Integrating Knowledge Artifacts and Inertial Measurement Unit Sensors for Decision Support

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Abstract: Modern wearable devices provide new opportunities for the development of knowledge artifacts and decision support systems. In this paper we present a recent development of KAFKA, a knowledge engineering methodology based on knowledge artifact notion, that make it able to manage real-time data detected and analyzed by means of Inertial Measurement Units sensors, mounted on Android wearables. This improvement makes KAFKA suitable to deal with many domains where real-time data are necessary, in particular the health-care and rehabilitation ones.

1 INTRODUCTION

Today, Wearable devices and Smartphones offer a great variety of sensors on board: ambient and body-temperature sensors, heart beat rate sensors, light presence sensors, barometric pressure sensors, and also Inertial Measurement Units (IMUs) sensors. IMUs have shown to be of particular importance in the field of situations assessment to determine body movements and type of executed actions (Bao, 2003; Avci et al., 2010). However, a lot must be still done in real case scenarios when the context may require either real-time abilities of analysis, and algorithms at the state of the art, or a neat and akin knowledge of the problems specific to the application domain. In this case the definition of information quality is a parameter not independent from the contingency of the situations: the quality of the data, the desired parameters, the "degree of freedom" given by actually used technology, and the specificities of the application domain, are all components that influence the final result. In this paper, we propose the integration of IMUs and Knowledge Artifacts for the development of time-evolving expert systems (Sartori and Melen, 2015), in order to analyze the data stream collected by wearables and transform it in valuable suggestions for the user. The result is a unique conceptual and computational framework that can be exploited in many domains. In particular, we are interested in developing recommendation systems for the promotion of physical activity in people risking cardiovascular diseases. In this context, the hybrid approach proposed in this paper should allow to monitor the accomplishment of a given activity, evaluating the quality of it and proposing a personalized training program for the future. The rest of the paper is organized as follows: section 2 briefly review literature about knowledge artifacts and IMUs, according to paper scopes. Sections 3 and 4 introduce the motivation of the presented work, that is improving the performance of the KAFKA KA-User component. Section 5 and 6 explain how this point has been from both the conceptual and computational point of view. Section 7 presents the typical application scenario of the improved KAFKA framework. Finally, conclusions and future works are briefly pointed out in section 8.

2 RELATED WORK

Holsapple and Joshi (2001) described knowledge artifacts as objects that convey or hold usable representations of knowledge. Accordingly, Salazar-Torres et al. (2008) argued that KAs are artifacts which represent executable encodings of knowledge, which can be suitably embodied as computer programs. Cabitza and Locoro (2014) grouped KA experiences into five conceptual clusters, where different KAs are used with different scopes, on the basis of objectivity and situativity dimensions: Artificial Intelligence (AI-KAs from now on), Knowledge Management, Computer Supported Cooperative Learning, Information

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Systems and Computer Supported Cooperative Work. Here, we are mainly interested in AI-KAs, devoted to design and implement decision support systems, expert systems and ontologies. In that classification, AI-KAs where lacking from the situativity point of view, meaning that they are less able to adapt to the context and situation at hand. This means that they cannot be applied in domains characterized by huge amounts of real-time data, where other kinds of KAs have been successfully applied in the past, like Health-Care (Cabitza et al., 2015). In the following, we propose the integration of IMUs and AI-KAs to overcome this limitation. IMUs can be used either i) to determine biomechanical parameters of the body movements or ii) to detect information about movements, with the aim to devise the state of the person. Using new recent approaches IMUs can also be used iii) to understand more complex aspects of the body movements, like the motion grammar (Pinardi and Bisiani, 2010; Mileo et al., 2009). In general, type and quality of movements are recognized by means of classification and pattern recognition methods, like Clustering, Bayesian rules, Hidden Markov Models (Bao, 2003; Avci et al., 2010), and even using reasoning rules (Bisiani et al., 2013; Mileo et al., 2010). In the following, we focus on the first and second aspects of body movement recognition, to detect the pre-determinants useful to understand the situation. In particular, we will describe an n-tier application which acquires biomechanical parameters, transforms them and graphically represent them at run-time. These data are then analyzed and, finally, stored for future use by AI-KAs, to develop decision support systems in the Health-Care application domain, where the suggestions are tailored on the user behavior.

