Knowledge-Enabled Complex Event Processing-based platform for health monitoring

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***Abstract*—An increasing number of applications that require real-time or near-real time processing of high-volume of data streams are changing the way that traditional data processing systems infrastructures operate. Timeliness and flow processing are crucial for justifying the need for developing a new class of systems that are capable of processing not only generic data, but also event notifications coming from different source to identify interesting situations, with respect to traditional Database Management System (DBMS). Accordingly, different systems emerged and are competing in the last years, namely Information Flow Processing (IFP) systems. In this paper we discuss how semantic technologies can contribute to the field of complex event and study their support in health monitoring domain. Complex Event Processing (CEP) systems associate a precise semantics to the information items being processing. We propose an approach that combines Semantic Web methodologies and CEP model in a health monitoring platform.**

Keywords–Complex Event Processing; Semantic Web; knowledge Representation; Health monitoring.

I. Introduction

Technological innovation is driving profound changes in all productive fields. Consequently it is contributing to a new definition of the organizations and processes, which increasingly require new skills and responsibilities profiles. This path has also involved the health field where technologies have taken a leading role, it is becoming an integral part of the health service and they are establishing more and more inseparable interconnections between health and technology. The progress in medical technology is driving a continuous improvement of health and predictive diagnostic and therapeutic outcomes. Throughout the industry that deals with health, but especially in hospitals, the significant presence of technology, must ensure safe and appropriate use in various phase of prevention, diagnosis and treatment. It is expected that the Healthcare Industrial IoT *(HealthIIoT)* will be one of the main players in the Industrial Internet of Things (IIoT)-driven healthcare industry. IIoT has had a remarkable influence across many large and small healthcare industries. As a result, an increasing number of wearable IoT devices, tools, and apps are being used for different monitoring applications (e.g., glucose monitors, ECG monitors, and blood pressure monitors) [1]. The concept of "Competence"covers a key role in each phase. Competence is the ability to orient themselves in certain situations. It does not reside in the resources to be mobilized but in the same mobilization of knowledge that are known to select, integrate and combine in a context and for a specific purpose. The emergency health situations represent a sudden event, often unpredictable, which endangers life if the person concerned is not made, within a few minutes, a rescue action in a timely and professional manner. There are many medical professions that are emerging, due to the complexity of the events, each with their own skills. We can say that Competence consists of three components: *Knowledge*, generally the scope of conceptual knowledge, *The ability (or skill)*: the operational aspect of competence, the implementation of principles that belong to the knowledge and the *The behavior (or way of acting)*: the performing tasks that affect relationships with others and the effectiveness of the mobilization of the entire competence itself. These three components are closely linked to each other and make up the complex areas of knowing how to act. The aim of this paper is to present an intelligent system architecture for the management of health data, in particular a support system in the prevention, diagnosis and treatment phases. According to G. Cugola and A. Margara [2] the concepts of timeliness and flow processing are crucial for justifying the need for a new class of systems. Indeed, traditional Database Management Systems (DBMSs): *(i)* require data to be (persistently) stored and indexed before it could be processed and *(ii)* process data only when explicitly asked by the users, that is, asynchronously with respect to its arrival. These limitations have led to the design of a number of systems specifically designed to process information as a set of flows according to a set of processing rules. Complex event Processing (CEP) is one of these emerging models to monitor and react to continuously arriving events in real-time or near-real. Critical factors for event-based systems are event detection and the enormous amount of information available on the events. The continuous streams of high-level events require real-time intelligent processors. Human knowledge domain will greatly affect the decision making support system. Knowledge Representation is the method used to encode knowledge in an intelligent systems knowledge base. Events-based semantic models can improve the quality of event processing by using metadata in combination with knowledge bases consisting of ontologies and rules. The proposed solution is based on the combination of this two discipline: CEP domain and Knowledge Representation. The remainder of this paper is structured as follows: Section 2 provides a background on CEP and ontology Knowledge Representation. Section 3 presents the application domain and Section 4 discusses the proposed approach and platform. Finally, Section 5 concludes and discusses future research work.

