Multi-Source Data Sensing in Mobile Personalized Healthcare Systems: Semantic Linking and Data Mining

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***Abstract*—The paper introduces an approach to collecting and mining health-related information on the patient based on sensed data from various medical devices as well as from other digitally-enabled sources. The regularly sensed data are semantically linked thus creating an additional information space—semantic layer. On the latter, a linked knowledge-rich structure—semantic network—is maintained and used to construct mobile services. The use of various medical devices and other data sources makes it possible to remotely monitor patients' vital physiological parameters and other important health-related events. It includes sensing the context of the physical environment, which is then coupled with the health state of the patient. Several patients and interested people can be virtually integrated into a group. Consequently, social methods can be used for enhancing the treatment adherence and for motivating the healthcare goals. As such, the healthcare services would have became more focused on the patients and their needs. Ultimately, the mobile healthcare moves towards the vision of At-Home Laboratory (AHL) that diminishes the necessity to visit the hospital and to directly use its facility.**

I. Introduction

The traditional style of healthcare is based on visiting a hospital or clinic to meet a doctor face-to-face and to pass through certain monitoring and analysis procedures using the professional medical equipment and direct expertise. This form of healthcare operation is expensive [1]. To make the operation more effective, continuous health monitoring and use personal analysis of the critical health parameters can be established for the remote patients. This demand drives the development of new approach to healthcare called mobile health or mHealth [2], [3].

Artificial intelligence (AI) is widely considered as a kind of a machine system that adopts human-like behavior and provides functions attributable to human intelligence (HI). Similarly to the basic human's brain ability the knowledge development is carried out by fusing the information obtained from the environment with the already accumulated knowledge [4]. This paper continues our earlier work [5], [6], in which we regarded AI as the mainstream of human brain evolution.

Modern AI methods employ Ambient Intelligence (AmI) environments [7]. Such an environment is digitalized using many embedded, mobile, and multimedia devices. In cooperation they construct services to support the people, including healthcare support [8]. This form of digital support is especially needed for elderly and disabled people. We focus on the existing opportunities of AmI environments for creating the personalized AmI-based support as At-Home Laboratory (AHL) in human everyday life [9], [10].

Our main contribution is shaping an approach to collecting and mining health-related information on the patient based on multi-source sensed data from various medical devices, which accompany the patient in her/his everyday life. Use of various medical devices and other data sources enables remote monitoring of patients' vital signs. The sensed context of the physical environment is associated with it the health state of the patient. In particular, we emphasized the role of video data, which can be used in advanced mobile healthcare services for AHL [11], [12].

The regularly sensed data are semantically linked on the semantic layer. This linking forms a knowledge-rich structure like a semantic network. This model leads to wide range of semantic methods of data mining. Furthermore, several patients can be virtually integrated into a social group that would have strongly enhanced their treatment adherence and motivated reaching their desire for health. As such, we propose linking all available valuable information into a semantic network. Also, applying the data mining methods creates new digital opportunities for health monitoring, treatment, and improvement of quality of life.

The introduced approach to collecting and mining health-related information on the patient the following beneficial properties. First, the system is patient-centric such that its services augment the patient's vision on the healthcare processes, thus motivating and accelerating. Second, the system provides a digital tool to physicians and other "supporting" people (e.g., relatives, friends) to control the healthcare processes, thus increasing the usability and comfort. Third, the system makes easier and more transparent human participation in the healthcare processes, thus making patients and physicians closer and more collaborative.

The rest of the paper is organized as follows. Section II provides an overview of mobile personalized healthcare services developed using modern information and communication technology. Section III considers the mobile sensing problem when description and the patient health status needs many data sources to analyze. Section IV describes the proposed concept model for mobile personalized healthcare systems

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based on multiple layers of data processing and knowledge reasoning. Section V discusses possible methods of semantic data mining when the data are collected from many sources and the semantics is represented as interlinked and converged structure. Section VI summarizes our current results.

