On the Semantic Approach to Service Development for Socio-Cyber-Medicine Systems

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***Abstract*—In a Cyber-Medicine System (CMS), the Internet is used to deliver healthcare services, such as medical consultations, diagnosis, and prescriptions. Services allow end-users (patients) online access to consultations and treatment with medical professionals. When the services benefit from the end-users activity and collaborative work, then the system becomes Social CMS (SCMS). In this position paper, we discuss how SCMS can be implemented based on the semantic approach. As in the generic case of smart environments, an additional layer is introduced—the semantic layer, where all system and domain objects are virtually integrated: multisource data, ongoing processes, situation attributes, reasoning rules, and human activity. The objects are dynamically related leading to a knowledge-rich structure in the form of a semantic network. Semantic algorithms are used for data mining in this network. The derived knowledge feeds construction of context-aware information services to support medical professionals as well as to assist mobile patients.**

I. Introduction

The traditional style of healthcare by visiting a hospital to meet a doctor is still very popular though very ineffective. To make healthcare more effective, continuous monitoring and subsequent semantic analysis of the whole dynamic complex of available data and context can be established for the remote patients. This demand drives the development of new approaches to healthcare [1], [2], [3], [4].

In a Cyber-Medicine System (CMS), the Internet is used to deliver healthcare services, such as medical consultations, diagnosis, and prescriptions. Services allow end-users (patients) online access to consultations and treatment with medical professionals. On the one hand, CMS means that the system consists of a large multitude of composed of many physical and virtual entities (as in any cyber-physical system). On the other hand, one of the key components are remote users, leading to the increased role of mobility [5], [6].

When the services benefit from the end-users activity and collaborative work, then the system becomes Social CMS (SCMS). In addition to pure service consumption, end-users become responsible for similar computation and generation functions as machine-based CMS components. In the medicine domain, this socio aspect plays even more important role since precisely human entities (e.g., doctors, medical personnel) are responsible for final decision-making.

In this work, we discuss what SCMS is and how such a system can be implemented based on the semantic approach. As in the generic case of smart environments [7], an additional layer is introduced—the semantic layer, where all system and domain objects are virtually integrated: multisource data, ongoing processes, situation attributes, reasoning rules, and human activity. The objects are dynamically related leading to a knowledge-rich structure in the form of a semantic network. Semantic algorithms are used for data mining in this network. The derived knowledge feeds construction of context-aware information services to support medical professionals as well as to assist mobile patients. We show how the semantic layer can be designed based on the well-known smart spaces approach [8], [9].

The rest of the paper is organized as follows. Section II studies existing approaches to development of modern healthcare applications. Section III considers information services of a SCMS. Section IV introduces a semantic layer as a concept for effective implementation of advanced healthcare services. Section V discusses possible data for integration on the semantic layer and possible models of semantic network analysis. Section VI overviews smart space based design to develop SCMS. Finally, Section VII concludes the paper.

II. Related work

Recently, IoT-enabled healthcare systems are still in their early research and development stage. Nevertheless, existing research prototypes showed the considerable potential impact on the healthcare service industry [1], [2], [3].

The essential role of user mobility, their personal mobile devices as gateways to the medical information system, and wireless medical sensors (wearable or implantable) has been already well understood, e.g., see [5], [6]. In particular, the IoT technology enables remote and continuous health monitoring or wellbeing assessment as well as mobile user devices become empowered with advanced Internet capabilities [10], [11]. On the side of medical facilities, the environment is enhanced with a dynamic multitude of remote users (patients and medical personnel). Services become accessible in the ubiquitous computing style—anytime, anyplace, anywhere—bridging the distance gap between the user and the services. Healthcare becomes mobile (mHealth) [4] and person-centric [12].

Ambient Assisted Living (AAL) aims at making IoT environments that support the people inhabiting them [13]. In particular, embedded devices play now the crucial role for development of health systems in home and living environments. Some examples include cognitive health monitoring systems based on activity recognition, persuasive systems for motivating users to change their health and wellness habits, and abnormal health condition detection systems.

The intelligence of healthcare monitoring was considered in SAPHIRE project [14] using two pilot applications: one is for bedside monitoring of cardiac patients at hospitals, the other is for homecare monitoring of patients after a revascularisation therapy. A vision of service intelligence was studied in [11], identifying three key solution components: (i) multi-agent architectures, (ii) semantics-oriented information sharing, and (iii) operation with multisource heterogeneous data.

Data mining and analytics techniques are applied in such scenarios as AAL for individuals with disabilities, ageing in place, and remote health monitoring or wellbeing assessment [15]. The analysis is based on monitoring daily behavior and predicting standard clinical assessment scores of the users. In particular, work [16] investigates this relationship between continuous sensor data collected from real-world smart homes and specific components of standard clinical assessment scores.

The role of ontologies for structured representation of multi-source data for effective processing in medical systems is presented in [17], [18]. Ontology for semantic representation of health questionnaires is introduced in [19] to form a base for further automatic processing by semantic methods.

III. Information Services of a Socio-Cyber-Medicine System

The traditional style of healthcare is limited by the time and space barriers. A patient always has to visit a doctor in hospital or clinic. Information and communication technologies (ICT), and the IoT technology in particular, introduces effective opportunities to break these barriers [10], [13], [4]. A typical healthcare information system provides backend services located in medical facility. The basic idea is to digitalize such a system with services that aim at remote (distant) consumption by mobile patients and medical personnel [20], [11].