II. Background

Currently, an increasing number of distributed applications requires continuous analysis of flows of data and real-time response to complex queries. Furthermore, it is very important decide the way data should be stored because this choice will determine later also the way in which data will be extracted.

Today ontologies are widely used to model and encode domain's knowledge and allow us to reason about this knowledge. The fusion of background knowledge with data from an event stream can help the event processing engine to know more about incoming events and their relationships to other related concepts. In this section, we provide a background on CEP and Knowledge Representation.

A. Complex Event Processing

The concept of CEP was introduced by David Luckham in his seminal work [3] as a "*defined set of tools and techniques for analyzing and controlling the complex series of interrelated events that drive modern distributed Information Systems (IS)*". This emerging technology helps IS and Information Technology (IT) professionals understand what is happening within the system, quickly identify and solve problems, and more effectively utilize events for enhanced operation, performance, and security."CEP systems can be classified as Advanced Decision Support Systems (ADSS) [4]. It is part of Event-Driven Architectures (EDA), which are architectures generally dealing with the production, detection, consumption of, and reaction to events [5]. The key characteristic of a CEP system is its capability to handle complex event situations, detecting patterns, creating correlations, aggregating events and making use of time windows. The capability of defining and managing the relationships between events is an important and integral part of event processing solutions. The relationship between events is called correlation and uses a collection of semantic rules to describe how specific events are related to each other [6]. When a problem or opportunity arises, it should be noticed in real time, to make sure the right action can be taken at the right moment. Otherwise there will only be historical data that reveals possible problems, which already have become a real problem or opportunities which already have vanished. With CEP it is possible to act in real time and make better use of the already available events. Specification languages for event patterns are frequently inspired by regular languages and therefore have automata based semantics [7]. CEP systems can be classified on the basis of the architecture of the CEP engine in *centralized, hierarchical, acyclic and peer-to-peer* [8], the forwarding schemes adopted by brokers [9], and the way processing of event patterns is distributed among brokers [10]. Several CEP systems have been developed in the last few years, each one proposing a different processing model. Currently, the most popular are: *Esper* [11], *Apache YARN* [12], *StreamDrill* [13].

B. Ontology for Knowledge Representation

The field of knowledge Representation tries to deal with the problems surrounding the incorporation of some body of knowledge in a computer system, for the purpose of automated, intelligent reasoning. In this sense, knowledge representation is the basic research topic in Artificial Intelligence (AI). Knowledge Management (KM) consists of techniques that use Information Technology tools for the information management, and its goal is to improve the efficiency of work teams; it studies methods for making knowledge explicit, and sharing professional expertise and informative resources. In the scientific literature, different approaches have emerged to classification of KM issues. Alavi and Leidner [14] group the problems of Knowledge Management, namely storage, creation, transfer and retrieval issues into four classes. Verwijs et al. in [15] analyzed different knowledge approaches in business processes, and categorized them as follows: *Knowledge storage approach*, *Knowledge processes approach*, *Learning processes approach*, *Intellectual capital approach*. A generic Knowledge Management System (KMS), supporting the creation and storage of knowledge, gives the opportunity to make data, information and knowledge from different sources readily available. It contains data and documents, and can also store tacit knowledge, which is more difficult to express, and includes peoples experiences, know-how and expertise. The issue of how to better capitalize and disseminate knowledge is one of the actual priorities in KM. To realize such goals, a KMS can make use of different technologies such as: *Document based technologies* for the creation, administration and sharing of different documents (e.g., doc, pdf, html); *Ontology/Taxonomy based technologies* which use ontologies and classification for knowledge representation; *Artificial Intelligence based technologies* which use particular inference engines to solve peculiar domain problems. The main components of a Knowledge-Based System [16] are the following: *(i)* the *Knowledge Base* is the passive component of a Knowledge-Based System. It plays a role similar to a database in a traditional informative system; *(ii)* the *Inference Engine* is the core of the system. It uses the Knowledge Base content to derive new knowledge using reasoning techniques; *(iii)*the *Knowledge Base Manager* manages coherence and consistency of the information stored in the Knowledge Base. KMS can represent knowledge in both human and machine-readable forms. Human-readable knowledge is typically accessed using browsers or intelligent search engine. Human-readable knowledge is represented using a wide range of approaches in Knowledge Management Systems. But in some case, as the development of an expert system for decision support, knowledge needs to be accessible in machine-readable forms. Therefore, one of the major questions of knowledge management is to obtain a method to represent knowledge in both human and machine-readable forms. To solve this problem, Ontologies [17] are generally used as knowledge containers for KMSs.

