Introducing Intelligence in Electronic Healthcare Systems: State of the Art and Future Trends

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Abstract This chapter introduces intelligent technologies applied in electronic healthcare systems and services. It presents an overview of healthcare technologies that enable the advanced patient data acquisition and management of medical information in electronic health records. The chapter presents the most important patient data classification methods, while special focus is placed on new concepts in intelligent healthcare platforms (i.e., advanced data mining, agents and context-aware systems) that provide enhanced means of medical data interpretation and manipulation. The chapter is concluded with the areas in which intelligent electronic healthcare systems are anticipated to make a difference in the near future.

1 Introduction

In this era of ubiquitous and mobile computing the vision in biomedical informatics is towards achieving two specific goals: the availability of software applications and medical information anywhere and anytime and the invisibility of computing [26]. Both these goals lead to the introduction of electronic healthcare computing concepts and features in e-health applications. Applications and interfaces that will be able to automatically process data provided by medical devices and sensors, exchange knowledge and make intelligent decisions in a given context are strongly desirable. Natural user interactions with such applications are based on autonomy, avoiding the need for the user to control every action, and adaptivity, so that they are contextualized and personalized, delivering the right information and decision at the right moment [27]. All the above recently introduced features provide added value in modern electronic healthcare systems.

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These technologies can support a wide range of applications and services including automated diagnosis, personalized medicine, patient monitoring, location-based medical services, emergency response and management, ubiquitous access to medical data, and home monitoring. This chapter presents a special branch of artificial intelligence tools and applications called intelligent electronic healthcare systems. In general, the term intelligent electronic healthcare systems refers to automated systems that process medical data such as clinical examinations or medical images and provide estimated diagnoses. The estimations are often based on the analysis of details that elude the human eye as well as large amounts of medical history that humans cannot possibly consider or analyzing non-visual characteristics of medical data. Although such systems typically do not reach 100% success, which means that they cannot substitute the working physician, the input they provide is extremely helpful as an independent source of evidence concerning a correct medical decision.

The development of intelligent health-care systems is a very promising area for commercial organizations active in the health monitoring domain. Currently, the cost effective provision of quality healthcare is a very important issue throughout the world since healthcare faces a significant funding crisis due to the increasing population of older people and the reappearance of diseases that should be controllable. Intelligent healthcare systems are capable of attacking all these challenges in an efficient and cost-effective way. Hardware and software is gradually becoming cost-affordable, can be installed and operated in numerous sites (frequently visited by patients), can be interfaced to a wide variety of medical information systems (e.g., patient databases, medical archives), thus involving numerous actors. Hence, the electronic health systems in general present a truly scalable architecture covering a wide spectrum of business roles and models [23].

This chapter aims at presenting the state of the art and new trends in intelligent healthcare systems. The chapter is structured as follows: Section 2 discusses the technologies that enable the use of healthcare computing (i.e., patient data acquisition methods and tools, medical data management, healthcare information systems and medical data exchange). Section 3 overviews the intelligent aspect that can be applied in electronic healthcare systems, while Section 4 focuses on new concepts in electronic healthcare applications such as intelligent agents and context-awareness and finally, Section 5 presents the challenges of the near future and concludes this chapter.

2 HealthCare Enabling Technologies

2.1 Patient Biosignals and Acquisition Methods

A broad definition of a signal is a 'measurable indication or representation of an actual phenomenon', which in the field of biosignals, refers to observable facts or stimuli of biological systems or life forms. In order to extract and document the meaning or the cause of a signal, a physician may utilize simple examination procedures, such as measuring the temperature of a human body or may have to resort to highly specialized and sometimes intrusive equipment, such as an endoscope. Following signal acquisition, physicians go on to a second step, that of interpreting its meaning, usually after some kind of signal enhancement or 'pre-processing', that separates the captured information from noise and prepares it for specialized processing, classification and decision support algorithms.

Biosignals require a digitization step in order to be converted into a digital form. This process begins with acquiring the raw signal in its analog form, which is then fed into an analog-to-digital (A/D) converter. Since computers cannot handle or store continuous data, the first step of the conversion procedure is to produce a discrete-time series from the analog form of the raw signal. This step is known as 'sampling' and is meant to create a sequence of values sampled from the original analog signals at predefined intervals, which can faithfully reconstruct the initial signal waveform. The second step of the digitization process is quantization, which works on the temporally sampled values of the initial signal and produces a signal, which is both temporally and quantitatively discrete; this means that the initial values are converted and encoded according to properties such as bit allocation and value range. Essentially, quantization maps the sampled signal into a range of values that is both compact and efficient for algorithms to work with. The most popular biosignals utilized in electronic healthcare applications ([1], [3], [4], [10], [11], [16], [17], [19], [20], [23]) are summarized in Table 1.

