Towards a Middleware to Infer the Risk Level of an Activity in Context-Aware Environments Using the SRK Model

Alfredo Del Fabro Neto, Rafael Boufleuer, Bruno Romero de Azevedo, Iara Augustin
Informatics Graduation Program
Federal University of Santa Maria
Santa Maria/RS, Brazil
emails: {alfredodfn, rafaboufler}@redes.UFSM.br, {brunodea, august}@inf.UFSM.br

João Carlos D. Lima
Department of Languages and Computer Systems
Federal University of Santa Maria
Santa Maria/RS, Brazil
email: caio@inf.UFSM.br

Cristiano C. Rocha
MobilEasy Technologies Ltda.
Florianópolis/SC, Brazil
email: cristiano.rocha@MobilEasy.com.br

***Abstract*—It is inherent that every activity (human or non-human) has an associated risk level to the actors involved. This risk level may vary from no-damage risk to a very high risk level. Based on the regular actor's behavior, the risk level of an activity can be changed to a higher or lower level (i.e., how apt the actor is related to an activity). This paper proposes a novel approach to analyze the risk level of activities considering the behavior of the actors using the Skill, Rule and Knowledge (SRK) cognitive architecture proposed by Rasmussen in 1983. Taking advantage of the Internet of Things paradigm we developed a context-aware middleware that analyzes the actors' behavior based on the SRK model to infer the risk level associated with their activities.**

Keywords*—*Activity Recognition; Activity Risk Level; Context-Awareness; SRK Model.

I. Introduction

The usage of technologies to obtain information about the environment has been increasing. It provided the ground for research areas in pervasive and ubiquitous systems making possible the ideas proposed in the famous paper by Weiser in 1991 [1]. One of these research areas is the so-called Internet of Things (IoT), which can be seen as the integration between humans and application seamlessly "through the new dimension of "Things" communication and integration" [2]. This means that everyday life objects could be embedded within a sensor that would provide information about it to anyone who wants it (i.e., other objects, systems, etc.) [3].

To meet these requirements it is necessary for the systems to access the context data in which their actors are included. It is important to notice that actors may not only be humans as they can also be, e.g., the environment. There are many definitions of what a context is. Dey [4] shows some of them and proposes his own definition: "Context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and application themselves". A system that uses the context informations to act and react to environmental instigations in a transparent way to its users can be called context-aware system [5], term that was first introduced by Schilit et al. [6].

The IoT community has been using context-aware paradigm in order to develop solutions for different domains, which are classified as [2]: industrial (e.g., sales, enterprise services, etc), environmental (e.g., recycling, energy management, etc) or social (e.g., e-inclusion, healthcare, etc). A useful feature for providing these domains with knowledge about the context that they are inserted into is activity recognition [7][8]. These activities may be seen as human or non-human activities, e.g., environmental or system actions. They may contain certain risks that could cause damage to the envolved actors. In this sense, our paper focuses on activity recognition to determine the risk level associated with it. We developed a middleware based on the Skill, Rule and Knowledge (SRK) [9] cognitive architecture to model the actor's behavior in order to provide the risk level categorization.

To test our middleware we believe that the target scenarios would involve monitoring the activities of people who need special care, the environmental activities (e.g., fire detection) and intrusion detection based on environmental behavior.

This paper is structured as follows: In Section II, we present a model activity that was used in our research. In Section III, we define the components of our middleware architecture, their correlations and the influence of the priority system in the information flow. In Section IV, we present the work to be done, and, in Section V, we draw our final considerations.

II. Activity Model

Since the main objective of this work requires the recognition of activities, it is necessary to understand what an activity is and its relation to the actor's context.

In order to design our middleware, we needed a well defined approach that could characterize an activity. In Subsection II-A, we present the Kuutti's approach [10] to represent the relationships between the components of the Activity Theory.

A. Activity Theory

The basic notion behind the Activity Theory is that the subject is participating in an activity because he wants to achieve some specific goal. His interest is focused on an activity's object that he wants to use and/or modify in order to achieve an expected result. The interaction between the subject

 ISBN: 978-1-61208-289-9

and the object is mediated by tools. This way, a basic triangle of “subject”, “object” and mediation by “artifact” is created.

