Recognition of Human Activities using the User's Context and the Activity Theory for Risk Prediction

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Abstract: Some of the activities performed daily by people may harm them physically. The performance of such activities in an inadequate manner or in an adverse environment can increase the risk of accidents. The development of context-aware systems capable of predicting these risks is important for human damage prevention. In this sense, we are developing an approach based on the Activity Theory and the Skill, Rule and Knowledge model for risk prediction of human activities in a context-aware middleware. To predict the risk in the activities, we identify the probability for the next actions and compare the current physiological context with its future state. In order to concept proving the proposed model, we developed a prototype and tested it with a public and a private dataset. The results show that the proposed model can assign an appropriate risk factor to the tested activities.

1 INTRODUCTION

It is often the case when an activity of daily living (ADL) (Katz et al., 1963) results in an injure for the person performing it. The reasons vary among external factors, such as uneven floors and stairs, slippery floors and low illumination, and/or personal factors, such as a bad performance or an unusual physiological condition (e.g., high blood pressure). It is specially true for the elderly, where they usually have a weaker health due to problems such as sedentarism, insomnia, osteoporosis, etc. Combining them with the external factors, the risk of physical damage is increased.

This way, we notice the need for a system capable of predicting and acting over situations that present some risk of injure to the user. An approach for addressing this matter is by analysing the user's behavior over time in order to identify anomalies either in his physiological, performance and/or environment situation while an activity is being performed.

Considering that the context-aware system must take into account the user's behavior, we used an approach based on the Skill-Rule-Knowledge (SRK) (Rasmussen, 1983) framework for determining the performance level of the user in an activity and the Activity Theory (AT) (Kuutti, 1996) for modeling activities and its predictions. Both models act over contextual information classified according to the taxonomy of context (Kofod-Petersen and Cassens, 2006), allowing for a well-defined separation of the attributes involved in the risk analysis.

This paper is structured as follows: Section 2 presents the core concepts that are essential for our work; Section 3 shows related works regarding activity and action prediction, risk prediction and performance measurement; Section 4 depicts our risk analysis model and how the related components are implemented; Section 5 presents the model evaluation by using two scenarios: one for risk in actions and another for performance inference; finally, Section 6 draws our final considerations and some future work.

2 CORE CONCEPTS

2.1 Giving Meaning to Contextual Data

In order to detect human activities, it is necessary to first detect the context and the changes that occur in an ubiquitous environment. For this purpose, in this work, we are modeling the context information using the Hyperspace Analogue to Context (HAC) model

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(Rasch, 2013). The major advantages of using the HAC model are the well-defined syntax and the operations that allow dealing with context data. It uses multiple dimensions to characterize the contexts in smart environments. These dimensions can be either numeric or nominal with values that range between defined thresholds. This context model makes easier the understanding of the environment, since it can capture all the context changes to assist in the detection of activities and to understand the users' behavior. Thus, the historical context information of the user and the context information of the environment can be used to determine the risk of all actions that compose the activity that is being performed.

2.2 Activity Theory

To better comprehend what an activity is and its relation to the user and the environment we use Kuuti's approach to represent the relationship between the components of the Activity Theory (AT) (Kuutti, 1996). In the AT, an activity is composed by actions, which are atomic units meaning that they are complete by themselves. For instance, the activity of taking a shower can be decomposed into several actions, such as: taking the clothes off in the bathroom, entering the bathtub, turning on the water flow, etc. We chose the AT because it considers not only the actions composing the activity, but also the interactions with other elements. For instance, the artifact used to achieve the goal desired by the subject. For this work, those interactions are important in the sense that they collaborate to measure the subject's performance and his interactions with the environment.

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

The context taxonomy proposed has a pragmatic view of artifacts' construction and incorporates to the context-aware systems the general concepts found in the Activity Theory (Mikalsen and Kofod-Petersen, 2004), allowing for a well-defined separation of the user's context.

