INTelligent patient monitoring

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1. Introduction

Patient monitoring in hospital and other settings involves the recording of a patient’s physiological parameters, such as heart and respiratory rate, electrocardiogram (ECG), collection of laboratory results (e.g., hematology and chemical tests), and assessment of a patient’s health status. Especially in acute care environments such as the intensive care unit (ICU) and the operating room (OR), patient monitoring is crucial because immediate reaction to acute events, support of patient vital functions (e.g., respiration), and therapeutic interventions might be needed.

In the patient monitoring process, health-care professionals have to cope with a vast amount of information and perform a series of control actions and decision-making tasks. The obtained physiological parameters along with information from therapeutic devices and other patient-related data (demographic, medical record, etc.) must be interpreted and validated. In addition to this data overload, health professionals must reach diagnostic conclusions and prescribe therapy plans based on their expertise and clinical judgment. However, the complexity of most clinical cases and the inherent vagueness among symptoms, signs, and diseases often impede accurate and reliable clinical decisions. It also requires a high degree of expertise that varies significantly among health professionals or even is not available (e.g., in rural health centers). In addition, the acuity of the clinical environment frequently necessitates real-time decision making, prompt response to life-threatening events, and handling of a variety of medical devices.

In this sense, patient monitoring might become a valuable tool if specialists’ expertise and knowledge can be used in the assessment of patient health status. Today, several patient monitoring systems are computer-based and collect and analyze patient data from a variety of medical devices. They provide processed data, and in some cases, they incorporate medical knowledge to help health professionals in the decision-making process. The capacity of such patient monitoring systems can be enhanced with artificial intelligence.

Artificial intelligence (AI) aims to simulate the way medical professionals analyze, think, reason, and draw decisions in patient care. Artificial intelligent systems can represent, organize, and/or learn the practical and theoretical medical knowledge of experienced specialists. They are autonomous and automated systems endowed with large quantities of knowledge on relations among a patient’s symptoms, signs, laboratory results, and other clinical findings, and their underlying pathologies to reach diagnostic and therapeutic decisions. Rather than simply collecting and storing a patient’s vital signs and providing raw data, the role of an intelligent patient monitoring system is to perform data interpretation and validation to offer the health professionals the information actually needed. Intelligent patient monitoring systems are responsible to assess a patient’s physiological status, notify of alarm conditions, give expert advice, react to critical events, make diagnostic decisions, and take, if possible, therapeutic actions. In addition, they contribute to the automation of the clinical workflow, carry routine clinical tasks, and control the function of life-supporting devices.

Such systems can be a part of clinical environments for the collection and processing of data from various medical devices that are located in different units. Usually, these systems are connected to the hospital information systems. They are parts of an integrated hospital environment and in most cases save time and make the patient management more effective.

Monitoring of critically ill patients in the OR and ICU encompasses the involvement of medical personnel and a variety of bedside computer-based monitors and
other specialized equipment. For example, anesthetists are responsible to monitor and control the depth of anesthesia to avoid awareness during surgical procedures, ensure pain relief, and achieve muscle relaxation. Monitoring the depth of anesthesia aims also at decreasing anesthetic requirements and thus provides faster emergence from anesthesia and ultimately faster discharge from the post-anesthesia care unit. On the other hand, intensivists’ responsibilities range from monitoring the function of a patient’s vital organs to the adjustment of the mechanical ventilation settings and the determination of weaning from the patient. This complex and dynamic process involves heavily instrumented patients often connected to many monitoring and therapeutic devices and the recording of a variety of data.

In other hospital departments, temperature readings, multilead ECG recordings, and laboratory chemical and hematological results are also collected from hospitalized patients. These data are recorded from bedside point-of-care monitors and in-hospital telemetry units and are transmitted through the hospital’s network to a centralized system to generate alerts and daily reports and to be integrated into the computer patient record for additional analysis.

Increasingly, such data are also obtained from patients in out-hospital environments. Continuous or intermittent monitoring of patients during their daily life or at the point-of-need, e.g., the accident sites, ambulances, outpatient surgeries, and remote places (rural areas, on-board ships, battlefields, etc.), becomes feasible through telemedicine solutions. Development of ambulatory and home monitoring systems facilitates the management of acute and chronic diseases, evaluation of the rehabilitation progress and early diagnosis, prevention, and prompt medical care. These systems often involve noninvasive sensors and record patients’ vital signs through portable or wearable devices. Traditional systems store collected data on tapes or smart cards to be used later by specialists, whereas up-to-date telemonitoring systems involve standard or advanced communication means. Such systems are capable of automatic collection and transmission of a patient’s vital signs to physicians’ offices and/or to centralized systems at hospitals, as well as the provision of medical services locally. These so-called patient-centric systems, however, require advanced wearable devices, micro- and nanotechnology, and access to data networks.

In general, intelligent patient monitoring systems are preferable, because they are unbiased and their decision competence is always in favor of the patient. Some systems exhibit high specificity when operated in their limited domain of expertise. They lack, however, flexibility and effectiveness when they are applied to more generic fields. Many systems and architectures have been developed over the last three decades primarily for the intelligent monitoring of patients in critical care environments. The emerging advances in information and communication technology and the rapid developments in biomedical instrumentation have revolutionized outpatient monitoring systems as well.

2. A REALISTIC SCENARIO

In a clinical environment equipped with intelligent patient monitoring systems, health professionals have the opportunity to be extremely effective and improve the quality of health care. They are the decision-making personnel, but this process is assisted and complemented by monitoring devices. The following scenario describes their clinical actions and the role of patient monitoring devices.