With the addition of “community”, the Activity Theory allowed the representation of social and cultural contexts as well as mediations between people and computing devices (smartphones and other artifacts developed for pervasive environments).

This way, the activity is turned into the basic unit of analysis and is the most important means to develop the object and the subject. Therefore, the simplest Activity Theory model already offers a solid approach to the task of comprehending the interaction between human beings and the world.

The Kuutti’s approach [10] to the Activity Theory is based on three relationships:

- between the subject and the object mediated by tools and artifacts;
- between the subject and the community mediated by rules; and
- between the object and the community mediated by division of labor.

Since the subject is an active part of the community and it has social activities, the relations between the subject and the community as well as the community and the object are mediated by a set of rules and the division of labor.

The formalization of the relationships between the components of the Activity Theory allows the use of this theory in interactions (mediation) between individuals, objects and the community. The IoT is based on this mediation, since the objects are embedded with sensors that provide: i) information about the object (artifacts), ii) the presence of individuals (rules) and iii) information about the community (division of labor).

B. Context-aware model based on Activity Theory

The Activity Theory is an important theoretical reference to aid the components’ explicitation that form the contextual knowledge to be incorporated in pervasive systems. The Activity Theory’s components can be related with the contextual knowledge taxonomy [11], as shown in Table I.

TABLE I: BASIC ASPECTS OF AN ACTIVITY AND THEIR RELATION TO A TAXONOMY OF CONTEXTUAL KNOWLEDGE [11]

CHAT aspect	Category
Subject	Personal Context
Object	Task Context
Community	Spatio-Temporal Context
Mediating Artefact	Environmental Context
Mediating Rules	Task Context
Mediating Division of Labour	Social Context

The Cultural Historical Activity Theory (CHAT) aspects were mapped in a flexible way, allowing two or more aspects to participate in the same context category. The contextual knowledge vision is based on the premise that there are different interpretations, i.e., the contextual information in a setting can be considered as part of the knowledge model, in another setting as the own knowledge model. This flexibility allows the designers of pervasive systems to concentrate on the aspects of the knowledge level instead of modeling irrelevant details.

The taxonomy of context proposed by [12] has a pragmatic view of construction artifacts and incorporates to the context-aware systems the general concepts found in the Activity Theory (Fig. 1).

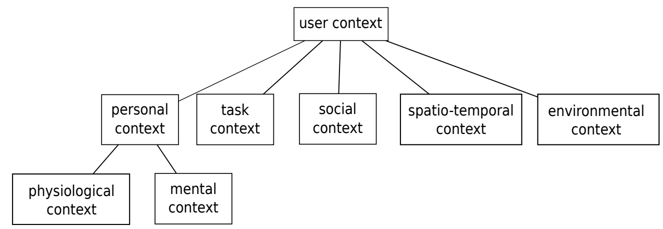

Figure 1. Context taxonomy [12]

C. Activities Recognition

The main objective of the activities recognition lies in recognizing the actors common activities in real situations interpreted from the retrieved sensor data.

The activity recognition process imposes some challenges related to interpretation because of the possibility of non-deterministic activities by the actor. Thus, probabilistic methods are apoppriated to activities recognition process [13][14]. Many researchers have been using algorithms based on probabilistic methods in order to construct activity models [15].

The comprehension of the human activities encompasses both the activities recognition and activities patterns discovery [15]. We extend this concept to not just humans, but different actors as a generic way to approach the subjects being analyzed. The activity recognition aims to the precision of the detection of activities based on a pre-defined activities model. On the other hand, the activities patterns discovery focus on the search for unknown patterns and it is directly performed over the data from low level context without any pre-defined model.

Although both techniques differs, they aim the perfectioning of the user-centric computing technology. This way, both of them are complementary, i.e., the discovery of activity patterns is capable of helping in the activity definitions that can be recognized and manipulated later.