3 MOTIVATION

Figure 1 shows the architecture of KAFKA, namely Knowledge Acquisition Framework based on Knowledge Artifacts. It is developed according to the client-server paradigm, where the client, i.e. the KA-User, is responsible for detecting data and observations about the environment and the server, i.e. the KA-Developer is responsible for the interpretation of these data on the basis of a three-tier knowledge representation model (Sartori and Melen, 2015). Till now, greater efforts have been spent on the design of KA-Developer, being able to automatically create a rule-based system from scratch in case of significant changes in the knowledge domain (Melen et al., 2015). These changes are mainly due to new observations made by the KA-User: in the current implementation of KAFKA, these changes are manually detected by the user on the field and sent to the KA-Developer through a JSON interface. In this paper we present a rethinking of the client side of KAFKA, where the data observations come from wearables. Doing so, the KA-User is provided with "intelligence" too, different from the past. Possible values of system inputs are the result of wearable sensors querying: the data are then interpreted and stored to be exploited by the KA-Developer in the decision making process. In this way, KAFKA is able to manage new kinds of data, related to the real-time status of the person equipped with wearable devices. These data can then be transformed into useful inputs for recommendation systems, depending on the application domain.

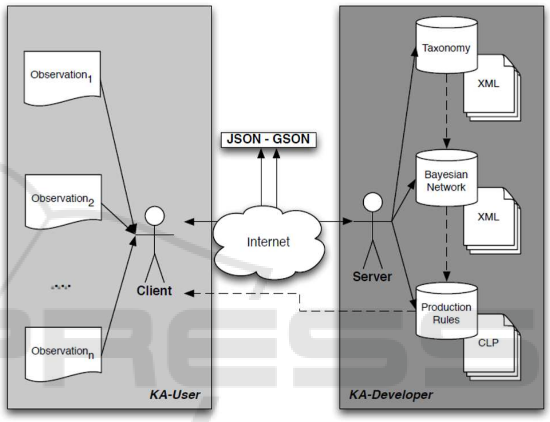

Figure 1: The multi–layered model of Knowledge Artifact in KAFKA.

4 KA-User IMPROVEMENT: THE IMU ROLE

As briefly introduced above, the aim of this paper is exploiting wearable devices to collect data about a given application domain, increasing significantly the role of KA-User in the development of recommendation systems through KAFKA. The challenge is demonstrating how a KA-User provided with simple and relatively low-cost technology can become a crucial source of information in potentially complex decision making processes. To this aim, it is important to point out that the human body is not merely a virtual mass-point in a physical model, it is a complex articulated-body with joints and body segments, with related masses and degrees of freedom. Via the IMUs sensors, it is possible to determine: i) the angular movements of a joint of the body and its geometrical trajectories, having some a-priori determinants, i.e. knowing which portion of the body the sensor is applied to and which exact position it is placed on; ii) the dynamics of the related motion, i.e. the accelerations and angular velocities to which the segment is subjected. These data are measured at run-time, and all information can be stored with their timestamps, for successive analysis and tests. In particular, we are interested in four aspects of human body motion: i) angles and accelerations of the joints, ii) movements and accelerations of the CoM (Center of Mass) of the human body, iii) orientation of the spine cord with respect to the vertical position, iv) direction (heading) of the person, while in motion or not. Semantically speaking, the motion of the human body is made of concurrent events (see Figure 2). For example, a person can stay still, turning of 90 degrees on the left, if he/she is sitting on a swivel chair; or he/she can move and rotate of 90 degrees on the left, if he/she rounds the corner walking down a corridor. In this case, moving and rounding are considered concurrent aspects of an action. The system should be able to detect all the concurrent aspects of the body movement to further combine them into a more complex event. An action is then composed by a time series of elementary concurrent movement-information and facts.