2.3 Cognitive Workload Framework

The behavioral model Skill, Rule and Knowledge (SRK) was created with the intention to represent the performance of human activities based on the cognitive workload required for the development of a particular activity (Rasmussen, 1983). This classification is defined in three levels representing the conscious control or planning used during the activity performance: (i) **skill based behavior (SBB)** the subject performs the activity in an *automatic* way, without extensive mental and cognitive workloads, e.g., taking the clothes off in the bathroom; (ii) **rule based behavior (RBB)** the subject performs a known activity in a familiar situation, but has the need to retrieve a stored rule learned previously, e.g., the sequence for taking a shower: taking the clothes off in the bathroom, entering the bathtub and then turning on the water flow; and (iii) **knowledge based behavior (KBB)** the subject needs to make an internal map of the environment to create a plan. The plan indicates the way the activity should be carried on.

2.4 Measuring Performance

According to Craven et al. (Craven et al., 2007), the cognitive workload spent can be estimated in a subjective way or from observable characteristics. The subjective ways of estimating the cognitive workload are: (i) by forms and/or reports that are usually filled by the user himself and (ii) the experts evaluation of the user's performance. This way, for this work, we consider this approach as invasive because the user has to report after he performed the activity. Therefore, it is inappropriate for a context-aware system based on the concepts of ubiquity.

Observable characteristics are used for the estimation by the user's performance related to the difficulty of the task and by neurophysiological responses measured by sensors. The techniques for the latter suppose that the cognitive workload is reflected by physiological variables, such as heart activity, brain activity and eye activity (Paas et al., 2003).

The cognitive workload estimated by the performance of the person can be subdivided in two subclasses: (i) primary-task measurement, where there is a direct measurement of a performance and (ii) secondary-task measurement by adding some secondary activity while the user is performing the primary activity (Craven et al., 2007) (Paas et al., 2003), that is, the level of success of the user in the secondary-task dictates how hard it is for him the primary activity (Craven et al., 2007)(ODonnell, 1986). For the primary-task measurement, we can assume that when the cognitive workload increase, the extra needed resources and processing capacity of the person will degrade the quality of his performance (ODonnell, 1986). This way, it is possible to use an approach that considers only one aspect relevant for an activity (e.g., number of errors, duration or speed of the performance) or an approach that considers many aspects for a more accurate estimation.

Since this work is based on concepts of ubiquitous computing, the secondary-task measurement technique is also not adequate, because the need for the user to perform a secondary-task for the estimation of the performance of the primary-task is intrusive. That is, the system would have to always add some secondary-task, this way the user would always remember its existence. Therefore, we can notice that the most adequate techniques for this work are the direct measure of the primary activity and the usage of physiological data.

3 RELATED WORKS

A system for classification of emergency situations for people that risk their lives in the line of duty, such as the firemen and the Civil Protection rescuers is presented in (Curone et al., 2010). The operators are equipped with two sensors in their protection clothes, an accelerometer and an ECG sensor. The system is composed by a classifier capable of recognizing many user states that correspond to many ADLs in real time. Tests were conducted in laboratory and the presented system had about 88.8% of accuracy in the activities classification.

In the work (Wang et al., 2014), an activity is defined as the combination of the trajectory and duration and an abnormal activity is defined as the activity that deviates significantly from the trajectories and durations of the normal activities. In order to determine the normal behavior of the user, the authors performed a frequent pattern mining to find the patterns of normal activities considering their duration and trajectory. This way, if the frequency of an item set (in this case, it is considered as an activity) exceeds the minimum threshold defined, it is classified as a normal activity. In an environment simulated by software, the accuracy was 96.2% (Wang et al., 2014).

A proposal for the prediction of household activities in a smart home is presented in (Gil-Quijano and Sabouret, 2010). The goal of the authors is to adapt the behavior of the house applications from the predicted human activities, in order to correct the behavior of devices and prepare the rooms to receive people in a pleasant condition to them. The proposal for the activities prediction is based on the construction of a directed graph for each occupant from the statistical analysis of the activities performed by him. This way, since each task is performed in a given environment, it is possible to predict the next displacement in the graph from the current task, characterizing the prediction of activities.

4 RISK ANALYSIS MODEL

The proposed model in this paper represents the layer *Activity Manager* of a developed middleware presented in previous works (Neto et al., 2013)(Neto et al., 2014), and has as goal the realization of different tasks, which are: (i) the detection of actions and activities; (ii) the assignment of a risk situation for each action; (iii) and the inference of future actions and activities, so it is possible to predict risk situations. The structure of our model is presented in Figure 1 and it works in the following way: after receiving the aggregated sensor data, the first step is to recognize the action being performed and infer the next action to be performed from this action and based on the history of actions and activities executed by the user.