This idea has been evolving in respect to the following concepts for the use of ICT in healthcare and well-being services.

eHealth (electronic health): healthcare is supported by digital services that are constructed using electronic processes and communication.

Telemedicine: a form of eHealth to provide clinical healthcare at a distance, including physical and psychological diagnosis based on telemonitoring of patients functions.

mHealth (mobile health): Personal mobile devices are used for continuous collecting, aggregating, and analysis of patient-level health data. On the one hand, services provide healthcare information to medical personnel as well as to the patients. On the other hand, direct provision of healthcare services can be performed using mobile telemedicine.

Cybermedicine: the Internet is used to deliver healthcare services, such as medical consultations, diagnosis, and prescriptions. Services allow patients online access to consultations and treatment with medical professional.

Healthcare services are constructed within IoT environments. Such an environment is associated with a physical spatial-restricted place with a variety of devices (embedded or brought by the users). In addition to local networking, the environment has access to the global Internet with its diversity of services and resources, including traditional medical information systems.

The IoT technology provides a base for applying artificial intelligence methods. In particular [21], ambient intelligence (AmI) makes people empowered through intelligent tools embedded in the surrounding environment or carried by people (mobile computers, wearable and implantable devices) and by objects that are aware of their presence and context (i.e., smart objects in the IoT sense). These tools are sensitive, adaptive, and responsive to each individual's needs, habits, gestures and emotions One example of AmI applications in healthcare [22] is for psychiatrists and psychologists that use augmented and virtual reality to improve the efficacy of available treatments for anxiety disorders, eating and weight disorders, and pain management. Using IoT an AmI application can overcome the limitation of clinical settings, allowing a real connection between the fragmented healthcare services and the daily experiences of the patient.

As in many other application domains, IoT can enable healthcare using fusion of real (physical) and virtual (information) worlds [11]. A new level is achieved for interconnection and convergence of service-oriented information coming from both worlds. The interconnection and convergence is realized within Cyber-Medicine Systems (CMS), where a CMS is composed of many physical and virtual entities (as in any cyber-physical system). Such entities are controlled or monitored by computer-based algorithms. Virtual counterparts to physical components are created, acting as smart objects in this IoT-enabled networked system.

In addition to pure service consumption, end-users can be active participants of the service construction. Human participants become responsible for similar computation and generation functions as machine-based smart objects. We yield a Socio-Cyber-Medical System (SCMS), in correspondence with such community-driven applications as social networking or collaborative work environments. In the medicine domain, this socio aspect plays even more important role since precisely human entities (e.g., doctors, medical personnel) are responsible for final decision-making.

In a CMS, the major focus is construction of control services, which operate with medical equipment (e.g., an implanted insulin pump). In a SCMS, the focus is shifted to information services, which provide analytical support and assistance (e.g., a recommendation for a patient to reduce the instant activity during the physical exercise). In general, an information service provides the information fragment appropriate to the end-user in her/his current situation. The user applies this fragment for situational decision-making, while the decision depends on both components: (a) input information produced by the service and (b) intelligence ability of the human. Note that the intellectual role of human is not replaced; the service just performs auxiliary assistance (the latter can be performed by the human with a similar result of higher cost).

IV. Semantic Layer

The layered structure for semantic-driven design of a service-oriented information system deployed in a given IoT environment is known [4], see Fig. 1. In particular, smart

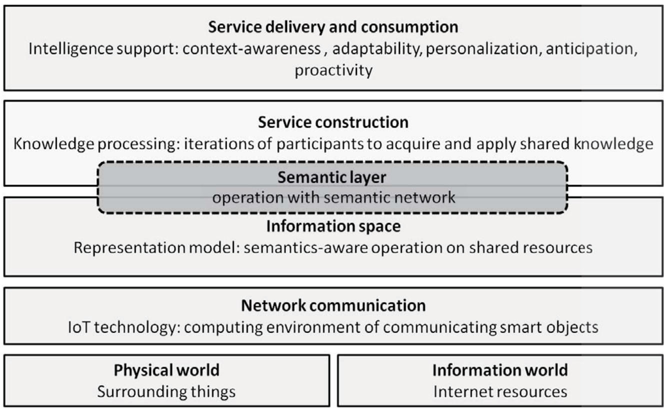

Fig. 1. Layers of service-oriented information system in IoT environment

spaces provide an approach to creating service-oriented information systems with high intelligence support [8], [7]. The approach provides methods for information collection from multiple sources, semantics representation and resource sharing, operation over this fragmented knowledge corpus, and cooperative service construction by all participants themselves.

Information services are constructed based on operation with descriptions of numerous physical and virtual objects that the SCMS is composed of. The descriptions are stored in the information space for the shared use. The representation model provides a structure to keep semantics: a semantic network is created on top of the knowledge corpus of descriptions. Network nodes are objects, links represent semantic relations between objects. Then semantic methods are used to analyse this semantic network, e.g., for searching appropriate information and selecting the most interesting facts (recommendations) for the user to study in her/his current situation.

