Multi-sensorial generative and descriptive self-awareness models for autonomous systems

Carlo Regazzoni, *Senior Member, IEEE,* Lucio Marcenaro, *Member, IEEE,* Damian Campo, *Member, IEEE,* and Bernhard Rinner, *Senior Member, IEEE,*

***Abstract*—In a computational context, self-awareness (SA) is a capability of an autonomous system to describe the acquired experience about itself and its surrounding environment with appropriate models and correlate them incrementally with the currently perceived situation to expand its knowledge continuously. This paper introduces a bio-inspired framework for generative and descriptive dynamic models that support SA in a computational and efficient way. Generative models facilitate predicting future states, while descriptive models enable the selection of the representation that best fits the current observation. Our framework is founded on the analysis and extension of three bio-inspired theories that have studied SA from different viewpoints, and we demonstrate how probabilistic techniques, such as Cognitive Dynamic Bayesian Networks and Generalized filtering paradigms, can learn appropriate models from multi-dimensional proprioceptive and exteroceptive signals acquired by the autonomous system. We discuss essential capabilities for SA and show how our modeling framework supports these capabilities in theory and by means of a case study where a mobile robot uses multi-sensorial data to determine its internal and environmental state as well as distinguishing among normal and abnormal behaviors.**

***Index Terms*—self-awareness; autobiographical memory; autobiographical self; cognitive dynamic systems; Bayesian inference; anomaly detection; model creation**

I. Introduction

Self-awareness (SA) is a broad concept that describes a cognitive property of a biological—typical human—agent. At a rather abstract level, SA can be defined as the capacity to become the object of one's own attention, which arises when an agent focuses not only on the external environment but also on the internal milieu. The agent becomes a reflective observer, processing self-information. It becomes aware that it is awake and actually experiencing specific mental events, emitting behaviors, and possessing unique characteristics [1]. Another classic SA definition is proposed by Fenigstein et al. [2], who state that a self-aware agent may focus on private or public self-aspects. Private self-aspects relate to externally unobservable events and characteristics such as emotions, physiological sensations, perceptions, values, goals, and motives, whereas public self-aspects are visible attributes such as behavior and physical appearance.

C. Regazzoni, L. Marcenaro and D. Campo are with Department of Electrical, Electronic, Telecommunications Engineering and Naval Architecture at University of Genoa, Italy

B. Rinner is with the Institute of Networked and Embedded Systems at University of Klagenfurt, Austria.

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Over the years, SA has been an object of intensive discussions and studies in different disciplines such as philosophy, psychology, and cognitive sciences (e.g., [3], [4], [5]). Common aspects of the proposed approaches lie on the conception of SA as *i)* a cognitive **embodied process** composed of representational and inferential operations of an agent situated in an environment, and *ii)* an agent's **property** which emerges in various forms, including the extent of the SA capabilities ("levels") [1], [6] and the scope of the processed information ("private and public") [2], [7]. More recently, SA concepts have been transferred to artificial systems aiming at either designing intelligent agents or analyzing their behavior. The driving motivation for the transfer of biological SA concepts to artificial systems is to improve autonomy, robustness, and scalability and has been investigated in different fields, including software engineering, machine learning, and robotics [8], [9], [10], [11], [12], [13], [14], [15]. A fundamental challenge in most of these approaches is how to **systematically** integrate SA capabilities into artificial agents.

In this paper, we approach SA from a **sensor data and signal processing perspective**. An artificial agent is considered self-aware if it can dynamically observe itself and its surrounding environment through different proprioceptive and exteroceptive sensors and learn and maintain a contextual representation by processing the observed multi-sensorial data. Proprioceptive sensors measure the internal agent's parameters, whereas exteroceptive sensors observe the agent's environment (cp. Fig. 1). The SA representation obtained by jointly and dynamically analyzing the sensory data endows the agent with introspection at different hierarchical levels. Since the term introspection allows a quite broad interpretation, we associate it with the agent's capability of estimating and representing dynamical causal relationships from the observed sensory data. Such representation allows the agent to model interactions between itself, as observed through proprioceptive sensors; and the environment, as observed through exteroceptive sensors.

The extent of the embodied SA capabilities influences the agent's performance when solving tasks and are assumed as reasons for the significant capability differences of the various biological species. Accordingly, this paper identifies the following capabilities as the minimum requirements in to consider an agent self-aware: **initialization**, **inference**, **anomaly detection**, **model creation** and **interface with control**. Table I describes the proposed SA capabilities and provides a relationship between each of them and biological agents, demonstrating how humans address these capabilities.

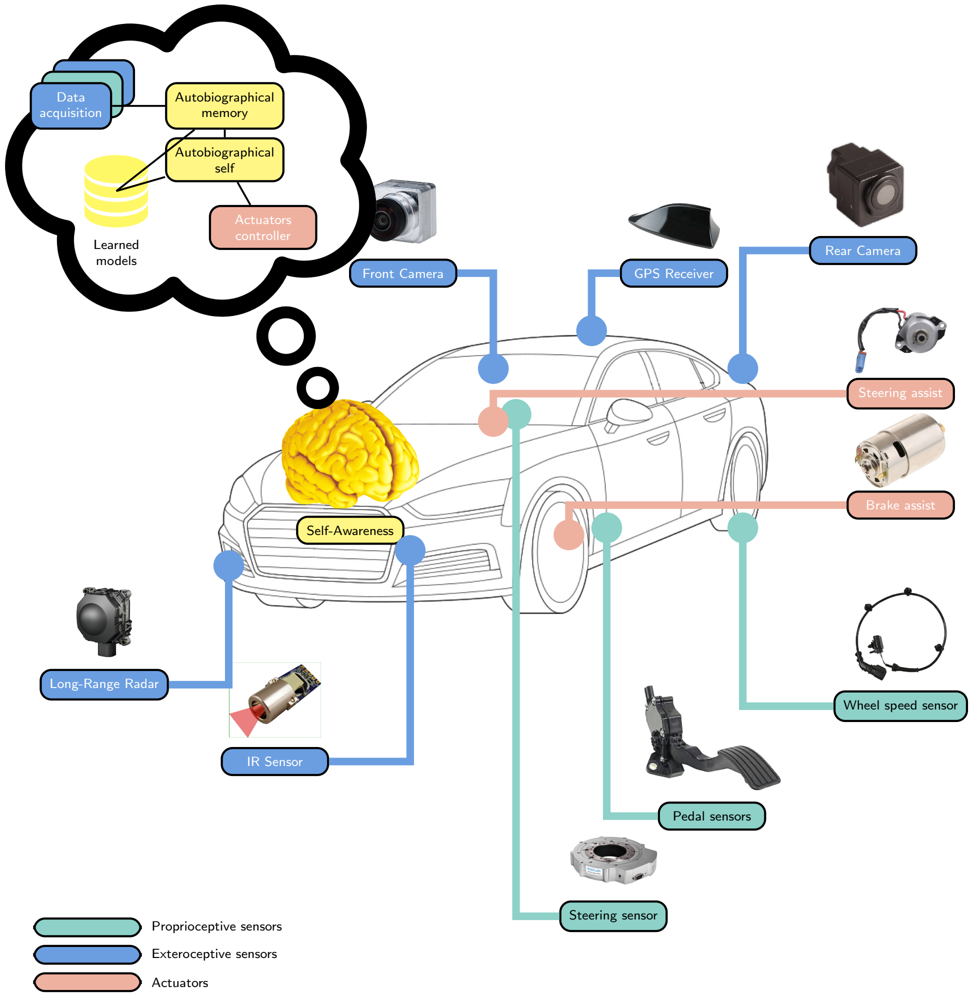


Fig. 1: Concept of a physical architecture for a self-aware autonomous system. The self-aware agent (here conceptually embedded in a vehicle) observes its surrounding environment with exteroceptive sensors (blue) and its internal state with proprioceptive sensors (green) and translates its autonomous decisions into actions through the actuators (in red). The SA core (yellow) is established based on internal representations from the autobiographical memory and the autobiographical self, together with a set of already learned models. The SA core is able to forecast the next state of the environment and the system itself, detects anomalies and executes the derived actions.

To the best of our knowledge, these SA capabilities haven't yet been sufficiently studied. We, therefore, propose a signal-driven modeling approach that facilitates SA capabilities.

It is important to note that our bio-inspired modeling approach aims to improve the autonomy of technical systems such as robots, IoT devices, or cyber-physical systems. Initialization, inference, anomaly detection, model creation, and interface with control are core capabilities of agents operating in highly dynamic, interactive, and uncertain environments in order to achieve reasonable autonomy. However, genuine autonomous systems are required to fulfill a variety of system properties, including efficiency (minimizing the resource consumption), security (protecting against threads), and safety (operating in conformance with requirements). We do not address these properties in this paper but refer to other papers of this issue and related literature (e.g., [22], [23], [24]). Instead, this paper aims at providing a general bio-inspired framework to model SA computationally employing Bayesian representations, probabilistic inferences, and machine learning techniques. The proposed framework is capable of comparing current experiences with previous ones. It makes it possible the learning of *descriptive* dynamic models that include semantic (symbolic) and continuous information, enabling them to interpret multisensory observations contextually. Accordingly, the proposed SA model represents multisensory experiences by using a probabilistic structure that jointly describes observations in a semantic, temporal, and hierarchical way. The learned models are generative at different levels, in the sense that errors obtained from such models (differences between already learned experiences and new ones) allow an agent to add new models incrementally by describing variations (i.e., errors) at different abstraction levels. The proposed framework can integrate several machine learning techniques (e.g., deep neural networks and clustering algorithms) to learn contex-

TABLE I: Definition of self-awareness capabilities and biological relationships.

Self-awareness capability	Definition	Biological relationship
Initialization	It refers to the initial knowledge from which an agent starts building its own memories. Such initial knowledge provides the agent with the essential tools to interact with its surroundings.	The basic structure of the brain is laid down primarily during the prenatal period, where its *initialization* depends largely on genetics [16].
Memorization	It refers to the agent's capacity of storing and retaining information such that it can be recovered and exploited in the future.	Long-term memories are stored throughout the brain as groups of neurons that fire together in the same pattern that created the original experience. Such operation is done by the process of memory allocation [17].
Inference	It consists of the agent's ability to make predictions about its own future states and its surroundings depending on its current state.	The brain is responsible for anticipating future events. The *predictive coding* theory [18] states that at each level of a cognitive process, the brain generates beliefs of the information it should be receiving from the level below it. These beliefs are translated into predictions about what should be experienced in a given situation.
Anomaly detection	It consists of the agent's ability to recognize observations that cannot be explained by its memories. These observations represent new events that the agent has not detected so far.	Brain predictions are sent as feedback to low-level sensory regions of the brain. The brain then compares its predictions [19] with the actual received sensory input and "explains" high differences (prediction errors) between them.
Model creation	It refers to the agent's capability of generating models that encode previous experiences, facilitating the prediction of the agent's future states and the posterior comparison with evidence.	The prediction errors that can't be explained away get passed up through connections to high levels of feedforward signals, where they are considered newsworthy. The internal models get adjusted so that the predicting error gets suppressed [20].
Decision-making influence	It refers to the ability to generate signals that can be employed by the agent's control system such that its actions are self-monitored dynamically	Muscles move based on commands from the brain [21]. Nerve cells in the spinal cord, called motor neurons, enable to convey and evaluate the brain's commands to the muscles.

tual relationships among multisensorial data and model their dynamics over time by using a multilevel Bayesian approach.

The remainder of this paper is organized as follows. Section II analyses and compares three bio-inspired SA theories. Section III describes the proposed methodology by which signal-driven SA models can be generated and incorporated into artificial agents. Section IV discusses the benefits of coupled proprioceptive and exteroceptive self-awareness. Section V concludes the paper.

II. Bio-inspired self-awareness theories

This section discusses three fundamental bio-inspired theories (proposed by Damasio [25], Haykin [26] and Friston [27]) that have studied SA from diverse viewpoints. We discuss and analyze the key concepts with a special focus on their SA capabilities (Table I). In the subsequent sections, we expand these concepts towards our approach for self-aware artificial agents.

A. Damasio's model

Neuroscientists such as Damasio [28] have provided evidence that neural patterns in the oldest parts of the human brain are organized to process and combine proprioceptive and exteroceptive sensorial information according to hierarchical neural layouts culminating into so-called **autobiographical memories** (AMs). AMs can constitute a sort of database for memorizing models of episodes that the agent has learned from previous experiences [5]. Bio-inspired AMs have already been investigated towards implementing self-awareness in artificial agents, for example, in [29]. Based on anatomical observations, Damasio suggests that episodes in AMs are represented by a language coding proprioceptive and exteroceptive information according to a temporally ordered causal representation. Fig. 2 depicts the combination of estimations of the agent's own the external world's state obtained by an early neural layout (named "proto" and "core", respectively) in the form of **temporal-causal** AM patterns.

According to Damasio, AM patterns are based on first-person situational descriptors that enable human agents to represent experienced episodes on the basis of a neural vocabulary (i.e., **information units**). These descriptors always represent exteroceptive data as contextualized to information coming from the agent's body, and vice versa. Thus, patters encoding episodic experiences are represented by coupling the agent and its **dynamic interaction** with the surrounding environment.

Elementary information units used in AMs define a temporal representation where an agent and the environment reciprocally take on the role of a context. Temporal changes of the internal representation of the state of one of them (that Damasio calls "dispositions") are observed as occurring in the context of the other one assuming a given state (see Fig. 2).

