Interaction, self-reference and contingency in computational neuroscience: analytical descriptions and information theoretic consequences

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We will attempt to show that we can use self reference in conjunction with signal theory (vis. electrical systems theory) to construct an artificial organism which complies with the demands of autopoietic systems. The organism is able to develop autonomous behaviour due to sensor-motor learning which is inspired by Piaget [Piaget (1971)]. Learning is achieved through the experience the organism gets while interacting with its environment. This interaction is characterised by closed sensor-motor loops and can not be reduced to a stimulus-response scheme moreover any interruption of the sensor-motor loop makes the system dysfunctional. In this sense our model is non reductionistic. The results of this investigation is expected to be useful for the understanding of social systems since in the organism's environment there are other organisms which also learn. This leads to mutual interaction between them. Thus, the environment is contingent to each individual organism since there are other organisms in the environment which exhibit unpredictable behaviour. As a consequence this is directly related to Luhmann's double contingency of the communication process.

The underlying information theory differs from the typical input/output paradigm and is a self-referential information theory or an information theory of the information which is gathered to improve behaviour (in this case to build up predictive structures).

Introduction

The system theory of social systems has become a powerful tool in understanding social interaction and communication [Luhmann (1995)]. It explains how and why social subsystems emerge, how communication can be interpreted and even how we can generalise the communication medium. The underlying paradigm, the general system theory of self-referential systems, has its origin in a variety of fields such as biology, cybernetics and philosophy [Rogers (1994)]. One of the most important principles of system theory is self reference [von Foerster (1985)]. This means that the elements of a system are self compatible with each other which has the advantage that the quality of the elements can be omitted (like temperature, neuronal activity or behaviour). Thus, the relations between the elements do not need to be converted from one quality to another: thus, neuronal activity follows neuronal activity and behaviour triggers behaviour.

Self-reference

The principle of self reference shall be the starting point of this work. Our task is to identify self-reference and its consequences in the field of computational neuroscience and its related areas like signal theory.

Self reference is given when (in Luhmann's words) compatible elements generate themselves again and again [Luhmann (1995): 33]. This is obviously only possible in recursive structures. In the area of control theory (or electrical systems theory) recursive structures are the basic tools for solving control problems [Oppenheim and

Schäfer (1975)]. Thus, signal theory seems to be a good candidate for describing self reference which will now be explored. The simplest form of recursive control is via feedback loops which are commonly used in a variety of every day situations. A classical example is room-temperature control. When the room temperature decreases the central heating is switched on and the room temperature will be increased in order to re-establish a certain desired temperature. Self reference seems to be established, in such a system, by the closed loop through the environment: every time the central heating is switched on the room temperature increases and the sensor senses this change.

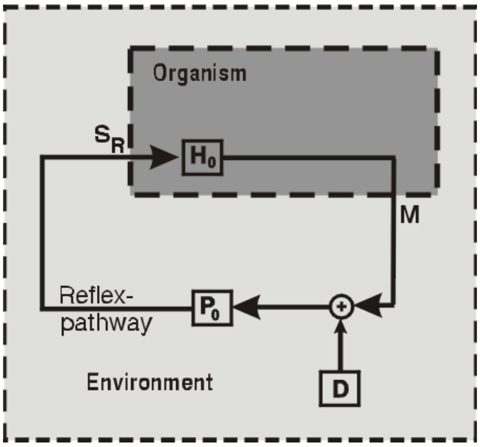

Fig. 1

The equivalent of a technical feedback loop in an organism is a simple reflex loop. Simple animals rely on reflexes, for example for walking or for finding food but the reflex is also a behaviour which is found in humans. For example, this behaviour can be seen when somebody touches a hot surface and then he/she pulls his/her hand away.

The expression "reflex" is to a certain extent misleading as it is tempting to see the system as a stimulus-response or input-output system. However, a stimulus-response system is an *open loop* system which does not correspond to the case of a reflex/feedback loop. From control theory it is well known that if we cut the feedback loop the system's properties deteriorate. Thus, already the simple feedback loop can only be explored as a whole and not if we cut the loop and turn it into an open loop system. We go as far as stating that this typical reductionist approach of treating systems as open loop I/O systems, used so often in the natural sciences can be very misleading when it comes to more complex closed loop situations. Therefore we call our approach *non-reductionistic* and we will only consider the organism's behaviour when it is embedded in its environment. The reason why an organism is often seen as a stimulus-response system is due to the fact that -naturally - an *observer* sees the organism in that way. As for the organism itself it is only possible to "see" itself as a closed loop system since the loop is essential in defining the properties of the whole system.