A 50-year-old man suffering from paroxysmal atrial fibrillation is admitted to the emergency room with chest pain and short-breath symptoms. A clinician examines the patient with an ECG microprocessor-based monitor and asks for biochemical and hematological tests. The processing algorithms of the monitor detect ST segment deviation, and the monitor indicates acute myocardial infarction, which is also confirmed by the biochemical findings. Immediately, thrombolytic treatment is offered to the patient, and the patient is transferred to the coronary ICU (CICU or CCU). A CCU nurse places a 12-lead ECG and attaches a blood pressure cuff to the patient, which are properly connected to the measurement modules of a bedside physiological monitor. At short time intervals, blood analysis tests are carried out at the point-of-care with a blood sample cartridge also connected to the monitor. The ECG waveforms, the blood pressure, and the test results are displayed on the monitor and are automatically transferred to the CCU information system. Trend plots and reports of the measured data are generated periodically for review and evaluation. Suddenly, the monitor detects a significant variation in the R–R intervals (the time interval between two consecutive ventricular depolarizations), and its decision-support capabilities classify this arrhythmia as atrial fibrillation. A visual and audible alert is set off, and the CCU professionals are prompted to provide the proper medication. The patient’s acute condition eventually results in a brain stroke, and the patient must be transferred to the ICU, where his respiration now is supported by a ventilator. To assess his pulmonary function, a finger-clip pulse oximeter measures the level of oxygen saturation (SpO₂), electrodes are applied for transcutaneous blood gas measurements, and a Swan–Ganz catheter is inserted through an arterial line to measure the cardiac output. Ventilator settings (inspiration, expiration rate, tidal volume, etc.) are controlled and adjusted according to a patient’s pulmonary function. Possible detachment of the breathing mask as well as of any other sensor will immediately trigger an alarm to notify the ICU personnel.

This case makes clear how monitoring systems endowed with intelligence can contribute to the automation of the various stages of the monitoring process. It also illustrates the plethora of data to be collected and the variety of devices that must be handled by the medical staff. It becomes manifest that proper interpretation of data, provision of alarms, and accurate assessment of the actual clinical situation are essential elements for physicians to obtain a better view of the patient status and perform effective decision making.
3. ACQUISITION AND ANALYSIS OF PHYSIOLOGICAL MEASUREMENTS

Biosensors, electrodes, and transducers interface with the human body to measure bioelectrical activity, physiological, chemical, and other biological events. Most monitored physiological parameters can be either directly sensed or transduced. We can classify physiological measurements into two categories:

- **Invasive**: The sensor is either inserted subcutaneously after a small incision or even placed inside the patient after a short operation.
- **Noninvasive**: An external sensor for the transcutaneous measurement of a physiological parameter.

External and intravascular sensors are used for measuring blood pressure, strain gauges and impedance for recording respiration rate; optical sensors for determining oxygen saturation; and electromagnetic probes for the transcutaneous monitoring of blood flow. Furthermore, novel pressure and flow sensors as well as miniature catheters have been developed for the assessment of a variety of cardiopulmonary parameters. Significant advances have also been made in the noninvasive measurement of blood gases ($\text{PO}_2$, $\text{PCO}_2$) with electrodes on the skin surface, pH through fiber optics, and other “dry” chemical sensors to determine the concentration of substances in solutions. An instantaneous value of these parameters is available after appropriate signal conditioning (amplification, calibration, filtering) and processing (e.g., compensation, detection of peak values). In addition, some other indicators can be derived from indirect measurements, such as cardiac output and pulmonary parameters.

However, the analysis of biosignals, such as the ECG and electroencephalogram (EEG), to obtain physiological parameters, such as heart rate and level of sedation, and to detect related events (arrhythmia, ischemic episodes) is not a trivial process. It involves advanced signal processing techniques for noise reduction, artifact removal, and calculation of signal characteristics and other information not evident in the raw signals. These techniques are usually based on the extraction of waveform features, such as R–R and QRS (the wave in ECG that corresponds to ventricular depolarization) complex morphology features in ECG and the estimation of the spectral content (with, for example, fast Fourier transform) (2). These features can then be used for statistical analysis, trend detection, and classification purposes (e.g., arrhythmia classification). In general, biosignal analysis is a faceted and wide domain involving a large corpus of research groups working worldwide.

4. PATIENT MONITORING TECHNOLOGY

The earliest monitors in the hospital settings were stand-alone devices solely dedicated to displaying physiological signals, with limited processing capabilities related to noise removal, filtering, and detection of values lying out of predefined upper and lower thresholds. Collection of various vital parameters and laboratory tests required the employment of multiple devices. Physicians had to spend a lot of time with data collection, storage, and printing and deal with raw signals and numeric values to transform data into valuable information.

Nowadays, since significant developments in biomedical instrumentation, monitors offer multiple embedded measurement modules that can simultaneously record and display an enormous amount of signals from a variety of sensors (Fig. 1). Real-time data analysis and advanced signal processing techniques are built in to provide numeric data and multichannel waveforms, extract features, issue alarms, and detect events. Clinicians and nurses can consult trend plots and statistical data and recall interesting recordings (3). These tasks can be performed at the patient’s side through user-friendly interfaces. In addition, bedside monitors and other devices transmit vital data and device settings to the existing information systems. Integration of patient signs with information from medical records and shift reports, access to data from remote sources and central laboratories, automatic generation of daily reports, reminders, and pager alerts assist physicians in their effort to achieve informed decision making and offer advanced patient care. In this respect, the Institute of Electrical and Electronics Engineers (IEEE) standards committee has developed a standard for medical device data communication, IEEE Std 1073—the Medical Information Bus (MIB) (4). Using this standard, interconnection of bedside monitors, intravenous (IV) infusion pumps, and ventilators becomes feasible in acute care environments. The IEEE committee makes a considerable effort to support interoperability with information systems based on Health Level 7 (HL-7) (5). Even though communication and data exchange between point-of-care devices
is imperative for the construction of intelligent patient monitoring, interoperability between medical devices remains problematic so far mainly because of the inherent technological difficulties.