The semantic network and operations over it introduce a new layer—semantic layer—that glues information space and service construction, as Figure 1 shows. Formally, a semantic network is defined as a directed graph consisting of nodes representing participating objects (real of virtual) and links representing semantic relations. The nodes correspond to physical and digital objects, patients and medical personnel, associated events and activity, etc. The links reflect interrelation of the objects. Both nodes and links can be assigned with additional descriptions that provide further semantics. As a result, the semantic network forms an advanced information model for CSCM, where medical data are enhanced with all available and appropriate data.

Let us introduce the following classes of information services that a SCMS can provide using the semantic layer.

1) Individual health monitoring based on continuous mobile sensing and assessment of patient's data.
2) Group health monitoring when several patients are clustered based on a certain criterion (e.g., geospatial proximity).
3) Survey-driven assessment when health questionnaires provide a base for making decisions.
4) Complex detection of patient status deviations based on multisource data analytics.

The introduced services are examples that show how the semantic layer can be applied to service development for SCMS. The provision of health and wellbeing knowledge becomes closer to the visitor's preferences, historical interest, and the current context. The semantic layer is made responsible for construction and delivery of such services based on operation with the semantic network. This way, SCMS creates a virtual distributed workspace with many mobile users and where the knowledge can be individually or cooperatively acquired, applied, and evolved by both medical personnel and patients.

An essential property of a SCMS is operation with heterogeneous data coming from many sources:

1) medical measurements of vital and other physiological parameters of the patient,
2) context data to describe situation of the patient and the physical reality around the patient,
3) parameters of social activity that the patient performs as well as perceived social influence from other people.

The semantic layer is introduced to integrate such data connecting multiple fragments into the semantic network.

V. Information sources and semantics

The role of semantic layer is to integrate this large, heterogeneous, and fragmented data corpus in such a way that the integration embeds the semantics. In this section, we focus is on models for representing and analyzing such data in a semantic network.

A. *Measurements classification*

The semantic network virtually integrates data from many patients, semantically relates the data with other informational sources, supports knowledge reasoning over this multidimensional, multi-domain, and fragmented corpus. Analysis of the structure of semantic network provides deduced knowledge for use in healthcare services.

Patient data obtained through surveys, physiological data read from wearable devices and the surrounding context can be used and interpreted on the network. Data directly obtained from the patient is reputed subjective because it expresses person's mind and may be interpreted differently.

Portable devices measurements may be considered objective, since they do not depend on the will or desire of person and come laden with characteristics of physiological processes. Persistent measurements are characterized by the need to obtain measurement series of the indicator over a distance of time. One such measurement does not contain information, and a set of measurements obtained with sufficiently high frequency, make it possible to interpret the measurement series. The activity rate of instant measurement is much lower in comparison with continuous measurement. It is necessary to repeat the instant measurements several times a day, once a day or less to track the dynamics.

B. *Subjective measurements*

The survey can be conducted 1) active, when a patient comes to the clinic with the direct participation of the doctor, and 2) passive, when patient answers surveys questions on health status distant. In case of passive variant preference is given to interactive electronic questionnaires because of the possibility to lay a lot of options for questions and links between them depending on patient response.

The patient may describe a set of symptoms that he feels at the moment or over a period of time. Symptom is a one of the individual features, frequent manifestation of a disease, pathological condition or disorder of any life process. Thus the patient can indicate the presence of pain. He can describe the intensity (on the scale of pain: Verbal descriptive rating scale of pain, facial pain scale, numeric scale of pain, etc.), the character of pain (permanent, temporary, seasonal, etc.) and the prevalence of pain throughout the body. Such information is readily obtained by periodic patient survey.

The survey may contain not only questions about health state, but also questions about nutrition. The qualitative and quantitative composition of food, the time it is taken determine the dietary regime and food ration. The diet is the adherence to a certain regime and meals rules by a person (either healthy or sick one). The description of a diet consist of functional, pathomorphological, exchange, enzymatic and other disturbances in an organism of the person.

By supervising what and how much to eat as well as what not to eat, we can maximize a patient's life quality through avoidance of unhealthy ingredients [23]. It is possible to obtain product protein fatty carbohydrate composition by dividing it into ingredients. Based on these data, the food ration, the metabolic index, the necessary level of physical activity calculate, therefore, to give recommendations on increasing or decreasing the proportion of ingredient in the diet and to monitor the correlation between the diet and physiological measurements.

C. *Objective measurements*

The variety of small portable devices available on the market enable obtaining the behavioral and physiological data digitized for storage and analysis. They comprise of a sensor that records vital parameters and preprocesses the raw signals, and the wireless data transferring module (Bluetooth or Wi-Fi). For example, electrocardiography (ECG) is acknowledged as one of the most informative and easy-to-do instrumental methods of diagnostics in cardiology. ECG monitor may send 150 to 300 digital values per second. As little as 10 QRS-interval are needed for relevant clinical interpretation by physician. ECG monitors are capable of continuous ECG recording for 12 - 48 hours depending on the model [24]. Blood glucose meter and blood pressure monitor may have also allowed instant measurement. Additionally, laboratory measurements (blood sample testing, etc.) could have been done when necessary.