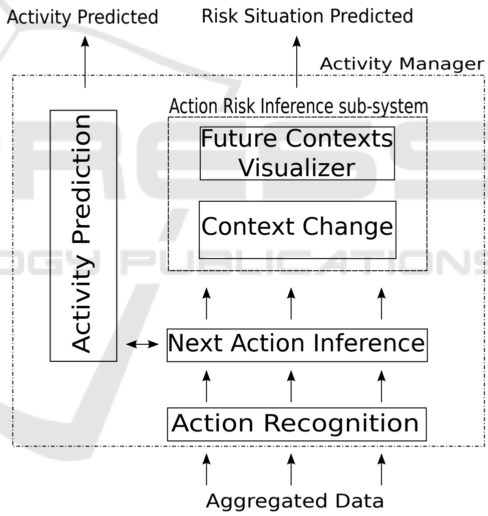

Figure 1: Proposed model for the Activity Manager layer.

With the next action to be detected, two distinct process are initiated in parallel order: (i) the activity prediction and (ii) the action risk inference.

For the activity prediction (i), the Activity Prediction component receives the probable next action and assumes it indeed happened, and requests to the Next Action Inference component a new future action, using as the current action the one that was previously detected. The Activity Prediction Component repeats this process until a sequence of actions that represents an activity is recognized.

In order to clarify this process, one can imagine that the Action Recognition component recognized the current action a_1, and the Next Action Inference component detects that the probable next action to be performed by the user is the action a_2. The Activity Prediction component requests to the Next Action Inference component the probable next action using as the base current action the action a_2. The process used to make this inference is explained in section 4.3; (ii) besides that, the Action Risk Inference sub-system associates a risk situation to each inferred action based on the context changes and on the future contexts yielded by these changes. Each of these components are explained in the next subsections.

4.1 Activity Recognition

Our model assumes that the activities are composed of actions and that the relationship between these actions determine how an activity happens. This way, if a certain set of actions is performed in a established time window, it is said that an activity has happened. In order to model the registered activities in the system, we used an approach similar to the one in reference (Naeem et al., 2007), which permits to define if actions are or not mandatory and if they must be performed in a defined order.

With this, two types of actions are defined: (i) core actions and (ii) secondary actions. The former represents the actions that are essential in order to achieve the goal of the activity, and, therefore, necessary for its recognition. The latter are actions that are related to some activity, but are not essential for its recognition, they are useful for adding meaning to the activity. For an activity to be recognized, each action that composes it must be performed in a pre-defined time window. This way, an initial time window is determined and in the preliminary phase it is adjusted for the system's calibration. Since this window depends on the frequency of each activity, it varies according to the user's behavior.

4.2 Action Recognition

The component Action Recognition receives the aggregated data from each type of sensor and, based on classification algorithms, compares the received data with the already classified data for each action registered in the system. In short, the set of sensor data will be classified according to the similarity that it has with the registered data for each action. The authors used the software WEKA in order to apply these algorithms over the raw data, with default patterns associated with each of the classifiers and applied to the data after the feature extraction process. The algorithm that was able to classify the highest number of samples correctly was the *K-star* and was the choosed algorithm for our model.

4.3 Next Action Inference

The inference of the next action to be performed by the user is based on the historical data of his already performed actions in order to reflect his usual behavior. For such, the algorithm 1 is based on the search for patterns of activities in the history H of the user, that is, the search for certain sequences of activities with the objective of discovering which action is the next one to probably be executed after these patterns.

Require: Max Pattern Length MPL
Require: History of performed actions H
$N_a^p \leftarrow initZero()$
$A \leftarrow H.getLastActions(MPL);$
$P \leftarrow getPatterns(A);$
for all $a \in A$ **do**
    for all $p \in P$ **do**
        $N_a^p \leftarrow getNumOccurrences(H, a, p);$
    end for
end for
$ap \leftarrow max(N)$
return ap

Algorithm 1: Algorithm for the action prediction.