Many patients recovering from an operational procedure or being discharged from the ICU need additional bedside monitoring and treatment in clinic and peripheral wards. After stabilization of their health condition, patients can be offered telemetry monitoring of their vital signs for increased mobilization and comfort. In the early days of patient monitoring, Holter ECG offered continuous monitoring of patients with arrhythmia symptoms (such as palpitations, frequent loss of consciousness). This early type of portable monitoring device does not support processing, communication, or other capabilities. Today, wireless portable monitors communicate a patient’s vital signs to the information system to be integrated with other relevant information. Radio standards for telemetry units are the industrial, scientific, and medical (ISM) (802.11), Bluetooth, and the new wireless medical telemetry service (WMTS) (6) in the United States and Canada. These systems have a short coverage range and are suitable for in-hospital use. Both ISM and Bluetooth support video transmission, whereas WMTS is currently restricted to biosignal transmission. However, only WMTS telemetry systems are protected from radio-frequency interferences, as for the first time, all medical telemetry becomes a primary user of a frequency band. As of 2003, all medical vendors must comply with the WMTS standard.

5. ARCHITECTURE OF INTELLIGENT MONITORING SYSTEMS

An intelligent monitoring system consists of the following three modules:

- The **data management module**, which performs the acquisition of the patient measurements and data retrieval from databases and other sources.
- The **knowledge base**, which represents, stores, organizes, or learns the expert medical knowledge necessary for the formulation, modeling, and solution of the problem.
- The **inference mechanism (or engine)**, which includes the reasoning strategies and interacts with the knowledge base to draw decisions and carry out monitoring actions.

As there is no consensus on the definition and structure of an artificial intelligent system, the aforesaid structure depicts only the basic modules and the functional specifications met in most intelligent systems (7). Figure 2 illustrates the architecture of an intelligent patient monitoring system. Common to all up-to-date monitoring systems is the systematic collection of all necessary patient data either directly from bedside monitors and therapeutic devices or retrieved from databases. In systems endowed with artificial intelligence, the data management module is responsible to interface with the incoming data and often incorporates appropriate submodules for low-level signal processing, feature extraction, and data validation. The inference engine applies the expert knowledge of the system to provide suitable decisions. These decisions are either presented to health professionals through user interfaces in the form of graphics, menus, illustrations, and so on and/or they intervene with life-supporting devices to control or modify their function.

6. DATA MANAGEMENT MODULE (DMM)

Physiological parameters and other patient-related data applied by intelligent monitoring systems are as follows:

Figure 2. Architecture of an intelligent patient monitoring system. (This figure is available in full color at http://www.mrw.interscience.wiley.com/obc.)
• Alphanumeric values such as patient gender, date of admission, and an instantaneous value of body temperature and oxygen saturation
• Signals including raw single-channel or multichannel waveforms, time-series data like data trending, feature vectors (e.g., ST segment (the distance between the S and the T waves in ECG) deviation), ventilator settings, and so on
• Images (e.g., x-rays, echocardiogram)
• Imprecise data (for instance, partial presence of symptoms, lack of precise sensor information)
• Symbols such as stable, improved, out-of-limit value, type, and dose of medication
• Other information (e.g., electrode detachment, types of alarms, contradiction of drugs) or even data in ad hoc format (e.g., manual entry, documents)

These data can be either directly acquired from real-time recordings or retrieved from medical records, databases, and another hospital information system. Data sources may be internal to the system, including nearby sensors, monitors permanently devoted to the data capture, and internal databases. On the other hand, external data stem from remote locations (laboratories, telemetry units), temporary sources, commercial databanks, the World Wide Web (WWW), and so on. Nevertheless, those terms can be interchanged and may have several or overlapping definitions.

6.1. Low-Level Processing and Feature Extraction

The role of the DMM is primarily to collect the patient data and select the problem-specific information. Toward data acquisition, the DMM needs to interact with data sources (disregard an instrument in case of malfunction, request additional information, etc.) and dynamically reconfigure data acquisition (e.g., in response to variations in signal characteristics, clinical situation, etc.). DMM often incorporates low-level signal processing and feature extraction. In many cases, raw data are either not available in numerical form (e.g., patient gender, type of disorder) or they are provided as time series (ECG, EEG). Feature extraction is primarily performed to enumerate all patient-related data, reduce their dimensionality, or even apply linear or nonlinear combinations between the signal characteristics to generate new input variables. A well-designed preprocessing strategy may provide informative features and result in a reduced number of input variables, while retaining the clinical context of them. This process can drastically increase the generalization ability (i.e., make reliable predictions for new inputs) of the system and reveal the data with the practical usefulness in the problem solving. Feature selection is usually accomplished by either simply selecting several important features with selection criteria or by the application of a dimensional reduction technique (e.g., principal component analysis) (8).

7. KNOWLEDGE BASE MODULE

The knowledge base (KB) module contains or learns the necessary medical knowledge for understanding, formulating, and solving the problem under investigation. Knowledge is a collection and representation of facts, rules, concepts, procedures, formulas, and examples. The acquisition, however, of the expert knowledge is not a trivial and straightforward task.

7.1. Knowledge Acquisition

Knowledge acquisition (KA) is the collection, accumulation, and transfer of the medical knowledge. This process may also add, refine, or otherwise improve knowledge to the existing KB. Methods for efficient and cost-effective knowledge extraction, elicitation, and transformation include interviews, sophisticated editors, and machine learning techniques.

One common technique for eliciting knowledge is by interviewing health experts (usually referred to as knowledge engineering). Interviews must be well planned and organized and should include focused and specific questioning, posing of counterexamples, drawing analogies, and use of questionnaires. Such an approach ensures the accurate interpretation and integration of the elicited information into knowledge. Other KA methodologies include medical databases, observation of physicians in clinical practice, and editing tools that guide experts to build the knowledge base.