Characteristics of the patient motion can be obtained with the built-in accelerometer in the mobile device or portable pedometer. It tracks the number of steps passed during locomotion (either walking or running). Interpretation of the pedometer data enables us to determine changes in the patients gait, which may be indicative of some neuromuscular deficits, for example, at parkinsonism, cerebellum disorders, polyneuropathy, stroke. The accelerometer detects and transmits its relative angle of slope to the Earths surface. These devices operate in a very wide range of frequencies (from several Hz to 30 kHz) and are various by their sensitivity, weight, size and shape.

The device or program for measurement of time parameters of external respiration determines the breathing type (thoracic, abdominal, or mixed) and the depth of its rhythm. The frequency of respiratory movements is the number of breaths (inhale-exhale cycle) per unit of time (usually a minute). The respiratory cycles are counted as the number of repetitive motions of chest and the anterior abdominal wall. Data are then presented as time series that informs on mechanical deviation of the chest. Another device that characterizes respiration is spirometer, that allows measuring the respiratory rate, breathing patterns, and also lung volumes. Fitness trackers, besides monitoring of heart and steps rate, also provide opportunity to typify the sleep phase. During sleep, pulse wave sensor and the accelerometer mounted on the body provide detection of the human limb movements. Sleep phase (paradoxical or the slow sleep) is determined by a combination of heart rate characteristics and limb mobility.

The measurements listed above could well be done in a form of a game. One can perform, for example, a tapping test in a playful way to timely detect bradykinesia, or slowed down motion, and thus diagnose some neurological disorders, such as parkinsonism. The tapping test is widely used in psychophysiological studies and appears as counting number of finger taps within 30 seconds, calculation of their rate, and frequency decay over time. Alternatively, this test could be performed with help of smart phone, or tablet. That also does not distract a patient from his routine activities. Also, using tablet, one can monitor the typing rate, the search speed in the contacts list, and so on. Fluctuations from norm in that kind of tests may be indicative of the of definite neurological disorders, such as parkinsonism. The physiological data obtained through game activities via mobile devices may be regarded as typical continuous signal and thus can be described using the semantic elements such as the ECG.

Additionally, heart rate monitors are currently commercially available in the form of a chest strap or watches. They are designed to record data for 20-200 hours in a row and to inform on the average heart rate per minute. The portable blood glucose meter controls the amount of glucose in body fluids, usually blood, either in the milligram percent (mg%) or milligrams per decilitre (mg / dl). The concentration of glucose in the blood at different times of the day varies depending on how many carbohydrates and other food man consumed. Either too low or too high concentration of glucose is regarded as dangerous to humans.

The blood pressure monitor is designed for indirect, non-invasive measurement of the systolic and diastolic blood pressure, at the reading range 20 to 280 mmHg with an accuracy 3% mmHg [24]. Also, new models of body thermometers appear all the time. The device designed for continuous temperature monitoring monitors the response of the circulatory system to external environmental factors. The degree of measurement accuracy is up to 0.02 degrees. Both blood pressure and monitors and thermosensors can be synchronized with a smart phone, which transfers all the data.

Instant measurement can be provided with help of games on smart phone. For example, the reaction time can be measured as a time between stimulus application (in a form of object or changing colour on screen) and touching the screen. These mobile games are available in the shops of mobile applications presents. For OS Android, best examples are reaction tests by GoldenTenor[1], Wait Now[2] to test reflexes and compare the results around the world, reaction test by Sinic[3] to track player statistics. The use of these analysis methods allows characterizing the reaction rate and its change synchronously with clinical symptoms. However, the doctor would prefer to deal with pre-processed and condensed information, rather than with row data. Therefore, characteristic features of obtained flow of data must be automatically classified, recognized and then utilized in appropriate for a patient mobile-based form.

Measurements from various devices could well be connected in a temporal semantic network. Synchronously obtained parameters more fully describe the clinical picture of a patient than when taken independently. The outcome of such joint analysis of indicators can help elaborating highly personalized description of the health state of the individual patient.

D. Context

A system is considered context-aware if it can express aspects of the user's situation and such information is used to help the system adapt its functionality to specific user characteristics and needs [25]. The IoT technology essentially enhances which information can describe context [26], [27]. In particular, in smart spaces a dedicated knowledge processors are introduced to control the data access [28].

For a SCMS we consider the following aspects of context.

- User context: user profile, location, social situation.
- Physical context: lighting, noise, traffic condition, temperature.
- Time context: time of a day, week, month and season of the year

As in many other domains, the context allows adaptation of services, i.e., the same service is provided differently in different contexts. In healthcare, interpretation (and processing) of measured medical data should be influenced by context. In particular, mobile monitoring of patients with chronic diseases (hypertension, diabetes, epilepsy, etc.) needs to identify patient contexts while she/he is being monitored, including physical activities such as sleeping or running, and their surrounding environment such as room temperature [29].

E. Social

General trends and events which require attention can be elucidated in a study recruiting a group of people. Consequently patients can be divided into groups with the same treatment path. The trajectory of the treatment in a form of a semantic network defines which measurements should be carried out and at which periodicity. Either under notable deviation from such trajectory or evident worsening of the health state, patient can be administered to another group with different trajectory of treatment.

Statistical methods on big data allow for analysis with the purpose of grouping patients and determine the trajectory of treatment. Article [30] suggests methods by which patients were subdivided into groups for more efficient care management planning. There are two directions of cluster analysis: Series treatment (number of investigation procedures for each patient) and Series time (waiting time for investigation procedures for each patient).