II. Mobile Personalized Healthcare Services

Operation of the traditional healthcare is essentially restricted to time and space [1], [13]. Basically, a patient has to visit a doctor at hospital or clinic for direct clinical and instrumented examination. Professional medical equipment is used. However, the progress of information and communication technologies (ICT) provide new digital opportunities to overcome such traditional style of the patient–doctor interaction [2], [3].

The progress in applying Internet of Things (IoT) technologies for advanced healthcare operation leads to digital fusing the real (physical) and cyber (information) worlds [6]. The social world also plays an important role in this fusion. The fusion of these three worlds leads to data interconnection and convergence. As a result, new generation of mobile healthcare services appears. Such services can be constructed by numerous physical and virtual entities (as in any cyber-physical system). Users (patients and medical personnel) are usually mobile and distributed, so the space restriction is not valid anymore. Data sensing and processing are automated and delivered to the users as information services. The provided information (as a service) is a result of processing based on data mining algorithms [14] and AmI methods [7], [8]. An important particular example of such service can be designed as a recommendation service that supports human activity when some cognitive function is degrading [10].

In many ICT applications for healthcare, the user merely consumes the provided information services. In advanced scenarios, the users are motivated to more active participation [3], including provision of own resources to construct such services (e.g., expertise, decision-making). However, being human (not a machine) the users, along with opportunities, become loaded with responsibility for data computation and knowledge generation. A kind of human–machine system is used in healthcare operation [6]. For instance, a patient is interested not only in 1) consuming recommendation to follow healthcare prescriptions but also in 2) making decisions when such recommendations are constructed and 3) how they then are implemented. Such involvement of the human user into the service construction process presumably guarantees the proper personalization of the service.

Another advancing is transparent involvement of the human users and their motivation to collaboration, i.e., evolution of healthcare services towards a social system [6]. There are many people-to-people relations, both on inter-individual and inter-group level. This kind of social semantics and resources can also be used in construction of information services. The user community shares certain control on the system with the opportunities of social networking and collaborative work [15]. In particular, such information in the social world as valuable opinions from other people can be effectively used in service construction, in service consumption, and in motivation of the patient to consume the service.

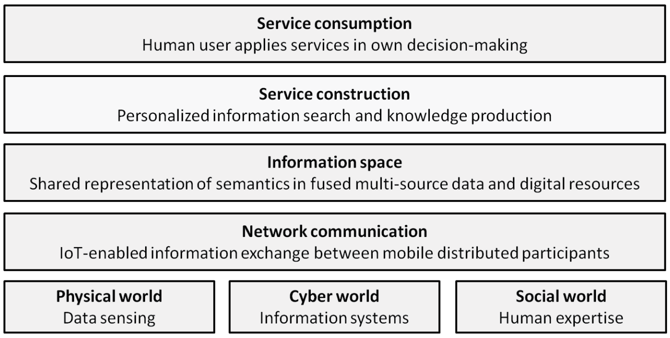

Fig. 1. Mobile personalized services based on multi-source data sensing

In contrast to more traditional digital control services (used for operation with medical equipment, e.g., an implanted insulin pump), an information service additionally provides analytical support or information assistance. In a way, the service substitutes some mere technical (data processing and analysis) function of HI, i.e., human can implement these functions but the task can be well delegated to AI methods. For instance, a patient receives a recommendation to reduce the physical activity and have some rest.

Conceptually, an information service derives some information fragment that is appropriate to the user in her/his current situation, see Fig. 1. The user can appear as either a patient, doctor, or another interested participant. The user applies the provided information, so focusing rather on the required situational decision-making, not on searching all appropriate information for the decision-making. Such decision and its quality clearly depends on the following factors:

- the information the service produces,
- the intelligence function the human user applies when using the information.

Note that the leading role of human is not diminished or eliminated at all. Human has to make healthcare decisions while a certain part of information analysis is automated.