KA editing tools can be roughly categorized as (9) symbol level (e.g., Tieresias, originally developed for the MYCIN infection monitoring system), method oriented, task specific (OPAL), and ontology oriented as the Protege. The interface of the task-specific KBWEdit tool is illustrated in Fig. 3. KBWEdit is an editor that constructs the KB of the KBWean ventilation management system (10). The editor enforces a certain prestructuring of the KB's components to prevent any syntactic and other errors common in KA.

7.2. Machine Learning Techniques

Machine learning can be considered as a specialized and autonomous form of KA. The knowledge of the system is learned through examples with either memorization (rote learning) or machine learning capabilities. The latter

Figure 3. The KBWEdit knowledge acquisition tool for building a ventilation management system. (This figure is available in full color at http://www.mrw.interscience.wiley.com/ebe.)
includes pattern recognition, artificial neural networks (ANNs or simply NNs), and support vector machines (SVMs). Fuzzy logic models and generic algorithms complement these techniques that are all together known as soft computing methodologies (11). In this class of knowledge acquisition, neither explicit formulation of expert knowledge is necessary nor a priori domain-specific knowledge. Learning through experimental data and examples can recover and associate the underlying dependencies between the patient-related data and his/her clinical status (pathologies, physiological performance, etc.). For this reason, these techniques are usually referred to as data-driven as opposed to the knowledge-based reasoning, which is based on existing human knowledge.

Learning of ANNs is a typical paradigm of machine learning. It is achieved with data from known cases to train a model (the network) to respond effectively in unknown cases. The most common application of ANNs is in classification problems (e.g., classification of arrhythmia to a cardiac disorder). Training is the process of adjusting the parameters (weights) of the network nodes (or neurons) with input data of which the class (output of the network) is known. The training dataset (consisting of the input vectors and their corresponding class) is iteratively tuning the nodal weights until an error function is satisfied. The classification ability of the trained model (measured for sensitivity, specificity, accuracy, and predictive power) is thereafter tested on unknown cases with a different dataset, namely, the test set. The trained ANN represents a high-dimensional, nonlinear mathematical model, which is obtained experimentally. The capability of providing such a mathematical model depicts the second application area of ANNs (and SVMs), which is the functional approximation and the mapping of input–output variables (regression). Clinical applications of functional approximation in patient monitoring include the estimation or optimization of a treatment plan (adjustment of the ventilator parameters (12)), development of closed-loop controllers (for instance, to determine the titration of anesthetic agents infused by IV pumps (13)), and so on.

Feature extraction and selection are key processes in machine learning as they can greatly reduce the training time and can reveal those features with high discriminative power for the classification problem. For instance, in a recent clinical study (14), a four-layer ANN was used by researchers for the discrimination of the anesthetic states of patients undergoing abdominal surgery from mid-latency auditory evoked potentials (MLAEPs) and hemodynamic parameters. The input variables to the network were chosen from a set of 11 candidate features (five latencies, three MLAEP-associated characteristics, and three hemodynamic parameters). The level of anesthesia was annotated by the pressure, rate, sweating, and tears score and was modeled as a four-class state. Best identification accuracy was achieved with only the five latencies, whereas additional use of the hemodynamic features yielded poorer results. This study suggested that the MLAEP contains useful information for assessing the anesthesia depth.

7.3. Standard Reference Databases

As already discussed, use of carefully selected datasets of representative cases is a key point for the construction, training, and evaluation of machine learning techniques. However, in most cases, large amounts of clinical data are either not available or deficient, are poorly characterized, or not acquired in a standardized and repeatable way. In this respect, various reference databases have been developed to facilitate researchers and practitioners in the biomedical field to overcome the aforesaid problems. For example the multiparameter intelligent monitoring for intensive care (MIMIC) database (15) includes two or three ECG signals as well as any other available parameter, such as arterial blood pressure, respiration, and pulse oximeter of about 90 patient records, each one typically containing between 24 and 48 hours of continuous recording from monitors in the ICUs and CCUs of Boston’s Beth Israel Hospital. Each record is accompanied by detailed clinical data derived from the patient’s medical record and from the hospital’s online medical information systems. Other available reference databases are the MIT-BIH Arrhythmia Database for arrhythmia classification, the European Society of Cardiology ST-T Database, and other multiparameter databases such as the MIT-BIH Polysomnographic Database for sleep and apnea monitoring. The recordings in these databases are annotated by medical experts and can be used for the selection of training and test datasets (Fig. 4).

7.4. Knowledge Representation

Once KA has been completed, the acquired knowledge must be organized and represented in the KB. Production rules are typical paradigms of knowledge representation, and their use resulted in the first knowledge-based medical systems. The knowledge is represented in the form of IF–THEN rules that represent condition-action pairs, namely:

IF condition (premise), THEN action (or conclusion)

Each rule represents a piece of medical knowledge and results in the “production” of a microdecision, which mimics to some extent the human cognitive behavior. This inference mechanism produces a chaining of reasoning and will be further discussed in the next section (16).

The first development of these so-called expert systems in clinical practice was the well-known MYCIN (17). Two offsprings of MYCIN were the ventilator manager (VM) (17) system for the data interpretation and advice-giving on the management of ICU patients who needed ventilation support and the PUFF system (18). The latter was designed for the interpretation of pulmonary function tests with lung disease. One example of the rule 31 of the PUFF system is as follows:

RULE31
IF
1. The severity of obstructive airways disease of the patient is greater than or equal to mild AND
2. the degree of diffusion defect is greater than or equal to mild AND
3. the TLC observed/predicted ratio is greater than or equal to 110, AND
4. the observed/predicted difference in RV/TLC is greater than or equal to 10
THEN
1. There is strongly suggestive evidence (0.9) that the subtype of obstructive airways disease is emphysema, and
2. It is definite (1.0) that ‘OAD, Diffusion Defect, elevated TLC, and elevated RV together indicate emphysema’ is one of the findings.