Relations between the states of health of patient populations can be found in the same way. Correlation within a group can be related to external conditions. For example, among the weather-sensitive people may be the relationship of health indicators on the weather on the air temperature, atmospheric pressure and etc. The dependence of some parameters on the residence or location of a group of people at the same time can be determined.

ICT provides never earlier seen opportunities to set people in so-called therapeutic groups or collaborative communities. There is long-lasting approach to treat some mental illnesses, personality disorders and drug addiction by means of participative group, based on the concept of ”community as a method” [31]. In such groups the clients and therapists may live together, thus creating therapeutic surroundings for patients. Under some personal or physical circumstances, patients cannot be physically grouped in one place, so ICT with its social networking and communication facilities may serve as a basis for a virtual therapeutic community (TC) that in some senses resemble virtual interest groups in social networks, with a therapist participating.

The TCs focuses on the whole person and intervenes with his lifestyle and has already shown promising results [32], [33]. We believe that transfer of its principles in a more “virtual” milieu may provide some benefits to the clients health and, therefore, to the state. Also, that experience would have added efficiency to such recognized problem as Parkinsons disease (PD). PD is mere neurological chronic motion disorder. Still, PD patients share many psychological and autonomic problems with more ”classic” pathologies, such as mental illnesses or personality disorders. As such, PD may be a relevant candidate for building up a therapeutic Internet network.

Thus, ubiquitous mobile internet connectivity and a variety of sensor devices open the opportunity to continuously assess the health state between visits to a doctor in patients with such long-term, or even life-long conditions, as arterial hypertension, diabetes and neurodegenerative diseases.

VI. Smart Space Based Design

Let us discuss possible solutions that support development of a SCMS providing information services with such generic properties of services in smart spaces as adaptation, context-awareness, personalization, and proactive delivery [7].

The M3 architecture (multidevice, multivendor, multidomain) enables concept development of smart spaces to host advanced service-oriented applications, including various cyber-physical systems [8]. A particular open source platform is

[1]https://play.google.com/store/apps/details?id=com.fix.reaction
[2]https://play.google.com/store/apps/details?id=com.waitnow.waitnow
[3]https://play.google.com/store/apps/details?id=belkas.reactiontest

Smart-M3 [9]. It provides an open source technology, which can be used in many application domains. Semantic information broker (SIB) is a central element. To collect information content the SIB provides an RDF-based knowledge base, which implements an RDF triplestore with support for information search and processing extensions. The RDF representation leads to interoperable information sharing. In the studied SCMS case, the RDF representation straightforwardly leads to a semantic network in the form of RDF graphs [34].

Agents directly communicates with their SIB to access the smart space content. In the simples case, read and write operations allows collecting and sharing the content (RDF triples are basic data unit). The subscription operation enables indirect cooperation of agents when one agent can detect changes in the shared content. The Smart-M3 term “knowledge processor” (KP) makes distinguishing for this class of software agents from the general term in multi-agent systems and agent-based communication. That is, KPs target asynchronous collective knowledge generation and utilization via information sharing and semantic relations.

The smart spaces based methods follow the design principles listed below [4].

Principle of information hub: An IoT environment has a knowledge base to create the smart space with ontological models to describe semantic representation of involved participants, service construction processes, and available resources.

Principle of external resources: External resources are accessible in the smart space using two models: (a) ontological model to virtualize the external resource and its operation and (b) agent-based model to define mediation activity of a KP assigned to operate with the external resource.

Principle of information-driven programming: Service construction applies an agent-based interaction model over the shared information where each KP operates in the following loop of information detection and reaction: (a) detect a given knowledge fact in the smart space and (b) make an appropriate reaction with production of new information and its (partial) publication in the smart space to share with other participants.

Based on these principles, our vision of the smart space based design is shown in Fig. 2. The information hub principle provides information localization when no need to deal with all available data in one giant storage. The external resources principle allows operation with many external data sources by virtualizing and semantically integrating them into the semantic network. Following the information-driven principle, the coordination in a smart space is based on reacting on observations in the shared, semantically-linked, and cooperatively-generated information.

The information hub stores and operates with heterogeneous data objects. The ontological description of each object is different from the other. Ontologies may be successfully linked to a common semantic network for building general trends and personalized recommendations

A number of ontologies exist to describe subjective measurements. Schedule a diet can bedefined using Food Ontology[35] built as an extension of widely used standardised ontology for products. In [19] the ontology of the survey is described. The semantic web survey uses Questionnaire and Feedback objects. Questionnaire object contains links to Question objects, Answer and Answer items objects, networked in the corresponding sequence. This storage variant is useful when semantic network contains one or a small number of questionnaires with rarely changing elements. In this case questionnaires are quite stable and do not carry a serious impacts on the hub. All questionnaire objects storage also gives the opportunity to use part of it separately or select the questions in some respects.

On the other hand this may lead to a large number of operations over the hub. It is possible to save objects, which stores objects described questions, answers, and answer items, by using external resource. Questionnaire object and link to the external resource are contained in hub. External resources is presented in a medical institution server. This makes it possible to simplify the procedure for the appointment of questionnaires to patient and store a large number of surveys in the hub.