Mobile healthcare services are constructed within digital environments created based on Internet of Things (IoT) technology [2], [3]. Such an environment is associated with a physical spatial-restricted place with a variety of devices (embedded or worn 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 effective ground for applying AI methods and the results are consumed in the form of information services. In particular [16], AmI makes people empowered through various digital tools embedded in the surrounding environment or carried/worn 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 sense of IoT). These tools implement services that are sensitive, adaptive, and responsive to each individual's needs, habits, gestures, and emotions. For instance, psychiatrists and psychologists can use augmented and virtual reality to improve the efficacy of available treatments for anxiety disorders, nutrition or weight disorders, and pain management [17]. Such services are mobile, executed beyond the traditional clinical settings, and improving the daily experiences of the patients.

An excellent example of such a service is the first aid assistance service [18]. It supports interaction of various participants of first aid treatment (patient, volunteers, remote physicians). Some people nearby (volunteers) can provide first aid to the patient in the case of emergency, i.e., before arrival of qualified medical personnel. Personal medical devices are used to collect digital recordings of biosignals and to make its processing. A volunteer can apply questionnaire for observable patient's health state. Based on the remotely provided information, the physician (distantly located) can estimate the symptoms more comprehensively, make diagnosis, and assist the volunteer on the first aid operation.

This example shows the use of multiple data sources for the service construction. The data are sensed from different worlds—physical, cyber, and social. Digital data fusing is an inevitable step in development of mobile personalized healthcare services. We expect that semantic linking can be used to relate the multitude of information objects and events from these three worlds.

III. MULTI-SOURCE DATA SENSING

In several studies, the most informative and reliable parameters on human health were identified and discussed. For example, Lara *et al.* [19] proposed more than 25 parameters for healthy ageing, grouped by 15 functions of 5 systems of organs. Normal values of these parameters tell about normal Ageing Phenotype with good perspective for longer and healthier ageing. Of these parameters, as much as 10 could be evaluated by means of mobile devices. For example, speed of gait, walking endurance, chair rising, body balance, Timed Up and Go test (function of locomotion), standing balance, manual dexterity, tapping test and reaction time (motor and cognitive functions), heart rate (cardiovascular system). In future, such biochemical metrics as blood glucose and lipids, and also memory tests, manual dexterity and coordination, execution tests, measures audition, vision, oxyhaemometria, and even measuring of olfaction and pain could be performed with tablets and mobiles.

In Cooper *et al.* [20] again, walking speed, standing balance, hand grip and chair rising are indicated as the most informative of physical capability and predictive of fractures (falling), cognitive decline and cardiovascular disease. These parameters have already been assessed by mobile devices. In particular, Kemp *et al.* [21] implemented this idea in a toolkit for the assessment and monitoring of musculoskeletal ageing, which includes biochemical and functional assessments of bone and muscle function.

As we have shown in our previous work [3], [15], [6], [10], semantic linking can be implemented using the smart space approach. The semantic network model is applied to interrelate large, heterogeneous, and fragmented data from the physical, cyber, and social worlds. For mobile personalized healthcare services the semantics from the following classes of data sources are important for representation in the semantic network.

Subjective measurements: The patient provides information about her/himself. A typical way is using surveys or questionnaires. In the active form, the medical personnel can make such a survey when directly communicating with the patient. In the passive form, the patient provides information without explicit coupling in space or time with medical personnel. Although the data come from a single person the multi-source property still exists. Such measurements are separated by topics (about a particular health component) and by time (initiated in a particular situation).

Formally, let us consider an object for survey based on the finite features or tags. Each feature is evaluated with a value. The information representation model is

$$Q = (f_1, f_2, \dots, f_n),$$

where Q denotes the object and f_i characterizes the state for $i = 1, 2, \dots, n$. For instance, the patient can provide evaluation of her/his mood in dependence on the day time

$$\mathsf{mood} = (\mathsf{morning}, \mathsf{day}, \mathsf{evening}, \mathsf{night}),$$

the amount of food the patient consumed today

$$\mathsf{food} = (\mathsf{vegetable}, \mathsf{meat}, \mathsf{fruits}, \mathsf{milk})$$

Objective measurements: Medical sensors provide physiological data for evaluation of patient's health parameters, either vital or supplementary ones. For instance, an electrocardiography (ECG) sensor provides $150 \dots 300$ values per second continuously during $12 \dots 28$ hours. Another example of personal medical sensors is blood glucose sensors and blood pressure sensors. The patient motion can be monitored using accelerometers, e.g., embedded into such personal mobile devices as smartphones.