This way, the algorithm 1 searches the list A of the last MPL performed actions, where MPL is the window size or the quantity of actions to be analyzed. Afterwards, a search is made for the list of patterns p in the user's history for each of the actions in A previously found. Thus, the number of occurrences for each of the actions a is updated for each pattern p found and related to at most MPL periods with each action a. The highest occurrence found is the probable future action.

4.4 Action Risk Inference

The determination of risk situations in actions and activities proposed assumes that each user has his own behavior pattern, since people are considered beings of habits (da Rocha et al., 2010). In order to determine the risk, the changes that each activity causes in the context has to be analyzed. It is worth mentioning that this analysis has to occur before an action is executed by the user. That is, it is necessary to predict the actions and, consequently, activities (composed of actions) that could be performed and this way identify if the user will be in a risk situation when he performs a certain action or activity. This approach implies in the need of (i) capturing the current user context, (ii) inferring which is the next action to be executed, (iii)

applying the context changes resulting from this action in the current context and (iv) evaluating the resulting context while looking for risk situations.

In order to achieve this goal, we proposed a solution to predict actions with a (i) component to discover the context changes and a (ii) component to simulate future contexts resulting from these changes (Action Risk Inference sub-system, Figure 1). From the predicted action, the Context Change component searches in the user's historical data which context changes were previously caused by it. Therefore, the Future Contexts Visualizer applies the context changes found in the current user context in order to generate a new context that represents the future state of the current context if the predicted action is performed. Based on this future context, the Future Contexts Visualizer looks in the user profile to see if it is not outside the safety thresholds preset for the user. If it is not, the user is considered to be in a risk situation.

4.5 Performance Inference and Prediction

The proposed model presented in Figure 2 is used for the inference and prediction of the user's performance. In order to accomplish it, the proposed model uses the *task context* and the *environmental context* to determine the user's performance considering his historical events. The user's current activity is composed by actions, as seen in Section 2.2, which are used by the *Performance Properties Estimation* component to estimate the values for the performance properties involved while the activity is still being performed. This analysis in real time is important because it allows the system (or application) to give to the user relevant information about the current activity that may aid him during his performance. Application domains can cover emergency situations, recommendation systems, decision support systems, among other domains that rely on user's performance and behavior.

In our model the influence of actions is represented by changes in the values of the performance properties. This way, the *Performance Properties Estimation* component uses this approach in order to estimate in real time the changes that each new action cause in the current activity. For the estimation of the current activity's performance, it is necessary to consider actions that were not yet performed and predict the changes they will possibly make in the activity. These actions are *inferred* by the component *Activity Manager* of the middleware, presented in previous works (Neto et al., 2013)(Neto et al., 2014), and used together with the already *elapsed* actions (i.e. already detected by the system) to give a better estimation.

Then, the estimated values for the performance properties are related to the environmental context considering the past events when the current activity was performed. This relationship is used for measuring how each property indicates how the user is *sensoring* the environment. The sensoring is analogous to the SRK's signals, signs and symbols, which represent how well known is the surroundings of the user while performing a specific activity. So, sensorings resulting, for example, in symbols are related to unfamiliar situations for the user, which means that the estimated values for the performance properties or the values from the environmental context are not in the patterns found in the past events of the activity (i.e., they are outliers).

However, for the cognitive workload inference, it is important for each performance property to have its value adjusted according to their relevance. The relevance level of the properties is taken into account due to the fact that they may or may not be relevant depending on the user and the activity being performed. For example, a performance property like *anxiety* may not be important for the activity *brushing teeth*. This can be noted by the fact that the user's performance is not dependent on the performance property.

The relevance for each property is measured according to the strength of the correlation of their values with their past sensorial inferences, the Pearson's correlation between the performance property *duration* and the sensorial inference, measured using the *Local Outlier Probabilities* (LoOP) technique (Kriegel et al., 2009). The strength of such correlation shows how important the performance property is for the sensoring inference, this way we can use it as the relevance level of the property.