III. PROPOSED ARCHITECTURE

To develop the proposed middleware architecture presented in Fig. 2, we relied on the layered conceptual framework for context-aware systems [5]. We chose this framework model because it separates in a well defined manner the components of sensoring, processing and management of the contextual data. It also provides the advantages of extensibility and reusability of systems. Therefore, our middleware extends this architecture and incorporates the SRK model in order to allow the actors’ behavior analysis.

Our work’s contribution relies in the introduction of a specialized layer (*SRK Classifier*) to create a well structured

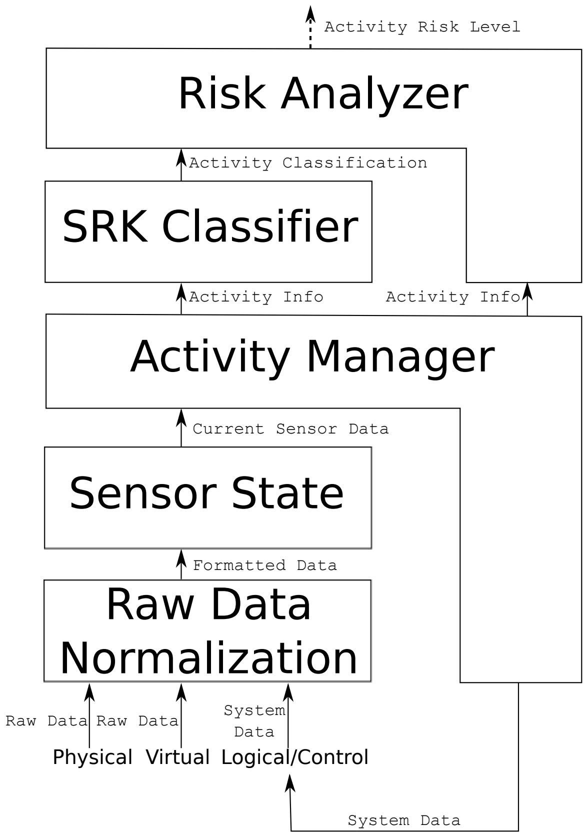

Figure 2. Middleware architecture proposed.

model of the user capabilities in performing some activity. It is important because each person has abilities that makes him more or less apt in doing a specific activity, which has a direct influence when the risk level analysis is made. The decisions of what should be done relies in this classification.

In the next subsections, we introduce the components of the proposed middleware (see Fig. 2).

A. Raw Data Normalization and Sensor State

The main goal of the *raw data normalization* component is to give meaning to the raw data retrieved from the different types of sensors (physical, virtual and logical) and format it to some defined pattern, e.g., the Message Queuing Telemetry Transport for Sensor Networks (MQTT-S) [16] standard [17]. It is from them that the context information is gathered. As it will be seen in section III-E, this layer gathers informations not only from the physical and virtual sensors, but from the logical sensors as well. These logical sensors are feeded by the system itself, incorporating informations that already have passed through some classification and semantic process. This aggregation of context information already treated allows the system to perform more precise analysis.

The *sensor state* component obtains the formatted sensor data and stores it to always provide to the above layers the latest relevant changes in the sensors values in a formatted way. This provisioning can be made by pushing the information accordingly to some priority criteria (the priority system is further explained in subsection III-E). There is also a subscription system that works like a blackboard model [5]. To make use of the subscription system, an activity has to subscribe to a certain event. An event is triggered when one or more sensores have a change in their state. In order to reduce the amount of events triggered (since a sensor may change their status with a really small variance) the system can define a certain minimum percentage necessary of changes in the state of each sensor for an event to be triggered.

B. Activity Manager

The *activity manager* component stores pre-defined activities registered manually and a log of activities that the system detected that happened. Each activity has associated sensors that describe the required values for the activity to be detected. With these informations and based on the sensors current states the *activity manager* can reason and then infer if an activity is happening, has happened or may happen. Using some learning techniques it might be possible for the system to correlate activities and sensors in order to identify new activities. It is interesting to notice that an activity may be used, e.g., to identify other activities thus acting as a logical sensor.

