Home Health Telecare: Proposal of an Architecture for Patient Monitoring and Critical Situation Detection

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***Abstract*--The development of medical remote care applications is crucial due to the general aging of the population and the likelihood of a doctor shortage in the future. This paper deals with the concept of a smart home for health care. It consists in fitting out a flat with multiple sensors and analysing their output signals closely along with other available information such as clinical data. The aim is to detect unusual situations that might give serious cause for concern. The smart home is connected to a large medical network, which provides a direct link to medical assistance in case of emergency. One of the main issues is to make a decision about the patient state so as to detect both short- and long-term critical evolutions, with a level of seriousness being associated to each detection. The complexity of the decision-making process entails building a multiple-level decision architecture. The methods and algorithms related to such a decision-making stem from pattern recognition and neural networks. Specific consideration regarding ethical, social and individual needs is also required.**

***Index Terms*--Data fusion, Decision-making, Home health Telecare, Multivariate time series analysis, Neural networks, Pattern recognition, Telemedicine.**

I. Introduction

Home health telecare concentrates on helping elderly people to remain living independently, and on enhancing their feeling of safety and security, in addition to the family and the nursing cares. The impact of real implementation of these remote monitoring systems might result in a significant decrease in the admissions to hospital, residential or nursing homes. Such systems may be particularly suited to elderly people living on their own, and more generally to people exposed to risks of motor (fall, etc.) or cognitive (depression, confusion, senile dementia, etc.) disorders, or needing specific medical care (diabetics, asthmatics, etc.).

A remote health care system is built upon a global medical information system made up of three main components: (1) a provision of automatic devices to adapt the living environment to the individual capabilities (motor and cognitive) and various sensors of different types (physiology, environment, and activity) installed and networked in the patient's home; (2) a local intelligence unit located at the patient's home and devoted to sensor-data processing, the management of a knowledge database related to the patient, and responsible for broadcasting messages and alarms; and (3) a remote control center which ensures the response in case of emergency, in addition to many actors (medical staff, the patient and their family members) involved in the health care process and allowed to access information on patients after logging in, and according to their access rights.

Experiments in remote health care systems carried out in the world are scattered and vary in their purposes and concepts. They focus either on implementing a generic architecture for the integrated medical information system, on improving the daily life of patients using various automatic devices, specific equipment, and basic alarms, or on providing health care services to patients suffering from specific diseases like asthma, diabetes, cardiac, pulmonary, or Alzheimer's. Rialle *et al.* have presented in [1] an overview of projects related to home health telecare.

The issue of patient monitoring and critical situation detection is handled in the local intelligence unit located in the home. This can be formulized as an issue of fusing and analyzing a set of data related to a patient, including: (1) data from sensors (rapid variations of values), (2) a set of clinical data (more stable values), and (3) a knowledge database comprising *a priori* information (scenarios of events, thresholds, etc.) and that is updated as the system is running.

This paper suggests a generic architecture for making a decision about the patient's status and detecting critical situations. This architecture gives rise to discussions about the parameters of the decision system, the methods for data fusion and analysis, and the short-term perspectives of research.

II. The Decision Issue

The purpose of the decision-making process is to detect, and if possible avoid, the occurrence of critical situations for a patient at home, such as falls, cardiac crisis, or in a longer-term confusion or early symptoms of depression for instance.

A. Assumptions

Home health telecare projects are as yet only at their first stages of development, and collection of data in realistic environments has just started. Therefore, knowledge about the joint evolution of parameters monitored by sensors (physiology, environment, and activity) according to the specificity of each individual patient (data from clinical records and learning tasks) could not have been acquired from experiments. Furthermore, considering a patient at home, it is inconceivable to describe all possible critical situations of any nature and level, just as we do not yet have any way of learning the occurrence of such situations (monitoring of patients getting to critical situations). This poor knowledge requires consideration of each patient individually, and to base the decision process on a very few *a priori* knowledge.

The decision-making system should then be designed for both learning and decision-making. The decision-making is partly based on information learnt as the system is running. At the early stages of an experiment, we do need to accept a high number of messages and alarms. The system should then become more reliable with a decreasing rate of false alarms as new information is included in the knowledge database.

B. Requirements

The decision system needs to fit the general purposes of monitoring: the detection of all critical situations (sensitivity) combined with a low rate of false alarms (specificity), with an acceptable detection time. As far as home health telecare is concerned, the real implementation of the decision systems raises many ethical, social, and individual issues: respect of privacy, confidentiality of data about patients, unobtrusiveness of input devices installed in the home, and improvement of patients' quality of life. Furthermore, those systems face strong economic constraints: restriction of charges being the responsibility of patients and reduction of public health costs. The individual and social acceptance of such systems depends on the how well they respect all of these requirements.

C. Formulation of the issue

The issue of deciding about the patient's health condition at home can then be formulated as the profiling of the behavior of the patient to detect critical situations by noting significant departure from this profile. Thus, the problem is quite close to anomaly detection in computer systems [2] – in this later case, the profile to build concerns a user or a program. The purpose is then to define and learn the usual values of relevant parameters to evaluate the health status of patients. A change from these usual values might signify a deterioration in health. Chan *et al.* [3] have for instance designed a system, based on infrared motion sensors, to model patients' moves – using a finite state automata – and report every suspicious behavior.

