Healthcare Framework for Smarter Cities with bio-sensory data

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***Abstract*— In recent years, innovations that occurred in technology caused an evolution in computational and communicational areas. These advancements allowed us to apply some capabilities of smartphones, smart devices, and wearable devices as well. Sensory data, produced by smart devices are essential for implementing a cognitive, scalable, autonomous, and extensible Smart City architecture. Based on it, we propose an architecture which could extend Smart City solutions in a way that recognizes new data sources and applies data categorization rules without introducing any side effects for maintenance while protecting data privacy definition that complies with the GDPR and providing an anonymized data repository that is publicly available for the client consumption to further produce useful, value-added data based on analytics. Considering the evolution of smart devices, it becomes a necessity to provide an architecture definition such as microservice orchestration that allows an easier adaption of new data types and domain requirements to keep the ever-maintainable state of the Smart City architecture in a technology-agnostic fashion. Our paper shows a small fragment of this field on a focus on eHealth.**

Keywords—smart city, cognitive health care, sensor data, microservices

I. Introduction

Nowadays, we recognize the evolution of technological devices firsthand in our daily routines. Smart devices produce valuable data to the user by the consumption of complex distributed services or utilization of the embedded smart sensors. Such adaptation of technology in the current state of socio-ecological structure opens up new possibilities to analyze and understand the data that are produced by individuals, to utilize the cognitive[1][2] tools to create a foundation for better and more human-centric habitats.

The definition of a Smart City solution should fulfill certain characteristics of a future-proof architecture. These characteristics can be segregated into disciplinary aspects of software architecture, ethical definitions of human-sourced data, and utilization of the aforementioned topics in order to increase the quality of life for the inhabitants. The disciplinary aspects of software architecture introduce domain-related requirements such as accessibility, maintainability, scalability, and extensibility of the actual software piece, alongside with the architectural design of the integration of the sensors to the Smart City architecture that is modeled in the domain-driven design concept [3]. The ethical definitions of human-sourced data [4] answer the questions of what the data will be, how the data will be collected, and why the data will be collected, in addition to the qualifications of privacy standards that are complying with the requirements of General Data Protection Regulation(GDPR). The utilization of the architectural and ethical definitions will underline the use cases of architectural orchestrations by providing physical workflows in a generic manner for the user devices for both production and consumption of the data for the betterment of the user habitat.

It is imperative to understand architectural modularization for the integration requirements of the expert systems or neural networks to the smart city solutions that own immense size of data repositories and flows, in order to ensure the sustainability of cognitive workflow consolidation to handle domains of health care and alike. Without such an understanding, it is not possible to establish a future-proof smart city solution that can follow and incorporate agnostic guidelines that allow cognitive function reusability between expert services.

II. Data Classification and Modelling

Due to the heterogeneous characteristics of data, the presupposition of a unified data definition in sensor data production is unexpected [5]. Each uniquely identified data source should implement its own converter which would then abide by the service contract to publish sensor data in a service understandable fashion. The public application programming interface (API) should provide the necessary tools to minimize deviation from the generic solution that is defined by the API. This deployment of the generalized data API allows the utilization of data mining functionalities to fulfill the cognitive requirements of the domain specification.

We dissect the data classification in two categories and two characteristics with respect to each other. The necessity of the categorization in this architecture solely due to the differences of data producers, sensors, and ethical definitions of the data.

A. Complex and Simplex Data Sources

Although the architecture should provide the necessary tools and means to achieve public accessibility for all its clients, this requirement should comply with the privacy and trust factors of the data. Therefore, the sensitive or faulty data that are produced by the individual client devices should not impact the aforementioned factors of public API. To avoid such predicaments, we categorize the data source as a complex or simplex data source.

The simplex data sources are the city-wide peripherals that provide non-complex data and are considered to define environmental variables. Such data sources can be addressed to Closed-circuit Television (CCTV) or environment measurement utilities.

On the other hand, the complex data sources are the sensor data producers that are used by the individuals or data produced by architecture agents. Examples of these sensors can be wearable devices or custom agents that are deployed by the architecture to do data gathering from social media or search engines. Along with the mentioned categories, the data will be classified as sensitive or public. This classification process will allow architecture to determine the value of the data and apply proper anonymization steps to keep sensitive data relative while providing further means of analysis and research.

III. Extensible Architecture Definition

In view of their simplistic and straight forward qualities, monolithic applications have been traditionally accepted architectures for several decades. Easier monitoring and data accessibility of monolithic applications are applicable without complex architectural orchestrations. Even though it is possible to create a Smart City solution as a monolithic application, it is not recommended due to its shortcomings regarding the topics of scalability and maintainability. A large architecture such as Smart City solution can be bottlenecked by the requirements of technology and user demands based on actual trends.