C. SRK Classifier

The *SRK classifier* component is proposed to define if an activity is a skill, rule or knowledge based on the work by Rasmussen [9], as follows:

- Skill: actions that the actor develops routinely without any conscious control or attention, e.g., walking with crutches;
- Rule: actions that need conscious control or attention, e.g., deviate from a hole while walking with crutches;
- Knowledge: actions where every option for solving the task through skill and rule based routines could not solve the problem, e.g., first attempt to walk with crutches.

According to Neal et al. [18], the more recent theories see habits as automated responses stimulated by aspects in the context or by the environment itself. The same way as humans, intelligent systems can control their actions and reactions based in an habitual behavior. In order to be a more generic middleware, we noted that skills should be characterized as habits, which makes more sense since actors can be anything (i.e., humans, environment, systems, etc).

The analyses performed by this component uses the historical data from the *activity manager* component and its own classification logs to determine which of the three classifications the activity belongs to. This classification also depends on the frequency and duration with which the activity is realized. Therefore, an activity may change levels, e.g., an activity that is classified as a rule may become an habit after some time practicing.

D. Risk Analyzer

The *risk analyzer* component receives a classified activity and determines the associated risk level. This is done by verifying the sensors' informations (which are requested to the *activity manager*) related to the activity being analyzed and its SRK classification. In order to clarify it, we present a simple example: An elderly person is walking in the kitchen of his house and its floor is wet. Our system would detect that the *walking* activity is complicated for this user (by managing its classification in the *SRK classifier*) and verify that the kitchen's floor is wet (by sensors spread in the environment). With this informations our system can calculate the risk level associated with that activity at that moment. This risk level can be used by other applications to aid some sort of decision-making (e.g., warn the user about the danger he might be in).

The priority system was developed because many activities may occur at the same time and that some of them may have related sensors with an abnormal data indicating that it needs to be processed first thus having higher priority. In Subsection III-E, the priority system will be discussed.

E. Data Flow and Priority System

The data flow is as follows (Fig. 2):

1) The system receives raw data from several sensors (physical, virtual and logical/control);
2) This data has to be normalized since it comes from different sources;
3) The latest formatted data from the sensors is kept in the *sensor state* layer, which can be queried from the layer above, *activity manager* (as presented in the Subsection III-A);
4) The *activity manager* gets the current sensors' data to detect activities;
5) Since activities can be created by the system itself, they can be used as logical sensors;
6) The *SRK classifier* gets activities and classify them according to the actor;
7) Lastly, the *risk analyzer* captures the classification of the activity being analyzed from the *SRK classifier* and its informations from the *activity manager* to infer its risk level.

However, the system data flow is affected by priorities, which have a major role in our middleware. The system first uses priority in the *raw data normalization* component to pass to the *sensor state* component the informations with higher priority. This way, the current state of the more relevant sensors will be updated first acting as a prioritized queue.

It is in the *sensor state* component where the priority of the sensors can be changed. As in the *raw data normalization* component, the information is passed according to its priority. The *activity manager* component is capable of creating a control sensor, which is an system activity that tells the *sensor state* to change the priority of one or more sensors. Besides that the priority is only used to determine which information goes first to the next component, which is the same and only function of the priorities in the *SRK classifier* component. The *risk analyzer* component has only the attribution of requesting the *activity manager* to change the priority of sensors.

IV. Research Agenda

We intend to verify and analyze which context model is more suitable to our middleware (object-oriented model or the use of ontologies) and then investigate standard protocols for the inter-layer communications (e.g., MQTT-S [16]).

After we have a complete and detailed model of our middleware and the flow of informations in it, we can specify different scenarios in a detailed way to evaluate the middleware. Since the collection of information for representing the behavior of people would be a time and resource consuming task, we intend to use public datasets of experiments made with this purpose to simulate the sensors states in our test scenarios.

V. Conclusion

This paper showed a novel idea for a middleware that analyzes the risk level of activities of some actor in a pervasive environment. In most studied researches, we could not observe the use a formal approach for activity recognition. So, this paper has two contributions: the use of the Activity Theory for modelling activities and the use of the SRK model for their classifications.