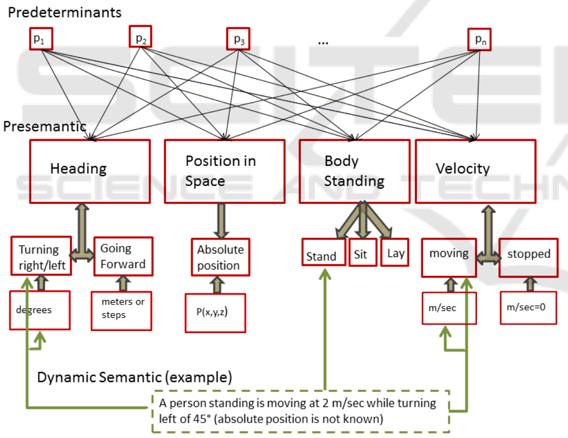

Figure 2: Determination of the personal state: movement section.

5 HOW DOES IT WORK?

To devise the motion determinants, IMUs use two reference systems: one inertial with respect to Earth, usually called *frame G*, and a second reference system co-moving with the sensor, called frame S. In general, given a reference system S_i where i indicates the *i-th sensor*, it is possible to identify: the angular velocities around the three axes of S_i; the rotation angles Φ, χ, anmd Ψ, namely *Yaw*, *Pitch* and *Roll*, which indicate, instant by instant, the rotation of the system S_i with respect to G, and the instantaneous accelerations of S_i on the three axes. These raw data can be then used to precisely determine the motion of the human body, deriving the motion parameters of its CoM and segments. Note that the purpose is not to determine the exact positions of the body segments, which would require to place a sensor on every body segment (fingers included), but to devise the general state of the person. In particular, we want to determine the activities and actions carried out in a specific context (drinking, running, climbing the stairs, sitting, etc.).

To this aim, the KA-User is designed according to a semantically driven rather than geometrically driven approach: understanding the action semantics is an important aspect in many application domain, especially in the medical one, in which the ADLs (Activities of Daily Living) are considered an affordable measure of the capacity of the person to be independent.

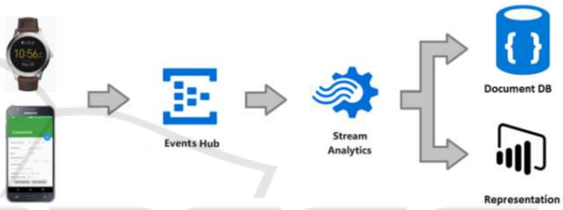

Figure 3: The data flow architecture.

6 KA-User COMPUTATIONAL MODEL

Today it is possible to seamlessly use any kind of sensor available on the market mounted in mobile phones and wrist bands or smart-watches. Market's low costs IMUs are valid instruments of measure, with their inherent precision and accuracy. Figure 3 shows the data flow of the KA-User.

The three key components of the architecture are: 1) a set of sensors (each equipped with three-axial accelerometers, gyroscopes and magnetometers, i.e. a three-axial IMU) to capture body data movements, and 2) an Android Smartphone to channel the data and eventually transport them via Wi-Fi to a Server; 3) a Server that i) stores the data for future analysis, ii) shows the data for an intuitive visual analysis, and iii) carries out body information at runtime (or during the offline analysis). The purpose is the determination of movement semantic artifacts, useful for situation assessment.

Note that the data and the derived information of the sensors can be sent to a concentrator or any other net-component in two possible ways: using a WSN (Wireless Sensor Network) and, for exam-

Figure 4: Server Side View, On top the tabs of the graphs view, At the center the data (e.g. magnetometer) of both the phone and smartwatch IMUs, of the given view; bottom-down the state of the person at the current time.