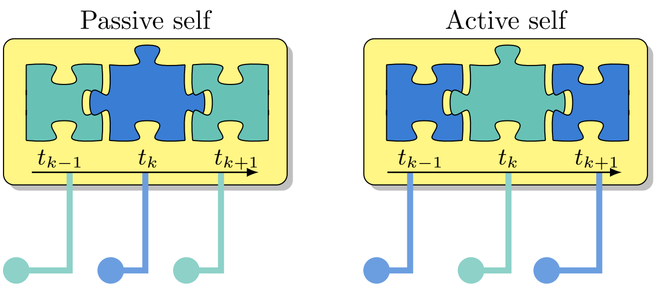


Fig. 2: Two elementary information units depicted in the yellow box correspond to the passive (left) and active (right) self [29]. The passive self unit stores triplets formed by data alternatively acquired from proprioceptive and exteroceptive sensors at different time instants. Proprioceptive data are acquired at time instant t_{k-1} and are followed by data from the environment at time t_k captured by exteroceptive sensors. They cause a change of the internal state of the system at time t_{k+1} that is monitored by proprioceptive sensors. Vice-versa, the active self elementary unit models the cause-effect relation between the data acquired by exteroceptive and proprioceptive sensors.

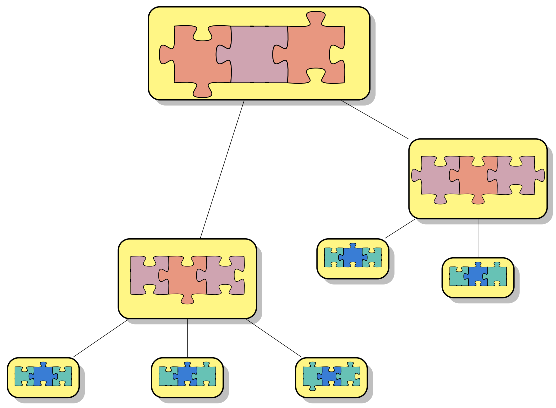


Fig. 3: Hierarchical organization of dispositional units in the autobiographical memory. According to Damasio [28], these elementary information units can be found at different levels in the brain and constitute temporal-causal representations of cognitive processes. This hierarchy expresses experiences at different time scales: directly connecting exteroceptive and proprioceptive data at the leaves and more complex and structured information corresponding to long terms goals at higher-level nodes.

Sequences of such patterns are stored in the AM representing episodes. Therefore, at least in humans and biological agents, SA is based on a **contextual** representation, which is essential for the emergence of the expected SA capabilities as listed in Table I.

A dynamic description of agent and environment changes based on their reciprocal states is a key element for the representation of SA knowledge. This is different from many traditional AI systems, where exteroceptive sensory data sequences are often represented at a primary level without explicit contextual information. As a consequence, high-level processing techniques, for example, classifiers based on supervised labeled learning [30], [31], [32], use implicit contextual information to cluster such data into homogeneous groups. Despite the impressive classification performance that can be achieved when testing data and training experiences belong to the same class, the observing artificial agent cannot reliably connect such classification results to its internal dynamical state when performing similar actions to the ones performed during training, simply because its state was not observed and memorized together with the observed exteroceptive data. It is therefore not trivial to use such classifiers as building blocks for an artificial agent due to the limited adaptability.

Damasio [28] proposed **dispositional units**, i.e., information units representing contextualized state changes of the agent or the environment, for modeling "cognitive cycles", i.e., episodes that can be found as the basis of human self-awareness. Moreover, he suggests that dispositional units can be hierarchically organized at different levels in the brain, for example for describing temporal-causal representations in the activation and processing results of neuron maps dedicated to different goals. Consequentially, an AMs should be **hierarchical** structured for providing SA models, and thus dispositional units' representations should be defined such that they can be organized in multi-level hierarchies (see Fig. 3).

Neuroscience observations show that the parts of the human brain storing AMs are linked and can exchange neural signals with other parts of the brain known to be activated within conscious inference processes [33]. The role of such neural maps is to analyze—at different hierarchical levels—proprioceptive and exteroceptive sensorial data originating from the current agent's experiences. The process of recalling and comparing multi-level AMs with respect to current experiences is an integral capability of self-awareness related to **inference and anomaly detection**, which is defined by Damasio as **autobiographical self** (AS).

The AS allows an agent to evaluate whether the current experience matches any episode stored in the AM. Moreover, the AS must provide inference processes to **interface** with other parts of the agent's brain (e.g., blocks dedicated to agent's **resource planning and control** of actuators) to maintain a dynamic stability condition, i.e., homeostasis [34]. In a SA model, the inference capability implies that activated AMs' dispositional units and currently experienced data elaborated by early neural maps can be managed by the AS inference process to perform, for example, predictions on the agent's future states. Based on the temporal-causal organization of the available episodes stored in the AM, the AS is able to predict future states at multiple abstraction levels by using **generative** models that represent possible alternative realizations of episodes already experienced adapted to currently observed data. As multiple episodes are stored in the AM, the AS inference processes need to identify models that better match the current experience, which requires the dispositional units' representation in a SA model to inherently provide a

discriminative property to assess current data characteristics.

An artificial AS is also required to determine the difference between episodes contained in its own AMs and the current experiences based on an appropriate metric, which can be interpreted as the basis for the **abnormality detection** capability (see Fig. 4). In order to assess the matching degree between predictions derived from the dispositional units of the set of potentially applicable episodes and the current observations, the SA agent must apply a computable metric invariant to the sensor modality. In this case, the agent should be aware that an abnormality, i.e., a non-stationary condition never experienced before, is currently present. Damasio does not address which specific computational neural characteristic included in the neural implementation is able to realize such computational behavior. He only suggests that such matching and prediction inference capabilities can be performed by the AS at different abstraction and temporal levels and so enabling an efficient selection of the hierarchical and dispositional representation of AMs episodes).

It is worth mentioning that for natural agents, Damasio suggests that the integrated SA system composed by AM and AS can also be used as a possible explanation of higher-level human regulatory psychological phenomena such as emotions and feelings [35]. Emotions and feelings can be considered as emergent results of evaluating current experiences based on multi-level hierarchical AMs by means of the AS [25]. For example, fear can emerge from the capability of detecting abnormalities, recognizing that the current experience does not match with past AMs, or it matches with AMs that describe dangerous episodes. Damasio's model implicitly implies that AS outcomes enable an agent to **incrementally update** internal AM models by coding abnormal experiences into **new models** as well as to define a SA system that derives inferences invariant to the involved sensor modalities.

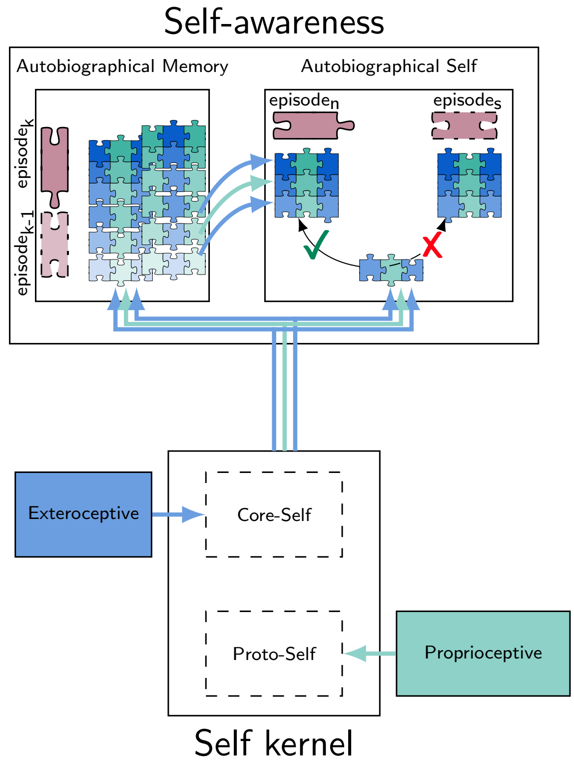


Fig. 4: Autobiographical memory (AM) and autobiographical self (AS) as core components of a self-aware agent founded on Damasio's model. The core-self and the proto-self process exteroceptive and proprioceptive information and store them as dispositional units in the AM. The AS is able to perform inference and anomaly detection based on the stored episodes.

B. Haykin's model

In comparison with Damasio's work, Haykin proposes a computational framework of neuroscience observations from an engineering perspective referred to as Cognitive Dynamic Systems (CDS) [36]. The proposed CDS model is based on the interactions that a Cognitive Controller (CC) part of a CDS has to maintain at multiple levels of abstractions with a Cognitive Perceptor (CP). The CP processes exteroceptive information coming from the environment at different hierarchical levels and can be seen as a hierarchical probabilistic filter, generating environment descriptions at different abstraction levels. Beyond providing information to higher levels, such a filter generates hierarchical feedback information to the CC, which in turn computes commands to actuators that are characterized by uncertainty. The CC block of Haykin's model is described as a top-down structure generating outputs towards lower levels. At the bottom layer, it directly generates outputs for the actuators.

The Probabilistic Reasoning Machine (PRM), introduced in a joint paper with J. Fuster [37], organizes probabilistic information coming from the CP, i.e., percepts and errors (prediction and update processes), together with information coming from the CC, i.e., planned actions with its related uncertainty. Such an organization is performed over time. As can be seen in Fig. 5, Haykin's model does not directly employ proprioceptive sensory data but uses internal strategies to generate commands towards actuators.

The main goal of the PRM is to maintain a meta-level representation of the perception-action cycle based on switching and adapting the behavior of CP and CC. As the control strategies embedded in the CP are hypothesized to maintain homeostasis, i.e., a dynamic equilibrium between the agent's state and the changes in the environment, the PRM is contributing to the continuous regulation of agents' processes by providing switching suggestions to CP and CC. Those suggestions are implicitly based on the knowledge that an agent must have been learned from experiences, and it is represented within the PRM. In this sense, the PRM block is strictly related to Damasio's SA model, as it has to process representations of actions and percepts organized in a temporal-causal order, and the PRM block can be related to AM and AS as SA model capabilities.

The PRM elementary representation requires organizing perception and actions into data structures capturing **causal and temporal interactions** between the agent's actions and percepts originated from the environment. Dispositional infor-

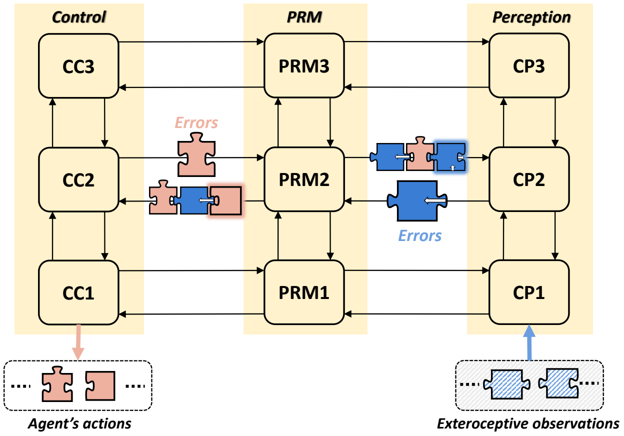


Fig. 5: Hierarchically structured probabilistic reasoning machine (PRM) adopted from [37]. The cognitive perceptor (CP) processes exteroceptive information ("percepts") at different hierarchical levels, and the cognitive controller (CC) generates outputs towards the actuators in a top-down structure. The PRM organizes probabilistic information from perception and control by data structures capturing causal-temporal interactions that are similar to "dispositional units".

mation units, as described by Damasio, also represent such interactions but are different because the state of the agent is directly observed by itself. This can be considered either as feedback for the SA agent to evaluate the outcome of commands it has sent to actuators and lower-level blocks or as a multi-sensor source of proprioceptive signals representing the agent state to itself. This concept is exploited in our SA model (depicted in Fig. 10). If this second view is taken, a modified PRM can be considered as a structure where appropriately modified dispositional units are processed based on hierarchical filters that work on proprioceptive feedback and in a bottom-up way also in the CC.

In Haykin's approach, the focus is on control instead of SA. Therefore, the PRM is designed to make a CDS capable of using interactive behavioral rules to switch among different perceptions and action modalities adaptively. Such inferences can drive actions that the agent's sensors and actuators should accomplish anticipatorily by activating available models in the PRM memory when it performs a given experience. This allows the CDS of an **attention** capability towards preferred control or sensing actions in a given homeostatic cycle. In the case of the SA model discussed here, the agent has no direct knowledge of the control strategy actions that are generated by its own decision-making subsystem, but it can observe and fuse their outcomes through parallel proprioceptive feedback from sensors coupled with exteroceptive environmental observations. Haykin's model, however, suggests how a SA model can provide useful data to adapt **decision making processes** behaviors at homogeneous hierarchical levels to the PRM. For example, SA can share with decision-making **estimates of present and predicted contextualized states** as well as **errors and deviations of models** describing previous agent experiences.

Furthermore, Haykin's model facilitates identifying temporal variations of **uncertainty** associated with actions and percepts, which is a key aspect for addressing a proper computational framework for the CDS design, i.e., a PRM in our SA model. Moreover, the organization of a PRM at multiple abstraction levels is coherent with the hierarchical characteristics of Damasio's dispositional units. In this case, actions and percepts as temporal aggregations (equivalent to dispositional units) at different hierarchical levels can describe the joint state of lower-level parts of the agent body down to the directly observed proprioceptive and exteroreceptive characteristics of the agent and the environment. Although Haykin's approach does not provide a specific probabilistic model for uncertainties and dependencies, it proposes a **Bayesian** framework to model uncertainty and causality and make inferences computationally, e.g., parametric conditional probability models.