The decision problem is also related to the issue of data fusion, since the decision is made from a set of heterogeneous data (quantitative and qualitative) collected from the sensors installed in the home, the database related to the patient, and a dynamic knowledge database (background of data and events, declarative knowledge, decision thresholds, etc.).

Considering the temporal component is also critical since the chronology and distribution of events and values of relevant parameters along the time is a key element to assess the patient's health status. Furthermore, even if some events, like a fall, seem to be time-independent because they are not easily predictable, setting these events in a temporal context may be a way to get a better knowledge of their context of occurrence and, ultimately, possibly enable their prediction. It is already known that many factors play a role in the occurrence of some critical events like a fall [4].

Finally, the decision-making consists in fusing and analysing multivariate time series. These temporal sequences are actually made up of both symbolic and numeric data, considering that qualitative data are symbolised or quantified. The purpose is to find structures or extract regularities in this time series in order to learn what is a usual behaviour and to define a behavioural pattern for the patient. Any deviation from this profile is considered as a possible critical situation.

III. Suggestion of an Architecture for the Decision-Making System

A. Principles of decision-making

An interesting approach to handle complex issues of decision-making is to decompose the process in several levels of understanding or knowledge. This approach is commonly used in many decision-making processes as in the recognition of human motions from video signals [5-6] or in intrusion detection in computer systems [7]. Using a multiple-level architecture to detect critical situations is well understandable since the activity of a person at home – directly related to their health status – is often intuitively described at several levels of detail – in terms of simple actions (getting up, closing a door, etc.) and then activities (sleeping, dressing, etc.) [8-9].

A deterioration of a patient's health status usually entails behavioral disorders whose observable symptoms range from an increase in the risk of falls, slowness in executing simple actions, forgetfulness in daily activities, to a global decrease in the patient's ability to perform activities of daily living (ADL). Clinical practice has already widely exploited this correlation between, on the one hand, the behavior and autonomy of a patient and, on the other hand, their health status. The evolution of a patient's health status is frequently estimated in terms of their ability to perform ADL such as getting washed, dressing, or feeding themselves. Several projects in home health telecare [8-10] have integrated in their concept the assessment of the ADL to monitor the patient's condition.

B. Architecture of the system: a granular approach

The decision system (Figure 1) is then composed of multiple-levels of decision making corresponding to increasing levels of understanding of the patient's condition (time scale). Each stage consists of its own sub-process of decision-making, integrated within the general decision-making issue. The architecture is founded on both data provided by sensors and clinical data related to the patient. Decision-making strongly depends on the content of a learning and knowledge-related database comprising decision thresholds, history of events, etc.

Several types of messages and alarms can be generated at each time-level of monitoring, along with an associated level of seriousness (seriousness scale). They range from the detection of single critical situations (stumbling, falling, etc.) to the observation of symptoms at a larger time-scale (forgetfulness, general decrease in activity, etc.). They result from different purposes of detection in the data analysis: (1) inconsistency in data, (2) overlapping of critical thresholds, and (3) matching sequences of events known to be critical for the patient. The distance to a preset threshold or the likelihood of occurrence of a pre-defined scenario of events are typical parameters used to define the seriousness of alarms. The increasing levels of complexity considered in the architecture are described below:

(1a) Sensors: raw data, or pre-processed data in the case of "smart sensors", collected from different classes of sensors: (i) activity (location, motion, etc.), (ii) environment (use of doors, lighting, temperature, etc.), and (iii) physiology (blood pressures, weight, etc.).

(1b) Clinical data: qualitative or quantitative information related to the patient's general health status.

(2) Movements: sampled, filtered, and organized raw data, which includes to align the raw data at the same frequency, remove all possible inconsistencies and redundancies, and lastly, get sequences of movements characterized by a level of uncertainty – using either probability or fuzzy theory.

(3) Actions: key characteristics related to the patient's condition obtained by selecting relevant movements and fusing information of similar nature. The size of the set of features involved in the decision-making and the sampling frequency may be reduced. The idea is to get a finite number of types of data – actions or groups – observed along time series, each of them being associated with a finite number of possible symbolic values – the classes.

(4) Activities of Daily Living (ADL): fusion of temporal sequences of actions to extract regularities in time and determine relevant parameters to characterize the daily activities of patients at home. We aim at reducing both the size of the decision space once again – ideally the time series of actions is aggregated into one time series of activities – and the sampling rate because activities are observed in a larger time-scale than actions. Activities are characterized by the joint consideration of series of actions and knowledge accumulated about the patient's behavior.

(5) Living habits: daily observation of the sequences of activities compared with a usual behavioral pattern built from learning in terms of frequency, intensity, duration, time, and/or distribution or order of activities for instance.

(6) Long-term evolution: global assessment of the patient's health status over a larger time-scale (several weeks) considering different daily information: (i) activities of daily living (mean level, similarity to profile, etc.), (ii) environment (indoor and outdoor temperatures, liable to affect blood pressures, etc.), (iii) physiology, (iv) clinical data (age, gender, etc.), and general criteria periodically updated in the database (cognition, vision, balance, etc.).