Formally, let us treat each data source as time series, i.e., a sequence of measurements made over time. At time t, an n-tuple X_t can be evaluated, where X_{it} is numerical estimation of component i. One (or more) component corresponds to measured data (e.g., sensed value or its short-window average). The other components are derived attributes (e.g., timestamp, moving average, regression value). For simple discrete time evolution we consider

$$X_1, X_2, \dots, X_t, \dots$$

For instance, the patient's heart state can be represented with following components

$$\mathsf{heart}_t = (\mathsf{rate}, \mathsf{average}, \mathsf{risk})^{\mathsf{T}},$$

thus keeping the current rate value, moving average, and estimation of the risk level (e.g., by counting the share of high heart rate values in the latest 1-hour observations).

Context information: Recent situation around the patient is characterized based on various IoT devices in the surrounding environment. The following context is considered in respect to healthcare services.

- User context: user profile, geo-location, social status.
- Physical context: parameters of the surrounding environment.
- Time context: time of a day, week, month, season, etc.

Formally, each type of the context can be described as an ontology class C with finite number of attributes. Each instance $c \in C$ represents a context information fragment. The information is updated over time.

Social resources: The patient can be supported with resources from other people, in addition to the professional medical support from physicians. First, it improves the motivation for the patient to follow the treatment and other healthcare or wellbeing recommendations. In particular, activity within a group of patients allows sharing experience between the patients. Second, the patient lives in a community, and its members (e.g., relatives, friends, volunteers) can provide essential help for personalized healthcare.

Much information can be extracted from the above data sources. For the integrative representation the semantic network model can be used. The semantic network is defined as directed graph $G = (V, L)$. Nodes $v \in V$ represent patient-related objects (e.g., data source, disease, health status). Links $l \in L$ represent relations between objects (e.g., data source confirms the disease). The graph G is multi-weighted using a set of functions F such that for $f \in F$ some weight value $f(x)$ is associated with a given node or link x. Subgraphs in G (typically connected structures) correspond to particular knowledge by interpreting as facts or events (e.g., occurrence of the disease and its progress level).

IV. Smart Space as Semantic Network

The layered structure in Fig. 1 can be realized based on the smart spaces approach [3]. The high-level view on the proposed concept model of patient's smart space is shown in Fig. 2. For the given patient her/his smart space is created that implements the following service-oriented actions.

1) Assisting the patient with mobile personalized services based on devices in the surrounding environments.
2) Providing the access to resources in remote parts of the physical, cyber, and social worlds, e.g., to healthcare backend services located in hospital.
3) Supporting the human intelligence functioning based on semantic linking together numerous physical, social, and virtual objects and data mining over this semantic network.

In the smart space concept model, computational participants are represented by software agents running on the devices and acting on behalf of human users and their needs in automated information search and knowledge processing. They collect information derived from multiple data sources, represent discovered semantics for resource sharing, and interact over this shared information and resources to cooperatively construct required services.

This way of constructing services is focused on the users [22]. Services support personalization—the service providers and users interact to create a value such that the service construction and delivery continuously adjust to user's individual and constantly changing needs. The following classes of mobile personalized healthcare services can be constructed within the proposed concept model of smart space.

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 information for making decisions.
4) Advanced detection of patient status deviations based on multisource data analytics.

To implement such services, the semantic network is applied as a virtual distributed workspace with many mobile users. In this network the knowledge can be individually or cooperatively acquired, applied, and evolved by both medical personnel and patients. The semantic network integrate multi-source data by connecting multiple fragments (links in the semantic network). Virtual counterparts to physical components are created (nodes in the semantic network), acting similarly as smart IoT objects. To construct services data mining is used based on analysis of the connection structure of the semantic network.

The semantic network $G = (V, L)$ collects and represents information based on domain-specific ontological model [6]. In semantic network $G = (V, L)$, the set V consists of objects (parameters, facts, and other instances of classes define in the ontology), whereas the set L consists of links (v, w) that represent particular semantic relations between objects $v, w \in V$. Possible types of relations are also defined in the ontology.