Although the goal of Haykin is not to specify a univocal PRM model but to provide a generic framework for CDSs, his model is essential for addressing the main techniques for SA in artificial agents. His work then suggests that SA models originating from a computational domain should be associated with an appropriate calculus of uncertainty propagation. In [38], a CDS inspired by such a probabilistic approach uses a simple PRM unit that allows a vision system on a mobile platform to make inferences about future states. Moreover, Haykin's work does not directly provide a unitary view of the techniques that could be used to store a coherent multi-level generative and discriminative PRM's knowledge. Nonetheless, our work integrates Haykin's viewpoint on uncertainty and makes a relation between the perception-control blocks and Damasio's theory, which includes AM and AS and dispositional units. Fig. 10 displays a revisited block scheme of Haykin's model.

C. *Friston's model*

Another relevant cognitive framework for SA that aims at establishing links between neuroscientific observations and computational models is the one proposed by Friston [39], [27]. Here, Bayesian dynamical systems are the computational tool that facilitates an **uncertain and hierarchical** self-coherent representation to **describe and generate** simulations of inferences performed by the human brain utilizing neuron firings. Friston's approach is innovative in the context of developing self-aware models for artificial agents due to the following characteristics: *i)* It formally relates a statistical mechanics' optimization framework, that can be summarized as **free energy and variational** based reasoning, with Bayesian inference. It founds a theoretical domain for describing SA knowledge and models (in the AM) as well as inference (in the AS). *ii)* It proposes the concept of **generalized states (GS)** to develop a class of computational and hierarchical Bayesian filters that we use to embed representation and inference over dispositional temporal knowledge.

The good regulator theorem [35] states that "every good regulator of a system must be a model of that system". In this sense, SA models can be considered as joint **discriminative and generative** models that contribute to the regulation of an artificial agent representing an adaptive code of the system itself and its incremental experiences at the same time. The free energy principle represents an optimization criterion that can be related with a variational computational framework to both define and discover optimal SA models from a given set of dynamic experiences, i.e., available data sequences originating from exteroceptive and proprioceptive sensors.

In [27], Friston suggests that establishing an equivalence between a probabilistic and a mechanical statistics' representation of the dynamic equilibrium in the sensed internal state and the contextual environment allows one to explain the observed neuron firing in the human brain through the free energy concept. He further shows that Bayesian inference is an equivalent way to do so. As SA in humans is based on brain inference processes, probabilistic dynamic representation and inference models are good candidates to form the language for expressing a SA model in an artificial agent as well. Such models must be capable of including temporally ordered descriptions of contextual dependencies between proprioceptive and exteroceptive variables.

The variational computational representation and inference techniques he proposes clarify how different models can describe statistically different sensorial experiences that can be seen as trajectories in generalized spaces. The models can also provide explicit measurements to evaluate or to **discriminate** best-fitting models of new observed sequences. At the same time, the same models, that can include multiple conditionally connected random variables at different hierarchical and temporal levels, are capable of predicting multi-level, temporal data series characterized by the same statistical properties of the training experiences from which they can be learned (thanks to their **generative** nature). Such a model, if used within the SA model of an artificial agent, together with appropriate learning techniques, can facilitate incremental **model creation**. An AS can so actively memorize incrementally generative and discriminative new models in the AM by processing sensorial experiences. Such models have to capture different causality interactions between the agent and the environment and serve as the basis for symbolic descriptors in an artificial SA agent.

The SA capability of abnormality detection can also be explained with Friston's model, i.e., the free energy that models generate when the AS compares them to a new experience. A metric can be defined to evaluate the amount of abnormality which is related to a particular component of free energy, describing the orthogonal perturbations to the dynamic equilibrium condition described by the model. Such a metric enables the AS to rank the abnormalities measured from a set of AM models, so relating the discriminative SA property of the model to the abnormality detection and inference capabilities.

Contribution ii) to the SA model definition is a specific class of Bayesian filters, namely GS filters. Friston et al. [40] explain that thanks to such filters, active and variational Bayesian inference techniques can be obtained with better performances. GSs describe a class of trajectories in terms of generalized coordinates of motion. The resulting model can be shown to better describe the dynamical nature of the pattern in terms

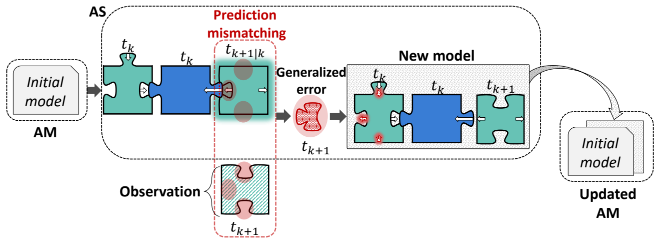


Fig. 6: An **initial** model is employed to predict passive self states, i.e., glowing green puzzle pieces at instant $t_{k+1|k}$. Errors from such a model are utilized to **create** new models, depicted as new *pages* in the **AM** structure. Such new models minimize the free energy between the agent's **inferences** and the observed data. Note that the same logic can be applied to an active self (blue-green-blue puzzle pieces).

of temporal and causal explainability of dependencies among states as well as computational benefits. In a SA model, hierarchical Bayesian models derived from GS filters can provide the description language for the AM, depicted as individual "pages" in Fig. 6. We will show how these models can be learned by observing proprioceptive and exteroceptive data series both independently and in a coupled way that is oriented to represent their dispositional nature. Such filters can be used both as generative and discriminative models, and they can be good candidates to be related to the "good regulator" code [35], as they can represent the rules that describe the agent, as well as such rules, can be used by the agent to predict the dynamic contextualized behavior where it is acting.

Coupled proprioceptive and exteroceptive signals of GS filters can efficiently represent Damasio's dispositional units in a SA model. For example, a Switching Dynamic Bayesian Network (DBN) [41], [42] uses multi-level discrete and continuous generalized states as variables that will be further discussed in the following sections.

Dynamic Expectation Maximization (DEM) filters [40] are **hierarchical** parametric GS filters that are here used to derive coupled GS-DBNs. These filters have been shown to jointly perform parameter, hyperparameters, and GS estimations within a continuous variable Bayesian network that is by itself a fully continuous DBN. However, discrete variables are needed in a SA model too. Such variables are used to represent different models (i.e., different pages in the AM structure) and to provide finer level discriminative descriptions of learned models to determine a different class of probabilistic dependencies within an episode, useful both for generative and discriminative purposes. Coupled GS-DBNs are, therefore, better-suited filters than DEM, in particular when all model properties are necessary to reach the SA capabilities (see Fig. 7).

III. Signal Representation and Model Learning

A. *Bio-inspired SA Model*

The main difference between Haykin's and Damasio's models is that the objective of the latter lies in the bottom-up explanation of neuroscientific observations, while the first one

TABLE II: Comparison of inherent self-awareness properties of the presented bio-inspired self-awareness theories.

Self-awareness properties	Damasio's model	Haykin's model	Friston's model
Generative modeling	Dispositional units are facilitated to make non-probabilistic predictions of future agent's states based on a top-down approach	Predictions of next actions and exteroceptive states performed by the PRM	Predictive GS probabilistic models
Discriminative modeling	Not considered	Not considered	Focused more on filtering than on semantic labeling of experiences
Interactive	It includes dispositional units but interactions are not explicitly explained	PRM relates information between exteroceptive data and agent's actions	Self-organization in agents explained as system of GS filters related to agent actions and sensory perceived environment
Hierarchical modeling	It considers several abstraction levels ranging from raw observations to feelings/emotions	Multilevel representation of control, PRM and perception, see Fig. 5	Continuous variables in upper inference levels parameterize predictive models in lower ones
Temporal reasoning	Dispositional units relate present states with future ones	Temporal dependencies between control and environment perception during time	In Bayesian DEM filters different temporal reasoning at abstraction levels of parameters and GSs
Uncertain reasoning	Not considered	Bayesian reasoning	Equivalence of active Bayesian inference and attractors in statistical mechanics

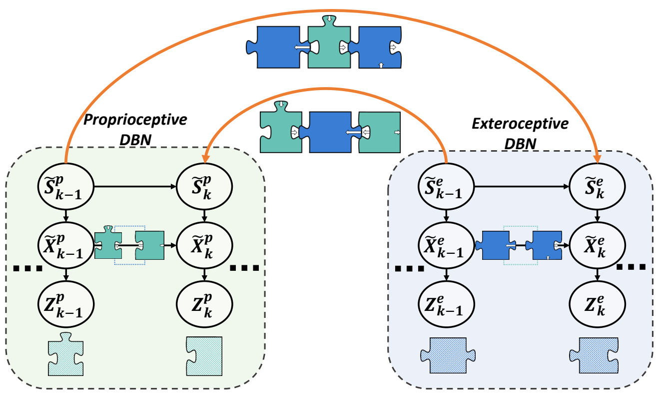


Fig. 7: Proprioceptive DBN (P-DBN) represented in a green block and exteroceptive DBN (E-DBN) represented in a blue block are connected by orange links that encode the agent's **contextual information**. Each DBN (P-DBN and E-DBN) performs continuous $\tilde{\boldsymbol{X}}$ and discrete $\tilde{\boldsymbol{S}}$ inferences. This coupling facilitates to model **interactions** between multi-sensory data and perform inferences within a contextual SA framework. Observations are represented as Z, and k encodes time instances. Proprioceptive and exteroceptive information is indexed as p and e, respectively.

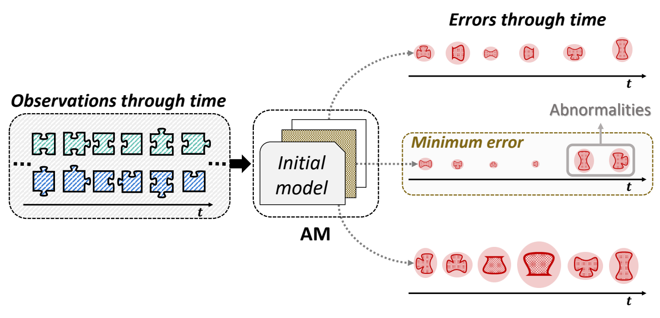


Fig. 8: Models in the agent's **memory** produce error measurements as observations arrive. The fittest model is identified/discriminated and **abnormalities** (high errors w.r.t a threshold) are extracted from it. Such high errors are then used to **create** new models incrementally as shown in Fig. 6.

focuses on the definition of control within a CDS. Similar to Haykin's model, Friston's approach is based on a Bayesian and computationally efficient approach for SA representations. Friston's approach is more focused on a bottom-up joint analysis of proprioceptive and exteroceptive signals, while Haykin's model aims at providing a framework for defining computational aspects of perception-action cycle decision making outcomes towards actuators in a CDS. A computational SA model for an artificial agent can be obtained by merging different aspects of the three frameworks. Such SA model should include SA properties as discussed in Section I and enlisted in Table II.

Through section III-A, we describe how the different capabilities can be jointly obtained by using a unique representation and inference approach. A formalization of this approach will be discussed in Section III-B, while here, we provide a higher-level representation of the proposed solution by introducing candidate representation and inference mechanisms.

Fig. 6 and Fig. 8 depict how the AM can be represented as a book containing multiple pages. Each page corresponds to a probabilistic model learned based on observed sequences of dispositional units during different experiences. Such a model should be both generative and discriminative. Fig. 6 shows that an initial reference model serves as a basis for initialization.

This initial model should represent quite general behavioral rules obtained in correspondence to a reference experience. For example, as we will show, it can contain knowledge useful to predict the agent's state, even if the environment does not interact with it, and therefore exteroceptive signals do not provide significant contextual temporal and causal information. In that case, the expected agent's state changes are null, except for random perturbations, and state and its derivatives estimated from proprioceptive signals can be stationary.

The initial model and all generated models in the AM must be generative, i.e., they should be capable, under the effect of a latent null variable, to generate a sequence of predictions in the form of expected probabilistic properties of the dispositional unit that could be observed as evidence. This has to happen as part of the inference process in the AS module. The AS module must bu capable of comparing the current set of dispositional units from the current experience with the predictions of the currently activated AM page. This comparison has to produce both an evaluation of the mismatch degree between predicted and observed dispositional units but also to describe such errors and memorizing them for further steps. When mismatches are relevant, i.e., abnormalities with respect to the initial model are too high, the sequences of dispositional units and related errors (generalized errors) are processed for describing the new experience. The model creation phase organizes such data series that can be considered as sparse acquisitions of generalized errors with respect to selected AM available models, e.g., by using unsupervised machine learning tools into new models. The results of the analysis of the sparse generalized errors are described again in terms of behavioral rules expressed using generative models with the same language of the initial models. Such new models can be seen as new pages to be added to the AM book. Memorization includes the capability to organize the learned models within the AM model as incremental pages in a book. Section II-B describes how this can be obtained starting from free energy and generalizes state concepts in a way inspired to Friston's approach.