ple, a ZigBee protocol, or using a socket connection (TCP/IP) over Wi-Fi. Our application was originally written as a full component of a grid of communication of a WSN, but the increasing preference of Wi-Fi/Bluetooth protocol by wearable devices, made mandatory to use a Wi-Fi/Bluetooth channel for the communication between components. In the current KA-User implementation, data are acquired by using two IMUs respectively present in two commercially available devices: an Android Smartphone with a three axial IMU, which is usually placed on a belt, i.e. in the proximity of the CoM of the body; and a LG W110 G Watch R SmartWatch, worn by the user on his/her left wrist (but a Microsoft Band or an Apple S watch will be perfectly usable, too). The code of the Android smartphone is written in Java and developed using Android Studio; the code of the smart-watch is an Android Wear component and contains also a Bluetooth Energy component for the bands. A component for Microsoft Bend was also developed in *C#*. The server used for the runtime visualization of the resulting data and for the data analysis, the most valuable component, was developed in *C#* using Visual Studio 2015. Communication between the Android Smartphone and the Server use a TCP/IP socket over a Wi-Fi channel.

7 AN APPLICATION SCENARIO

A typical example of acquisition is described in the following: given a person wearing a smartphone on the belt and the smart-watch on the left wrist, the purpose is to detect in real time, instant by instant, the position of the body (standing, sitting, laying), the direction (heading) of the person, and the quantity of movement (the person is still or moving); we want also to know the path followed by the person from a specific point, for a few minutes, without having other sources of information (see Figure 4). Furthermore, we want to know the Hearth Beat Rate of the person, instant by instant, while the actions are performed. These data are considered pre-determinants for a more complex description of the person status.

Figure 5 shows the output provided by the KA-User in response to the first question. Inclination of g vector with respect to the spinal cord is used to determine if the person is standing, sitting or laying. The direction, or heading, is determined using Euler angles, typically the Yaw data, while the quantity of movement is calculated as a proportion of standard deviation of the magnitude of the accelerometer. Note that direction and position of the body requires the a priori knowledge of the position of the sensor with re-