Table 1. Broadly used biosignals with corresponding metric ranges, number of sensors required and information rate.

Biomedical Measurements (Broadly Used Biosignals)	Voltage range (V)	Number of sensors	Information rate (b/s)
ECG	0.5-4 m	5-9	15000
Heart sound	Extremely small	2-4	120000
Heart rate	0.5-4 m	2	600
EEG	2-200 µ	20	4200

EMG	0.1-5 m	2+	600000
Respiratory rate	Small	1	800
Temperature of body	0-100 m	1+	80

In addition to the aforementioned biosignals, patient physiological data (e,g., body movement information based on accelerometer values), and context-aware data (e.g., location, environment and age group information) have also been used by electronic healthcare applications ([1], [2], [3], [4], [6], [13], [14], [15], [18], [20], [21], [24]). The utilization of the latter information is discussed in the following sections.

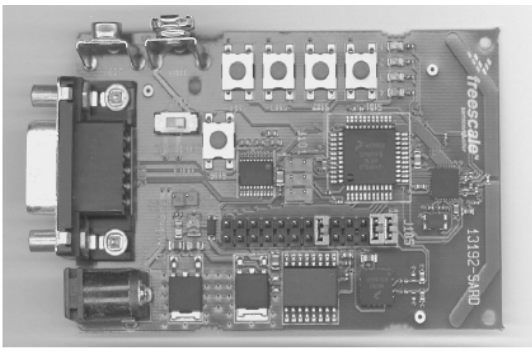

Fig. 1. Accelerometer sensor device that can be attached on patient's body and transmit movement data wirelessly to the monitoring unit [21].

Fig. 2. CodeBlue [9]: A wearable ECG and pulse oximeter measurement device.

In the context of healthcare applications, the acquisition of biomedical signals is performed through special devices (i.e. sensors) attached on the patients body (see Fig. 1) or special wearable devices (see Fig. 2). Regarding the contextual information, most applications are based on data collected from video cameras, microphones, movement and vibration sensors.

2.2 Healthcare Information Systems and Medical Data Exchange

The use of healthcare information systems and potential applications are numerous nowadays. Medical platforms allowing doctors to access Electronic Health Records (EHR) are already set up in several countries [33], [34], [35]. An EHR is an electronic version of a patient's medical history, that is maintained by the healthcare provider over time, and includes all of the key administrative clinical data relevant to that person's care under a particular provider, including demographics, progress notes, problems, medications, vital signs, past medical history, immunizations, laboratory data, medical images and radiology reports.

Table 2. Electronic Health Records (EHR) data modalities

Digital Data	**Contrast / Resolution (No. of samples per second x bits per sample)**	**Data Size**
Demographic Data		~ 100 KB
Clinical Data (Biosignals)		~ 100 KB / incident
Digital audio stethoscope (Heart Sound)	10000 x 12	~ 120 kbps
Electrocardiogram ECG	1250 x 12	~ 15 Kbps
Electroencephalogram EEG	350 x 12	~ 10 Kbps
Electromyogram EMG	50000 x 12	~ 600 Kbps
Ultrasound, Cardiology, Radiology	512x512x8	256 KB (image size)
Magnetic resonance image	512x512x8	384 KB (image size)
Scanned x-ray	1024x1250x12	1.8 MB (image size)
Digital radiography	2048x2048x12	6 MB (image size)
Mammogram	4096x4096x12	24 MB (image size)
Compressed and full motion video (telemedicine)	-	384 kbps to 1.544 Mb/s (speed)

The EHR automates access to information and has the potential to streamline the clinician's workflow. The EHR also has the ability to support other care-related activities directly or indirectly through various interfaces, including evidence-based decision support, quality management, and outcomes reporting. The type of data included in EHR systems are presented in Table 2.

EHR systems provide the hospitals with the infrastructure to collaborate efficiently at a technical level. Hospitals are sufficiently rich in their infrastructure to handle the internal administrative and clinical processes and the need to integrate the processes of geographically distributed and organizationally independent organizations is evident. At business level, however, the need to integrate the processes of geographically distributed and organizationally independent organizations led the design of architecture of health information systems to combine the principles of different approaches to interoperability: Workflow Management Systems (WfMSs), the Middleware approaches to interoperability such as Message Oriented Middleware, the Semantic Web and Visual Integration. A brief reference to the above approaches is given in the following paragraphs.

