Domain-dependent and Observer-dependent Follow-up of Human Activity

A Normative Multi-agent Approach

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Abstract: We propose in this paper a novel approach for human activity follow-up that draws on a distinction between domain-dependent and observer-dependent viewpoints. While the domain-dependent (or intrinsic) viewpoint calls for the follow-up and interpretation of human activity *per se*, the observer-dependent (or extrinsic) viewpoint calls for a more subjective approach, which may involve an evaluative dimension, regarding the human activity or the interpretation process itself. Of interest are the mutual dependencies that tie both processes over time: the observer viewpoint is known to shape domain-dependent interpretation, while domain-dependent interpretation is core to the evolution of the observer viewpoint. We make a case for using a normative multi-agent approach to design monitoring systems articulating both viewpoints. We illustrate the proposed approach potential by examples from daily life scenarios.

1 INTRODUCTION

We propose in this paper a novel architecture for human activity monitoring, which draws on a distinction between two complementing universes of discourse: the intrinsic universe of the activity domain, and the extrinsic universe of the observer(s) following this activity. While the domain-dependent (or intrinsic) viewpoint calls for the follow-up and interpretation of human activity per se, the observer-dependent (or extrinsic) viewpoint calls for a more subjective approach, which may involve an evaluative dimension, regarding the human activity or the interpretation process itself. Of interest are the mutual dependencies that tie both processes over time: the observer viewpoint is known to shape domain-dependent interpretation, while domain-dependent interpretation is core to the evolution of the observer viewpoint. We make a case for using a normative multi-agent approach to design monitoring systems articulating both viewpoints. In this approach, we distinguish between intrinsic agents, whose role is to build interpretation hypotheses from the data at hand, and extrinsic agents, whose role is to observe, adapt and frame the former process. Both kinds of agents are launched by norms that express in a declarative way the intrinsic and extrinsic constraints that shape their activity. They share a common multidimensional trace and evolve in mutual dependency: intrinsic agents processing may result in the launching of extrinsic agents, which may in turn frame back intrinsic agents activities. We illustrate the proposed approach potential by examples from daily life scenarios.

2 STATE OF THE ART

We consider interpretation as a matter of generating, selecting and testing hypotheses in front of evolving data, contexts and requirements. Context representation is a major issue in both Monitoring and Ambient Intelligence (Brémond and Thonnat, 1998). In monitoring, human activity is captured in the form of multi-sensor temporal data, that are redundant, incomplete and ambiguous: the physiological profile of a person may vary according to various factors like the time of the day or the geographical location; conversely, a given set of data may correspond to several different patterns of activity. Context sensitivity, personalization and pro-activeness are important properties of the system to be designed; their embodiment within broader social contexts calls for considering other factors like

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compliance with social conventions, awareness to the inner state of emotion or motives, or the ability to act and interact in a consistent and transparent way (Aarts and de Ruyter, 2009). The analysis process must therefore imply several levels of abstraction, from the local level of the data to a more global level of norms, functional requirements and goals (Weber and Glynn, 2006). Although some contextual situations are fairly stable, discernible, and predictable, there are many others that are not: for (Greenberg, 2001), context must be seen as a dynamic construct evolving with time, episodes of use, social interaction, internal goals, and local influences. Following (Klein et al., 2006), we will approach interpretation not as a state of knowledge, but rather as “a process of fitting data into a frame that is continuously replaced and adapted to fit the data”. As a consequence, we may not reduce the understanding process to the description and handling of contextual elements, nor to the mere application of data-driven or goal-driven methods. On the contrary, this process must be seen as the constant perception-action loop, which consists in focus, perception, interpretation, context modelling and anticipation. The paradigm of Multi-Agent Systems allows for multiple, heterogeneous entities to be handled through a unified communication / cooperation frame (Isern et al., 2010). The heterogeneity of agents is considered as a requirement to encompass the variety of states a person can find oneself in; a large knowledge base of interconnected interpretation models can thus be explored, as a dynamic population of multiple hypotheses on several levels of abstraction. A law enforcement approach has been proposed (Carvalho et al., 2005) to support dependable open software development in the context of ambient intelligence environments. Following these lines of approach, we propose using the normative agent paradigm as a way to design flexible context-aware norm-driven systems. Normative MAS are a class of Multi-Agent Systems in which agent behaviour is not only guided by their mere individual objectives but also regulated by norms specifying in a declarative way which actions are considered as legal or not by the group (Castelfranchi, 2006). Agents acting in such a system may be seen as “socially autonomous": they do not only pursue their own goals but are also able to adopt goals from the outside, and act in the best interest of the society. An additional control over the adoption of goals is therefore needed, in the form of norms, which operate as external incentives for action (Dignum et al., 2000). These norms are designed as condition-action rules, triggered by a dedicated engine, and result in agent notifications. Agents subscribe to norms and may adopt them or not, which may result in penalties. Norms may finally be adapted to cope with the evolution of context (Boissier et al., 2011). The system dynamics therefore depends not only on the agent dynamics but also on the dynamic of the norms.