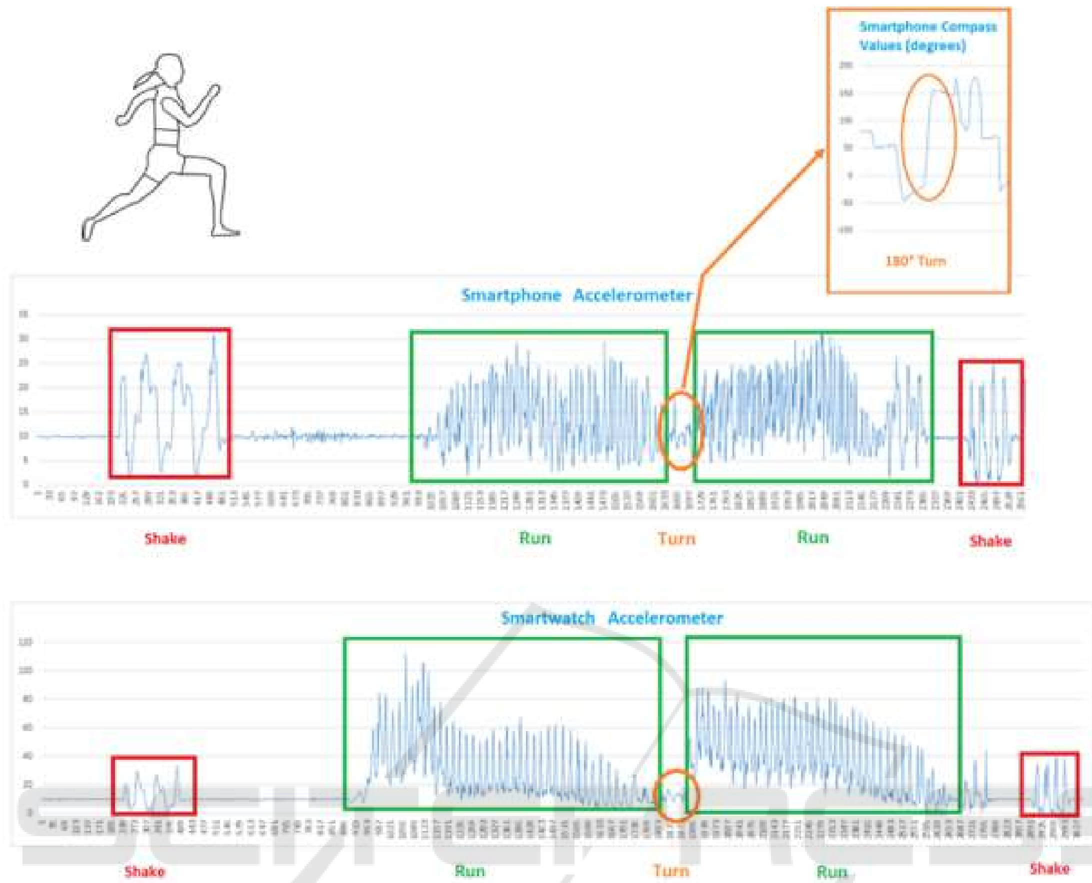

Figure 5: A KA-User Server Side Data-Example: movements quality and quantity.

spect to the body (i.e. with respect to the G reference system), while the magnitude is independent by rotations, being a scalar quantity.

To reconstruct the movements of the person in the space we use a dead reckoning approach: it is important to remember that dead reckoning approaches, without any further correction, are subject to errors, so the reconstructed position tends to separate and to diverge with respect to the actual position. Hence, any useful reckoning method requires an external source of information of position to reconcile the prediction to the actual position. A Bayesian filter, or an Extended Kalman Filter is normally used to maintain consistent the prediction to the real position.

Figure 6 shows the output provided by the KA-User in response to the second question. Heart Beat Reat (HBR) simply requires to read the relative data from the smartwatch that constantly monitor the HBR of the wrist. This piece of information flows from the smartwatch to the smartphone, and then goes to the server where is coupled with the motion information.

Figure 7 show a sketch the final KA-User architecture on the basis of new improvements. The most interesting feature is its transformation into client-server module: the client is made up of hardware and software components to collect and analyze data, the server is made of software components to make correct interpretation of them according to the application domain. The client receives real-time data from sensors placed on wearable devices. The IMU module is then responsible for the extraction of useful information from them: this information is then sent to the server for next interpretation. Given that the most interesting feature of the current KA-User implementation is its capability to automatically query wearable devices, it has been provided with a graphical user interface for manual input by user. This feature allows recording data like personal user information (e.g. name, surname and so on), security data (like user-name and password for server connection) and so on. The data interpreted by the IMU module are then stored by the server into a proper MySql database, for future use by KAFKA. For example, a KA-Developer can exploit them to build up knowledge artifacts for recommendation systems development, as shown in Melen et al. (2015).