Workflow is defined [36] as the computerized facilitation or automation of a business process, in whole or part and a Workflow Management System is a system that completely defines, manages and executes “workflows” through the execution of software whose order of execution is driven by a computer representation of the workflow logic. Interoperability among workflow products concerns a standardized set of interfaces and data interchange formats between such components in the health care sector.

2.2.1 The Semantic Web – Web Services

The World Wide Web was initially designed for unstructured information exchange, but that led to lack of uniformity for accessing web services. To facilitate access to complex services, a group of companies standardized on SOAP (Simple Object Access Protocol) as a light-weight protocol based on XML for exchanging messages over the Web. Similarly higher-level service layers have been defined such as WSDL (Web Service Description Language) and UDDI (Universal Description, Discovery and Integration). The use of ontology is suggested and languages for specification and representation of knowledge in the semantic web like OWL, OIL, DAML+OIL, UDDI are used.

2.2.2 Message Oriented Standards – HL7

Health Level Seven, Inc. ([37]) is a not-for-profit, ANSI-Accredited Standards Developing Organization that provides standards for the exchange, management and integration of data that supports clinical patient care and the management, delivery and evaluation of healthcare services. Data exchange is implemented by exchanging messages. HL7 corresponds to the conceptual definition of an application-to-application interface placed in the 7th layer of the OSI model. HL7 achieves interoperability through syntactically and semantically standardized messages. In the US and in many European countries the HL7 standard has become the main communication standard for healthcare system integration.

2.2.3 Message Oriented Standards – CEN/TC 251 health informatics

CEN is a European collaboration of the formal standards bodies of 19 countries with strong links to the politics of the European Union and with Eastern European countries as associate members. The standardization of Health Informatics started in 1990 and has resulted in a number of message standards based on information models, most often implemented in Edifact, but since 1999, also implementable in XML. The standards work of CEN/TC 251 complements HL7 work in the areas of security, healthcare record architecture and device communication. The standard that has been defined for the field of health informatics is a messaging standard and also provides the architecture concept for the middleware layer for healthcare-specific applications.

2.2.4 Message Oriented Standards – DICOM

The great majority of equipment that deals with digital medical imaging and communication supports DICOM. It supports operation in a networked environment using the industry standard networking protocol TCP/IP. The standard specifies how devices react to commands and data being exchanged. The creation of DICOM Structured Reporting (DICOM-SR), in the year 2000, has established a method for constructing and transferring information objects that encode structured documents. Structured reports ease the search for specific information, report translation and comparison between different findings. The standard explicitly describes how reports are structured, using controlled terminology like SNOMED.

2.2.5 CORBA

Distributed application frameworks required to build complex services have been around for a while. Popular ones are (or have been) COM (Component Object Model), DCOM (Distributed COM), and COM+ which are Microsoft specific, EJB (Enterprise Java Beans) which is Java specific, and CORBA (Common Object Request Broker Architecture) [37] which is both platform and language independent. CORBA is created and maintained by the Object Management Group (OMG), an international, non-profit software organization driven and supported by information system vendors' software developers and technology users. To address the needs of the rapidly changing healthcare industry, the OMG established a Healthcare Task Force, the CORBAmed. A key difference between CORBA and Web Service Technologies (UDDI/WSDL/SOAP) is that CORBA provides true object-oriented component architecture unlike the Web services, which are primarily message–based [38]. Moreover CORBA also comes with a standard set of services (Events, Naming, Trading) that allow application writers to focus on the business logic rather than on the details of the communication infrastructure.

The above mentioned standards enable the interoperability of electronic healthcare systems and in addition facilitate the collection of large medical datasets describing logical organization of same or similar pathological conditions for one or many patients. These medical datasets are the basis for the development of intelligent systems, allowing the advanced processing and interpretation of physiological, clinical and image medical data. These systems are encountered mostly as advanced Medical Decision Support Systems (MDSS) that could help medical professionals as diagnostic adjuncts promoting the quality of medical services, especially in underserved populations, where expert medical knowledge is unavailable. This aspect of electronic healthcare systems is discussed in the next section.

