM model.

The developed model enables the use of the IIT, since the δ and κ values can be set in such a way that maximum Φ^{Max} values of a complex are achieved. In addition, the model can be applied to the development of consciousness in humans both in individuals in the course of life and on an evolutionary scale, since the length of the interval between the changes can be changed at will. Therefore, this approach can not only correspond to the rate of change of the neuron connections, but also to larger, up to evolutionarily relevant time periods. However, for larger T_0 values, the δ and κ values need to be considered as statistical values.

If one assumes a simple neural network at the beginning, the possible δ and κ values may not be sufficient to allow a higher number of cycles. Specifically, this means that the cycle is initially severely limited if no stimuli from the environment are received, since there is a high propability that all relevance vectors have the magnitude zero. In more complex systems, however, the cycles can last longer without stimuli, since this probability decreases with an increasing number of connections to be considered. This circumstance reflects two relationships: First, the ability of a neural network to develop depends on the number of neurons. Second, the development of a conscious system is only possible if enough information is perceived by the environment, which then has an indirect effect on the neural network in the ongoing processes in $(D_m)_{fy}$. Therefore, both the experiences as described in [2], as well as the creation of models for prediction, are strongly dependent on perception, as has already been discussed on a phenomenological basis [7]. It should be noted that an isolated, lasting development of a neural network, as soon as it is able to maintain over a significant period of time, also means an alienation of the models formed from the perceived reality with increasing duration. The models formed by the neural network are applied to the experiences already made. Without further stimuli from the environment, the models are still accepted as the standard. If, however, the stimuli following the response to the environment are absent, a neural network cannot verify whether the models already established are, in fact, realistic.

Another aspect of the model is that, without exception, *everything* outside of the neural networks is considered to belong to the environment. This means that, from a purely technical point of view, the rest of an agent's own body also belongs to the environment. Only with a sufficiently precise model formation (due to a sufficiently pronounced structure), the neural network can create models that interpret the perceived body parts as belonging to the agent, or implement an understanding of itself at all. A transfer of this self-perception seems to be confirmed by the mirror test [12,13], which is used as a consciousness test for chimpanzees as well as for humans in the early stages of consciousness. Only with a system that is complex enough and thus can generate high Φ^{Max} values, the body is understood as one's own in the mirror image. This additional performance cannot be observed in case of most other animal species or sufficiently young infants. In fact, some researches already analyzed the according mirror neurons [14,15], which can be used as an orientation point for further development application of the IDM model.

Further developments of the IDM model.

The exact formulation of the interactions between brain regions remains unclear. The relationships shown in equations (4.18) and (4.19) represent a pure summation of ducti and functions without expressing their interdependence. Therefore, these basic formulations can be solely used in demarcated brain areas and in simple processes. In order to explicitly express any interdependencies within the cortical area, the model yet requires to be elaborated. In addition, the same considerations apply to interdependencies within the environment. Therefore, suitable expressions are required for both intrinsic and extrinsic interdependencies in order to provide a global description of the development of neural networks in a realistic way.

Furthermore, although the learning progress is shown in its elementary steps as an adaptation of the neural network with respect to the environment, it must be grasped in a larger context in order to have an adequate oversight to describe the process. For this purpose, the PARTS algorithm [3] describes the development of scientific theories. In its formulation, a theory is understood as an ordered pair of model and application quantity. If one interprets the experiment as experience and the model as a prediction of the neural system, a learning sequence can be formulated based on the algorithm, which then describes the larger framework of the learning process. Together with a more sophisticated version of the IDM model and taking the IIT into account, a detailed theory of learning processes on a neural level may be developed.

5.3. Conclusions

Overall, the IDM model provides a description of the development of neural networks that can be applied as precise as desired. Based on the IIT, it contains fundamental aspects for the development of consciousness. Framework conditions for the properties of artificial neural networks are also included, which, therefore, are suitable to develop an artificial consciousness. However, before the attempt to develop such an artificial network can be started, further theoretical adjustments are required in order to formulate the most precise possible representation of the development process and thus the most concrete requirements possible for a neural network. The intrinsic and extrinsic interdependencies as well as the learning process are still unexplained, albeit the existing theoretical construct offers certain flexibility for its elaboration.

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