Feedback object is an object that represents a particular patient responses. Links between the objects of survey questions and the patient’s responses are defined to match what question has been answered. Since the patient can fill out the questionnaire with some intervals it is not necessary to keep all Feedback objects in the hub. In this case, the storage of Feedback object and links to patient’s responses on external resources is suitable.

Objective measurements and also context information are obtained from wearable devices. These objects can be defined by using the Semantic Sensor Network ontology[36]. The SSN ontology describe sensors in terms of capabilities, measurement processes, observations and deployments. Another variant is to store device’s measurements in the terms of physical parameters[37].

Although the data come from multiple sources, the semantic layer does not operate directly with big numerical or lengthy flow data. Long time series as well as other massive data are stored in dedicated information systems. For accessing additional information the object provides references to appropriate information systems.

Consequently, traditional analysis of individual time series of a patient can be performed at the specialized backend servers. In turn, the result can be used to update the semantic network, i.e., supporting its knowledge evolution. For example, personalized recommendations on motional activity are associated with the patient in an adaptive style.

In addition, combined multi-person analysis is possible. For instance, searching similar time series among different patients can be performed at the backend servers.

Measurements interpretation storage is more relevant to the doctor’s needs. In [38] Symptom ontology is proposed. Included among these characteristics are 1) a hierarchy of common symptoms, 2) clear associations between specific symptoms and the axioms of the languages they violate and 3) a means for relating individual symptoms back to the specific constructs. Matching patients answers to Symptoms makes possible to trace the dynamics of specific symptom changes. Number of symptoms describes disease and therefore Symptom object has a casual relation with Disease object. The

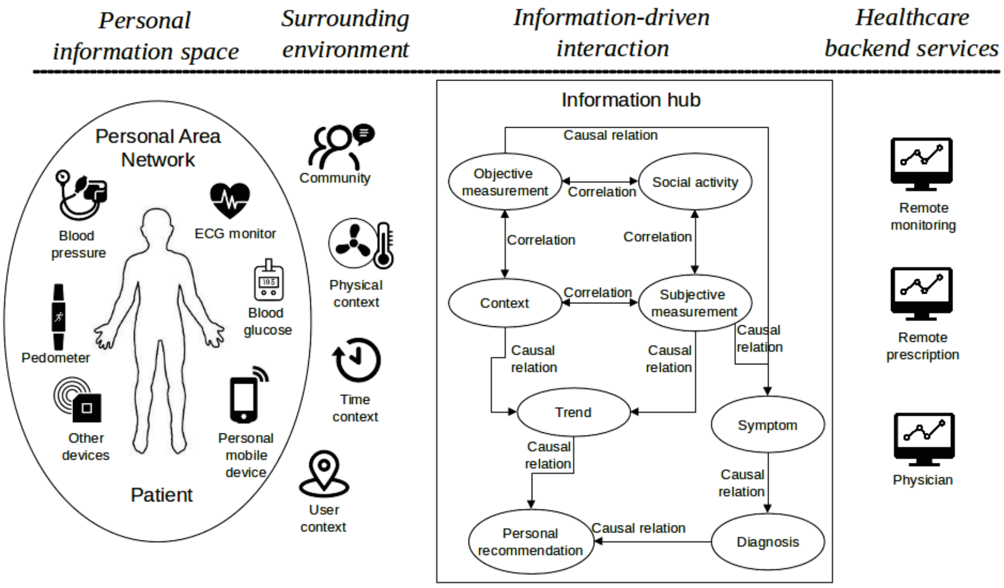

Fig. 2. Smart space based design for connecting a remote patient to the system

repeated measurenments of group of patients in same context identifies trends, it is a casual relation too. So objective and subjective measurenments may be synchronized by times (it is a variant of correlation link) and transmit aggregated data to Sympom object.

Diseases ontology is also represented in [39]. The DO is an open source ontological description of human disease, organized from a clinical perspective of disease etiology and location.

That is, the semantic layer enables representation of person-to-person relationships. Similarly, the measurements can also be related with other available information, e.g., patient profiles and medical notes from physicians [40].

This heterogeneous fragmented corpus, which is structured in the form of a semantic network, can be further semantically interlinked to support knowledge reasoning. The known effective technology for representing such semantics is RDF from Semantic Web. In this case, establishing a relation becomes a simple act of publishing few RDF triples. In particular, the M3 architecture and its realization in the Smart-M3 platform can be employed for the above construction of the semantic layer with a semantic network and operations over it.

VII. Conclusion

This paper discussed the role of semantic approach to service development for socio-cyber-medicine systems. We introduced the semantic layer where all system-related objects, either real or informational, are virtualized in the smart space in the form of a semantic network. The latter relates the virtualized objects to represent their semantics. As a result, many advanced services can be constructed using semantic algorithms that analyze (and evolve) this network.

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References

[1] S. M. R. Islam, D. Kwak, M. H. Kabir, M. Hossain, and K. S. Kwak, "The internet of things for health care: A comprehensive survey," *IEEE Access*, vol. 3, pp. 678–708, 2015.

[2] E. Balandina, S. Balandin, Y. Koucheryavy, and D. Mouromtsev, "IoT use cases in healthcare and tourism," in *Proc. IEEE 17th Conf. on Business Informatics (CBI 2015)*, vol. 2, Jul. 2015, pp. 37–44.