Fig. 8 highlights the inference capability of the AS when the AM is composed of multiple pages, i.e., to discriminatively select a page that better fits to the current experience. Again, this can be obtained by comparing the generalized errors obtained by processing in multiple parallel models and evaluating when the minimum detected error is sufficiently small. The page which produced such a set of generalized error also contains the causal and temporal knowledge to predict the dynamic evolution of the contextual state of the agent and the environment, so providing to the agent a symbolic and continuous SA description of what is happening compared to past experiences. The minimum abnormality criterion to discriminate the most fitting model can be considered as the selection of the model characterized by the lowest generalized error, evaluated by using an appropriate metric. Therefore, the SA discriminative capability results by comparing the current experience to the generated predictions of a set of models of experiences available at a given moment in an agent. Fig. 8 shows how the inference process in the AS can also generate useful information for decision making. In particular, the

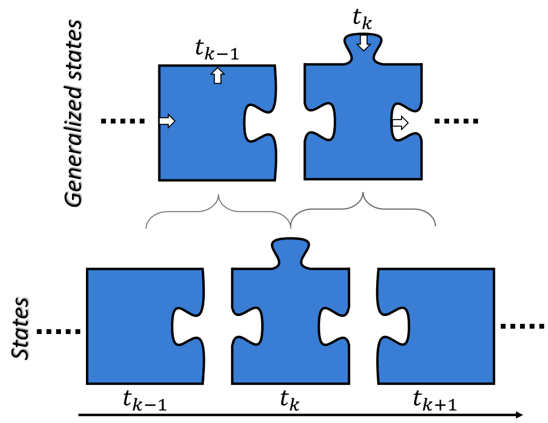


Fig. 9: Relationships between exteroceptive states (bottom) and generalized states (top). Two consecutive states are abstracted into a generalized state that has information about *i)* the current state (depicted by the shape of the puzzle piece) and *ii)* its derivative (depicted by the arrows pointing at the expected state's change in the succeeding time instant). Note that the same logic can be applied to proprioceptive data (green puzzle pieces).

set of predictions and related errors derived from comparing activated models with the current dispositional units can be used by a decision making block to plan resources usage as well as to decide among alternative actuator signals to perform planned actions.

Fig. 9 shows that, in contrast to Haykin's theory, the SA model does not explain the perception-action cycle, so it does not include a hierarchical control block. Instead, proprioceptive signals provided by observing agent actuators are processed in parallel in a bottom-up way with exteroceptive signals processed in the block defined as Perception in [43]. As can be seen in Fig. 10, the PRM is replaced by the SA model as it aims to organize extero and proprio percepts, with the latter being considered as the feedback generated by actuators controls by the agent itself.

For the proposed model to be effective, it must fulfill the properties listed in Table II. In particular, we note that the content of AM pages represents models organized into random variables that should come from observations of dispositional units (i.e., interactive variables embedding causal and temporal aspects). They are random variables at multiple hierarchical levels. Moreover, the SA process has to be autopoietic in the sense that it should be able to learn new pages of the AM book from computed generalized errors by generating predictions from pages already available in the AM book. As a function of generalized errors over the generalized state-space describes the differences between the current experience and the existing AM page, this means that a new page generated during model creation should provide a generalized null error, i.e., that learning process should be capable of representing a function of generalized error over the generalized state space as a book page model.

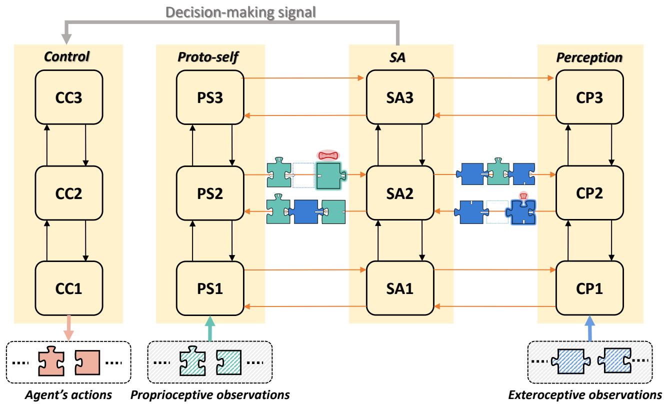


Fig. 10: Proposed SA model based on a PRM with generalized states and proprioceptive/exteroceptive context. SA models replace Haykin's PRM and are able to store and probabilistically model exteroceptive and proprioceptive information at different abstraction levels. Proprioceptive information is acquired from internal sensors but also derived from the control signals of actuators. Orange links between that enter and exit from the SA blocks represent the interactions shown in Fig. 7, since the SA block combines information between proprioceptive and exteroceptive data.

B. Representation and inference in SA model

Based on the capabilities enlisted in Table I, this section introduces our computational SA model and sketches a formal description of the SA properties (see Table II for a comparison of the SA properties of the available bio-inspired models). The GSs and free energy/variational probabilistic reasoning schemes provided by [40] are extended towards becoming capable of representing multiple hierarchical levels and dispositional units' patterns. First, we describe representations that enable the separation of proprioceptive and exteroceptive sensory channels in the SA model. Then, we show how the representation obtained can be extended to consider interactions by such channels, so making the SA model able to include a dynamic coupling between the agent and the contextual environment. Finally, we discuss the representation patterns based on temporal dynamic descriptors derived from GSs and corresponding to probabilistic dispositional units. Table III summarizes how our model facilitates the SA properties.

1) Generalized states and filters: A GS $\tilde{\boldsymbol{X}}$ represents a pattern that can be written as a vector of dynamical components including a random state and its derivatives up to a given order d such that $\tilde{\boldsymbol{X}} = [\boldsymbol{X}, \boldsymbol{X}', \boldsymbol{X}'', \cdots, \boldsymbol{X}^{(d)}]$. Following [27], by assuming ergodic conditions, dynamic models based on GSs consist of an instantaneous flow $f(\tilde{\boldsymbol{X}})$ that depends on an initial generalized state such that

$$\tilde{\boldsymbol{X}}' = f(\tilde{\boldsymbol{X}}) + \tilde{\omega}. \tag{1}$$

Perturbations of the flow $\tilde{\omega}$ are represented by an additive noise vector that includes the state and all its derivatives. Under ergodicity conditions and the variational calculus framework, it can be shown that the dynamic system defined by the stochastic Fokker-Planck flow equation will converge to a set of states according to a differential equation that describes the temporal dynamics of the probabilities of GSs [44]. The solution of such an equation can be represented as a probability density function that defines behavioral rules of the dynamic system over a generalized state-space $p(\tilde{\boldsymbol{X}})$. Moreover, such density function can be expressed as an exponential function of a Lagrangian, i.e., a scalar potential vectorial field defined over the GSs $L(\tilde{\boldsymbol{X}})$, such that

$$p(\tilde{\boldsymbol{X}}) = e^{-L(\tilde{\boldsymbol{X}})}. \tag{2}$$

Friston et al. [27] observed that the flow can also be written in terms of the Lagrangian by using the Helmholtz decomposition

$$f(\tilde{\boldsymbol{X}}) = \underbrace{D\tilde{\boldsymbol{X}}}_{\text{Divergence-free}} - \underbrace{\Gamma\nabla L(\tilde{\boldsymbol{X}})}_{\text{Curl-free}} + \tilde{\omega}, \tag{3}$$

where $D\tilde{\boldsymbol{X}}$ describes a conservative, divergence-free flow identified in the generalized motion. This term acts as an attractor in the absence of external perturbating forces. $\Gamma\nabla L(\tilde{\boldsymbol{X}})$ is a curl-free component that attracts the solution towards probable regions of the GSs' space in a given context.

Friston et al. [27] also show that the generalized motion can be defined as the temporal changes of the GSs, i.e., $D\tilde{\boldsymbol{X}} = [\boldsymbol{X}', \boldsymbol{X}'', \cdots, \boldsymbol{X}^{(d+1)}]$. It can be written in terms of the Lagrangian as $Q\nabla L(\tilde{\boldsymbol{X}})$, where Q is an antisymmetric matrix. As is the case with classic Bayesian filters, e.g., Kalman or Particle filters, filtering GS models can be described as an iterated inference procedure composed by prediction and update steps, where GS's dynamic and observation models are used instead of state-based ones. As shown in [40], the representation of dynamics in terms of generalized coordinates facilitates to describe conditional dynamic models in a given path depending on mean properties of higher-order time derivatives included in the GS vector, which is seen as parameters that describe different conditions along the experienced path. The mean field of state changes is an example of such a parameter.

The descriptor of a given experience can be associated with a time-variant density (to be estimated by the filter based on GSs) describing transitions among different parametric values. In [40], online filtering is performed on trajectory data, and an a priori parametric set of functions is fixed for the dynamic model.

2) Abnormality detection using GS-filters: GS-filters using a flow model associated with an attractor, as described by the generalized motion, can be used in a SA model for abnormality detection purposes. Each defined attractor is related to a new agent's experience, so determining a set of models indexed by $m = 1, \ldots, M$. Thus, each model has a flow described as

$$f(\tilde{\boldsymbol{X}}) = D^m\tilde{\boldsymbol{X}} + \tilde{\omega}. \tag{4}$$

When observing new experiences, it is possible to employ the flows in Eq. (4) for making predictions about the next GSs. Differences between such estimations and the evidence can be interpreted as orthogonal components to the attractor's dynamics. In other words, the errors from each filter can be matched with the residual term, $\Gamma^m\nabla L^m(\tilde{\boldsymbol{X}})$ in Eq. (3), which varies for each model m according to the differential tensor Γ^m.

Let $\boldsymbol{Z} = \{Z_k; k = 1, \ldots, K\}$ be a series of observations. Then, the corresponding set of errors with respect to the predictions (obtained by Eq. (4)) for a model m, can be written as $\tilde{\Theta}_Z^m = \{\tilde{\epsilon}_k^m : k = 1, \ldots, K\}$. Such errors are generalized, i.e., they consist of a vector that describes the effect of the observation as changes w.r.t. the predicted state and its derivatives. Elements in Θ_Z^m can be directly associated with the orthogonal curl-free component summed to the perturbation noise in Eq. (3), such that

$$\tilde{\epsilon}_k^m = \Gamma^m \nabla L^m(\tilde{\boldsymbol{X}}_k) + \tilde{\omega}. \tag{5}$$

To obtain an abnormality measure that can be compared through different GS-filters, one can use density functions of generalized errors. For avoiding using explicit knowledge of the Lagrangian model to normalize such measurements, the curl-free term pointing in the direction of higher density regions can be assumed to be $\Gamma^m = 0$. This assumption implies that a higher imprecision of the model will be present in GSs where a curl-free term is necessary to carry back the model towards the higher density zones. In such zones, the local generalized error cannot be written only as zero-mean Gaussian random vector $\tilde{\omega}$.

For identifying errors that cannot be represented through a zero-mean Gaussian random vector, it is necessary to define a measurement of abnormality that evaluates how much the observed generalized errors differ from the null mean Gaussian perturbation term. This is equivalent to compare the matching of the new observations to the predictions generated by the model attractor $D^m\tilde{\boldsymbol{X}}$. Accordingly, we propose to measure the distance between the perturbation's probability density $p(\tilde{\omega})$ and the GS model-dependent likelihood $p(\tilde{\epsilon}_k^m|\tilde{\boldsymbol{X}}_k)$ for measuring abnormalities. In general, such a distance can be defined as a dissimilarity measurement between two probability distributions p and q by $\Delta_\Pi(p, q)$ (e.g., Bhattacharyya distance). The abnormality measurement θ_k^m over model m can also be defined as

$$\theta_k^m = \Delta_\Pi(p(\tilde{\omega}), p(\tilde{\epsilon}_k^m|\tilde{\boldsymbol{X}}_k)). \tag{6}$$

In Fig. 8, the distance between the zero-mean Gaussian perturbation and the generalized error likelihood is represented by the size of the abnormalities. Eq. (6) can be approximated by specific probabilistic distance metrics as we will show in Section IV.

In addition to estimating the abnormality of a model m when observing an experience through a set of either proprioceptive or exteroceptive observations Z, errors in Θ_Z^m can also be used for estimating new models. The principle is that a new model $(m + 1)$ should integrate abnormalities from the existent model m. Generating a new attractor $D^1\tilde{\boldsymbol{X}} = Q\nabla L^{m+1}(\tilde{\boldsymbol{X}})$, which describes a new model $m+1$, i.e., $f^{m+1}(\tilde{\boldsymbol{X}}) = D^{m+1}\tilde{\boldsymbol{X}} + \tilde{\omega}$. Prediction errors from such a new filter should result to be due only to $\tilde{\omega}$, i.e., they should correspond to zero mean perturbations when applied to the abnormal experiences detected by the model m.

3) From hierarchical GS-filters to hierarchical SA models: Friston et al. [27] apply GS-filters in Cognitive Dynamic Systems analysis showing that they are well suited to be used for **hierarchical** representations. In Dynamic Expectation Maximization (DEM) filters [40], optimal joint estimations of hidden parameters are presented together with the GSs' estimation. Parameter ϕ is used to describe a family of dynamic models that can be adaptively selected during the inference process. DEM filters consider a hidden parameter that works as a random continuous switching variable distinguishing among an infinite set of dynamic models, such that

$$f(\tilde{\boldsymbol{X}}) = f(\tilde{\boldsymbol{X}}, \phi), \tag{7}$$

where ϕ is the hidden continuous parameter. The joint optimization over $(\tilde{\boldsymbol{X}}, \phi)$ [40] allows one to define an online inference method that converges through a step-by-step iterative DEM mechanism to a solution that provides an optimal estimation of the hidden dynamic parameters and GSs through time.

For a SA model, the agent should be first and foremost able to discriminate and describe instantaneous deviations when statistically different episodes are included in the AM. One can model such episodes by using a finite set of filters $m = 1, \ldots, M$, where m is associated with a hidden discrete parameter. In this sense, by following Eq. (7), one can write the flow as $f(\tilde{\boldsymbol{X}}) = f(\tilde{\boldsymbol{X}}, m)$ with m as a discrete parameter. However, when the dimensionality of the problem allows it, the agent should be capable of having a symbolic (not continuous) representation of the experience and segment experiences at a higher discriminative resolution than the one of the different episodes in the AM.