III. APPLICATION DOMAIN

The aim of this paper will be the design of an integrated platform consisting of integrated components designed to remotely manage the paths of prevention, diagnosis and treatment. With respect to the prevention processes, there are three levels of prevention: *Primary* that aims to intervene on external pathogens and/or the individual's defenses, prevent a disease from developing; *Secondary* that aims to early detect the disease process already begun before symptoms appears; *Tertiary* that seeks to remove or repair the results of a disease that has already manifested through symptoms. In order to comply these three levels of prevention, the platform should provide a monitoring system integrated with a module of management of clinic compliance (care process), the real time management of the events by a CEP system and a connection system to the own caregiver or physician for the management of teleconsultation (diagnosis process). The diagnostic process should provide the possibility of a consultation and remote activation of health facilities in the event of hospitalization or specialized investigation. We identified the following functionalities:

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- the use of digital medical record;
- the connection to the Electronic Health Record;
- the ability to analyze the patient's medical history and retrieve digitally reports;
- the ability to link the medical plan allows one to manage the entire cycle in dematerialized form and to reduce the clinical risk related to patient care with unsuitable or contradict each other.

The process of care management involves the management of compliance and must include the link to the medical plan. Also, it must provide the delivery of care using any devices in the patient's home. In particular, all scenarios to the three health-related processes should include a system of systematic data collection and their organization in a knowledge base used by decision makers at all levels and the definition of dashboards for the governance of health care. A personal health monitor is one example application [18]. A health monitor is a personalized system that allows a person and their caregivers to monitor the persons health status. Health monitors may be particularly useful for chronically ill people as well as for elderly citizens [19]. The data may be captured from sensors and devices at the person as well as from stationary sensors in their home or in a specific clinical area for the atmosphere data collection. Alarms are set up to alert the person and, if necessary, doctors or a remote caregiver. Sensors automatically capture personalized health data such as heart rate, blood pressure, respiration rate, ECG, oxygen saturation in blood, the location of the person in reference to a room,. In addition, specific regular measurements for particular health conditions are performed by the person and the results are filtered for emergency situations, as well as kept for long term observation. Health monitors offer many challenges derived from the high volume of low level events and the need to derive higher level events that must be propagated. This application is particularly sensitive to false negatives and false positives.

IV. PROPOSED PLATFORM

Healthcare has many applications for event-based systems. EDA integrates relational, non-relational and stream data structures to create a unified analytics environment. EDA enables discovery, or exploratory, analytics, which rely on low-latency continuous processing techniques and high frequency querying on real-time data. This type of architecture requires a different class of tools and system interfaces to promote a looser coupling of applications to streamline data access, integration, exploration, and analysis. Real-time data allows information to be disseminated in a timely manner, when and where it is needed. Real-time capability and related process automation assist in accessing data to build event-driven applications enriched with other relevant information and bringing them together in a scalable platform. This section of the paper describes the proposed architecture platform depicted in Fig. 1. The modeled real-time platform is based on CEP and semantic web technologies and approaches. Together, these components create an agile, high performance, scalable platform that can deliver fast insights through real-time queries, pattern matching and anomaly detection, continuous analytics and triggers notifications and alerts based on a CEP engine. Detection and Aggregation- oriented Complex Event Processing focuses on *(i)* detecting combinations or patterns of events; *(ii)* executing