Formally, the ontology describes a system of concepts $\{C_i\}_{i=1}^n$ (ontology classes) such that any particular node $v \in V$ (ontology class object, instance or individual) belongs to one or more concepts. The ontology describes the interlinking structure for L, i.e., between which concepts a relation can be and possible types of such relations. The links represent the primary semantics. The ontology describes attributes that $v \in V$ and $l \in L$ may have to reflect additional semantics (e.g., keywords).

V. Semantic Data Mining

Development of mobile personalized healthcare services can employ data mining methods for constructing recommendations. The generic recommendation construction scheme for use in smart spaces is derived from [18], see Fig. 3.

Semantic data mining methods are used to analyze the created and evolved semantic network. Analysis results are used to construct recommendations. The construction is based on searching appropriate information and selecting the most interesting facts to provide to the patient. Formally, the service needs to find $k > 0$ the most appropriate information facts. A fact can be a node $v \in V$, a link $l \in L$, or a connected graph structure s in G (e.g., a path from u to v can have healthcare-valued interpretation for some $u, v \in V$).

The selection is reduced to the ranking problem, which can be used in various smart spaces applications [23]. Basically, a rank value $r_v \geq 0$ can be associated with any object $u \in V$. This data mining can be reduced to the ranking problem when rank values $r_v \geq 0$ or $r_l \geq 0$ are associated with nodes or links. The higher rank the better is appropriateness of