3 PROPOSED ARCHITECTURE

3.1 Proposed View

According to (Hébert, 2002), we propose to distinguish between intrinsic and extrinsic perspectives to interpretation. Intrinsic interpretation is domain-dependent: it is based on attributes and classes that are inherent to the activity domain. Intrinsic interpretation drives the construction of hypotheses, which may be concurrent and contradictory, as to whether a person is running, walking, or staying quiet. Extrinsic interpretation is observer-dependent: it relies on attributes and classes that are inherent to the observer domain. Extrinsic interpretation drives the construction of an evaluative view over human activity, regarding whether this activity is normal or alarming. It may further apply to the way intrinsic interpretation is conducted and provides a view as to whether this process is efficient, informative, or for example open or restricted to few hypotheses. These two universes of discourse are mutually dependent. Indeed, the evolution of intrinsic activity properties may yield the evolution of extrinsic evaluation models, e.g. a skiing or walking activity calls for different evaluative models. Conversely, the observer’s extrinsic evaluation provides a perspective view that drives what is looked at, e.g. focus on speed if there is a risk of fall for a skiing activity, focus on location if there is a risk of getting lost for a walking activity.

Interpretation is modelled as a dynamic exploration process driven in a context-sensitive way. As proposed in a previous paper (Vettier and Garbay, 2014), it is abductive in nature and modelled as a perception-action loop combining prediction and verification stances. This process is situated with respect to a set of intrinsic and extrinsic require-ments. Intrinsic requirements are domain-dependent: interpretation hypotheses are to be grounded into the evidence of data and the realm of the activity at hand. Their confidence has to be high enough for the hypothesis to be maintained: otherwise other hypotheses must be evaluated.

Extrinsic require-ments are domain-independent but observer-dependent (focus on a given range of activity, drive the interpretation process toward a given efficiency). These heterogeneous frames of interpretation are subject to evolution, to cope with the evolving contexts or requirements from the observer: the current focus or expected performance may be modified in front of unexpected critical states for example. These features of monitoring system were stated early by (Hayes-Roth, 1995).

We propose normative, rule-governed agents as a way to design declarative, flexible context-aware policy-driven systems, embedding sense-making within constraints from various domains. As illustrated in Figure 1, there are two main types of agents, intrinsic and extrinsic. These agents are formalized as a tuple: A = ⟨Role, Range, Regular, Corrective⟩. Role denotes the role of the agent (interpretation hypothesis followed by the intrinsic agent, requirement checked by the extrinsic agent). Range denotes the level of achievement of the agent's role (confidence of the interpretation process or fitness of requirement). Regular defines regular methods for data interpretation (intrinsic agent) or requirement checking (extrinsic agent), depending on the type of the agent. The corrective method defines how to regulate the interpretation process (deposit new interpretation hypotheses, modify intrinsic or extrinsic requirements). The agent is situated with respect to a shared, multidimensional trace. This trace is formalized as a tuple: T = ⟨IntState, IntPast, Intrinsic, Extrinsic⟩. It involves information about the current and past state of interpretation (IntState, IntPast): current hypotheses with their confidence degree, running agents, current interpretation efficiency… as well as information about current Intrinsic and Extrinsic requirements. The agent activity is framed by a set of norms expressing intrinsic or extrinsic requirements. The norms are triggered depending on patterns from the trace and launch the agents. Any norm, intrinsic or extrinsic, is formalized as a tuple: N = ⟨Type, Weight, Context, Flag, |Bearer|, Object⟩. Type defines the type of the norm. Weight allows to prioritize the rules. Context represents an overall evaluation condition (as the overall system state or human situation). Flag allows to bypass the requirement when necessary. |Bearer| denotes the targeted element (agent or trace). Object is a compound field, typically written as "launch (conditions actions)", characterizing the conditional action attached to the norm (launching of agent behaviour). The role of intrinsic norms and agents is to evolve the state of interpretation while the role of extrinsic norms and agents is to evolve the frame of interpretation.