Self reference demands the compatibility of the self reproducing elements such as neuronal signals which are expected to generate neuronal signals or behaviour which also is expected to generate other behaviour. In the above examples this seems not to be the case since neuronal activity is transformed into motor reactions (e.g. force) and the motor reactions are transformed to sensor events (e.g. pressure, temperature, ...). However, it is necessary to transform neuronal activity directly into other neuronal activity. This problem can simply be solved if, in a radical approach, we take the organism's perspective. Von Foerster [von Foerster (1985): 5-41] argued that at the sensor surfaces of the organism all sensorial qualities are eliminated and converted to neuronal signals. The same applies to the motor output but only the other way round. Since the motor output feeds back to the sensor surfaces every motor *signal* leads again to a sensor *signal*. The sensor-motor loop can now be completely closed when we accept that, from the organism's point of view, only signals are of interest which actually feed back from the motor output to the sensor input. The transfer from the motor output to the sensor inputs happens in the environment but is expressed in terms of the *organism's signals.* Thus, we will use the *internal* signals (elements) of the organism for the description of the *external* environment. Any motor reaction which "goes into the world and will never return" can not be of any interest to the organism. In terms of signal theory this means that the feedback loop determines for the organism what is a signal (useful) and what is noise (useless): only motor reactions which feed back to the sensor inputs are potential candidates for becoming a signal (which is useful). Otherwise they are noise. Noise is from the organism's point of view the source of contingency. Formally this is introduced by the disturbance D (Fig.1) in the environment. This disturbance is again described from the organism's point of view as there are an infinite number of disturbances in the world but only those disturbances which disturb the feedback loop can be of any interest to the organism. Since the feedback loop is described in terms of neuronal signals the disturbance can also be described by the organism's internal neuronal signals.

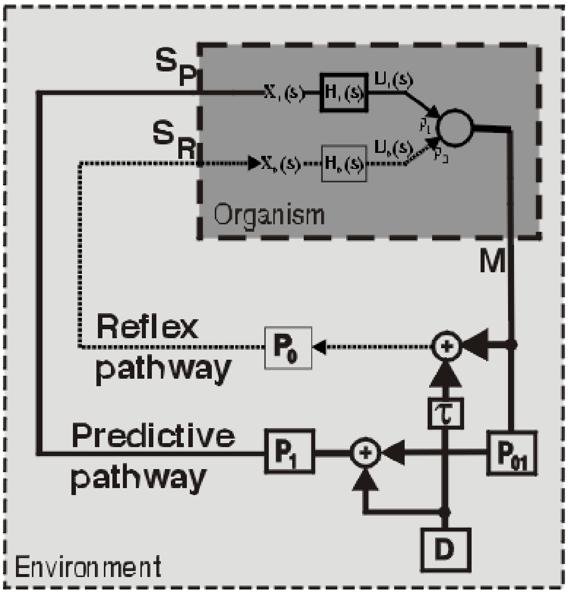

Fig. 2

Self-referential temporal sequence learning

Any feedback loop has the inherent disadvantage that the organism can not predict when the disturbance D will actually happen [Azzo (1988): 147]. It can only react after the disturbance has occurred which poses a problem for the organism which should be solved. This can be achieved if the organism can turn the contingency of D into certainty. Thus, if the organism would be able to *predict* the disturbance D. We start again with the reflex example: the reflex itself can not prevent that the sensor event "pain" will occur since it can react only after it has occurred. Only if the organism is able to *learn* the relation between the pain and, for example, the heat radiation (which foregoes it) it can avoid the painful stimulus by generating an anticipatory motor reaction. As heat radiation and pain follow in a *sequence,* learning has the task of learning this temporal sequence in order to generate an early motor reaction. Thus, in general, temporal sequence learning of sensor events enables the organism to generate *anticipatory behaviour* in order to react faster than before.

How is temporal sequence learning achieved in our model? Fig.2 shows the extended circuit of the formal organism and the formal environment. Again we have the reflex pathway with transfer functions H_0 and P_0. Additionally we added a pathway from the disturbance D to the input S_1 and a delay τ which triggers the reflex pathway later than the predictive pathway via S_1. Thus, the disturbance enters the organism early via S_1 and late via S_0. If the organism is able to learn the temporal relation between S_0 and S_1 it should be able to generate an early motor reaction which eliminates the disturbance before it reaches the input S_0. Temporal sequence learning can be used to eliminate this objective disadvantage of a reflex that is to say that it reacts always too late. Consequently learning takes place when the reflex is triggered and the past is analysed if predicting signals exist which could used to generate a motor reaction in order to prevent triggering of the reflex.