The PUFF system contains about 400 production rules (initially written in LISP) to deal with 76 clinical parameters (pulmonary function test, patient demographics, and data derived from the rules such as findings associated with a disease). The production rules operate on associative triples (attribute-object-value), where attributes are the clinical parameters, the object is the patient, and the values are given by the clinical parameters. The system comes up with a set of interpretation statements and provides with a final diagnosis accompanied with explanation reasoning and report. The PUFF system became operational in 1979, and since then, it has undergone several modifications and has been used by health professionals on a routine basis in hundreds of hospitals.

One major advantage of rule-based systems is the separation of the KB and the inference mechanism. New or updated knowledge can be inserted in the KB without altering the reasoning process. Several additional types of knowledge representation exist including decision trees, frames, semantic networks, and object-oriented approaches.

8. INFERENCE MECHANISM

If intelligent systems get their power from knowledge, the inference mechanism endows the system with the reasoning strategies to draw decisions. Reasoning about the problem solving can be heuristic (i.e., rule of thumb) and empirical or may be based on a deeper understanding of the structure and the function of the system.

There are two strategies of making inferences in rule-base systems: the forward and backward reasoning (chaining). In backward reasoning, there is a goal to be satisfied that in turn causes a chaining of rules to be invoked (19). In the aforementioned PUFF system, a backward reasoning (goal-driven) approach has been followed. The goal of the system is at any time to determine an appropriate value for a given clinical parameter. In this respect, it tries a list of rules whose actions conclude values for the clinical parameter. In case the rules fail to conclude a value for a parameter, a question is then asked to the user to obtain that value. In forward reasoning, the algorithm starts with input data and if a condition matches the situation, a conclusion is made. For example, a forward reasoning system was proposed in (20), which classifies cardiac beats as normal or ischemic. The system is founded on the following rule:

IF
ST depression > 0.08 mV AND ST slope > 65°
OR
ST elevation > 0.08 mV
OR
T-wave is inverted
where ST and T-wave are well-known ECG features. In case of ischemic beat classification, a windowing technique (sliding adaptive window) is applied to detect ischemic episodes. In general, rule-based alarming systems are often developed with forward reasoning, because their task is to issue a notification when a condition is met.

Rule-based and other heuristic monitoring systems exhibit high competence in their domain of expertise; they fall short, however, when employed in more generic and complex fields. Intelligent systems, on the other hand, with deep inference mechanisms can model the functional components of a system and their interactions (21). Such models may also describe the temporal behavior of the system and reason with uncertainties.

Monitoring of a patient’s status over time can yield valuable prognostic information about the patient’s future behavior and can assist in the selection of suitable therapy plans and control actions (22). Temporal parameters such as periods of stability, gradual evolution, and periodicity can provide an overview of the clinical condition. The VM system was the first to introduce temporal reasoning in patient monitoring. Based on a temporal abstraction of the patient’s physiologic status, it suggests adjustments to the therapy plan of patients undergoing mechanical ventilation. VM is an open-loop system that is not designed to intervene in the ventilation’s operation but only make proposals to the ICU personnel (9).

NeoGanesh (22) is a ventilator management system intended to perform automatic closed-loop control of the ventilator. Temporal reasoning is applied to keep the patient in a comfortable condition (control task) and gradually reduce ventilation support as well as assess the point of weaning from the mechanical ventilation (planning task). The system is connected to the ventilator for recording the respiratory rate and tidal volume and to a gas analyzer for measuring end tidal partial pressure of CO\textsubscript{2} (PETCO\textsubscript{2}). Temporal abstraction relies on two basic mechanisms: aggregation of similar observed situations and forgetting of nonrelevant information. Based on an object-oriented paradigm and forward chaining rules, the patient’s evolution is modeled as a discrete-state transition problem. The system tries to keep the patient within a respiratory rate range, a tidal volume above a minimum threshold, and a PETCO\textsubscript{2} below a maximum threshold. All patients are ventilated in the pressure support mode to reach and stay at the above-defined targets. Action plans are dynamically adapted depending on how long the patient has been at a given state. For example, in case of stable normal ventilation, the support may be lowered, and in case of persistent tachypnea, the support is greatly increased. Special knowledge is introduced to allow differentiation between apnea and disconnection. NeoGanesh develops a therapeutic strategy to gradually re-educate the respiratory muscles of the patient and evaluates the capacity to breathe without mechanical support. NeoGanesh and its commercial successor Automedon have been tested and evaluated by a multicenter European study involving six university hospitals for their ability to both control the level of assistance in accordance to the patient’s needs and determine the point of weaning. A similar methodology has been also followed by the Vie-Vent project (23) designed for the mechanical ventilation of newborn infants to optimize therapy planning and to support neonatologists in their daily routine. An extensive review of knowledge-based ventilation management systems can be found in reference 22.

Fuzzy logic has been introduced into patient monitoring to describe uncertainties in the response of the patient to an acute condition and changes of a therapy plan. In addition, physiological measurements and other biomedically variables can be defined as fuzzy sets. The degree to which a variable or an observation belongs to a fuzzy set is expressed through its membership function. Several fuzzy advisor systems for ventilator management have existed in the ICU. They are rule-based systems with fuzzy rules, and their fuzzy membership function is obtained either heuristically or by clinicians and KA editors (as shown in Fig. 3) (24,25). In an attempt to computationally derive the rule-based knowledge, an adaptive neuro-fuzzy inference system (ANFIS) has been used by Kwok et al. (25). The target was to advise on the acceptable level of the inspired fraction of oxygen (FiO\textsubscript{2}) (ventilator setting) according to the values of the arterial oxygen tension (PaO\textsubscript{2}), the positive end-respiratory pressure (PEEP) and (FiO\textsubscript{2}). To model this input–output mapping, a reference dataset was constructed with a patient simulator (SOPAVent) in which nine consultant anesthetists adjusted the FiO\textsubscript{2} under 71 clinical scenarios. The derived ANFIS model resulted in 11 rules in the form:

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\text{IF } (\text{PaO}_2 \text{ is } A_i) \text{ AND } (\text{FiO}_2 \text{ is } A_j) \text{ AND } (\text{PEEP is } A_k) \text{ THEN } \text{FiO}_2 \text{ is } x_n, \]

where \( A_i, A_j, A_k \) are fuzzy sets and \( x_n \) is a constant. The developed ANFIS rule-base system was shown to model the expert’s decision making as well as to be more interpretable by the clinicians. However, the patient simulator addresses only a limited range of the actual FiO\textsubscript{2}, PaO\textsubscript{2}, and PEEP values and clinicians need to adjust additional ventilator settings in real practice.