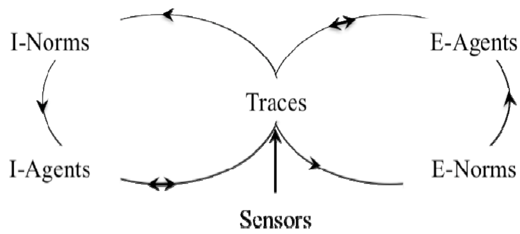

Figure 1: A dual perspective on human activity follow-up. I-agents perform data interpretation, governed by intrinsic norms. This domain-dependent interpretation process is framed by E-Agents, working under extrinsic or observer-dependent requirements.

3.2 I-Agents Life Cycle

The role of an I-Agent is to interpret incoming data at given abstraction levels, according to provided field of perception and models. Reasoning is of an abductive nature and the agents navigate among several behaviours (Initialization, Exploration, Anticipation, Termination), according to a life cycle governed by intrinsic norms (Figure 2).

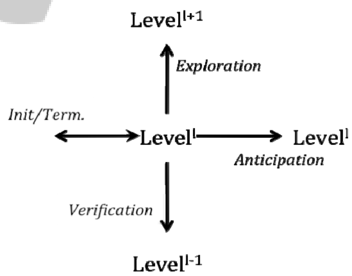

Figure 2: Agents life cycle as governed by intrinsic filters.

An intrinsic agent is a tuple: I-Agent = ⟨Hyp, Conf, Verif, Pred⟩. Hyp denotes the hypothesis followed by the agent and Conf a confidence range (low, medium, high) for this hypothesis: this field is time stamped. Verif denotes the Regular agent behaviour: its role is to proceed to confidence computation, according to provided components and model. This confidence value will be deposited in the trace and processed by norms. Pred denotes the Corrective agent behaviour: its role is to propose further interpretation hypotheses. We distinguish between three prediction mechanisms: Anticipation, Exploration and Termination. Anticipation is raised by the corresponding norms in case of a lowering confidence that is persistent over time: a transition toward another hypothesis at the same abstraction level has to be proposed. Conversely, Exploration is raised by the corresponding norms in case of a high level confidence that is persistent over time: a transition toward a higher level hypotheses might be proposed, to open the current interpretation toward new hypotheses spaces. The agents deposit the new hypotheses in the Trace, with a null confidence. They will be processed by dedicated norms, whose role is to launch Intrinsic agents (Initialization behaviour) for further processing (Verification). Termination is launched in case of a low confidence range persistent over some additional time, to stop processing the corresponding hypothesis.

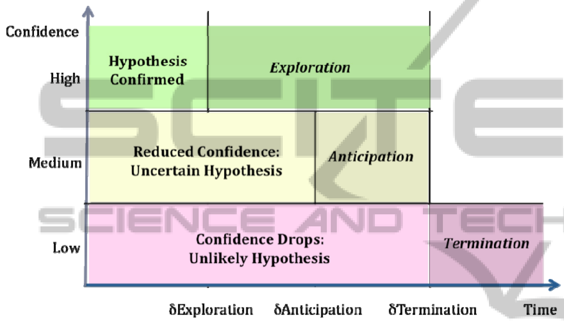

Figure 3: Correspondence between confidence degree and I-Agents behaviours.

Figure 3 illustrates the correspondence between Confidence level evolution and behaviour launch. As may be seen, this process is regulated by several parameters: two confidence thresholds C_{low} and C_{medium} to assess whether an hypothesis has a low, medium or high confidence, and three durations thresholds: δ_{Term}, δ_{Ant}, δ_{Expl}, to assess whether the agent must be launched within an Exploration, Anticipation or Termination behaviour. These thresholds are part of the current agent Intrinsic requirements and are shared through the Trace. They may be subject to evolution, depending on the action of Extrinsic agents.