[3] N. Majedi, M. Naeem, and A. Anpalagan, "Telecommunication integration in e-healthcare: Technologies, applications and challenges," *Trans. Emerg. Telecommun. Technol.*, vol. 27, no. 6, pp. 775–789, Jun. 2016.

[4] D. G. Korzun, "Internet of things meets mobile health systems in smart spaces: An overview," in *Internet of Things and Big Data Technologies for Next Generation Healthcare*, ser. Studies in Big Data, C. Bhatt, N. Dey, and A. S. Ashour, Eds. Springer International Publishing, 2017, vol. 23, pp. 111–129.

[5] H. Demirkan, "A smart healthcare systems framework," *IT Professional*, vol. 15, no. 5, pp. 38–45, Sep. 2013. [Online]. Available: http://dx.doi.org/10.1109/MITP.2013.35

[6] H. Alemdar and C. Ersoy, "Wireless sensor networks for healthcare: A survey," *Computer Networks*, vol. 54, no. 15, pp. 2688–2710, Oct. 2010. [Online]. Available: http://dx.doi.org/10.1016/j.comnet.2010.05.003

[7] D. Korzun, "Service formalism and architectural abstractions for smart space applications," in *Proc. 10th Central & Eastern European Software Engineering Conference in Russia (CEE-SECR 2014)*. ACM, Oct. 2014, pp. 19:1–19:7.

[8] S. Balandin and H. Waris, "Key properties in the development of smart spaces," in *Proc. 5th Int'l Conf. Universal Access in Human-Computer Interaction (UAHCI '09). Part II: Intelligent and Ubiquitous Interaction Environments, LNCS 5615*, C. Stephanidis, Ed. Springer-Verlag, Jul. 2009, pp. 3–12.

[9] J. Honkola, H. Laine, R. Brown, and O. Tyrkkö, "Smart-M3 information sharing platform," in *Proc. IEEE Symp. Computers and Communications (ISCC'10)*. IEEE Computer Society, Jun. 2010, pp. 1041–1046.

[10] A. J. Jara, M. A. Zamora-Izquierdo, and A. F. Skarmeta, "Interconnection framework for mHealth and remote monitoring based on the Internet of Things," *IEEE Journal on Selected Areas in Communications*, vol. 31, no. 9, pp. 47–65, Sep. 2013.

[11] D. Korzun, I. Nikolaevskiy, and A. Gurtov, "Service intelligence and communication security for ambient assisted living," *International Journal of Embedded and Real-Time Communication Systems (IJERTCS)*, vol. 6, no. 1, pp. 76–99, 2015.

[12] F. Vergari, T. S. Cinotti, A. D'Elia, L. Roffia, G. Zamagni, and C. Lamberti, "An integrated framework to achieve interoperability in person-centric health management," *Int. J. Telemedicine Appl.*, vol. 2011, pp. 5:1–5:10, Jan. 2011. [Online]. Available: http://dx.doi.org/10.1155/2011/549282

[13] G. Acampora, D. J. Cook, P. Rashidi, and A. V. Vasilakos, "A survey on ambient intelligence in healthcare," *Proceedings of the IEEE*, vol. 101, pp. 2470–2494, Dec. 2013.

[14] O. Nee, A. Hein, T. Gorath, N. Hulsmann, G. B. Laleci, M. Yuksel, M. Olduz, I. Tasyurt, U. Orhan, A. Dogac, A. Fruntelata, S. Ghiorghe, and R. Ludwig, "SAPHIRE: intelligent healthcare monitoring based on semantic interoperability platform: pilot applications," *IET Communications*, vol. 2, no. 2, pp. 192–201, 2008.

[15] G. Acampora, D. J. Cook, P. Rashidi, and A. V. Vasilakos, "Data analytics for pervasive health," in *Healthcare Data Analytics.*, C. K. Reddy and C. C. Aggarwal, Eds. Chapman and Hall/CRC, 2015, pp. 533–576.

[16] P. N. Dawadi, D. J. Cook, and M. Schmitter-Edgecombe, "Automated cognitive health assessment from smart home-based behavior data," *IEEE Journal of Biomedical and Health Informatics*, vol. 20, no. 4, pp. 1188–1194, July 2016.

[17] D. Riaño, F. Real, J. A. López-Vallverdú, F. Campana, S. Ercolani, P. Mecocci, R. Annicchiarico, and C. Caltagirone, "An ontology-based personalization of health-care knowledge to support clinical decisions for chronically ill patients," *J. of Biomedical Informatics*, vol. 45, no. 3, pp. 429–446, Jun. 2012.

[18] A. Valls, K. Gibert, D. Sánchez, and M. Batet, "Using ontologies for structuring organizational knowledge in home care assistance," *International Journal of Medical Informatics*, vol. 79, no. 5, pp. 370–387, 2010.

[19] A. V. Borodin and Y. V. Zavyalova, "An ontology-based semantic design of the survey questionnaires," in *Proc. 19th Conf. Open Innovations Association FRUCT*, S. Balandin and T. Tyutina, Eds., Nov. 2016, pp. 10–15.

[20] U. Varshney, "Mobile health," *Decis. Support Syst.*, vol. 66, no. C, pp. 20–35, Oct. 2014.