At this stage it is necessary to concentrate on the different learning paradigms of sequence learning which are offered in computational neuroscience and to decide if one can develop autonomous behaviour. Learning of sequences has a long tradition in Psychology which began with Pawlow's classical conditioning and has been mathematically formalised by Sutton and Barto in the form of Temporal Difference (TD) learning [Sutton and Barto (1982)]. The learning scheme by Suttor and Barto is a *supervised learning* scheme which needs an *external teacher* (in the environment). Since we want to describe autonomous behaviour we can not use a learning rule which relies on teacher-like evaluation arising from the environment. We need a learning rule which is non-evaluative and self-organising. This leads to another class of learning rules which are called *unsupervised learning rules.* Amongst these unsupervised learning rules there is one learning rule which is of special interest in this context since it learns temporal sequences and is biologically inspired. New results from neurophysiological experiments suggest that the temporal timing of neuronal signals is crucial to synaptic learning and therefore to synaptic weight change: if the presynaptic activity precedes the postsynaptic activity then the synaptic weight is increased and if the timing is reversed it is decreased [Zhang et al. (1998)]. This rule is called spike timing dependent synaptic plasticity (STDP) or simply "Temporal Hebb" since it is a special form of classical associative Hebbian learning: while standard Hebbian learning only develops associations between events which occur around the *same* time temporal Hebb learns associations between sequences of events. The learning rule operates unsupervised which seems to be good for explaining autonomous behaviour of an organism since this is *self-organising.* The rule develops by itself freely and is guided only by using a general paradigm, in our case the learning of temporal sequences. The unsupervised learning rule seems to have direct links to constructivism (and post-modernism), as it claims that all constructions are freely self constructed by the organism. This is the outstanding feature but also the curse of such learning: Self-organisation has always the inherent danger that the results become *arbitrary* and therefore *useless* to the organism. Many have criticised the constructivists precisely for that reason: anything goes, the results of the "constructions" (or unsupervised learning) are completely arbitrary [Hachmeister (1992)]. The standard solution of the theory of neural networks is that so called "boundary conditions" are introduced which reduce the degrees of freedom (thus limiting the manifold for possible constructions), so that the network becomes constricted within sensible boundaries. However, these boundary conditions really only camouflage the experimenter outside the organism who actively interferes preventing the network from becoming arbitrary. Thus, it seems to be that purely unsupervised learning is not applicable and it is clear that some form of reference must exist. In our autonomous organism the solution is again the reflex pathway which can be seen as a "genetic" basis: the reference we have demanded is given by the pre-wired fixed reflex pathway. The reflex pathway defines what is zero in time and therefore what is earlier and what is later. Every sensor signal which arrives *earlier* than the reflex signal is beneficial to the organism in the sense of *predicting* the unwanted reflex and every sensor signal which comes later is useless. However, the reflex is only the starting point for the development of more complex sensor-motor loops which can be build up by recursively predicting each other. But it is the reflex which kick-starts learning and prevents the organism from developing arbitrary behaviour. Thus, in this sense we can say that temporal Hebb in conjunction with feedback loops is self referenced unsupervised learning with the objective to improve the organism's feedback loops. For that purpose we have modified the pure unsupervised temporal Hebb learning rule and developed a special learning rule which incorporates both properties: it is unsupervised but it has its initial reference in the form of the reflex loop. Learning starts with the reflex loop and then develops more complex behaviour in superseding the reflex loop with more complex sensor-motor loops.