For each m, a symbolic description of how the global flow of an episode can be segmented into a set of flows is desirable. A natural way for such a description consists of segmenting the GS's space $\tilde{\boldsymbol{X}}$ into regions where the attractor can be defined with sufficient precision. A vocabulary of variables can be formed by a discrete set of region labels. Accordingly, let $\boldsymbol{s}$ be a label identifying a GS's space regions $R_s = \{\tilde{\boldsymbol{X}}_s\}$. Then, the parametric flow model introduced in Eq. (7) can be further characterized by using a discrete switching variable $\boldsymbol{s}$ together with m. Consequently, for each $\boldsymbol{s}$, a different flow used within an episode m can be described. However, as a specific probabilistic sequence of flows can form an episode, it should be possible to define a flow model at the region's discrete level. Such a model consists of the transition probability among regions, which Hidden Markov models [45], [46], can be expressed as a set of conditional probabilities among regions in the vocabulary. To allow such a representation, a GS discrete variable $\tilde{\boldsymbol{S}} = [\boldsymbol{S}, \boldsymbol{S}' \ldots]$ is defined. The set of possible transitions among regions is considered as the equivalent of the time derivative in continuous variables. Such transitions have been sometimes defined as events [29]. As models of different episodes can generate partitions of the GS's space into different regions, then the parameters describing episodes as sequences of flows can be indexed by the couple of discrete variables $(m, \tilde{\boldsymbol{S}}_m)$. By using again Eq. (7), each flow of a vocabulary can be written as

$$f(\tilde{\boldsymbol{X}}) = f(\tilde{\boldsymbol{X}}, m, \tilde{\boldsymbol{S}}_m). \tag{8}$$

4) Model creation: A SA model m can so be defined as the set of flows that make it possible to generate and describe a set of trajectories. By using Eq. (4), each pair of discrete variables $(m, \tilde{\boldsymbol{S}}_m)$ can be seen as a hidden switching variable that identifies a generalized motion attractor $D^{m,\tilde{\boldsymbol{S}}_m}\tilde{\boldsymbol{X}}$. Therefore, each model m can be seen as a vocabulary of possible attractors of a given model m

$$V_m = \{D^{m,\tilde{\boldsymbol{S}}_m}\tilde{\boldsymbol{X}}, m = 1, \ldots, M, \tilde{\boldsymbol{S}}_m = 1, \ldots, N_m\}. \tag{9}$$

where N_m is the number of flows employed to describe model m. By using Eq. (6) and Eq. (5), it is possible to approximate $\tilde{\epsilon}_k^m \sim \tilde{\omega}$. in a region close to the attractor. Then, Eq. (4) can be used to observe that $D^{m,\tilde{\boldsymbol{S}}_m}\tilde{\boldsymbol{X}}$ generates a low abnormality measurement when a new experience locally fits the episode flow. As a consequence, $p(\tilde{\epsilon}_k^m|\tilde{\boldsymbol{X}}_k)$ should be distributed as a null mean perturbation $\tilde{\omega}$. If this does not happen, the model m does not describe well the sequence of new observations, and generalized errors can be used to find a new model. To this end, one can observe that points in GS space closer to the attractor solution should be characterized by null mean errors. At those generalized coordinates, the curl-free term should be almost null, i.e., $\Gamma^m = 0$ as well as should be on average 0 in regions symmetrically extended wrt. the attractor. A high value of abnormality so indicates that close to attractors of model m no experience has been observed before when the abnormality θ_k^m is significantly high. If this happens for all models m, then a new model has to be created to describe the new experience. This new model allows the agent to define a new vocabulary of attractors whose measured errors can be confused everywhere in the GS space with a null mean Gaussian perturbation.

The sequence of generalized errors observed with a previously available model can be used as the input for new model creation. An experience Z can be written as a contextualized generalized error set: $C\Theta_Z^m = \{(\tilde{\epsilon}_k^m, \tilde{\boldsymbol{X}}_k), : k = 1, \ldots, K\}$. Since the contextualized generalized error is different for each model m, the problem here is to choose a reference model among the available ones in the AM. We assume the model with the highest similarity, i.e., the lowest abnormality distance, is selected. This is depicted in Fig. 8 as the model producing the smallest error sizes. Using Eq. (6), we can deduce a new model m' should minimize the abnormality computed from the model m over the sequence Z, i.e.,

$$m' = \arg\min_r \theta_k^r = \arg\min_r \Delta_\Pi(p(\tilde{\omega}), p_r(\epsilon_k^r|\tilde{\boldsymbol{X}}_k)), \tag{10}$$

where the minimum condition in Eq. (10) can be obtained when

$$p(\tilde{\omega}) = p(\epsilon_k^{m'}|\tilde{\boldsymbol{X}}_k) = \mathcal{N}(0, \Sigma_{\tilde{\omega}}). \tag{11}$$

Each attractor $D^{m',\tilde{\boldsymbol{S}}_{m'}}\tilde{\boldsymbol{X}}$ included in the new model $V_{m'}$ to be learned, has to be associated with a filter whose flow generates Gaussian null mean perturbations in a region of the GS space. Using GSs and variational interpretation as in [40], the solution can be found by considering that an almost constant value should characterize the mean value of the error in each region symmetrical around the new attractor. This means that we require to partition the state space for the new model in a set of regions $\tilde{\boldsymbol{X}} = \{\bigcup_s R_s, s = 1 \ldots N_{m'}\}$ such that in each region the generalized error should be be associated with a parameter $\psi(\tilde{\boldsymbol{s}})$ that makes the generalized error distributed as a null mean perturbation. The contextualized Generalized Error $C\Theta_Z^m$ and the previous vocabulary of model m can be used to this end. $C\Theta_Z^m$ includes sparse information as the errors are available only in GS points observed along the sequence. A regularizing criterion needs to be defined to facilitate the clustering of GS regions. For example, in [47], a functional whose minimization can provide such a criterion, can prefer a particular partition among the set of possible divisions P, such a partition is characterized by

$$\{R_s\}^{m'} = \arg\min_P \sum_s \Sigma(\tilde{\epsilon}_s^m) + \beta\Sigma(\boldsymbol{X}_s)^{-1}, \tag{12}$$

where Σ is the covariance operator and $\boldsymbol{X}_s$ are the zero-time derivatives associated with GSs assigned to region s. The criterion in Eq. (12) favors a piecewise constant error segmentation of the generalized space and prefers larger connected regions (so providing a more efficient coding represented by a lower dimensionality of the vocabulary). $\beta \in [0, 1]$ weights the importance of larger regions with respect to the compactness of errors. Unsupervised learning algorithms [48], [49] can learn optimal or suboptimal partitions for describing the new model. Following [40], one can observe that Eq. (12) can be interpreted as a functional similar to free energy. Moreover, the solution individuates a set of mean generalized error values for each region s, $\bar{\tilde{\epsilon}}_s^m$ that can be related with parameters in Eq. (7), by allowing one to write such parameters $\psi(\tilde{s})$ as

$$\psi(\tilde{\boldsymbol{s}}) = \bar{\tilde{\epsilon}}_s^m(\tilde{\boldsymbol{X}}), \tilde{\boldsymbol{X}} \in R_s. \tag{13}$$

In this way, the mean generalized error can be related to the mean field parameter in the example described in [40]. However, in the case of the SA model, a discrete number of piecewise constant continuous parameters is found to characterize the partition in Eq. (12), whose dimension is equal to the dimension of the optimal vocabulary necessary to describe the experience Z. The new learned model $V_{m'}$ can be written as a set of attractors

$$D^{m',\tilde{\boldsymbol{s}}}\tilde{\boldsymbol{X}} = D^{m',\tilde{\boldsymbol{s}}}\tilde{\boldsymbol{X}} + \bar{\tilde{\epsilon}}_s(\tilde{\boldsymbol{X}}). \tag{14}$$

The mean generalized error of points in a region R_s obtained by clustering the generalized error as described above provides a different (and so state variant) approximation of the mean field valid in each region s. Such a model generates lower abnormality distances value when evaluated on the same sequence. Generalized errors produced by the new model in zone s should be statistically described by perturbations in Eq. (11). This also means that the new model can be described by a set of flows, each one associated with a switching variable s, describing the new model as a piecewise composition of S flow models.

Examples of techniques that can be employed to minimize the above functional include Gaussian Processes [50], [51], Self Organizing Maps [52], Growing Neural Gas [53] or Generative Adversarial Networks [54]. It should be noted that similar to [29]; the reasoning can be iterated at higher levels by considering flow models over discrete variables in S. In this case, flow models describe events that are transitions between regions that can also be estimated from the sequence of generalized errors. This allows us to write also S as a generalized discrete variable, where the derivatives have to be understood as discrete changes of S labels between consecutive instants.

5) Generalized state dynamic Bayesian networks: The attractors $D^{m,\tilde{\boldsymbol{S}}_m}\tilde{\boldsymbol{X}}$ can be represented as Probabilistic Graphical Models (PGMs) [55], namely in our case as Dynamic Bayesian networks (DBNs). DBNs are a specific class of PGMs where temporal dynamics are explicit. It can be shown [56], [57], [58] that basic Bayesian filters, such as Kalman filter, Particle filter, and hidden Markov models, can be represented as two-level DBNs [59]. Adaptive Kalman filters, using different observation and dynamic models, can be generalized to switching models representable as DBNS with an additional level of variables. Markov Jump Particle filters (MPJF) [60], [61], [62] can be seen as an example for such filters. Similarly, Rao-Blackwellized filters [63] can be considered as switching models over alternative non-linear dynamic models [64].

Each random variable in a DBN represents either a generalized continuous or discrete state. Observations Z and models m can be also associated with a node of a DBN. Nodes can be organized hierarchically within slices, each slice being associated with variables representing instances at a given time instant. A particular type of DBNs is two-slice temporal Bayes nets (2TBN) [65], where two slices related to two consecutive time instants are used to model a stationary set of dynamic rules. Probabilistic dependencies among variables within the same slice are defined as intra-slice (LA) links [66] that connect the nodes at different DBN levels. LA links are characterized by conditional probabilities among connected variables that contain information from which causality among variable settings can be explained. Dependencies between variables at consecutive slices (often assuming uniform sampling of observations through time) are defined as inter-slice (LE) links. In general, LE links describe flow dependencies among variables of the same level. Therefore, a DBN whose nodes J are $J^m = \{\tilde{\boldsymbol{X}}, \tilde{\boldsymbol{S}^m}, m,\}$ together with a set of LA and LE links, i.e., $DBN = \{J, LA^m, LE^m\}$ characterized by links LE^m can be used to describe a model V_m that is composed by a set of flow models as in Eq. (9).

The variable m can be seen as a switching variable for the M models in the AM. Variables $\tilde{\boldsymbol{S}^m}$ act as switches among different models $D^{m,\tilde{\boldsymbol{S}}_m}\tilde{\boldsymbol{X}}$, each one associated with a filter characterized by the relative flow. LA^m links are equivalent to likelihood models at different levels of abstraction within a DBN slice, while LE^m links over nodes of continuous slices are more directly related to the vocabulary of attractor models. In Fig. 7 blue and green blocks contain examples of DBNs that can be used to describe proprioceptive and exteroceptive generalized states DBNs that we refer to as GS-DBN in the following. PGMs and also DBNs inherently provide an equivalence between the graphical representation of a model and the inference mechanisms that the model uses [67].

Since GS-DBNs represent an equivalent way to describe a vocabulary for a model m, they can be used as language for the pages of the AM book in an artificial agent. Pages can be organized in different ways such as creating new models (see Eq. (10)) derived from previous models according to different selection criteria or by considering the order in which experiences are observed by the agent[1]. Proprioceptive GS-DBNs (P-DBNs) and exteroceptive GS-DBNs (E-DBN) in general do not require synchronous data observations for learning. However, when P-DBN and E-DBN represent two vocabularies describing simultaneous observations from different sensors obtained along the same experience synchronized observations might be necessary (cp. Fig. 7).

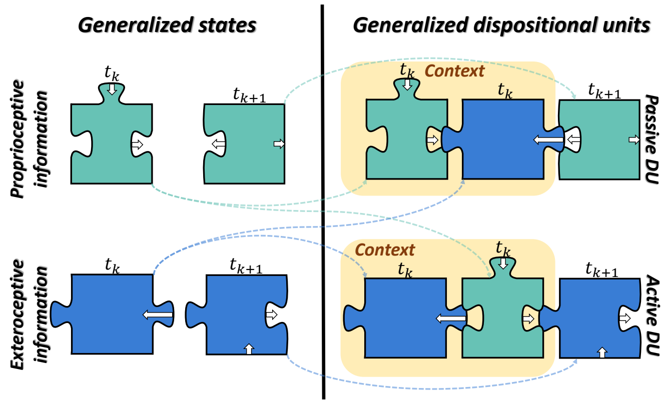


Fig. 11: Definition of generalized dispositional units (DUs) based on generalized states from proprioceptive and exteroceptive information. Inter-slice connections between proprioceptive and exteroceptive DBNs model the interactions between internal and external states of the self-aware agent. The yellow blocks represent the contextual information obtained by combining proprioceptive and exteroceptive data at the same time instant.

A GS-DBN obeys the good regulator theorem [68], as they can intrinsically encode behavior predictions of the agent and the environment. This happens when AM book pages are activated and passed to the AS, facilitating SA properties such as inference and abnormality detection. GS-DBNs can be considered as generative at two levels: *i)* Due to their capability of performing inferences by prediction/update cycles, Bayesian prediction allows the model to generate a description of expected realizations of the process before observing them. *ii)* New GS-DBNs, i.e., node variables and links, can be learned by observing inference results obtained by other already available GS-DBNs. The nodes and the links of the new GS-DBN's model m', can be learned, starting from a contextualized generalized error set obtained by filtering the sequence with a GS-DBN at page m. Various methods have demonstrated the possibility of learning new models based on criteria derived from Eq. (12) [64], [69], [70], [71]. In the following, we discuss such examples in some detail.