3 Artificial Intelligence in Electronic Healthcare Systems

The objective of computer-assisted decision making in healthcare aims to allow the medical professional to use the computer as a tool in the decision process. The most important processes in the development and operation of Medical Decision Support Systems (MDSS) are (i) the acquisition of information regarding the diagnosis classes and (ii) the actual classification of a given case to a diagnosis. The two steps are actually closely related to each other, as the type of classifier chosen in most cases also indicates the training methodology to use. Although there is an extremely wide variety of classification methodologies that one may choose to apply, the most well known and widely applied genres of approaches can be briefly summarized and categorized as follows:

1. The examined case is compared directly to other cases in the EHR and similarities are used in order to provide a most probable diagnosis.
2. Different types of classifiers are trained based on available health records, so that the underlying data patterns are automatically identified and utilized in order to provide more reliable classification of future data.
3. Information extracted automatically from medical history, or provided manually by human experts, is organized so that diagnosis estimation is provided in a dialogical manner through a series of question/answer sessions.
4. Multiple simple classifiers are combined in order to minimize the error margin.

5. Information provide by human experts in the form of simple rules is utilized by a fuzzy systems in order to evaluate the case in hand.

The following subsections discuss briefly the data classification methods used in MDSS and the corresponding evaluation methodologies.

3.1 Patient Data Classification Methods

Data classification is an important problem in a variety of engineering and scientific disciplines such biology, psychology, medicine, marketing, computer vision, and artificial intelligence [30]. Its main object is to classify objects into a number of categories or classes. Depending on the application, these objects can be images or signal waveforms or any type of measurements that need to be classified. Given a specific data feature, its classification may consist of one of the following two tasks: a) supervised classification in which the input pattern is identified as a member of a predefined class; b) unsupervised classification in which the pattern is assigned to a hitherto unknown class.

In statistical data classification, input data are represented by a set of n features, or attributes, viewed as an n-dimensional feature vector. The classification system is operated in two modes: training and classification. Data preprocessing can be also performed in order to segment the pattern of interest from the background, remove noise, normalize the pattern, and any other operation which will contribute in defining a compact representation of the pattern. In the training mode, the feature extraction/selection module finds the appropriate features for representing the input patterns and the classifier is trained to partition the feature space. The feedback path allows a designer to optimize the preprocessing and feature extraction/selection strategies. In the classification mode, the trained classifier assigns the input pattern to one of the pattern classes under consideration based on the measured features.

There is a vast array of established classification techniques, ranging from classical statistical methods, such as linear and logistic regression, to neural network and tree-based techniques. In the following we review the main categories of classification systems that find application in an MDSS framework.

3.1.1 k- **Nearest Neighbours**

The *k*-Nearest Neighbours methodology, often referred to as *k*-NN, constitutes a breed of classifiers that attempt to classify the given patient data by identifying other similar cases in his or other health records. The simplest, as well as most common, case is when all considered features extracted by medical data are scalars. The *k*-NN methodology has found many applications in the field of MDSSs [44], [45], [46].

3.1.2 Artificial Neural Networks

Artificial Neural Networks (ANNs) are the main representatives of a more robust approach to classification; these classifiers, prior to being put to use, process available medical data in EHRs in order to extract useful information concerning the underlying data patterns and structure, thus also acquiring the information required in order to optimize the classification process. Following a massively parallel architecture, quite similar to that of neurons in the human brain, ANNs construct powerful processing and decision making engines through the combination of quite trivial processing units – also named neurons. ANNs are exhaustively used in MDSS. For instance, the following works are based on applications of ANNs [47], [48], [49], [50], while [51] reviews the benefits of ANN application in medicine in general.

The characteristic that makes ANNs so popular is the fact that given a set of labeled data (extracted by the EHR) an ANN will tune itself in an automated manner so as to match these data in the best possible way. Unfortunately, this training process is not a trivial one. Numerous methodologies are presented in the literature for training ANNs, each one focusing on a different feature or situation. Thus, different training methodologies (as well as network structure) can be used when the amount of training data is small, computing resources are limited, some or all of the medical data are unlabelled. Therefore the adoption of the standards discussed in section 2 is considered a necessity.

3.1.3 Self Organizing Maps

The fact that one needs to have a clear idea concerning the structure of the network (count of layers, count of neurons) before even training and testing can start is a very important limitation for ANNs. Kohonen's Self Organizing Maps (SOMs) constitute a more interesting and robust approach to training a network with no prior knowledge of the underlying data structures. A number of details about the selection of the parameters, variants of the map, and many other aspects have been covered in the monograph [52]. Due to their excellent properties and characteristics, SOMs have found numerous applications in MDSSs, such as [53], [54], [55], [56].