Information theory

Information theoretic issues are usually performance measures and we want to explore if the existing measures are useful to our model. In classical information theory [Shannon and Weaver (1976)] the performance is usually measured by the effectiveness of how a signal is transmitted. In our theory this does not make sense since the information measure has to measure the organism's performance from the organism's point of view and not its input-output properties. Again we start with the reflex loop. Ashby's measure of the requisite variety can be taken to describe the performance of the feedback loop when there is no predictive learning involved [Ashby (1972)]. The requisite variety measures whether the organism can cope with disturbances at its feedback loop. Only if the requisite variety is high enough can the disturbances be fully compensated otherwise compensation is incomplete. But even if the requisite variety is high enough the inherent problem of the sluggishness of feedback loops can not be eliminated. Only predictions of the looming feedback reaction can improve the organism's behaviour as stated above. Thus, when learning is involved we need a measure which accounts for learning of the *temporal patterns* which are used to improve the feedback behaviour. Consequently the reference is again the reflex loop: as long as no predictions have been learned the information measure can be assumed to be zero. From the moment the disturbances can be anticipated by other sensorial inputs and can be eliminated by the motor reaction the measure should increase. This information measure must take explicitly into account that not all information in the world is useful to the organism. Information is only useful when perturbations/disturbances in the feedback loop can be reduced with other sensor inputs which form new sensor-motor loops. In the worst case it could happen that none of the sensors can predict a disturbance, even if there are signals which are highly temporally correlated. This view opposes the standard info-max principle of computational neuroscience where any information is integrated [Linsker (1988)], regardless of what use it serves to the organism. This principle is called info-max and is the result of completely unsupervised Hebbian learning. As stated before completely unsupervised learning is often useless and therefore there have been extensions of the Linsker model which integrate these constraints. Such constraints are often called "contextual information" [Smyth (1996)] where this information in these models is supplied by additional inputs. However, these models remain typical input/output models whereas our model is strictly self referential in using a loop as a reference and not a signal. An information measure of an organism must take into account the fact that feedback loops are closed entities. The organism measures its performance in relation to its past performance which is in the first instance the performance of the feedback reflex loop. Additional loops again build up on the former loops so that an information measure should measure all accumulated improvements. From our knowledge there is no such measure available in the field of computational neuroscience and signal theory. Below we will suggest a measure for our robot application.

Social implications

After having explored the neuronal level of a single organism we have to explore the interaction between organisms. Maturana [Maturana (1991)], Luhmann [Luhmann (1995): 103] and others have stated that out of the self referent neuronal system other self referential systems emerge like the behavioural system or more abstract: our communication system. These systems describing the interaction between organisms have no access to the organism's internal structure (neuronal signals) but exist in a causal relationship with the neuronal level. Self reference in a system which emerges out of neuronal systems, can be identified by elements of behaviour (behaviour follows behaviour) [Parsons (1951)] or by the elements of communication (utterance/information) [Luhmann (1995): 137]. Problems arise when the different levels are mixed. On the level of behaviour (especially language) we have the problem that we don't have access to the neuronal level. Thus, we need metaphors on the level of behaviour to explain the neuronal level. A good example is "free will". On the level of neurons this concept does not make sense since the neuronal system works in a deterministic way. We follow Maturana's view here that every organism can be described by its neuronal signals, chemical potentials, etc [Maturana (1991)]. With regard to behaviour this makes sense since we do not have complete knowledge about the neuronal structures and we don't have access to them. We can not explain behaviour in looking at neuronal activity. We can only explain behaviour with behaviour (as often done by language). Thus, we have to compensate for the lack of knowledge which arises from the fact that we are not able to look into the brain. Another example for the crossing of system levels comes from neurophysiology and is the construct of the "grandmother cell". The assumption is, that since we label a person "grandmother", we have cells which fire when we see the grandmother. Neurophysiologists have been searching for decades for these neurons but eventually gave up (similar examples exist in the field of emotions and motivations). There is always the danger that we will run into problems when we use descriptions of the behavioural level to explain the neuronal level which only consists of neuronal signals. Self reference separates the different system layers and points out the problems that we get when we mix different levels.

Autonomy

Based on the background of the two system levels (behaviour/communication and neuronal signals) it now becomes possible to define autonomy. We define autonomy from the observer's point of view (thus, from the behavioural level): an organism is autonomous from the moment that the organism shows behaviour which is no longer completely predictable from the observer's point of view. This is always the case when the organism has *more than one choice* of what it could do but the observer does not know what has been the reason for the organism's decision. The observer's problem is due to the fact that the observer doesn't have access to the internal neuronal mechanisms and can only use the behavioural level to try to predict (explain) the organism's behaviour. Thus, autonomy emerges from the moment the sensor-motor reaction is no longer reflex-like or from the moment when it is no longer clear why the robot has chosen a specific behaviour. Obviously this is the case *after* learning when the organism has eliminated its stereotype reflex behaviour and has generated more sophisticated behavioural strategies by itself. This phenomenon is only a problem for the observer since the organism itself is still, in theory, completely describable by its internal states (nervous signals, chemical potentials,...) but for us these are usually not accessible. This type of learning leads to the effect that an observer perceives the organism's behaviour as more and more contingent.