Fuzzy logic has also been applied to medical control problems (22,26). In the field of anesthesia, fuzzy rule-based systems have been developed to control the drug infusion for maintaining the depth of the anesthesia constant, which brings muscle relaxation to the target level and keeps the patient in a desired state. In reference 26, a fuzzy controller was used by the authors for the hemodynamic management of patients with congestive heart failure. The control variables were the mean arterial pressure, and the cardiac output and the input variables were two vasoactive drugs. The controller has three different modes, the critical condition mode and the noncritical condition modes. The critical mode is rule based, whereas the noncritical is a fuzzy controller and the system switches from one to another when conditions are met. The system was initially evaluated on a nonlinear
hemodynamic model and then applied in animal trials for additional enhancement. The study showed an adequate control of the hemodynamic variables within the prescribed limits and a fast response to input changes.

Other deep reasoning methodologies that have been proven valuable in patient monitoring include case-based reasoning (CBR) and causal models. CBR is a problem-solving paradigm that uses the "operative" knowledge of previously experienced successful situations, called cases. Past cases, similar to the current one, are retrieved from a case library and adapted to tackle the current problem situation (see also the T-IDDM system in the next section). On the other hand, causal models describe cause-and-effect relationships between pathophysiological states and can be suitably fitted for explanation tasks. In the DIA-BTel system (27), a causal probabilistic network (CPN) is applied to diabetic patient monitoring to perform the "cause identification" task. This CPN model detects whether anomalies in patient data (blood glucose, keton- ury measurements) appear regularly or sporadically (because of patient deviation from insulin therapy plans). In biomedical applications, however, it is difficult to develop causal systems because of the complexity and the multi-parametric dependence of biological systems (16). In many cases, researchers use hybrid systems to benefit from a combination of reasoning schemes and technologies.

9. CURRENT TRENDS

In patient monitoring, analysis of complex and dynamic situations, often under real-time constraints, necessitates the employment of various reasoning skills as well as the planning and execution of multiple tasks. Agent-based systems have been developed to integrate multimodal knowledge representation and reasoning schemes to perform specialized monitoring and diagnostic and control tasks. Intelligent agents are software entities enriched with decision support and learning capabilities and some degree of autonomy that operate in uncertain environments. They can perform three functions: perception of dynamic conditions in the environment, action to affect conditions in the environment, and reasoning to interpret perceptions and draw inferences. Agents can also be highly adaptive to currently available information and can modify their behavior. Furthermore, intelligent multi-agent systems in distributed environments can share common knowledge and coordinate their actions as a team, with each agent performing specialized monitoring and diagnostic subtasks. In addition, mobile agents operating in a decentralized manner can be suitable for remote patient monitoring systems.

Guardian (28) is a knowledge-based system for monitoring and diagnosis of post-cardiac surgery patients in the ICU. It is designed as an autonomous agent-based system with a flexible and adaptive blackboard architecture, in which several algorithms cooperate to address a wide range of problems under hard real-time conditions. The proposed reference architecture supports two levels of physical and cognitive behaviors. The physical level interacts with the external environment to perform perception of the patient’s physiological condition (through data abstraction and reduction), action to set closed-loop ventilator parameters, and action to communicate with clinicians. The cognitive level employs a variety of reasoning activities, such as condition monitoring, diagnosis, planning, and explanation. The physical level sends perceived information and feedback from action execution to the cognitive level, which in turn sends control plans to the physical level. Guardian’s knowledge is based on a shared ontology to accommodate and support the interpretation and therapy tasks of the agent. The system has been tested on a series of realistic scenarios with simulated and recorded patient data.

Patient monitoring is performed on the basis of information collected from different sensors and sources. Information fusion is the process that associates, correlates, and combines data and information from single and multiple sources to provide with better estimates of the environment and assist in the decision-making process (29). Fusion can be applied to redundant data from sensors that are recording the same physiological process and/or to complementary data representing different types of information. It is modeled as a multilevel hierarchical process in which the role of the low-level fusion is to carry out data association and correlation, whereas the high-level fusion is responsible for detection, assessment, or even decision-making tasks. AI techniques are widely used in this process to support and complement fusion at the high-level processing. Information fusion may either be an open-loop or a feedback closed-loop process in which a sensor manager continuously uses information from the fusion levels to plan and refine future sensor actions. Intelligent fusers have been successfully employed in many engineering problems, such as military applications for identification of targets, and transportation problems for traffic control.

A multisensor fusion has been proposed for the detection of atrial and ventricular activity in CCU patient monitoring (30). In this method, multilead ECG signals are associated with complementary hemodynamic parameters and esophageal ECG signals. A distributed three-level fuser enhances the activity of interest, associates sensor data for false alarms minimization, and performs local event detections. Local detections are thereafter merged with a data fusion method (optimal fusion) to produce final detection of atrial and ventricular activities. SIMON (21,31) is another monitoring system that employs sensor fusion. The system is based on a distributed architecture and supports signal interpretation tasks for CCU patient monitoring.