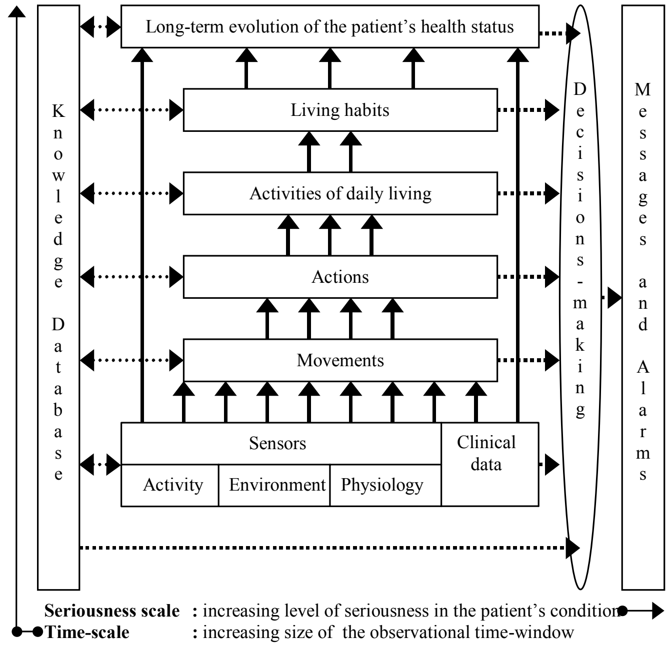

Fig. 1. A multi-level approach to detect critical situations of a patient at home. Each stage contains its own sub-process of decision-making, integrated within the general decision-making issue.

IV. Discussion about Parameters and Methods for the Decision-making Process

A. Relevant parameters for decision-making

The selection of relevant parameters to handle considering the decision sub-systems and, ultimately, the top-level decision issue is an essential dimension of critical situation detection. This choice is strongly constrained by individual and social requirements: unobtrusiveness of the devices (the home should look like any other and devices should make daily life easier to patients without disturbing them), respect of privacy (no video sensors for instance), low costs, etc. The aim is to identify the critical behaviors usually reported at home and significant in respect to the evolution of the patient's health status, to define the parameters relevant to detect these behaviors and then the way they could be evaluated from the set of data potentially available at the local intelligence unit located in the home.

B. Methods of decision-making: pattern recognition and neural networks

Each level of decision-making involves different types of techniques, but all stemmed from pattern recognition methods. There are two fundamental approaches to implementing a pattern recognition system [11]: (1) the statistical approaches – description of the object of study in terms of quantitative features extracted from the data (mean, standard deviation, etc.) and classification based on statistical methods such as similarity – and (2) the structural (or syntactic) approaches – description by a set of primitives identified within the data and their interrelationships (relational graph) and classification by parsing the relational graph by syntactic grammars, one for each group of classification. This later approach requires a large set of *a priori* knowledge to extract primitives and infer grammars. A combination of both approaches within the same pattern recognition system should also be considered.

The development of the concept of neural networks has had a great impact on pattern recognition practice for several years [12]. Neural networks have proven to be particularly efficient for classification and especially prediction tasks [13] and have been widely used in many areas of research. To deal with temporal sequences of data correlated along a large time window, the most efficient method is to introduce memory in the networks, then called recurrent neural networks, using an internal layer of neurons to store information passing through the hidden layers. Samples include Elman networks [2,14].

An efficient approach may be to implement a hybrid concept as hierarchical – to decompose the decision process into several successive stages – or parallel – to reinforce the decision at each stage – arrangements. Some samples are presented, respectively, in [15] and [16]. The selection of the most appropriate methods is largely constrained by the youth of the area of research, which is the cause of a lack of both *a priori* knowledge and realistic collection of data.

V. Conclusion

Home health telecare systems present high stakes for several classes of citizen. At the moment pilot projects conducted around the world are various and scattered in their concepts and purposes.

The assessment of a patient's general health status corresponds to a complex issue that needs to be handled with multiple levels of decision-making. At the top-level of decision, the issue requires joint study of the evolutions of parameters related to activity, environment, and physiology. The poor knowledge of these joint evolutions along with the lack of realistic set of data to be available in the short-term make this study somewhat premature. The good or bad health status of a patient is, however, strongly linked to their activities of daily living. Therefore, a first relevant stage to assess a patient's condition may be to study their activities of daily living and then to detect some significant deviations in their behavior as possible critical situations. Moreover, partial and targeted studies can be conducted at any level of decision-making to define significant sets of messages and alarms [17].

The study of the activities of daily living of a patient at home requires collaboration with experts in gerontology to define relevant parameters to deal with this issue. Pattern recognition methods need to be reviewed to identify and experiment with the most appropriate ones to evaluate the condition of patients. Input data may be either produced from an experimentation of scenario of behavior with patients at home or from a process of data simulation. A data collection at a larger scale and in a realistic environment of telecare also needs to be set up, which means for instance to equip rooms in residential or nursing homes.

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