6) Coupled exteroceptive and proprioceptive GS-DBNs as Generalized Dispositional Units: P-DBNs and E-DBNs can provide the properties required by a SA model representa-

[1]The optimal ordering of AM pages represents an open research issue for the organization of SA models which is not considered in this paper.

tion, see Table III. They are based on random variables, intrinsically associated with uncertainties. Each of their slices represents hierarchical variables and their dependencies. Inter-slice dependencies can be associated with temporal properties, implicitly connected with space-variant characteristics of attractors. As previously discussed, the models are also generative and discriminative. However, a SA model must also represent interactions between the agent and the environment, and this interaction should reflect the introduced GS-DBN model and Generalized Dispositional Units (GDU) as depicted in Fig. 11. By considering the left column as a representation of generalized states at two consecutive time instants in a P-DBN and a E-DBN ($\tilde{\boldsymbol{X}}^{\boldsymbol{p}}$ and $\tilde{\boldsymbol{X}}^{\boldsymbol{e}}$), then a GDU description requires that GSs are organized in a standard data structure. The essence of GDUs is that they should allow the AM to represent how the agent or the environment GS can be predicted using the reciprocal entity as a contextual variable. As the agent and the environment state are described by a P-DBN and E-DBN, respectively, the GDU representation should include ways to link variables in the two GS-DBNS.

P-DBNs and E-DBNs should, therefore, not treated as separate parallel networks; a coupling among variables should be included. This can be used to represent two different attractors associated with flows $f_e(\tilde{\boldsymbol{X}}, m, \tilde{\boldsymbol{S}}^e)$ and $f_p(\tilde{\boldsymbol{X}}, m, \tilde{\boldsymbol{S}}^p)$, A coupled GS-DBN model defines (and learns) an additional set of probabilistic dependencies in the form of a set of links LD^m for each interaction model m, defined here as Dispositional links. Such links connect nodes of a P-DBN and an E-DBN as shown in Fig. 12. Nodes in the first slice of a P-DBN and in the E-DBN models are connected with nodes in the following slice in either P-DBN or E-DBN. Two subclasses of LD links can be defined either as active or passive GDUs.

In a coupled PE-DBN, a vocabulary of attractors related to a given interaction experience can be used to model active dispositions (i.e., effects of the agent contextualized state on environmental GS changes) $f_e(\tilde{\boldsymbol{X}}, m, \tilde{\boldsymbol{S}}^e, \tilde{\boldsymbol{S}}^p)$ and passive dispositions (i.e., effects of the environment contextualized state on agent GS changes) $f_p(\tilde{\boldsymbol{X}}, m, \tilde{\boldsymbol{S}}^e, \tilde{\boldsymbol{S}}^p)$. The dispositions characterize the probabilistic dependency model of Dispositional links LD.

Coupled Bayesian networks [72], [73] and DBNs [74], [75] in general have been used to represent and predict the states of multisensory data. Fig. 7 sketches the coupling of the complete SA model for a given model m. Interaction links among P-DBN and E-DBN are shown as orange inter-DBN links. However, defining and learning PE-DBNs in SA models must start from a coupled set of observations covering both proprioceptive and exteroceptive sensorial data from the same experience. The abnormality detection and model creation steps for PE-DBN are similar to what has been described for separate P-DBN and E-DBN, except for a potentially higher computational effort. Abnormalities can be represented via passive and active models in order to describe deviations in the agent's and the environment's behavior, respectively. In addition, the switching models are defined as a couple of regions in the P-DBN and E-DBN GSs. Therefore, the clustering process for learning from generalized contextual errors derived from a previous model can be more critical if experiences are observed with an insufficient set of samples. However, the general approach described for separate P and E modality remains valid. In the following section, we highlight issues related to coupled GDUs learning with coupled GS-DBNs by a dedicated case study.

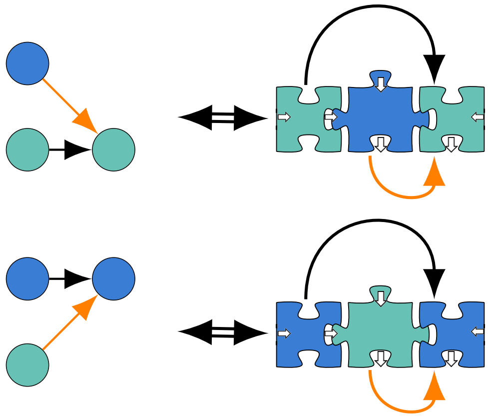


Fig. 12: Passive (top) and active (bottom) self Generalized Dispositional Units correspond to nodes and links within two consecutive slices of a P-DBN and an E-DBN. First layer nodes represent the context for the flow that generates the node in the next slice. Passive and active GDUs depend on either a P (green circle) or an E (blue circle) node.

Fig. 13: Robotic vehicle of our case study used for assessing proprioceptive and exteroceptive models.

IV. Coupled Proprioceptive and Exteroceptive Self-Awareness

As mentioned previously and shown in Fig. 1, a SA agent can perceive and distinguish two types of sensory information related to *i)* its own internal states by proprioceptive sensors and *ii)* its surroundings by exteroceptive sensors. Accordingly, SA in artificial agents is here modeled as a multisensory problem, where internal and external perceptions are employed to make inferences of future agent's states based on models that are learned incrementally as it faces new experiences. Section IV-A introduces a case of study consisting of an artificial agent (vehicle shown in Fig. 13) endowed with multiple sensors [76].

TABLE III: Self-awareness properties of proposed model.

Self-awareness properties	Realization by our proposed model
Generative modeling	Starting with an initial model, new models incrementally created as new experiences are obtained (see Fig. 6 and Section III-B *4)*. The derived models are further able to generate future state predictions at different abstraction levels using probabilistic inference techniques such as MJPF. Such predictions are depicted by glow puzzle pieces in Fig. 6 and Fig. 10.
Discriminative modeling	By detecting and using abnormalities, our models can identify the fittest model wrt. current observations, use it for predictions and eventually create a new model that encodes the detected abnormalities. Fig. 8 depicts model identification and abnormality detection based on the derived error.
Interactive	Synchronization of proprioceptive and exteroceptive sensory information is employed for creating models that consider the agent's own internal and external states for embedding the interaction with its surroundings into the agent's knowledge. Interactive modeling enables decision-making exploiting contextual information (compare Fig. 7, Fig. 10 and the proposed coupled models in Section III-B *6)*).
Hierarchical modeling	The proposed DBNs are composed of at least two levels of inference: *i)* a continuous inference based on GSs (see Fig. 9) obtained from observations and *ii)* a discrete inference base on discrete variables that encode certain dynamics in state regions for both exteroceptive and proprioceptive models (see Section III-B *3)*). The continuous variables depend on discrete ones, which facilitates a hierarchical Bayesian representation as shown in Fig. 7.
Temporal reasoning	The proposed generalized DUs enable inferences of the future based on the current contextual information (see Fig. 11). Additionally, the proposed DBN reasoning implies a description of temporal causalities between different GSs at different inference levels (see Fig. 12). As DBNs are employed, a slice of random discrete/continuous variables can be obtained at each time instant.
Uncertain reasoning	The selected Bayesian representation, see Fig. 7, facilitates the inferences of random variables at different inference levels, see Fig. 3. Such representation of uncertainties enables to define abnormalities in a general probabilistic as shown Eq. (6).

A. Proprioceptive and exteroceptive models

The *proprioceptive model* (PM) arises from the necessity of understanding the proprioceptive stimuli of an agent. Consistently, the PM allows an artificial agent to identify and make inferences of sensory information related to its actions and interior states; see blue sensory data in Fig. 1. In other words, the PM helps agents to understand their *personal* features and recognize their capabilities and limitations.

The PM characterizes how an agent behaves in conditions where the interactions with its surroundings are not considered explicitly. The PM takes as input a series of proprioceptive sensory data and creates models that predict its future internal states based on past experiences. The work in [77] presents an example of a PM on a set of vehicle's proprioceptive sensors consisting of the steering angle (s), consumed power (p) and rotor's velocity (v). Such a work proposes a probabilistic predictive model that describes the internal states of the vehicle while executing a *reference (normal) task* in a closed environment.

The *exteroceptive model* (EM), on the other hand, is in charge of explaining and modeling the exteroceptive stimuli of an agent. The EM facilitates the inference of sensory information that measures properties of the agent's surroundings; see green sensory data in Fig. 1.

In [78] and [79], it is employed a first-person camera (exteroceptive sensor) on a vehicle. An EM is utilized to build models that encode the normal conditions of the surroundings when the vehicle executes a reference task.

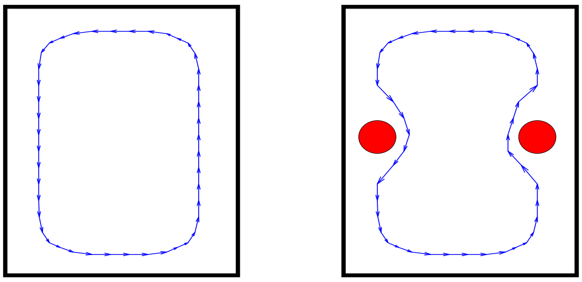
Fig. 14a shows an example of a vehicle's reference task. Fig. 14b displays an abnormal experience where the vehicle changes its regular path due to the presence of a static obstacle. Fig. 15 shows part of the proprioceptive data (steering angle and rotor's velocity) obtained while the vehicle performed the abnormal scenario, see Fig. 14b. Additionally, Fig. 16 shows the exteroceptive data in case of abnormalities; more specifically, it shows the consecutive images obtained from the vehicle's camera in the case of the avoidance maneuver.

Note that both tasks, shown in Fig. 14, can be considered to build a PM and EM independently based on the vehicle's multisensory data described previously.The PM and EM proposed in [77] and [78], [79] respectively, are discussed as follows with respect to the SA's capabilities described in Table I.

1) Initialization: For the PM, the work in [77] uses a *random walk dynamics* as the initial model from which experiences are coded incrementally. Such an initial model assumes that the vehicle's internal control states at a time instant $k+1$ will be equal to the ones observed at k except by some low errors representing minor oscillations around observations at k. For the EM, the works in [78], [79] consider an initial model consisting of a constant change in the image's optical flow, which is learned based on a training set of images when the vehicle was following a linear (straight) motion at a constant velocity. Both models can be written as a dynamic process

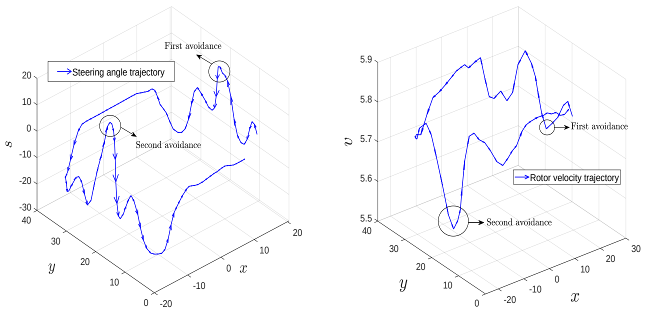
$$\tilde{\boldsymbol{X}}_{k+1} = \tilde{\boldsymbol{X}}_k + D^{0,\tilde{\boldsymbol{S}}_0^p}\tilde{\boldsymbol{X}}_k + \tilde{w}_k, \quad (15)$$

where $\tilde{w}_k$ is the noise model at instant k. $D^{0,\tilde{\boldsymbol{S}}_0^p}\tilde{\boldsymbol{X}}_k$ represents the initial flow model ($m=0$) employed for predicting the following states, which summed with the noise corresponds directly with f^0 in Eq. (4). $\tilde{\boldsymbol{X}}_k$ represents the GS at time k,



(a) Reference task (b) Abnormal task

Fig. 14: Blue arrows represent the vehicle's motion for (a) a reference (normal) task and (b) an abnormal task. The black borders represent the limits (walls) of the closed environment and red circles represent static obstacles in the scene.



(a) Steering data (b) Velocity data

Fig. 15: Blue arrows represent trajectory data in terms of steering angle s in (a) and rotor's velocity v in (b) for the case of the abnormal scenario. Avoidance maneuvers are shown for both cases.

Fig. 16: First person images in case of abnormalities (avoidance maneuver), black arrows indicate the passage from one image to the next one during time.

which in both cases (PM and EM), takes into consideration the first time derivative of the input sensory data, such that:

$$\tilde{\boldsymbol{X}}_k = [\boldsymbol{X}_k, \boldsymbol{X}_k^{'}]. \tag{16}$$

Accordingly, GSs at time k can be written as $\tilde{\boldsymbol{X}}_k = [s_k, p_k, v_k, \dot{s}_k, \dot{p}_k, \dot{v}_k]$ for the PM and $\tilde{\boldsymbol{X}}_k = [F_k, \dot{F}_k]$ for the EM, where F_k is the first person filtered image at the instant k and $\dot{F}_k$ its optical flow.

The instantaneous attractor flow introduced in Eq. (1) can be written as $D^{0,\tilde{\boldsymbol{S}}_0^p}\tilde{\boldsymbol{X}}_k \sim 0$ for the random walk dynamics used in the PM, which implies an absence of motivation. For the EM, the initial model consists of GAN that codifies image changes associated with the vehicle's linear (straight) motions. In this case, $D^{0,\tilde{\boldsymbol{S}}_0^e}\tilde{\boldsymbol{X}}_k$ cannot be used to generate errors that can be explicitly associated with the GS represented by the image and its optical flow, as this is done implicitly in the Generative network on the high dimensional image space. However, the model is capable of evaluating abnormalities from its Adversarial network component, as shown in [80].