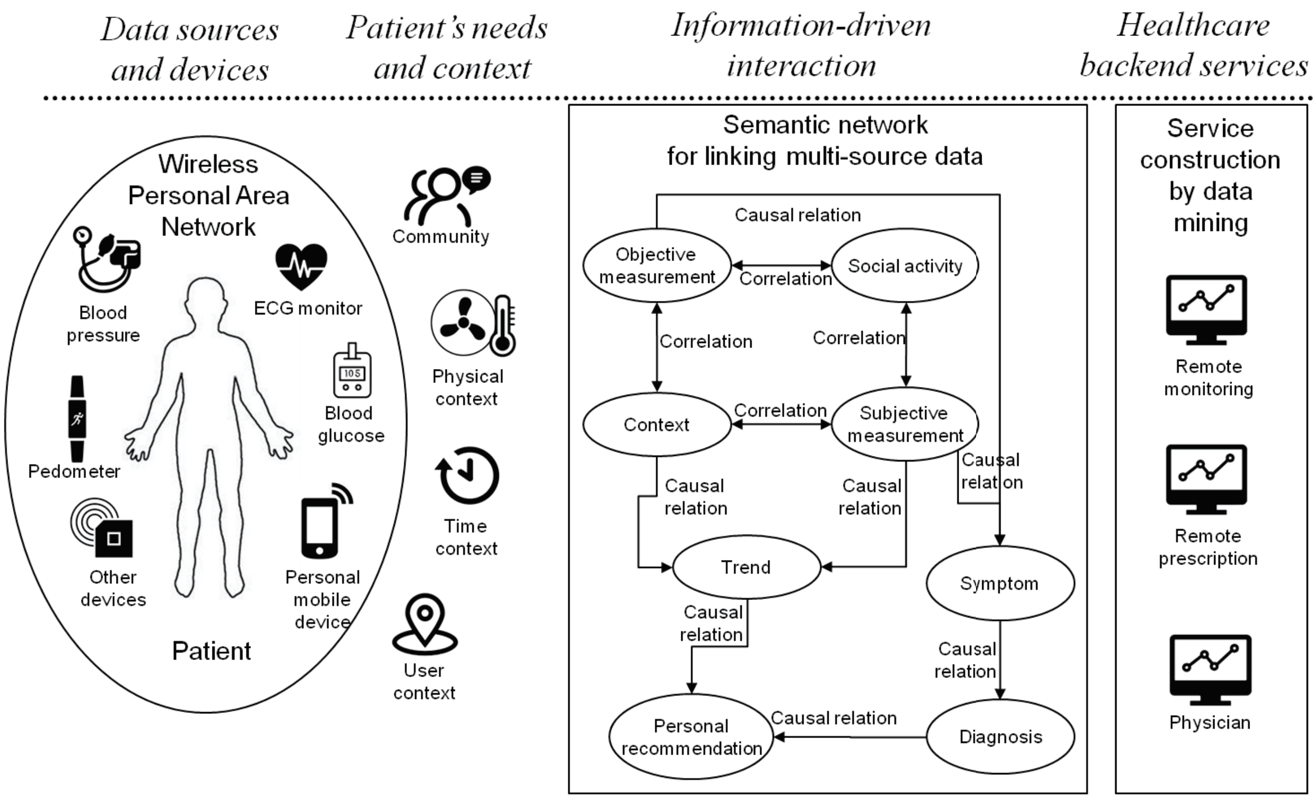

Fig. 2. Smart space created around the patient

the information. The rank of a connected graph structure is calculated based on ranks of the composed nodes and links. We consider three techniques for this kind of ranking.

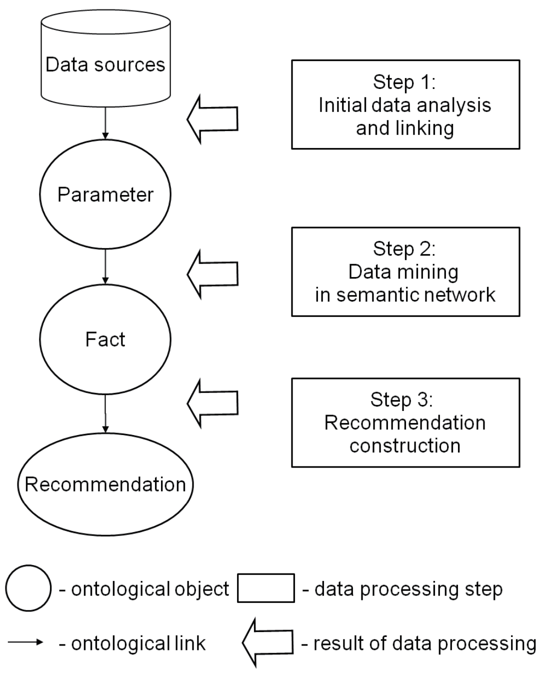

Fig. 3. Recommendation construction scheme

Individual ranking: Rank r_v is computed based primarily on the informational content of v and/or its neighbors in the semantic network. In particular, a recommendation is constructed from the most ranked objects.

Local ranking: Two or more objects are analyzed for similarity based on their content and overlapping of this content. The rank is computed to reflect some semantic distance $\rho(u, v)$ between the given object u and all other objects v:

$$r_v(u) = 1/\rho(u, v).$$

That is, u is selected by some condition and then a recommendation is constructed from the semantically closest objects (semantic neighborhood).

Structural ranking: The global linkage structure of semantic network is used for computing the ranks, similarly as it happens in the PageRank algorithm for web pages. Ranks r_v for all $v \in V$ are computed iteratively starting from some initial values $r_v^{(0)}$:

$$r_v^{(i+1)} = \alpha \sum_{\forall w: v \to w} p_{wv} r_w^{(i)} + (1 - \alpha)\pi_v,$$

where $v \to w$ is a link in G, p_{vw} is the weight of the link, α is the damping factor denoting the probability of following the link structure, and π is a personalization vector of damping factors for all objects.

VI. Conclusion

The paper described an approach to collecting and mining health-related information on the patient based on mobile multi-source sensed data from various medical devices. The concept of mobile personalized healthcare systems is described with emphasis on the use of progressing ICT. The problem of mobile multi-source data sensing for patient health parameters is considered in respect to hidden semantics in this multitude of data as a whole. The multi-layer concept for the generic class of mobile personalized healthcare systems is proposed in order to structure the complex operation of data processing and knowledge reasoning. Methods of semantic data mining are discussed to explain possible ways of discovering the semantics hidden in collected multi-source data.

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