3.1.4 Support Vector Machines

The Support Vector Machine (SVM) is a novel algorithm for data classification and regression. It was introduced by Vapnic and is clearly connected with statistical learning theory [57], [58], [59]. The SVM is an estimation algorithm that separates data in two classes, but since all classification problems can be restricted to consideration of the two-class classification problem without loss of generality, SVMs can be applied to classification problems in general. SVMs allow the expansion of the information provided by a training data set as a linear combination of a subset of the data in the training set (support vectors). These vectors locate a hypersurface that separates the input data with a very good degree of generalization. The SVM algorithm is a learning machine; therefore it is based on training, testing and performance evaluation, which are common steps in every learning procedure. Training involves optimization of a convex cost function where there are no local minima to complicate the learning process. Testing is based on the model evaluation using the support vectors to classify a test data set. Performance is based on error rate determination as test set data size tends to infinity. Due to the fact that SVMs focus on maximizing the margin between classes, thus minimizing the probability of misclassification, they are extremely popular in MDSSs, where the cost of a misclassification may have a direct impact on human life. The following works are just a few examples of works in the medical field that are based on SVM learning [60], [61], [62], [63], [64].

3.1.5 Decision Trees

Physicians using MDSSs are often reluctant to leave important medical decisions to a sub-symbolic, and thus generally incomprehensible, automated engine. Decision trees offer an alternative computing methodology which reaches a decision through consecutive, simple question and answer sessions.

In the learning phase (when the decision tree is constructed) exactly one of the available features needs to be selected as the root feature, i.e. the most important feature in determining the diagnosis. Then data are split according to the value they have for this feature, and each group of data is used in order to create the corresponding child (sub-tree) of the root. If all of the data in a group belongs to the same diagnosis, then that child becomes a leaf to the tree and is assigned that diagnosis. Otherwise, another feature is selected for that group, and data are again split leading to new groups and new children for this node. Decision trees are also widely used for the development of MDSS [65], [66], [67], [68], [69]. A review of decision tree applications in medicine is available in [70].

3.2 Performance Evaluation of Classification Systems

The performance of each classifier is tested using an ideally large set of manually classified data. A subset of them, e.g., 80% is used as the training set and the remaining 20% of the samples are used for testing using the trained classifier. The training and test data are exchanged for all possible combinations to avoid bias in the solution. Classification performance of MDSS is typically based on a true/false and positive/negative scheme. When adopted in the medical case, true positive (TP) is correct illness estimation, true negative (TN) a correct healthy estimation, false positive (FP) illness estimation for a healthy case and a false negative (FN) a healthy estimation for an ill case. Based on these, accuracy is defined as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad \textit{(Equation 1)}$$

The simplistic approach of simply counting correct and incorrect classifications in order to estimate accuracy, although generally accepted in other expert systems and classifiers, is not sufficient for the case of medical systems, where one type of mistake may be much more important – as far as the possible consequences are concerned – compared to another. For example a false positive estimation has the result of a patient taking extra tests in order to verify their health status, whereas a false negative diagnosis may deprive them of early diagnosis and treatment. Finally, classes in a medical setting are rarely balanced; it is typical that only a small percentage of people examined will actually be ill. As a result, a system that always provides a “healthy” diagnosis reaches high classification rates.

In order to compensate for this, a more flexible consideration of errors needs to be used, in order for class probabilities to be considered as well. A simple approach that is commonly followed in this direction is the utilization of specificity and sensitivity measures, defined as follows:

$$Specificity = \frac{TN}{TN + FP} \qquad \textit{(Equation 2)}$$

$$Sensitivity = \frac{TP}{TP + FN} \qquad \textit{(Equation 3)}$$

where specificity and sensitivity are actually measures of accuracy, when considering only healthy or only ill cases, respectively, thus decoupling the measures from class probabilities.

A graphical representation of classification performance is the Receiver Operating Characteristic (ROC) curve (see Fig. 3), which displays the “tradeoff” between sensitivity (i.e. TPF) and specificity (i.e. TNF) that results from the overlap between the distribution of lesion scores for ill and healthy data. A good classifier is one with close to 100% sensitivity at a threshold such that high specificity is also obtained. The ROC for such a classifier will plot as a steeply rising curve. When different classifiers are compared, the one whose curve rises fastest should be best. If sensitivity and specificity were weighted equally, the greater the area under the ROC curve (AUC), the better the classifier. An extension of ROC analysis found in the literature [39] is the three-way ROC analysis that applies to trichotomous tests. It summarizes the discriminatory power of a trichotomous test in a single value, called the volume under surface (VUS) by analogy to the AUC value for dichotomous tests. Just as the AUC value for dichotomous tests is equivalent to the probability of correctly ranking a given pair of normal and abnormal cases, the VUS value for trichotomous tests is equivalent to the probability of correctly distinguishing three cases, where each case is from a different class.