Table 1: I-Norms examples (type, weights and flags omitted).

Context	Bearer	Object	
Conf ≠ Null	Physio. State	Conf < high & δT > δAnticipation	Anticipation
Conf ≠ Null	Activity State	Conf = high & δT > δExploration	Exploration

The role of I-Norms is to frame the interpretation process according to intrinsic requirements. To this end, they launch their targeted I-Agents into one of these 4 Corrective behaviours, depending on their current hypothesis confidence degree and on the time spent within the same confidence range. Some I-Norm examples are provided in Table 1.

3.3 E-Agents Life Cycle

The role of E-agent is to ensure the follow-up of the interpretation process according to observer-dependent requirements. An Extrinsic-agent E is a tuple: E-Agent = ⟨Requirt, Fit, Verif, Corr⟩. Requirt denotes the requirement that the agent follows (e.g. stay in a Basal physiological state, keep interpretation Parsimonious or Readable …). Fit denotes a fitness range (low, medium, high) for this hypothesis: this field is time stamped. Verif denotes the regular E-agent behaviour: check the extent to which the requirement is followed. Corr denotes the corrective agent behaviour. It is launched by E-Norms in case of a lack of compliance with the considered requirement. Its role is to ensure the "fitness" between the interpretation process and the observer's requirements.

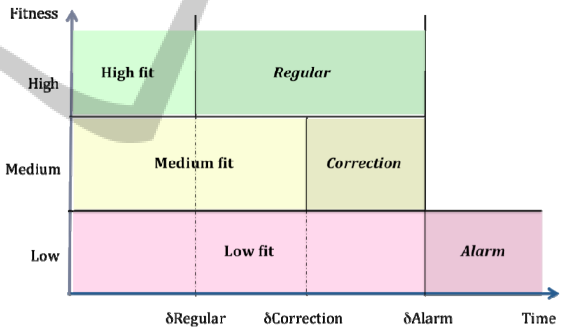

Figure 4: Correspondence between fitness level and E-Agents behaviours.

We distinguish between three corrective mechanisms: I-Corr, E-Corr and Alarm. I-Corr holds when a modification of intrinsic requirements will ensure a better fit of the interpretation process to existing extrinsic requirement. On the contrary, E-Corr holds when the extrinsic requirements themselves have to evolve to fit some transitions in the observed situation. Alarm will be raised in case of a failure of the corrective attempts, which results in a persistent lack of fit between the observer and the interpretative process. Figure 4 illustrates the correspondence between Fitness level and launching of behaviours. As in Figure 3, this process is regulated by several parameters. The role of the E-Norm is to launch the proper regular or corrective measures, depending on context. I-Corr (resp. E-

Corr) corrective measures will modify some intrinsic (resp. extrinsic) parameters in the trace: e.g. rate of anticipation, level of confidence required (resp. expected level of performance, expected activity). Examples of such norms are provided in Table 2.

Table 2: E-Norms examples.

Context	Bearer	Object	
Parsimony	I-Agent	NHyp > δParsimony	I-Corr (Thigh)
Basal	E-Agent	Winded	E-Corr (Heart disease)

The Parsimony norm in Table 2 relates to how well the hypothesis generation works: its role is to control the current number of hypotheses to be actively processed. Both lack and plethora of likely hypotheses bring ambiguity and uncertainty, and therefore low effectiveness. A solution to correct these deviations is to modify the confidence and duration thresholds: in case of lacking hypotheses, reducing δAnticipation will push more agents in the Anticipation policy and thus increase resampling; conversely, in case of too many hypotheses, increasing the Thigh threshold will discriminate more so that only the most likely hypotheses are validated. Regulation at the extrinsic level may occur in case of deviation from basal state: this may require the verification of some further pathological state. This is the role of the "Basal" E-Norm example in Table 2: the occurrence of a Winded Hypothesis, when the person is supposed to be in a basal state, during a daily life scenario calls for checking specific non basal physiological states and therefore for a modification of the observer expectations (extrinsic requirements Heart disease) as regards the current state of the person.

4 APPLICATION

We present in this section an application to human monitoring. The person is wearing a combination of physiological (heart rate, breath rate...) and actimetric (acceleration, position) unobtrusive sensors capturing its physiology and activity. He/she is following an outdoor scenario (hiking).