[21] J. Bravo, D. J. Cook, and G. Riva, "Ambient intelligence for health environments," *Journal of Biomedical Informatics*, vol. 64, pp. 207–210, 2016.

[22] I. A. C. Giglioli, F. Pallavicini, E. Pedroli, S. Serino, and G. Riva, "Augmented reality: A brand new challenge for the assessment and treatment of psychological disorders," *Comp. Math. Methods in Medicine*, vol. 2015, pp. 862 942:1–862 942:12, 2015.

[23] D. Celik, "Foodwiki: Ontology-driven mobile safe food consumption system," *The Scientific World Journal*, vol. 2015, 2015.

[24] A. Borodin, Y. Zavyalova, A. Zaharov, and I. Yamushev, "Architectural approach to the multisource health monitoring application design," in *Proc. 17th Conf. of Open Innovations Association FRUCT*. ITMO University, Apr. 2015, pp. 36–43.

[25] M. Baldauf, S. Dustdar, and F. Rosenberg, "A survey on context-aware systems," *Int. J. Ad Hoc Ubiquitous Comput.*, vol. 2, no. 4, pp. 263–277, 2007.

[26] V. Cristea, C. Dobre, and F. Pop, *Internet of Things and Intercooperative Computational Technologies for Collective Intelligence*. Springer Berlin Heidelberg, 2013, ch. Context-Aware Environments for the Internet of Things, pp. 25–49.

[27] C. Perera, A. Zaslavsky, P. Christen, and D. Georgakopoulos, "Context aware computing for the Internet of Things: A survey," *IEEE Communications Surveys Tutorials*, vol. 16, no. 1, pp. 414–454, Feb. 2014.

[28] A. Kashevnik and N. Teslya, "Context-aware access control model for smart-m3 platform," in *Proc. 13th Conf. of Open Innovations Association FRUCT and 2nd Seminar on e-Tourism for Karelia and Oulu Region*, S. Balandin and U. Trifonova, Eds. SUAI, Apr. 2013, pp. 42–52.

[29] S. Sneha and U. Varshney, "Enabling ubiquitous patient monitoring: Model, decision protocols, opportunities and challenges," *Decis. Support Syst.*, vol. 46, no. 3, pp. 606–619, Feb. 2009.

[30] O. Kolesnichenko, A. Mazelis, A. Nikolaev, L. Mazelis, and S. Balandin, "ipatient in medical information systems and future of internet of health," in *Proceeding of the 20th Conference of Open Innovations Association FRUCT, Helsinki, Finland*, 2017.

[31] M. H. Dye, L. J. Ducharme, J. A. Johnson, H. K. Knudsen, and P. M. Roman, "Modified therapeutic communities and adherence to traditional elements," *Journal of psychoactive drugs*, vol. 41, no. 3, pp. 275–283, 2009.

[32] W. Vanderplasschen, K. Colpaert, M. Autrique, R. C. Rapp, S. Pearce, E. Broekaert, and S. Vandevelde, "Therapeutic communities for addictions: a review of their effectiveness from a recovery-oriented perspective," *The Scientific World Journal*, vol. 2013, 2013.

[33] G. De Leon, "Is the therapeutic community an evidence-based treatment? what the evidence says," *Therapeutic communities*, vol. 31, no. 2, p. 104, 2010.

[34] C. Gutierrez, C. A. Hurtado, A. O. Mendelzon, and J. Pérez, "Foundations of semantic web databases," *J. Comput. Syst. Sci.*, vol. 77, no. 3, pp. 520–541, May 2011.

[35] M. Kolchin and D. Zamula, "Food product ontology: Initial implementation of a vocabulary for describing food products," in *Proceeding of the 14th Conference of Open Innovations Association FRUCT, Helsinki, Finland*, 2013, pp. 11–15.

[36] M. Compton, P. Barnaghi, L. Bermudez, R. GarcíA-Castro, O. Corcho, S. Cox, J. Graybeal, M. Hauswirth, C. Henson, A. Herzog *et al.*, "The ssn ontology of the w3c semantic sensor network incubator group," *Web semantics: science, services and agents on the World Wide Web*, vol. 17, pp. 25–32, 2012.

[37] F. Paganelli and D. Giuli, "An ontology-based system for context-aware and configurable services to support home-based continuous care," *IEEE Transactions on Information Technology in Biomedicine*, vol. 15, no. 2, pp. 324–333, 2011.

[38] K. Baclawski, C. J. Matheus, M. M. Kokar, J. Letkowski, and P. A. Kogut, "Towards a symptom ontology for semantic web applications," in *International Semantic Web Conference*. Springer, 2004, pp. 650–667.

[39] L. M. Schriml, C. Arze, S. Nadendla, Y.-W. W. Chang, M. Mazaitis, V. Felix, G. Feng, and W. A. Kibbe, "Disease ontology: a backbone for disease semantic integration," *Nucleic acids research*, vol. 40, no. D1, pp. D940–D946, 2012.

[40] K. D. Mandl, J. C. Mandel, S. N. Murphy, E. V. Bernstam, R. L. Ramoni, D. A. Kreda, J. M. McCoy, B. Adida, and I. S. Kohane, "The SMART platform: early experience enabling substitutable applications for electronic health records," *Journal of the American Medical Informatics Association*, vol. 19, no. 4, pp. 597–603, Jul. 2012.