The context in which this idea was first conceived was to help people who need special care. However, we tried to design the middleware in a way that it could be used to more generic scenarios, including actors not only as people but as, e.g., objects or systems as well. Our aim was to provide the capability of verifying the risk level associated with an activity to applications with different domains. It could be applied even for non-human activities like a burning house or an opened door when everyone in the house is sleeping, etc.

Using the SRK cognitive architecture in our middleware to help analyze and infer the risk level of activities seems to be a promising technique, because it uses the aptitude of the actor to perform some activity based on his activity historical performance. The SRK model also allows the adjustment of the capability classification (skill/habit, rule or knowledge) of the actor to perform the same activity over time.

References

[1] M. Weiser, "The computer for the 21st century," vol. 265, no. 3. Nature Publishing Group, 1991, pp. 94–104.

[2] L. Atzori, A. Iera, and G. Morabito, "The internet of things: A survey," vol. 54, no. 15. Elsevier, 2010, pp. 2787–2805.

[3] C. C. Aggarwal, N. Ashish, and A. Sheth, "The internet of things: A survey from the data-centric perspective," in *Managing and Mining Sensor Data*. Springer, 2013, pp. 383–428.

[4] A. K. Dey, "Providing architectural support for building context-aware applications," Ph.D. dissertation, Georgia Institute of Technology, 2000.

[5] M. Baldauf, S. Dustdar, and F. Rosenberg, "A survey on context-aware systems," vol. 2, no. 4. Inderscience, 2007, pp. 263–277.

[6] B. Schilit, N. Adams, and R. Want, "Context-aware computing applications," in *Mobile Computing Systems and Applications, 1994. WMCSA 1994. First Workshop on*. IEEE, 1994, pp. 85–90.

[7] C. F. Crispim-Junior, F. Bremond, and V. Joumier, "A multi-sensor approach for activity recognition in older patients," in *The Second International Conference on Ambient Computing, Applications, Services and Technologies-AMBIENT*, 2012.

[8] C.-H. Lu and L.-C. Fu, "Robust location-aware activity recognition using wireless sensor network in an attentive home," vol. 6, no. 4. IEEE, 2009, pp. 598–609.

[9] J. Rasmussen, "Skills, rules, and knowledge; signals, signs, and symbols, and other distinctions in human performance models," no. 3. IEEE, 1983, pp. 257–266.

[10] K. Kuutti, “Activity theory as a potential framework for human-computer interaction research,” 1996, pp. 17–44.

[11] A. Kofod-Petersen and J. Cassens, “Using activity theory to model context awareness,” in *Modeling and Retrieval of Context*. Springer, 2006, pp. 1–17.

[12] M. Mikalsen and A. Kofod-Petersen, “Representing and reasoning about context in a mobile environment,” 2004, pp. 25–35.

[13] T. Gu, Z. Wu, X. Tao, H. K. Pung, and J. Lu, “epsicar: An emerging patterns based approach to sequential, interleaved and concurrent activity recognition,” in *Pervasive Computing and Communications, 2009. PerCom 2009. IEEE International Conference on*. IEEE, 2009, pp. 1–9.

[14] P. Srivastava and W.-C. Wong, “Hierarchical human activity recognition using gmm,” in *AMBIENT 2012, The Second International Conference on Ambient Computing, Applications, Services and Technologies*, 2012, pp. 32–37.

[15] E. Kim, S. Helal, and D. Cook, “Human activity recognition and pattern discovery,” vol. 9, no. 1. IEEE, 2010, pp. 48–53.

[16] U. Hunkeler, H. L. Truong, and A. Stanford-Clark, “Mqtt-sa publish/subscribe protocol for wireless sensor networks,” in *Communication Systems Software and Middleware and Workshops, 2008. COMSWARE 2008. 3rd International Conference on*. IEEE, 2008, pp. 791–798.

[17] J. Indulska, R. Robinson, A. Rakotonirainy, and K. Henricksen, “Experiences in using cc/pp in context-aware systems,” in *Mobile Data Management*. Springer, 2003, pp. 247–261.

[18] D. T. Neal, W. Wood, and J. M. Quinn, “Habits–a repeat performance,” vol. 15, no. 4. SAGE Publications, 2006, pp. 198–202.

 ISBN: 978-1-61208-289-9