Service-Oriented Architecture (SOA) has the means of providing necessary characteristics of scalable, maintainable, extensible, and multi-tenant capable applications. SOA allows applications to solely focus on the business-centric definitions while preventing the architecture from tightly coupling with the non-business or non-domain related relationships. SOA does not claim any attributes to identify an architecture as a standard which makes it a good candidate to describe a Smart City architecture to create autonomous and agnostic services [6] to achieve a certain technological independency from the standard protocol definitions such as Internet Inter-ORB Protocol (IIOP) or Simple Object Access Protocol (SOAP). Independency of technological requirements allows SOA to incorporate with different interfaces without any implementation restriction of communication of the environment utilities.

The extensibility characteristic of the architecture allows the capability of expert system integration to answer domain requirements. Such expert systems can be deployed as data consumption and production units to cognitively produce value over the data services. Expert system behavior can be declared as city-wide agents that are deployed to provide health care, education, traffic, and solutions alike to the clients.

Technological independence is a necessity for the Smart City architecture due to its indeterministic environment and the need for integration of new sensory devices to further evolve as a novel solution. Although the definition of SOA can be held to account for a huge architectural spectrum, the definition of SOA can be briefly recognized as a blueprint for the basis of Smart City architecture.

A. Public Data API

Under the compliance of GDPR, the public usage of data that is produced by individuals for data mining purposes requires anonymization of the data. The following statements can be considered as guidelines and can be expanded upon to fulfill the aforementioned requirements. The storage of the data should be defined by the user requirements and its ethical directives. Under the given directives, the first-hand data should not be available or traceable back to the individual who produced the data. It should always be contained in private data services to prevent any violations of privacy. The definition of the private data service shall be determined by the legal entities and only be accessible by the individual and expert systems or services which are to be regulated and maintained in accordance with the aforementioned legal entities to carry out computational tasks to further assist the individual or inhabitants of the Smart City. On the other hand, the public data services aim to provide a statistical framework and tools for the researchers and clients to be able to further determine necessary use-cases or relational patterns where it is applicable to assist the inhabitants and build a human-centered living environment for the future via a further generalization of the private data services.

For an extensible architecture, the data solutions of the Smart City should follow the microservice definition of data architecture. This discipline can increase the integrability of the new data models to the architecture without introducing any side-effects. This segregated structure of the data, allows services to be scaled and related far easier than the traditional solutions that we see in software architectures and scalability is a necessary characteristic of the Smart City architecture to comply with the ever-growing technological needs of the inhabitants due to the indeterministic future of the smart devices that can be acquired by the inhabitants and interface to the architecture.

B. Microservice Integration

The microservices are a novel methodology of implementing service architecture in a modularized fashion. Such architectural aspects provide a certain level of abstraction to allow service to handle unique domain problems in an encapsulated manner while avoiding any introduction of technical definition to be leaked into other service definitions.

For the Smart City architecture, it is beneficial to understand the trust factor of the services and handle any sort of catastrophic events without introducing any impact to the Smart City architecture. One of the main characteristics of microservices [7] is its ability to be easily replaced due to their autonomous architecture. Different microservice implementations can be inaugurated to the microservice orchestration with identical explicit interface declaration for a given communication layer to substitute for a microservice entity in orchestration. (Fig. 1.)

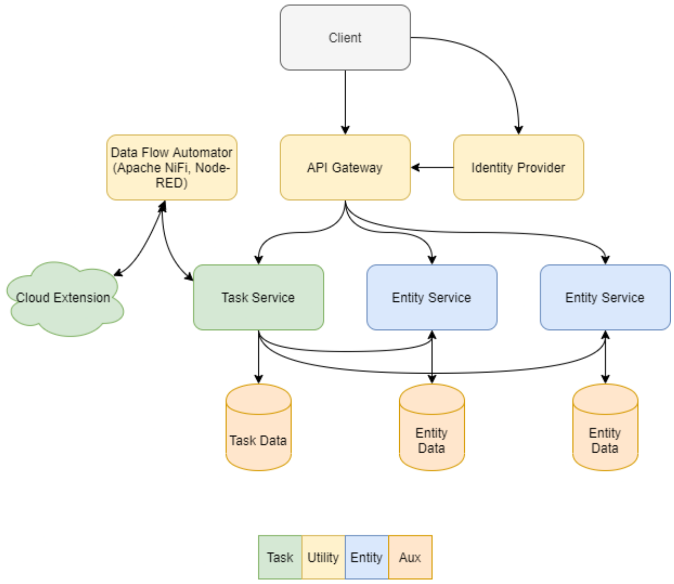

Fig. 1. Reference architecture

C. Scalability of the Architecture

Microservices' solutions to domain-specific problems make it possible to scale each individual service without any dependency requirement. Unlike monolithically implemented architectures, this aspect allows Smart City solutions to be agile and efficient in a sense of accessibility and robustness. Considering that there is no need for scaling the whole Smart City infrastructure, it is possible to argue that the architecture itself does not recognize any methodological boundaries to adapt for futureproofing.[8]