The organism's perspective during learning is the opposite: when having to rely only on the reflex behaviour the organism has least knowledge about the environment and experiences highest contingency from the environment (here in form of the disturbance D). After having successfully learned to avoid the reflex the organism has learned to cope with the contingencies in the environment and thus, has gained security.

With more than one organism in the world each experiences the others as additional sources of disturbances and vice versa. Learning has still the task that one organism has to learn predictions about its environment. However, now the environment contains "the others" which also try to do the same in predicting "their others". This leads to Luhmann's double contingency which is a basic property when two organisms try to predict each other [Luhmann (1995): 103]. Thus, our organisms are able to generate a social system in the sense of double contingency.

Robot Application:

In this section we will show that a robot can incorporate important aspects of autonomous behaviour which we find in "real" organisms. We follow Maturana's argumentation that a biological organism works deterministically. This means that all processes in the organism can be explained by causal relations, in our case by signal theory.

Fig.3a shows the robot and the schematic drawing shows the the internal connections. The robot has two "neurons" which represent its speed (ds) and the steering angle ($d\phi$). The standard behaviour of the robot is to simply drive straight ahead. Two different sensor types are installed on the robot: bump sensors and vision sensors. The

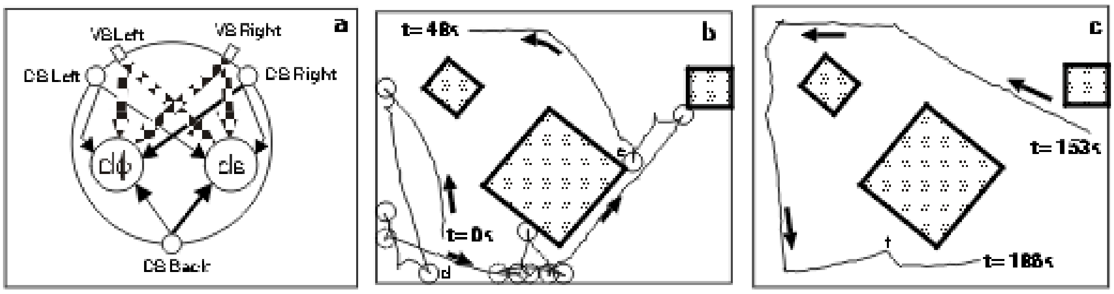

Fig. 3

bump sensors are connected with fixed synapses to the 2 neurons (thin lines). These predefined and fixed connections establish the robot's reflex: every time the robot senses a bump it performs a stereotypical reflex like retraction reaction in order to avoid the obstacle. The reflex enables the robot to continue with its journey. The connections from the vision sensors are first set to zero strength so that the robot uses only his reflex mechanism when a collision occurs (Fig.3b).

In this case the robot experiences its environment as maximally contingent but the observer experiences the robot as completely predictable in its behaviour. Learning has the task of detecting the temporal relation between the vision- and the bump sensors. After having successfully learned the relationship between the vision sensors and the bump sensors the robot is able to change its direction before it bumps into a wall (Fig.3c). In order to achieve this, learning is completely self organising and needs no external teacher: the reflex behaviour just drives the learning. The reflex determines the reference in time and learning has the task of determining those sensor events which are earlier than the reflex. The behaviour after or during learning (and learning in our example never stops) is for an observer not completely predictable. It is only obvious that the robot learns to avoid bumps after a while but *how* this is actually done is always different. In one experiment the robot simply waits in front of an obstacle and rests there. In another experiment the robot develops more complex reactions. But every experiment is unique and develops "another" robot.

Engineering and biology

We have presented the robot experiment. Now, we shall attempt to demonstrate the differences between our model and those of a typical engineering model. In engineering we have an external observer, the engineer, who wants the system (for example the robot) to do precisely what he/she wants. This can be achieved by hard-wiring all properties into the system or by "teaching" the system the desired response which is a standard technique (and idea) in computational neuroscience. Before "learning" the neural network does not behave in the desired manner, so the engineer "teaches" the system with a special signal until it has reached the desired behaviour. Thus, first the system exhibits unpredictable or undesired behaviour. Then later (after learning) it becomes completely predictable in the sense that it is now useful for the engineer (who is part of the environment).