2) Memorization: The works in [77] and [78], [79] employ an onboard computer to store dynamical models that describe the agent's internal/external experiences. Such storage is done incrementally as models are created based on identified new events. Learned models in the PM consist of linear motion dynamics valid in clustered regions of the state space. In EM, learned models consist of vehicle dynamics that produce homogeneous changes in the images' optical flow.

3) Inference: At each time instant, PM and EM make estimations of subsequent GSs by using all available models through a hierarchical structure similar to the proprioceptive/exteroceptive DBNs shown in Fig. 7.More precisely, the PM's hierarchical model corresponds to the left part of Fig. 7 (DBN with green background), where the lowest level (Z^p) represents the vehicle's proprioceptive measurements (s, p and p). The intermediate inference level ($\tilde{\boldsymbol{X}}^p$) corresponds to the PM's GSs defined previously, whereas the highest level ($\tilde{\boldsymbol{S}}^p$) represents zones where linear behaviors of proprioceptive information were identified.

For EM's case, its hierarchical model corresponds to the right part of Fig. 7 (DBN with blue background). The lowest level (Z^e) represents the vehicle's measured images. The intermediate level ($\tilde{\boldsymbol{X}}^e$) corresponds to the EM's GSs defined previously and the highest level ($\tilde{\boldsymbol{S}}^e$) represents regions where homogeneous changes in the image's optical flow were identified.

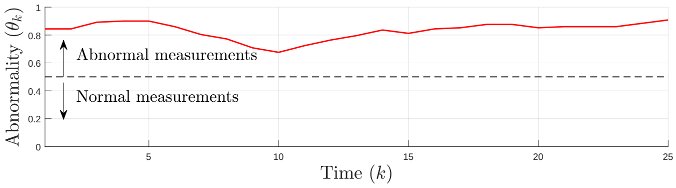
Accordingly, the generalized motions of learned in PMs and EMs depend on higher levels of inference ($\tilde{\boldsymbol{S}}^p$ and $\tilde{\boldsymbol{S}}^e$) belonging to a certain model m (AM's book page in Fig. 6) as shown in Eq. (8). In the PM's case, future discrete states of $\tilde{\boldsymbol{S}}^p$ are estimated through a Markov Jump particle filter, where discrete switching variables and the related attractor facilitate to make predictions at the continuous GSs level. In the EM, a set of Generative adversarial networks (GANs) is employed to predict the next image that the vehicle will face, and generated errors (mismatches) are employed to infer which future GAN's model ($\tilde{\boldsymbol{S}}^e$) will fit better the observations.

4) Abnormality detection: A measurement of the discrepancy between the models' predictions and actual observations is considered for identifying irregular situations, i.e., events that the vehicle with its current knowledge cannot forecast/handle. In the PM, the work in [77] uses the Hellinger distance [81] between predicted states and observed evidence as a measurement of abnormalities. Accordingly, let $p(\tilde{\boldsymbol{X}}_k^{(m)}|\tilde{\boldsymbol{X}}_{k-1}^{(m)})$ be the predicted GSs of a given model m and $p(Z_k|\tilde{\boldsymbol{X}}_k^{(m)})$ be the observation evidence at a time k. In this case, the abnormality measurement can be written as

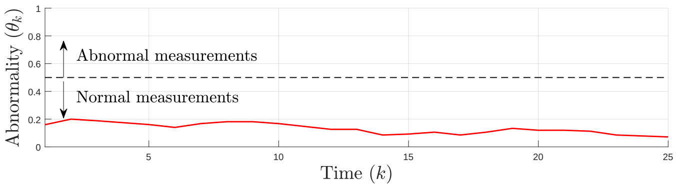
$$\theta_k^m = \sqrt{1 - \lambda_k^m}, \tag{17}$$

where λ_k is defined as the Bhattacharyya coefficient [82], such that $\lambda_k^m = \int \sqrt{p(\tilde{\boldsymbol{X}}_k^{(m)}|\tilde{\boldsymbol{X}}_{k-1}^{(m)})p(Z_k|\tilde{\boldsymbol{X}}_k^{(m)})}\, \mathrm{d}\tilde{\boldsymbol{X}}_k^{(m)}$.

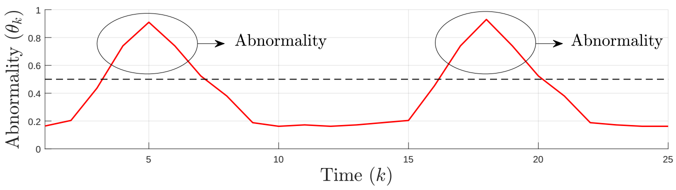
For EM, the works in [78] and [79] use GAN models to predict the following agent's state. Namely, in [78], the ab-



(a) Abnormality signal derived from the initial models when evaluated with training data (reference task).



(b) Abnormality signal derived from the created models when evaluated with training data (reference task).



(c) Abnormality signal derived from the created models when evaluated with testing data (abnormal task).

Fig. 17: Examples of normalized abnormality signals generated from different learning phases. The threshold for distinguishing normal and abnormal data is shown as a dotted line. Since the abnormality measurements θ_k lies in $[0, 1]$, we propose to set the threshold at the central value (0.5) of the interval.

normality measurement from a GAN model m can be written as $\theta_k^m = ||Z_k - \hat{D}^m(\boldsymbol{X}_k)||_1$, where Z_k is the observation at the instant k and $\hat{D}^m(\boldsymbol{X}_{k-1})$ is the agent's state prediction by the discriminator of the model m given observations until $k-1$.

The abnormalities proposed in both cases, PM and EM, follow intuitively the general definition proposed in Eq. (6) where anomalies are defined based on dissimilarities between the obtained error and a null Gaussian distribution.

As shown in Fig. 14, normal and abnormal tasks are used to evaluate PM and EM. Accordingly, for both cases, two different phases can be distinguished for detecting abnormalities: *phase I*, when the initial model is evaluated on training data and *phase II*, when models learned based on training data are evaluated on training/testing data. Each phase generates abnormality signals that encode how well the proposed models explain observations and what kind of information should be learned by our models in following learning steps.

Abnormalities can be seen as high mismatches (errors) between predictions and observations (compare red puzzle pieces in Fig. 6 and Fig. 8). Consistently, abnormalities in phase I lead to the creation of the first agent's model, i.e., AM's created book page shown in Fig. 6. Accordingly, Fig. 17a shows an example of abnormality signals generated in phase I, i.e., by using the model $m = 0$, while the agent performs a reference task (Fig. 14a). As can be seen, the initial filters produce predictions that constantly mismatch with the observations, generating a series of high abnormality measurements. For the PM, this corresponds to observations that do not stay equal during the time, as proposed by the random walk filter. For the EM, this corresponds to optical flows produced by vehicle's curving motions, such that the initial model based on linear dynamics is not valid.

In phase II, the created model ($m = 1$) based on the abnormalities generated in phase I is employed to make inferences on already known (reference task) and unseen (abnormal task) scenarios. Consistently, Fig. 17b and 17c display abnormality signals generated by the model $m = 1$ when the vehicle faces the reference and abnormal tasks, respectively.

5) Model creation: As the vehicle gets experiences, its AM gets updated based on detected abnormalities from available models (Fig. 6). For detecting such abnormalities, it is necessary to define a threshold value that distinguishes high abnormality values measured through Eq. (6), see distinguished big shapes tagged as "abnormalities" in Fig. 6 and dotted lines (threshold) in Fig. 17. After abnormalities are identified wrt. a certain model m, they are employed for minimizing the free energy of the new proposed model.

In the PM, it is proposed to cluster agent's GSs into groups (high-level discrete variables $\tilde{\boldsymbol{S}}^p$) that encode state regions where their time derivatives are quasi-constant. The result of the clustering process consists of a vocabulary of discrete states that define diverse flow models Eq. (9). For obtaining such a vocabulary, unsupervised clustering algorithms, e.g., GNN [83], [84] or SOM [85], [86] can be used. Clustering algorithms take GSs as inputs and output a set of discrete values consisting of parametric flow models, see Eq. (8), valid in specific state-regions. For the PM's case, information at each node represents a movement towards a single motivation. Such flow models generated from the initial one are further employed for inference purposes and can be written as

$$\tilde{\boldsymbol{X}}_{k+1} = \tilde{\boldsymbol{X}}_k + D^{0,\tilde{\boldsymbol{S}}_0^p}\tilde{\boldsymbol{X}}_k + \Gamma^0 L^0(\tilde{\boldsymbol{X}}_k) + w_k, \tag{18}$$

where $D^{0,\tilde{\boldsymbol{S}}_0^p}\tilde{\boldsymbol{X}}_k$ represents the initial proposed flow (quasi-static dynamics) and $\Gamma^0 L^0(\tilde{\boldsymbol{X}}_k)$ is the local —abnormal— error produced by the initial model which in turn corrects the new model in Eq (18). Since such a new flow model is built based on the errors produced by the initial one, it is possible to rewrite Eq. (18) as

$$\tilde{\boldsymbol{X}}_{k+1} = \tilde{\boldsymbol{X}}_k + f^{1,\tilde{\boldsymbol{S}}^p}(\tilde{\boldsymbol{X}}_k), \tag{19}$$

where $f^{1,\tilde{\boldsymbol{S}}^p}(\tilde{\boldsymbol{X}}_k) \sim f^0(\tilde{\boldsymbol{X}}_k) + \Gamma^0 L^0(\tilde{\boldsymbol{X}}_k)$, which relates the new model's flow with the identified abnormal deviation $\Gamma^0 L^0(\tilde{\boldsymbol{X}}_k)$ produced by the initial model.

In the case of the vehicle's EM, since images are considered, the complexity of the input data increases, and different techniques should be employed to process/infer data. Nonetheless, the model creation in EM follows a similar process to the one described above for the PM. Accordingly, let Θ_Z^0 be set of homogeneous abnormalities wrt. the initial model $m = 0$

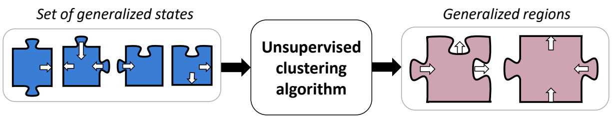


Fig. 18: Machine learning algorithms are employed to cluster GSs into discrete regions that describe higher levels of hierarchy encoding discrete concepts inside DBNs. Note that the process shown here with exteroceptive data can also be performed for the proprioceptive case.

when observing a set of measurements Z. Such abnormalities are employed to define a new model $m = 1$, such that

$$f^{1,\tilde{\boldsymbol{S}}^e_m}(\boldsymbol{X}_k) = G^{\tilde{S}^e_m}(\Theta^0_Z) + \tilde{w}_k, \tag{20}$$

where $G^{\tilde{\boldsymbol{S}}^e_m}(\cdot)$ represents a GAN's estimation of the GS's changes at the time k based on the vocabulary element $\tilde{\boldsymbol{S}}^e_m$. Accordingly, both learned flow models $f^{1,\tilde{\boldsymbol{S}}^p}$ and $f^{1,\tilde{\boldsymbol{S}}^e}$ are employed to infer future instances of proprioceptive and exteroceptive data independently.

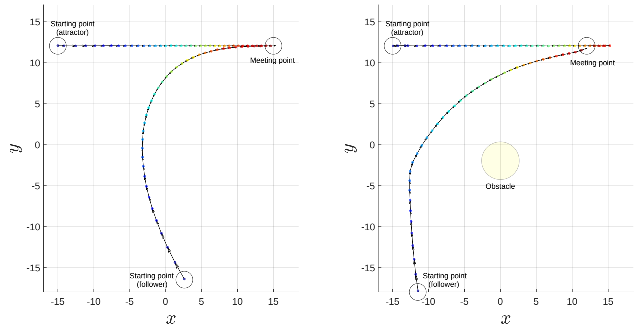
6) Interface with control: The PM and EM models are designed in such a way that messages from abnormality signals can be transferred at each time instant into the artificial agent such that it can modify its actions and improve its decision-making at a multilevel way, see Fig. 10. Nonetheless, until this moment, both models have been treated independently, and the SA architecture proposed in Fig. 10 that connects proprioceptive and exteroceptive information is missing.

B. Coupled exteroceptive-proprioceptive model

Coupling of exteroceptive and proprioceptive models arises from the need to identify causalities/interactions between multisensory data perceived by an artificial agent. By coupling the PM and EM, it is possible to build a model that takes into consideration a contextual viewpoint for making inferences about future perceived information. Accordingly, here the context comprises the internal and external perceptions of the agent at a given time instant k. The main idea is to use such information to predict the following internal (passive-self) or external (active-self) states, see Fig. 2. It is worth mentioning that the considered GSs in both PM and EM facilitate the creation of GS-DUs, such as shown in Fig. 11, that in turn enable to make inferences at different levels of abstraction.

For explaining how the aforementioned GS-DUs can be modeled as a coupled DBN problem, we consider a simulated situation where an agent moves towards another one that follows a linear path, as shown in Fig. 19. More specifically, Fig. 19a shows an example of both agents, namely a follower agent and a moving attractor. Accordingly, the follower moves from the scene's bottom towards the attractor until the meeting point is reached. Additionally, Fig. 19b depicts an abnormal scenario caused by introducing an obstacle interfering with the normal interactive model between both agents.

The proposed scenes in Fig. 19 assume synchronized sensory data from both agents' locations. Accordingly, the movement of both agents is simulated at each time instant by interacting rules that depend on their positions and motions. Such



(a) Normal interaction data (b) Abnormal interaction data

Fig. 19: Simulated trajectories of interacting agents. The starting point of the trajectories is represented in blue and ending points in red. The left graph (a) depicts a normal behavior between both agents, whereas the left graph (b) depicts an abnormal initial scenario caused by a static obstacle. The initial position of the follower is randomly selected inside the rage $[-15, 15]$ in x and $[-20-15]$ in y, whereas the attractor's position is initialized at the point $(-15, 12)$.

interacting rules are only employed for simulation purposes to generate coupled trajectory data. The main idea behind analyzing such multisensory data is to encode the coupled agents' behavior as probabilities into DBN models. Obtained models are SA due to their capabilities of measure the **abnormalities** and incrementally **learn/create** new coupled models (**memorized** in an agent's AM), derived from an **initial** one, that affect the **decision-making** of an agent.