LoOP is an outlier detection method that provides an outlier score in the range of $[0,1]$ that is directly interpretable as a probability of a data object for being an outlier. We use a detection outlier technique based on outlier factor due to the fact that it enables us to gather evidence of how is the user's behavior. By using a technique that tells us the probability that some data object is an outlier, we can obtain a probability of how inadequate is the user's behavior. In fact, it is possible to make an analogy with the SRK model, where LoOP values close to 0 indicate SBBs and values close to 1 indicate KBBs, whereas values in between indicate RBBs.

5 MODEL EVALUATION

The detection of risk situations proposed in this work is based on the prediction of actions performed by an

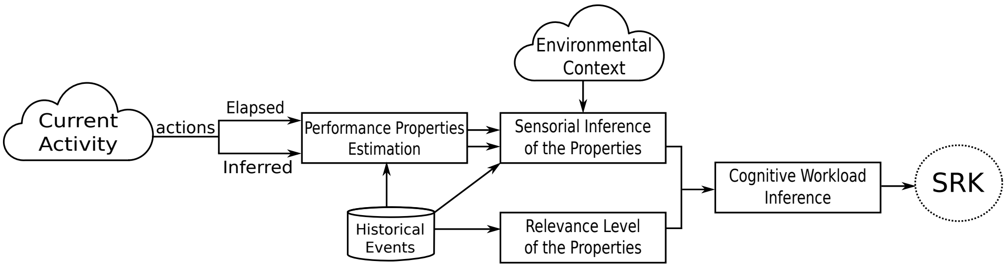

Figure 2: Model for performance inference.

user's previous behavior, as well as in context changes yielded by such action. In this sense, it is necessary the system to be (i) able to correctly predict the probable next actions to be executed, as well as (ii) estimate if the context changes yielded by an action will imply in a risky context for the user. In order to validate the proposal of this work, we conducted two distinct experiments. The first one intends to analyze the accuracy of the presented prediction model, while the second one intends to validate the model for the detection of risk situations based on the context changes yielded by actions in the user's context.

5.1 Evaluation of Actions Prediction

In order to evaluate the proposed model in this work, we opted for the usage of public dataset, called Aruba Dataset (Cook, 2011), because it allows the results of the model of actions predictions to be compared to other correlated proposals, since it is a widely used dataset in researches of activity recognition in the ubiquitous computing area. The dataset has 11 different activities registered using 42 sensors. Thus, in this work, the obtained accuracy from the used dataset was 78.69%.

5.2 Evaluation of the Risk Situation in Actions

The evaluation of risk in actions was made in a dataset of our own, since we did not find public datasets with relevant information, that is, with annotated actions and some user's physiological data. In this sense, the dataset is composed by the actions walking, sitting, running, lying and standing, which where captured from accelerometer and gyroscope data coupled in a smartphone. The physiological data gathered was the heart rate obtained from a sensor connected to an Arduino.

This way, from the 2455 entries, the model detected 49 risk situations and had an accuracy of 98.94%. This accuracy was measured based on the values true-positives (36), true-negatives (2393), false-positives (13) and false-negatives (13). These values were obtained from the analysis of the comparison between the values for the current heart rate, the predicted thresholds for the current action and the real thresholds for the current action. The predicted thresholds are determined based on the preceding action, such that it is used the median of the context changes performed by it and the value of the heart rate while it was being developed.

5.3 Performance Evaluation

The experiments were also performed on Aruba's dataset. For our experiment, the *duration* of the activities was considered as the performance property and the *temperature* as the environmental property.

We performed our tests for all the activities. However, here we present the results only for the activity *Housekeeping* due to issues regarding space in this paper. In Table 1 is shown the values used for the cognitive workload (C. W.) inference and if the result is considered a SBB, RBB or KBB. In order to choose between them, we defined manually thresholds for the C.W. (based on the SRK analogy with the LoOP, presented in Subsection 4.5): $0-0.24$ as SBB, $0.25-0.74$ as RBB and $0.75-1.0$ as KBB. We understand that this values are arbitrary and that they must be adjusted by some learning algorithm, however this is not the current focus of our work.

Table 1: Example of obtained values for some entries for the activity *Housekeeping*.