4.1 Knowledge Elements

A priori knowledge is provided to the agents, in the form of an ontology (Figure 5), together with models to interpret incoming data and norms to regulate interpretation. We distinguish between 4 abstraction levels: the one of the overall scenario, the one of the micro-scenario (conjunction of states), the one of the states (designing physiology or activity), and the one of the data.

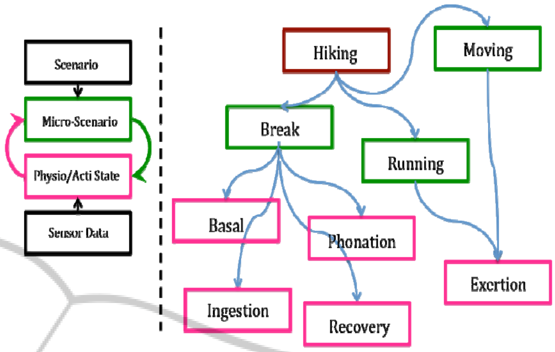

Figure 5: An example view of a hypothesis network corresponding to a hiking scenario.

For state agents, confidence is computed from raw data elements. For example, computation of the Basal State confidence φBasal will involve: φBasal.K == {HeartRate, BreathRate, SkinTemp}. For micro-scenario agent, it is computed from state components. For example, a Break micro-scenario will involve the following states:
Break:K =={Recovery ∧ Phonation ∨ Basal}.

4.2 Experiments

Figure 6 shows the follow-up of a hiking activity. We show in this experiment that modifying an extrinsic requirement as regards a micro-scenario to be verified modifies the way interpretation develops.

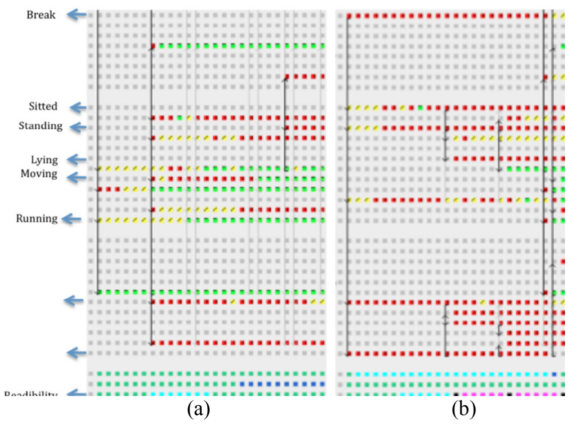

Figure 6: Influence of extrinsic requirement on interpretation: (a) hike; (b) break.

The dot's colors indicate the level of confidence in the considered hypothesis (red for Low, yellow for

Medium, green for High). In case (a), the interpretation is oriented toward a “hiking” micro-scenario, which is consistent with the data, while it is oriented toward a “break” in (b), which is not consistent. As may be seen, the readability in case (b) is bad. The system is lost in a collection of wrong hypotheses. We show in figure 7a the result of modifying the confidence thresholds so that hypothesis verification becomes more difficult. This was performed on the experiment of Figure 6a. A better readability is obtained. A dynamic modification of the verification rate, for the example on Figure 6b is illustrated in Figure 7b. We observe a reduced number of low hypothesis, due to a higher termination rate (with some latency).

(a) (b)

Figure 7: Influence of intrinsic requirement on interpretation: (a) increase of high threshold on case 6a; (b) increase of verification rate on case 6b, while the system is running (indicated by the vertical arrow).

5 CONCLUSIONS

We have proposed in this paper a novel approach to handle both domain-dependent (or intrinsic) and observer-dependent (or extrinsic) viewpoints on human activity follow-up. A normative multi-agent architecture is proposed, which draw on a distinction between I-Agents and E-Agents, whose role is respectively to ensure the follow-up of the observed activity and the running interpretation. Their processing result in the modification of a common trace where results from both follow-up are stored. Our design further draws on a distinction between I-Norms and E-Norms, which regulate the behaviour of the corresponding agents, based on information from the trace, and express domain-dependent as well as observer-dependent requirements. Further work is needed to better formalize the approach (in particular the deontic dimension of norm application) and increase the experimental background.

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