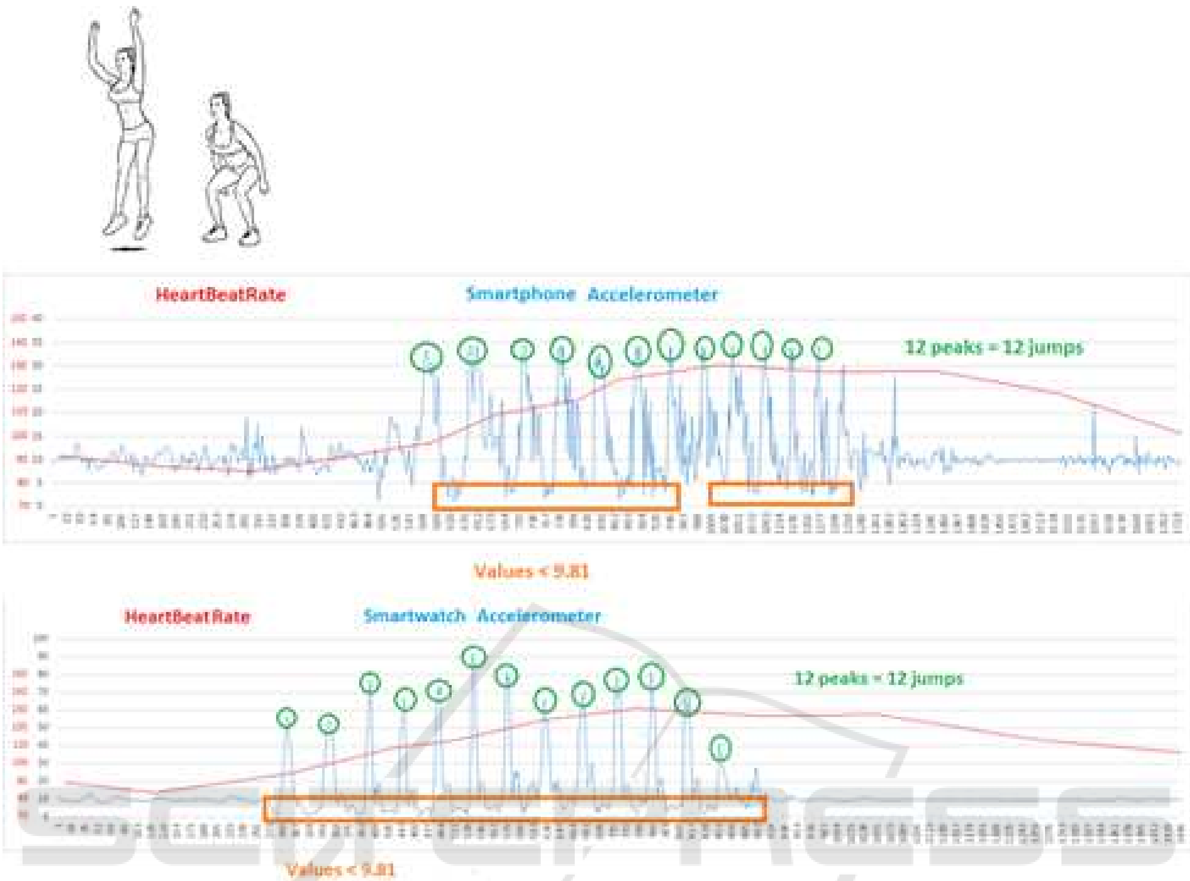

Figure 6: A KA-User Server Side Data-Example: Heart Beat Rate detection.

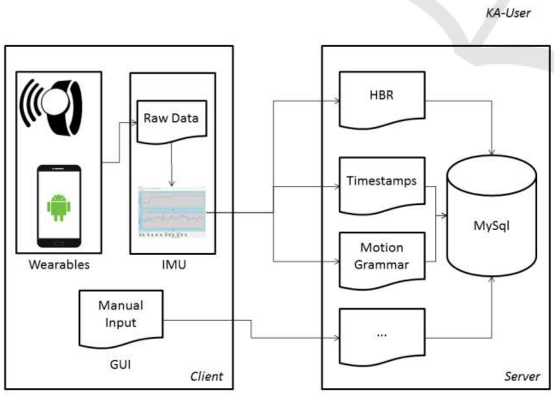

Figure 7: The final KA-User architecture.

8 CONCLUSIONS AND FUTURE WORKS

This paper has presented an improvement of the KA-User role in the KAFKA framework, aiming at wearable device exploitation to detect and analyse new observations on the field. These observations can be profitably used in many domains: in particular, we are collaborating with psychologists of the University of Milano-Bicocca in the design and development of mobile apps for the promotion of physical activity in people potentially affected by cardiovascular diseases (Baretta et al., 2016), taking care of both quantitative (like HBR) and qualitative (like *self-efficacy*) variables.

Physical activity (PA) is considered one of the most important factors for the prevention and management of non-communicable diseases (NCDs). Mobile technologies offer several opportunities for supporting PA, especially if combined with psychological aspects, model-based reasoning systems and personalized human computer interaction. Given that people carry smartphones and can access data anywhere and anytime, physical activity behaviour change promotion apps offer the opportunity to provide tailored feedback and advice at the appropriate time and place. Therefore, apps offer new opportunities to deliver individually tailored interventions, including real-time assessment and feedback that are more likely to be effective.

The integration of IMUs and KAFKA in this context will allow expanding the range of recommendations suggested to the user, analyzing from both the quantitative (e.g. detecting and elaborating his/her HBR) and qualitative (e.g. understanding how the physical activity is conducted) points of view his/her physical and psychological status, with the final aim to build up a complete and innovative framework for personalized training.

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