From the follower's perspective, it is possible to consider its location measurements as proprioceptive data, whereas the relative position of the attractor represents the exteroceptive information. Accordingly, the follower's locations can be modeled as the left side DBN in Fig. 7, whereas the attractor's positions can be represented as the right side DBN. The modeling of each DBN follows the same reasoning as introduced in Section IV-A. In particular, since low dimensional data is considered (2D positions), the processing of data for building a multilevel inference model is similar to the PM's case presented previously in Section IV-A.

As described in [87], the problem of modeling both agents can be done by merging the generated exteroceptive and proprioceptive vocabularies $\tilde{\boldsymbol{S}}^p$ and $\tilde{\boldsymbol{S}}^e$ into a higher hierarchy variable $\boldsymbol{D}$ which encodes the statistical representative co-occurrence of PM and EM vocabularies. Accordingly, $\boldsymbol{D}$ encodes the context of internal and external data, and it is employed to make inferences that take into consideration the coupled states of EM and PM. Fig. 20 shows how the variable $\boldsymbol{D}$ can be introduced into the DBN structure depicted in Fig. 7.

Similar to Section IV-A, we briefly discuss the realization of the SA capabilities for the coupled-DBN case.

1) Initialization: Similar to the uncoupled PM, a random walk model is employed as an initial model from which more complex motions are learned. Such a simple model is used for both agents (follower and attractor in Fig. 19), assuming that both will remain at their positions in the following time

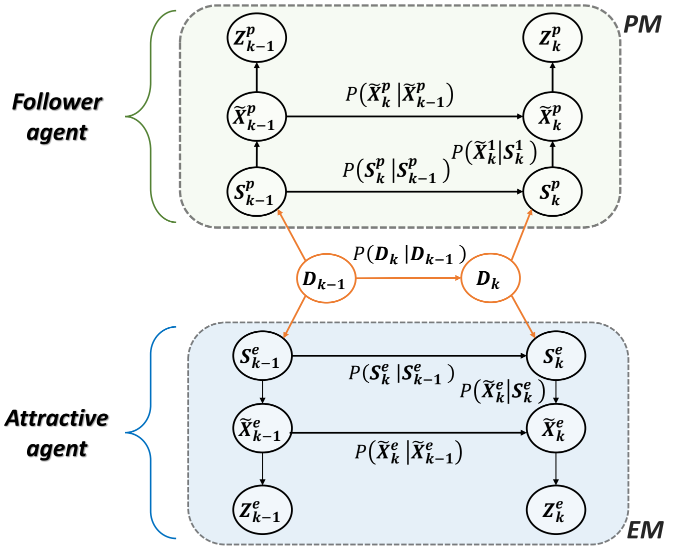


Fig. 20: A switching DBN for an interactive system. Arrows represent conditional probabilities between the involved variables. Vertical arrows describe causalities between both continuous and discrete levels of inference and observed measurements. Horizontal arrows explain temporal causalities between hidden variables. In particular, orange arrow encodes the interaction of couples, i.e., contextual coupled information of the PM and EM

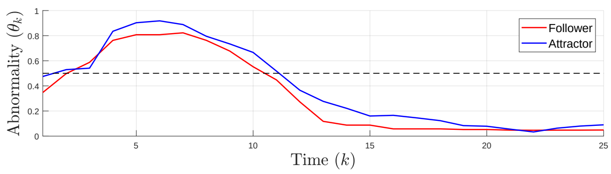


Fig. 21: Abnormality signals produced by coupled DBN under abnormal situation presented in Fig. 19b

instant, i.e., no interaction between them.

2) Memorization: Since a follower's perspective is taken into consideration, the created models are incrementally stored in the follower's AM so that its predictions and decision-making can be updated as more experiences are acquired.

3) Inference: Similar to the uncoupled PM, the DBN's structure in Fig. 20 is employed to make estimations about subsequent states. More specifically, a MJPF, consisting of a bank of KFs coupled with a particle filter, is employed for prediction purposes, such as explained in [87].

4) Abnormality detection: Since two agents are considered whose motions depend on the simulated interacting rules, an abnormality measurement is considered for each agent. Similar to the PM previously discussed in Section IV-A, abnormalities are measured for each agent based on the Hellinger distance.

Fig. 21 depicts the evaluation of the first coupled DBN model learned by looking at the normal experience shown in Fig. 19a and evaluated in the abnormal scene shown in Fig. 19b. It can be seen that the initial abnormal measurements exhibit high values and significantly drop at $k \approx 11$. These high initial abnormalities correspond to a contextual new experience introduced by the obstacle. Once the follower has passed the obstacle, the abnormality signals are reduced.

5) Model creation: As more pairs of agents' positions are observed and analyzed by the coupled DBN, models that take into account the joint state of both agents are created and updated by two clustering processes. Accordingly, a first cluster procedure is performed by considering the positions and the velocities (GSs) of both agents, prioritizing the velocity of only one agent. The motivation behind this approach is to identify similar agent's reactions (motions) to different contextual cases. The second clustering takes a similar approach, except for prioritizing the reactions of the other agent.

Each aforementioned clustering procedure generates a vocabulary that favors the actions of each agent, given its contextual state. Accordingly, both generated vocabularies are fused into a dictionary, which in turn represents prediction models that follow Eq. (3) for each agent. Consistently, each agent's model is employed to make inferences about the future configurations (actions) of the agents.

6) Interface with control: The whole set of variables in the coupled DBNs, including predictions and abnormalities, can be used by a control block to allocate resources better. In the case of the follower-attractor interplay, the follower's control could select among different motion strategies by considering the expectations about where the target will go and prediction errors. The abnormality signals produced by the coupled DBN model could be continuously sent to the actuators of both agents, such that learned normal interactions could be verified and corrected by both agents at each time instant.

C. Case studies discussion

The above examples show that the development of a SA model of an artificial agent like an (autonomous) car can be driven by bio-inspired considerations, as described in previous sections. The lessons learned so far when considering EM and PM independently are that the dimensionality of sensorial data can make it necessary to apply different signal processing solutions to obtain SA capabilities related to initialization and model creation. In the case of low dimensionality data, e.g., PM presented in section IV-A, initial models can be related to quite general equilibrium cases (e.g., static assumptions) while subsequent models can be derived by using unsupervised clustering processes. The key issue, in this case, is to define the optimization criteria coherently. For higher dimensionality cases, e.g., EM presented in section IV-A, the direct identification of initial models using a priori designed filters fully is not possible. However, we suggested that other tools coming from the Deep Learning evolution of last years can help. GANs of GSs, e.g., image and optical flow, are an example of a generative model that can be used to provide an initial model. In this case, it is needed a preliminary supervised selection of image sequences that should form the initial model, e.g., images when the agent goes in a linear (straight) motion. Derivation of successive models can be done by embedding abnormality detection with the Adversarial part of the network. So solutions are still possible. Many steps in this sense have to be done by research, e.g., establishing a strong link between

Bayesian Inference and Deep learning, but ideas start to appear in this direction [88].

In the last part, we considered a more complete scenario, in which despite its simplicity due to low dimensionality signals, we manage to show how coupled PE-DBNs can be related to the concept of Dispositional Units. The interesting part here is that the experiment suggests that vocabularies of flows learned for coupled attractors can require the adaptation of vocabularies learned with a single modality. As the core of SA models should rely on such dispositional models, the possibility to derive coupled representations from individual ones opens the possibility to start studying optimal representations in terms of between Bayesian inference and attractors. The lessons learned cover also other aspects, as the importance of synchronization techniques and the availability of datasets coming from different agents to study not only single agent but also multi-agent cooperative extended SA models.

V. Conclusion

Self-awareness is a broad concept describing the property of a biological or artificial agent that maintains knowledge of itself and its environment based on proprioceptive and exteroceptive information. In this paper, we have approached self-awareness from a sensor and signal processing perspective and derived a multisensorial model for self-aware autonomous systems. For this endeavor, we identified essential self-awareness capabilities and analyzed three fundamental bio-inspired theories. Our SA model is based on generalized states and free energy and variational reasoning schemes. The adopted coupled GS-DBN architecture facilitates fundamental SA properties necessary for computationally efficient realizations of SA artificial agents. Our mobile robot case study demonstrates the SA properties achieved in an independent and coupled modeling approach.

The proposed novel SA framework, comprised of a unique, hierarchical representation and an inference approach, can be efficiently integrated into real devices. The presented bio-inspired probabilistic representation facilitates a semantic interpretation of multisensorial data in a data-driven way by using the agents' signals and well-established techniques from probabilistic modeling and machine learning. By using the generative properties of the introduced model, we have successfully demonstrated the detection of abnormalities in a mobile robot case study, which opens the possibilities of testing the proposed framework in more complex scenarios.

As future work, we plan to study in more detail incremental learning of SA models in a fully unsupervised fashion as proposed in this paper and analyze the limitations of our method in terms of scalability. Beside the creation of distributed awareness in agents' networks, challenging problems include the number of involved sensors, the dimensionality of the provided data and the complexity and number of experiences that can be included in a SA agent [89]. A promising research direction consists of the integration of more probabilistic oriented deep learning techniques such as variational autoencoders [90] to describe observation models looking at high-dimensional data within the proposed Bayesian models. Additionally, an assessment of the derived models and learned experiences is necessary according to standards/regulations concerning safety, security, and resilience.

Despite the achieved encouraging results, self-aware autonomous systems are still at its infancy and substantial further research is necessary to achieve a sufficient level of self-awareness capable of handling complex real-world settings. Without any doubt, human level self-awareness will not be achievable in artificial agents in the near future, but we hope research presented in this paper can contribute to initial computational steps in this direction.

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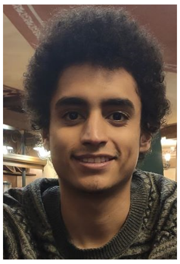
Carlo Regazzoni is Full Professor of cognitive telecommunications systems with DITEN, University of Genoa, Italy. He has been responsible for several national and EU funded research projects. He is Coordinator of international Ph.D. course on interactive and cognitive environments involving several European universities. He served as the General Chair for several conferences and Associate Editor/ Guest Editor for many international technical journals. He served in many roles within governance bodies of IEEE SPS, being IEEE SPS Vice President Conferences from 2015 to 2017.

Carlo Regazzoni has been Associate Editor of several international journals (e.g., IEEE Trans. On Circuits and Systems for Video Technology, IEEE Trans. on Image Processing, IEEE Signal Processing Letters and others). He has been Guest editor of special issues of international journals including: Proceedings of the IEEE, IEEE Signal Processing Magazine, and others. He has been co-editor of 4 edited books (Kluwer) on intelligent video surveillance. He is author/co-author of more than 100 papers on International Scientific Journals and of more than 300 papers at peer reviewed International Conferences.

Lucio Marcenaro received the degree in electronic engineering and the Ph.D. degree in computer science and electronic engineering from Genoa University in 1999 and 2003, respectively. Since 2011, he has been an Assistant Professor of Telecommunications with the Department of Electrical, Electronic, Telecommunications Engineering and Naval Architecture (DITEN), University of Genoa. He has 20 years of experience in image and video sequence analysis. He has authored about 130 technical papers on signal and video processing for computer vision.

Lucio Marcenaro is associate editor of the IEEE Transactions on Image Processing and IEEE Transactions on Circuits and Systems for Video Technology, technical program co-chair for 13th International Conference on Distributed Smart Cameras (ICDSC) and co-organizer for the 2019 Summer School on Signal Processing (S3P), General Chair of the Symposium on Signal Processing for Understanding Crowd Dynamics. He is active within the IEEE Signal Processing Italy Chapter and Director of Student Services Committee (2018-2020) of the IEEE SPS.



Damian Campo received a degree in engineering physics from EAFIT University, Medellin, Colombia, in 2014, and a Ph.D. degree in cognitive environments from the University of Genoa, Italy, in 2018. Since 2018, he has been a postdoc researcher in the Department of Engineering and Naval architecture (DITEN), University of Genoa. His interests include the use of machine learning techniques and probabilistic theory for modeling and predicting the states of multisensory data.

Bernhard Rinner is full professor at the University of Klagenfurt where he is heading the Pervasive Computing group. He received both his PhD and MSc in Telematics from Graz University of Technology in 1996 and 1993, respectively. Before joining the University of Klagenfurt in 2007, he was with Graz University of Technology and held research positions at the Department of Computer Sciences at the University of Texas at Austin in 1995 and 1998/99. His current research interests include sensor networks, multi-robot systems, self-organization and pervasive computing. He has authored and co-authored more than 230 papers for journals, conferences and workshops.

Bernhard Rinner is associate editor of the Ad Hoc Networks Journal and has co-edited a book on "Self-aware computing systems". He has co-founded the ACM/IEEE International Conference on Distributed Smart Cameras and has served as guest editor of various special issues, e.g., in the Proceedings of the IEEE, IEEE Computer and IEEE Selected Topics in Signal Processing. Together with partners from four European universities, he has jointly initiated the Erasmus Mundus Joint Doctorate Program on Interactive and Cognitive Environments (ICE). He is chair of the doctoral advisory board of the Faculty of Technical Sciences and member of the board of the Austrian Science Fund.