Our system behaves the other way round: for an *observer,* first the behaviour of the robot is completely predictable due to its reflex. After learning the robot's behaviour is no longer predictable for an observer since the robot has found one behavioural solution out of many possible solutions. From experiment to experiment the robot develops differently so that, in spite of the fact that the robot starts always from the same "genetics" (reflex), the behaviour after learning is always different. Having two robots developing in this playground would create different behaviour. Thus, the robot's behaviour is no longer completely predictable. This leads to a problem in the environment: the robot's environment has to cope with the robot's unpredictability or autonomy. This is completely opposite to a technical solution: in a technical solution the observer wants to have a predictable system. Thus, we can differentiate between two different paradigms: the "Engineering paradigm" and the the "Biology paradigm". The "Engineering Paradigm" is always interested in a particular desired behaviour which is achieved by an external evaluation of the system's behaviour. In the "Biology paradigm" the organism follows its internal objectives and there is no external evaluation.

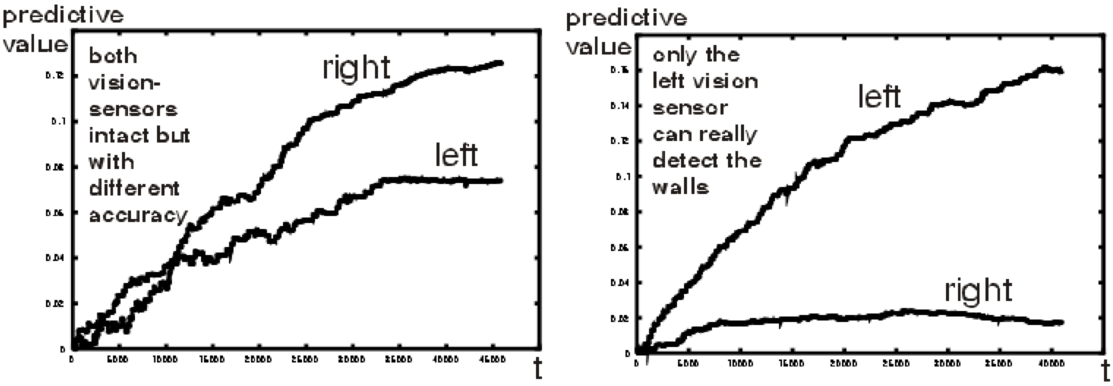

Fig. 4

Predictive value

We have developed an information measurement which measures the robot's internal ability of predicting the triggering of the reflex which we call *predictive value.* It reflects the use of the vision sensors to prevent the trigger of the bump sensors. Fig.4 shows the development of the predictive value for the 2 vision sensors in relation to the steering angle. In Fig.4a both sensors are intact and used for the prediction of the bump events which occur (or would occur). In Fig.4b the left vision sensor is partly blindfolded giving a very bad response. This leads to a low predictive value on the left vision sensor. Thus, this information measurement can show how the robot integrates new environmental signals in order to reduce the uncertainty of the feedback loop.

Now we switch over to an external observer in the outside world who has no access to the robot's internal structure. For an observer the growth of the predictive value can be interpreted (apparently paradoxical) as a *growth in unpredictability.* This is due to the fact that the robot develops *different* strategies (namely more than one) to avoid bumping into objects. As mentioned before Fig.3c show only the outcome of one experiment. In other experiments the robot simply waits in front of a wall and does nothing. Thus, the environment experiences the robot's behaviour as more and more unpredictable. This rise in unpredictability poses an additional problem for another robot which wants to predict its environment where other robots behave in a quite unpredictable manner. This effect is described by Luhmann as the double contingency and is in his theory the basis for communication. Both organisms try to reduce their internal uncertainty but at exactly the same moment they generate uncertainty in the environment. In our robot example it can be seen that due to learning a new level of complexity arises from the moment when two organisms try to predict each other. Further studies have to be done to explore this field of double contingency. But already in the existing robot application we can show that double contingency emerges which is a result of a reciprocal generation of uncertainty in the environment.

Conclusion

Applying self reference in conjunction with learning to a technical system (here: a robot) leads inevitably to autonomous behaviour. Autonomy is defined internally to the ends that the organism has to reduce the environment's contingency. For an observer it is the other way round: while the organism is gaining certainty about the environment the observer (viz the environment) experiences the organism as more and more unpredictable. To have other organisms in the environment poses the problem that each organism becomes during learning a source of contingency for the other organisms. This is described by Luhmann as double contingency and is the basis for social systems.

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