LoOP	r^2	**C. W.**	**SRK**
0.00	0.41	0.0	SBB
0.67	0.41	0.27	RBB
0.10	0.40	0.04	SBB
0.06	0.41	0.03	SBB
0.00	0.41	0.0	SBB

As can be observed in Table 1, one of the values was inferred as RBB, which indicates an unusual behavior for the performance. In this case, the duration is unusual for the activity *Housekeeping* . It

Table 2: Comparison of the related works with our approach.

Work	Accuracy	Dataset	Category		Algorithm	Attributes
			Act. Pred.	Risk Det.		
(Curone et al., 2010)	88.8%	Own (in lab)		X	Rule Based	Accelerometer, ECG
(Wang et al., 2014)	96.2%	Own (by software)		X	Distributed	Trajectory, Duration
[Gil-Quijano, 2010]	61.28%	Aruba	X		Directed Graph	Action Sequence
Our Work	78.69% (act. pred.) 98.94% (risk det.)	Aruba (act. pred.) Own (risk det.)	X	X	Patterns (act. pred.) Thresholds (risk det.)	Action Sequence, Physiological Context

is interesting to notice that the value for the C. W. inferred was 0.27, which is almost a SBB behavior, even though the LoOP is much higher (0.67). This happens because the performance property *duration* has a relevance of only 0.41, which shows us that it is not a very relevant performance property.

Therefore, with our model for performance inference using the LoOP technique we can associate the user's behavior with the theoretical SRK framework for the understanding of the user's behavior. Also, by using the LoOP technique and detecting automatically the relevance for the performance properties, our model adjusts itself according to the behavior of each different user.

5.4 Comparison

In order to compare our proposal with the related works presented in subsection 3, we considered some aspects, such as: accuracy of the approach, dataset used, category (for risk detection or action prediction), algorithm used and attributes used for the risk detection. Table 2 summarizes this comparison.

In reference (Curone et al., 2010) the detection of risk situations is made by the usage of a predetermined set of combinations between known activities, similar to a rule system. For this system to be able to identify new kind of risk situations, it is necessary the addition of new possible combinations between activities. In our approach, we consider the variation in the user's physiological data while he is performing some activity, which allows the definition of adjustable thresholds (for the risk situation detection) based on the user's history. That is, the system is able to adapt itself to changes in the user's execution of his activities, making the system more flexible.

The work (Wang et al., 2014) uses an approach similar to ours, which considers deviations in the user's normal behavior as a risk situation. However, in such work, the authors only consider the trajectory and the duration of the activity's execution. This way, they do not account for the physiological aspects of the users that are performing activities, thus, risk situations related to changes in such physiological aspects are not detected.

The approach based on the usage of a directed graph for action prediction that considers as parameter for the measurement of the probability the ratio between the number of times that a sequence (two actions) was performed by the person and the number of times that he performed the initial action in the same edge (Gil-Quijano and Sabouret, 2010), was worse than our approach because it only considers the last action performed for the inference of the next action. In this sense, we obtained better results by using an approach that allows the discovery of an appropriate pattern length for each case (based on the user's historical data), which can be used to consider not only the last action, but also a higher number of previously performed actions.

This way, considering the algorithm 1, the best value for the MPL is 2 with an accuracy of 78.69%, higher than the result obtained from the directed graph algorithm proposed in (Gil-Quijano and Sabouret, 2010), which was 61.28% for the same dataset. This represents a gain of 28.41% in the future actions inference.

6 FINAL CONSIDERATIONS

The prediction of risk situations is important in order to allow context-aware system to act in a preventive manner, aided in the user's decision making. Thus, this work presented a model for the action prediction and detection of future risk situations based on the Activity Theory and on the Hyperspace Analogue to Context. The used techniques were superior to other related works, since in the actions prediction we obtained an accuracy of 78.69% and in the evaluation of risk situations we obtained a accuracy of 98.94%.

In some cases the physiological state may not be abnormal, however the user can be in a risk situation due to the fact that his performance might be influenced by some external factor (e.g., if the user is in a strange environmental condition) or some internal factor (i.e., his mental context). Since the SRK framework considers both factors, it was used in our model for the cognitive workload inference and performance estimation. In order to evaluate the model we used a public dataset and verified that the approach used is capable of classifying activities according to the SRK model, which is useful for the risk analysis.