IV. SMART HEALTHCARE SOLUTIONS

A. IoT in healthcare solutions

Smart cities are equipped with different types of IoT sensors. The smart city systems are collecting sensor data and they are using the insights gained from the processed data. The extracted information can be used to manage assets, resources, or to improve the services. Smart cities able to share the gained information or the collected data with other cities or smart institutions in the city. Supported by the data, both professionals and services can make much better decisions.

Physically, smart homes are part of smart cities, they can help each other to make more efficient decisions. Smart homes are equipped with a lot of sensors. However, these sensors have different purposes. Basically, their job is to provide data that will allow the building to function efficiently. There are some types of sensors in a smart home that can produce useful data to a smart city or its facilities as well. In that sense, the smart cities are consumers of the smart homes, and smart homes are producers of the smart cities. Smart homes also can integrate other devices and sensors from their environment. For example, health-related measurement data collected by the smart homes should be useful to the health-related institutions in the smart cities.

Health care services also should be as smart as possible in a smart city. To achieve this goal, the smart city must produce data for health care services. Not all the sensor data suitable to make the health care services more efficient. However, the produced health-related sensor data from smart homes helps to improve the services and monitoring in the city. A simple medical examination could be more accurate if the doctor uses medical information from other sources than the hospital information system. The remote health monitoring could be more reliable too if the monitoring system receives information continuously from the patient.

B. Using biosensor data

These days, most people have one or more biosensor devices, some of them wearable (e.g.: fitness trackers, smartwatches), and some of them not (e.g.: smart scale), but all of them continuously produce useful biosensor data about the individuals. There are a lot of independent mobile applications for wearable devices, most of them forward the measurement data to own data servers. The servers are independent, they cannot share information with each other, so the data are visible only to the servers that registered it. This is a common problem with these systems. The health-related measurements have meaning in a well-defined context, the individual measurements are insignificant. An individual measurement data without context can be measurement error or outstanding value. However, if the measured sensor data are integrated into one or more common, public health-related services or directly into the hospital information system, then the collected data can be evaluated in a useful context.[9][10] The different types of bio-sensory data have relationships, for example, the weight and age influence the heart rate values.

C. How Med-i-hub helps smart healthcare solutions

In a smart city, it is a basic expectation that health care solutions are also smart, and health care solutions can only be smart if they are supported by data. The more data available, the easier and more accurate the decision can be made. The common wearable devices can be integrated into the smart homes and thus smart cities as well, and so the health care institutions can easily integrate bio sensory data through the smart cities' interfaces. The biggest challenge is to collect, record, and classify the sensor data in real-time. It is hard to integrate and process the time series of bio sensory data. It is hard to integrate and process the time series of bio sensory data.[11]

Our Med-i-hub (prototype) system helps to overcome these difficulties. It provides an opportunity to integrate bio sensory data streams without serious architectural modification, through open application programming interfaces.[12] The integrator does not need to buy expensive hardware components or licenses, it should only connect to the hub system through the standard interface.[13][14] The Med-i-hub system uses international standards (e.g.: Health Level Seven - HL7) to exchange, integrate, and retrieve electronic health information and thus its integration is also simple. The hub system collects, transforms, and stores the received data, and the integrated systems may request a subset of it.

D. Smart personal assistant application

There are some personal health assistants available on the market. However, the research team created a revolutionary solution. Our system differs from the others in that it evaluates and combines the measurement data by wearable devices, Google calendar entries, and other personal feedback from the owner. This means combining data from up to three or more different sources, allowing us to determine the context of our measurement more accurately.[15]

Our solution uses the calendar to analyze the user's habits and determine their current activity based on the events registered there. In addition, the user can set several data that can influence the evaluation of the measurement data, for example, specify their mood on a scale from 1 to 10. The advantage of this solution is that it also considers several factors when evaluating the data that can help interpret the measurement data. As a result, the personal assistant can give the user a picture of what his or her data measured by the seasons is changing during social or sports activities.