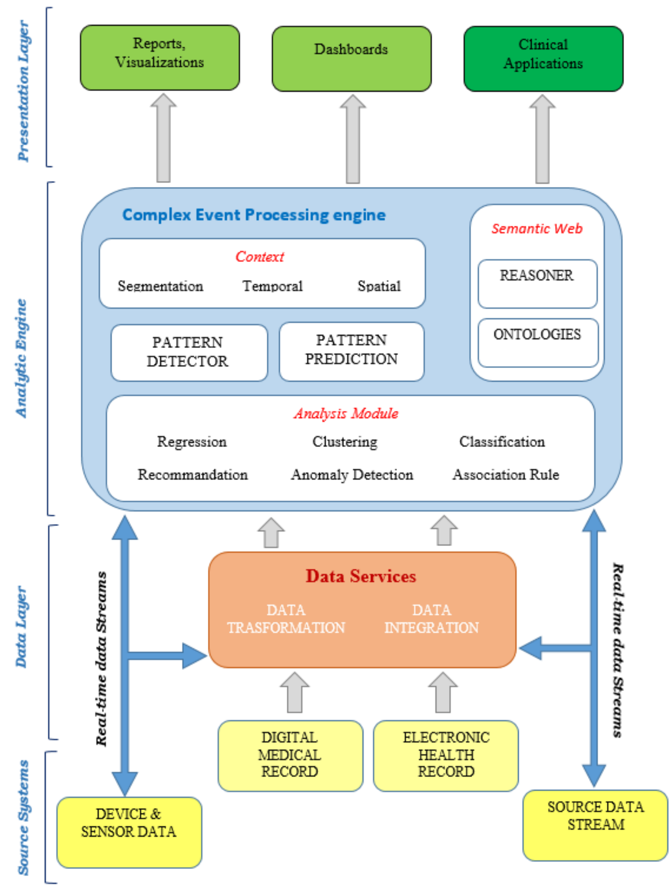

Figure 1. Proposed functional Architecture.

algorithms as a response to system input. Sources includes real-time data by sensors, medical devices, data stream generate real-time data that are captured by other systems for continuous monitoring, together with patient's historical data (Digital medical record, Electronic health record). Depending on the scenario, anomalies may be resolved by automated responses or alerts for human or machine intervention. CEP extends this capability by correlating multiple events through a common interface that invokes an embedded rules engine. Event filtering evaluates a specified logical condition based on event attributes, and, if the condition is true, publishes the event to the destination stream as a notification or alert. The main challenge is the huge amount of data collection and their organization in a knowledge base. Ontologies play an important key role in the knowledge-based CEP. They cover the conceptualization of the application domain to allow reasoning on events and other non-event concepts. We propose that event processing domain should be described by a modular and layered ontology model, which can be reused in different scenario application. Important general concepts, such as event, action, situation, space/place, time, agent and process should be defined based on meta-models and pluggable ontologies which are in a modularized ontological top-level structure. These general concepts defined in the top-level ontologies can be further specialized with existing domain ontologies and ontologies for generic tasks and activities.

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V. Conclusion

For the healthcare industry, a real-time capability is required to exceed future standards of care, provider competence and patient engagement expectations and to accommodate the currently transformation in the healthcare industry focused on opening up health data to facilitate exchange between actors. All the challenges introduced in Section 2 necessitate next-generation technologies designed to extract value from very large volumes of disparate, multi-structured data by enabling high-velocity capture, discovery, and analysis. CEP systems offer the ability to detect, manage and predict events, situations, opportunities, rules, conditions and threats in very complex networks. The presented platform based on CEP and Semantic Web technologies, providers will be able to process high volumes of underlying technical events to derive clinical decision support. The modeled real-time platform is based on requirements for providing minimally acceptable timeliness of information based on feasibility and clinical necessity. In collecting, processing and analyzing real-time data, there is inherent latency depending on data rates, volume, aggregation method, processing power, embedded analytics and throughput. The presented platform is work in progress. We are currently preparing different case studies for the management of all different health data.

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