In future works, we intend to create an adaptive algorithm that learns with the user's behavior and adjust the values for the thresholds used for the classification of a behavior as skill, rule or knowledge. We also intend to improve the approach for actions prediction, considering the evaluation of the performance of the algorithms. Besides that, we intend to perform tests in public datasets with a higher number of user's physiological information in order to allow a more complete evaluation of the calculated risks.

REFERENCES

Cook, D. (2011). Learning setting-generalized activity models for smart spaces. *IEEE Intelligent Systems*.

Craven, P. L., Belov, N., Tremoulet, P., Thomas, M., Berka, C., Levendowski, D., and Davis, G. (2007). Cognitive workload gauge development: comparison of real-time classification methods. *Foundations of Augmented Cognition*, pages 75–84.

Curone, D., Tognetti, A., Secco, E. L., Anania, G., Carbonaro, N., De Rossi, D., and Magenes, G. (2010). Heart rate and accelerometer data fusion for activity assessment of rescuers during emergency interventions. *Information Technology in Biomedicine, IEEE Transactions on*, 14(3):702–710.

da Rocha, C. C., Lima, J. C. D., Viera, M., Capretz, M. A., Bauer, M. A., Augustin, I., and Dantas, M. A. (2010). A context-aware authentication approach based on behavioral definitions. In *IKE*, pages 178–184.

Gil-Quijano, J. and Sabouret, N. (2010). Prediction of humans' activity for learning the behaviors of electrical appliances in an intelligent ambient environment. In *Web Intelligence and Intelligent Agent Technology (WI-IAT), 2010 IEEE/WIC/ACM International Conference on*, volume 2, pages 283–286. IEEE.

Katz, S., Ford, A. B., Moskowitz, R. W., Jackson, B. A., and Jaffe, M. W. (1963). Studies of illness in the aged: the index of adl: a standardized measure of biological and psychosocial function. *Jama*, 185(12):914–919.

Kofod-Petersen, A. and Cassens, J. (2006). Using activity theory to model context awareness. In *Modeling and Retrieval of Context*, pages 1–17. Springer.

Kriegel, H.-P., Kröger, P., Schubert, E., and Zimek, A. (2009). Loop: local outlier probabilities. pages 1649–1652.

Kuutti, K. (1996). Activity theory as a potential framework for human-computer interaction research. pages 17–44.

Mikalsen, M. and Kofod-Petersen, A. (2004). Representing and reasoning about context in a mobile environment. pages 25–35.

Naeem, U., Bigham, J., and Wang, J. (2007). Recognising activities of daily life using hierarchical plans. In *Smart Sensing and Context*, pages 175–189. Springer.

Neto, A. D. F., Boufleuer, R., Romero de Azevedo, B., Augustin, I., Carlos D. Lima, J., and C. Rocha, C. (2013). Towards a middleware to infer the risk level of an activity in context-aware environments using the srk model. In *UBICOMM 2013, The Seventh International Conference on Mobile Ubiquitous Computing, Systems, Services and Technologies*, pages 38–42.

Neto, A. D. F., de Azevedo, B. R., Boufleuer, R., Lima, J. C. D., Augustin, I., and Pasin, M. (2014). An approach based on activity theory and the srk model for risk and performance evaluation of human activities in a context-aware middleware. In *Proceedings of the 13th International Conference on Mobile and Ubiquitous Multimedia*, pages 40–47. ACM.

ODonnell, R.D. & Eggemeier, F. (1986). Workload assessment methodology. In Boff, K., Kaufman, L., and Thomas, J., editors, *Handbook of perception and human performance.*, volume 2, pages 42/1–42/49. John Wiley & Sons.

Paas, F., Tuovinen, J. E., Tabbers, H., and Van Gerven, P. W. (2003). Cognitive load measurement as a means to advance cognitive load theory. *Educational psychologist*, 38(1):63–71.

Rasch, K. (2013). Smart assistants for smart homes.

Rasmussen, J. (1983). Skills, rules, and knowledge; signals, signs, and symbols, and other distinctions in human performance models. Number 3, pages 257–266. IEEE.

Wang, C., Zheng, Q., Peng, Y., De, D., and Song, W.-Z. (2014). Distributed abnormal activity detection in smart environments. *International Journal of Distributed Sensor Networks*, 2014.