E. Risk monitoring and disease prevention

Risk analysis and prevention of possible incidents can be a basic service of a smart city's health system if measurement data are available. The Med-i-hub system provides the ability to monitor and prevent by analyzing the data stream. The system uses simple mathematical methods for analysis that have already been proven in other areas (Fig. 2.).

One such method is the moving average, which, for example, makes it quite easy to filter out erroneous data. In the case of a pulse data set, the chronological order of the measurements is important to be able to filter out outstanding values. Such values can be easily filtered using the moving average from the data series:

$$\bar{v} = \frac{v_M + v_{M-1} + \cdots + v_{M-(n-1)}}{n} = \frac{1}{n}\sum_{i=0}^{n-1} v_{M-i}$$

where v is a heart rate value, $\bar{v}$ is the average heart rate, n is the number of the values in the series; M is the total number of healthcare records.

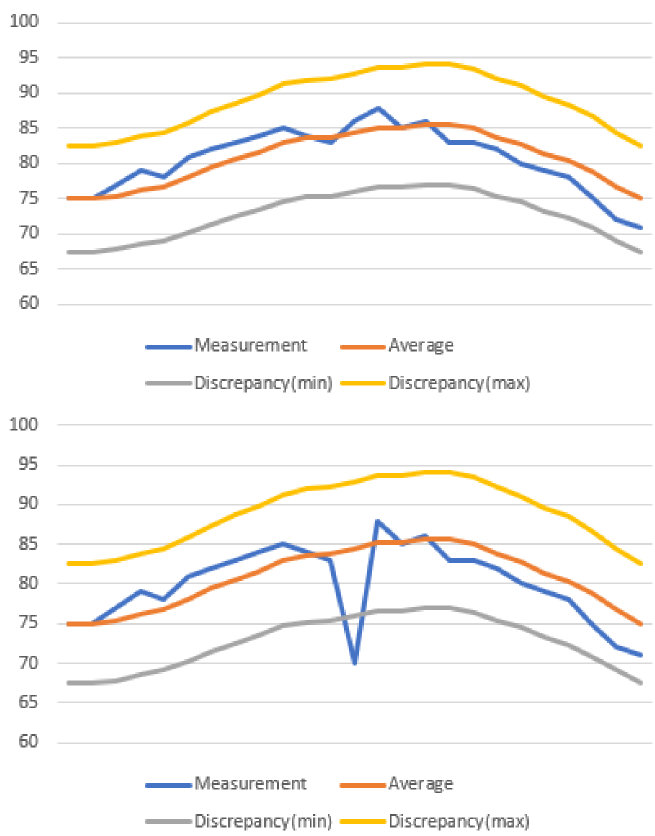

Fig. 2. Filter erroneous values with moving average

When examining deviations from the mean, other attributes need to be examined to filter out measurement errors or possible health problems. For example, it is important to be aware of the environment, an individual's activity, and previous health problems during the measurement. The deviation from the mean is therefore not an exact number but an adaptive value.

The reliability of a measurement data can be calculated as a deviation from the average. If there is a threshold value at which the deviation cannot be greater, the outliers can be easily filtered. When determining the threshold value, we need to know the measurement's environment, as the activity can affect the magnitude of the threshold value. The quality of the measurement can be calculated as follows:

$$quality = 1 - \frac{|\bar{v} - measurement\ value|}{\bar{v}}$$

where $\bar{v}$ is the average heart rate.

V. Conclusion and Future Work

Abstract capabilities of smart cities bring a new idea where the living environment reacts to the requirements of its inhabitants. It is not realistic to determine a static architecture, as in traditional methodologies, for a smart city system to provide solutions for ever-evolving requirement definitions of individuals. We understand the necessity of a scalable, maintainable, and reproducible architectural design that can apply autonomous characteristics to allow further enhancements of the system with cognitive development. The extensible characteristic of the architecture enables the insertion of new domains such as health care solutions and considers it a modularized expansion.

Our personal assistant pilot application helps the users monitor their health and evaluate their measurement results. If we can contextualize the data, we can evaluate it much more accurately. In contrast to the available applications, our personal assistant allows you to assign context to the measurement data.

Processing sensor data is not an easy task, so it is important that the processing requires few resources. Using simple mathematical methods, data transmitted by biosensors can be processed in near real time. With the solution described, smart cities can be endowed with capabilities that create the conditions for the development of cognitive health services. Smart cities can be extended in a way that does not require deep architectural transformation.

As a next step, we will improve our smart personal assistant and integrate it with more valuable data sources that are available in mobile environments. The improved personal assistant can help us to put the proof our proposed architecture. Our architecture suitable for use as a data source by external services, the research group will work to integrate such services.

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