9.1. Out-Hospital Monitoring

Availability of remote monitoring and the delivery of prompt expert medical care are of vital importance for patients in out-hospital conditions. Telemedicine provides the information and communication tools for remote monitoring or telemonitoring (32). The World Health Organization defines telemedicine as “…the practice of medical care using interactive audiovisual and data communications including medical care delivery, diagnosis, consultation and treatment, as well as education and the transfer of medical data” (33).
A plethora of medical cases necessitate monitoring of patients at their home, during their daily life, or at the point-of-need. For instance, patients discharged from hospital health care often need home monitoring until their health status is stabilized. Systems that assess their health progress and notify physicians of any complication may also save the costs of possible prolonged hospitalization and promote patient mobility and comfort. Furthermore, patients with symptoms can be short- or long-term monitored (ranging from 24 hours to several weeks) during their normal activities, which facilitates the recording of their symptoms or even makes possible the detection of intermittent and rare events, while eliminating the need for patient visits to health-care institutions.

In addition, availability of medical expertise to patients suffering from permanent and chronic diseases (e.g., diabetes, asthma) can aid the lifelong management of their disease and ensure their welfare. Such monitoring systems may determine their health condition and provide reminders and expert advice on their correct medication dosage. This so-called “continuity of health care” can also support elderly and disabled people in independent living and personal care (34). In other cases, athletes rehabilitating from an injury or an operation can benefit from monitoring systems that evaluate their progress and suggest alternative exercise plans, which may also ultimately result in reduced follow-ups and the earlier recovery to their activity. Furthermore, systems to support pregnant women to self-monitor their blood glucose, fetal ECG, uterine contractions, and other parameters can prevent preterm labor and other gestation-related complications (35).

Telemonitoring systems can also provide effective and prompt care in emergency conditions and at remote or isolated areas (36). Ambulances equipped with telemetry monitors and wireless links to hospitals assist in the prehospital patient management and survival. Portable monitors, cameras, and other imaging devices (e.g., portable ultrasound units) can be used at the accident site as well as throughout the patient transfer to the hospital. Real-time wireless transmission of vital signs and on-scene images to a centralized station at a hospital institution allows specialists to advise the paramedical staff on a series of handling actions. Furthermore, understaffed rural and other areas, such as remote villages, board ships, battlefields, and space expeditions also require telemedicine solutions for expert consultation and immediate decision-making support.

A telemonitoring system encompasses two physically separated units, namely, the

- **Telemedicine unit**, which is located at the patient’s site and often consists of two modules: the signal acquisition and the communication module. The former is responsible for the collection and storage of patient measurements and in many cases can be complemented with data analysis and decision-making capabilities. Usually, these two modules are incorporated into a desktop, portable, or wearable device.

- **Centralized unit**, based at a hospital, a doctor’s office, or a health provider. This unit receives and analyzes data from the communication module and stores them in a database. Physicians can either have direct access to the data or the central system can deliver patient information to the physician’s site. Also, in many cases, the telemonitoring system must support bidirectional (two-way) interactive communication among the physician, the central system, and the patient.

Figure 5 illustrates the architecture of a remote monitoring system. Communication among the various parties of a telemonitoring system (that is the patient, the physician, and the centralized unit) is supported by a network infrastructure, such as the telephony system, data lines, and mobile telephone networks. Patients may have their physiological parameters monitored while at home or during their daily activities.

One major consideration in the development of a telemonitoring system is the mode of data communication. Most telemonitoring systems are designed to operate either in the store-and-forward (asynchronous) or in the real-time (synchronous) mode. In the former modality, the telemedicine unit stores locally the acquired patient data and initiates data transfer at a later instance. In real-time communication, the centralized module is “present” during data collection and can synchronously provide information as well as interact with the telemedicine module. There are significant technological and time-efficiency differences between the two modalities. Asynchronous data
transmission can be performed over standard data lines (with the telephony system or TCP/IP networks) and usually has low-cost and transmission rate requirements. On the other hand, real-time data exchange necessitates advanced telecommunication networks. Especially, transmission of biosignals and images demands broadband communication technologies. Moreover, in continuous ambulatory monitoring and in emergency conditions, establishment of point-to-point connections among the various parties of the telemonitoring system often imposes wireless communication solutions. These solutions include mobile telephone networks (e.g., GSM, GPRS), satellite links, or other customized and ad hoc wireless infrastructures.

A typical paradigm of disorders requiring continuous monitoring and personal management is type 1 diabetes mellitus (also referred to as insulin-dependent diabetes mellitus, IDDM), one major chronic disease deriving from no endogenous secretion of insulin. In recent studies (27,37), decision support systems have been developed for the analysis of home monitoring data and the prescription of effective insulin treatment. IDDM patients often need intensive insulin therapy consisting of three to four exogenous insulin injections per day or subcutaneous insulin pumps to regulate the blood glucose metabolism. Effective prescription and update of therapeutic insulin protocol requires, however, the patient self-monitoring of blood glucose level, recording of the injected insulin dosage together with additional information on patient’s diet and lifestyle, as well as periodic assessment of the achieved metabolic control. The telematic management of the IDDM (T-IDDM) system (37) incorporates a web-based architecture and a multimodal reasoning methodology to support both IDDM patients and their clinicians. The system relies on a patient unit (PU) located at the patient’s home or other nonclinical environments and a medical unit (MU) used by diabetologists at the hospital. The PU is a computer-based platform with a degree of autonomy and is responsible to collect data from a blood glucose reflectometer, to asynchronously upload measurements to the MU through a telecommunication system (Internet or public switched telephone network, PSTN), and if needed, to suggest insulin dosage adjustments. The MU is a web-based application that performs data analysis, treatment suggestions, and final selection. Temporal abstraction is employed to handle missing data, aggregate BGL values, and interpret the therapy effects. Thereafter, the system provides a set of suggestions and a rule-based system adjusts the current insulin dosage according to the suggestions. To handle poorly controlled patients, the system also incorporates a CBR methodology to exploit the contextual knowledge of past successful problem-solution cases similar to the current one. In this sense, the rules are “specialized” on the basis of a patient’s characteristics and the final protocol selection is provided to the clinician. The patient is automatically informed of any updates in the insulin and diet plans through the PU. The T-IDDM system has been evaluated at hospitals in four European countries involving, however, clinical trials limited to a small number of patients with the absence of a control group.

Another system is a web-based ECG system (38), which facilitates collection, review, analysis, and archiving of a longitudinal ECG record for the home monitoring of at-risk patients. The system consists of a PC-based measurement module used for the acquisition of ECG signals at the patient's home and a central database server where patient information and clinical data are uploaded. An intelligent software agent is activated either at regular intervals or whenever new incoming clinical data are sent to the server to compare historical data with the newly acquired data. An interpretation module performs disease classification with ANNs. A short report, along with reminders and suggestions for action, is sent to the doctor and patient by e-mail.

In another research project (USBone, ultrasound in bone healing) (39), an ultrasound wearable platform has been developed for monitoring and enhancement of the osteogenesis process of long bones (femur, tibia, etc.). The system is applicable to patients with open fresh fractures, to delayed unions treated with external fixation, as well as to distraction osteogenesis cases. Two miniature ultrasound transducers are implanted into the affected region to operate in the axial-transmission mode. The system comprises two units, namely the ultrasound wearable unit and the central unit. The wearable unit is implemented as a small battery-operated device composed of two functional modules: the sensing and the control module. The wearable unit initiates, on a daily basis, therapy sessions of subcutaneous low-intensity pulsed ultrasound to enhance and accelerate the repairing mechanisms of the healing bones. Moreover, the system makes use of the axial wave propagation to determine the mechanical properties of the healing bone. Ultrasound measurements are commanded by the surgeon on duty through the centralized unit or automatically by the control module at short time intervals. The measurements are wirelessly transferred to the centralized unit to provide an estimation of the healing progress, to notify of complications (e.g., delayed union), and to identify the endpoint of healing and the time for fixation removal. Machine learning is employed to tackle the problem because of the limited knowledge of the relation between the properties of a healing bone and the ultrasound wave propagation through it. Bone healing is modeled as a four-stage process, and an annotated dataset has been constructed from a series of animal experiments and clinical trials.

There is a plethora of leading-edge telemonitoring systems. Most systems have not gone into clinical and commercial practice; they constitute, however, a natural starting point for the home-based and ambulatory patient monitoring process. Incorporation of automation and AI in this process contributes significantly to the effective and expert provision of patient care, followed also by major social and economical benefits. However, security, safety, privacy, confidentiality, and other issues originate from these so-called patient-centric systems.

1 An orthopedic technique for the correction of skeletal deformities, for example, the gradual elongation of limbs to restore extensive loss of bone mass.
9.2. Future Emerging Directions

Advances in micro- and nanotechnologies, information processing, and communication networks offer the possibility for small miniaturization, noninvasive (or even noncontact) sensing, as well as wearable computing. For example, digital signal processing microchips provide high-performance, high-speed computational frameworks suitable for embedded solutions and neuroprocessors can be designed to perform ANNs operations.

Related research work has been focused on the development of frameworks for distributed, intelligent healthcare devices in the home. The so-called “health smart home” equipped with sensors, cameras, wearable devices, and so on will permit the continuous monitoring of patients’ health state, prevent harmful events (falls, accidents), understand facial expressions, and recognize when an individual is in pain, experiencing an elliptic seizure, or having a heart attack (40). Smart clothes (with sensors fabricated within fibers and textiles) will continuously record vital signs, floors (e.g., smart carpets) incorporating pressure sensors will measure a patient’s weight and kinetic data, and smart toilets will perform chemical urine analyses. In addition, intelligent spaces supplied with novel sensors (e.g., laser rangers, humidity sensors, etc.) dispersed in and around the home may also track a patient’s location and provide environmental data. Distributed sensors and data fusion modules will provide highly adaptive schemes to process information within context.

Smart homes and “hospitals without walls” require pervasive (or ubiquitous) computing environments. In such environments, computers and communication are available everywhere, anytime with minimal obstruction to an individual’s activities. Sensors and smart devices are context-aware and interact with one another. Mobile agents and intelligence are embedded into the environment to support monitoring and other health-care decisions.

10. DISCUSSION AND CONCLUSIONS

Patient monitoring is a multifarious process involving the contextual acquisition and interpretation of patient-related data as well as the performance of diagnostic and therapeutic tasks. AI techniques have been incorporated into computer-based patient monitoring systems to assist health-care professionals in their decision making and automate the monitoring process. Many intelligent monitoring systems have been primarily developed for critical care environments, where immediate response to acute events and therapeutic actions are of vital importance. In general, intelligent patient monitoring systems are preferable, because they are unbiased and their decision competence is always in favor of the patient. Most systems are designed to operate in specific clinical applications; they lack, however, effectiveness and flexibility when operated in more generic domains.

Telemedicine solutions have revolutionized monitoring systems in out-hospital conditions. Home-based and ambulatory systems make feasible the monitoring and management of patients throughout their everyday live, with minimum obstruction to their normal activities. Availability of patient-centric monitoring systems and the provision of the so-called “continuity of health care” is associated with significant social and economical benefits.

However, legal and ethical concerns originate from the diffusion of information technology in medical practice (41). Security, privacy, and confidentiality are key issues to be resolved because of the sensitive nature of medical information (19). On the other hand, the particular relationship between patients and physicians will only benefit from innovation in technology. Physicians will continue to be the responsible personnel for making medical decisions. AI aims to offer automation, assistance, and complementary arguments in this process.

BIBLIOGRAPHY