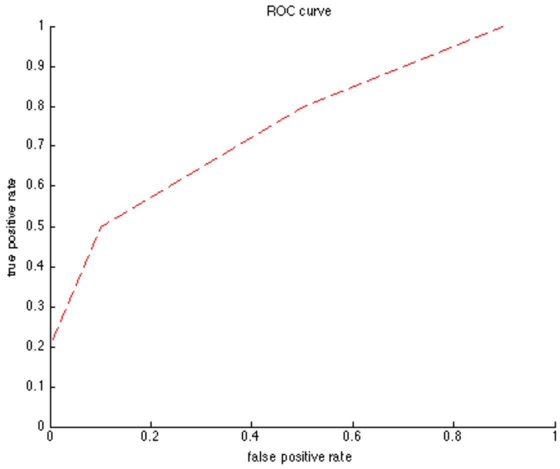

Fig. 3. Example of ROC curve. X-axis represents the false positive rate (1-Sp, where Sp is the specificity) and the Y-axis the true positive rate (or Sensitivity, Se).

4 New concepts: Intelligent Agents and Context Awareness

As can be seen from the above section, several research efforts dealing with machine intelligence techniques on clinician settings providing advanced healthcare services exist in the literature. All of the surveyed works present corresponding clinical trials of the effects and patient outcomes from the application of such Medical Decision Support Systems (MDSS). State of the art works in the field of intelligent electronic healthcare systems, report that the new concepts and approaches deal with advanced data mining and intelligent agents, while context awareness is the new desirable feature of e-health applications. The next two subsections analyze the aforementioned newly introduced approaches.

4.1 Data Mining and Intelligent Agents

The proliferation of healthcare data has resulted in a large number of efforts to inductively manipulate, interpret and discover ‘useful’ knowledge from the collected data. Interesting results have been reported by health informatics researchers using a variety of advanced Data Mining (DM) algorithms [31], [32].

The most important anticipated tasks for the medical repositories are summarized into the following:

- Problem analysis and specification, which guides the choice of ‘appropriate’ DM
- Establishing a communication channel to enable remote access to the data repositories of multiple hospitals. Technically this involves the exchange of messages.
- Collection of ‘relevant’ data to complete each individual task need to be first identified and subsequently retrieved from the respective data repositories.
- Synthesis of heterogeneous data originating from multiple data repositories.
- Preparation of the data according to the specification of the DM service packages.
- Execution of the DM algorithm.
- Generation of a DM report for the end-user.

Due to the existence of multiple heterogeneous data repositories in a healthcare enterprise, a distributed data community should be established, such that any DM effort draws upon the ‘holistic’ data available within the entire healthcare enterprise. Multi Agent-Based Data Mining Info-Structures (ADMI), responsible for the generation of data-mediated diagnostic-support and strategic services have been proposed. The latter takes advantage of a multi-agent architecture, which features the amalgamation of various types of intelligent agents.
Intelligent agents can be viewed as autonomous software (or hardware) constructs that are proactively involved in achieving a predetermined task and at the same time reacting to its environment. According to [29], agents are capable of:

- performing tasks (on behalf of users or other agents).
- interacting with users to receive instructions and give responses.
- operating autonomously without direct intervention by users, including monitoring the environment and acting upon the environment to bring about changes.
- showing intelligence – to interpret monitored events and make appropriate decisions.

Agents can be proactive, in terms of being able to exhibit goal-directed behavior, reactive; being able to respond to changes in the environment, including detecting and communicating to other agents, autonomous; making decisions and controlling their actions independently of others. Intelligent agents can be also considered as social entities where they can communicate with other agents using an agent-communication language in the process of carrying out their tasks. Software agents can also be used in order to perform distributed analysis of vital data and give an alarm indication to previously-selected physicians and family members [11]. Agents may also assist patients or treatment experts to perform basic tasks like meal preparation and medication [11], [12].

Additional Agent-based techniques [7] can often be utilized for modeling application components as somewhat autonomous agents that easily reflect healthcare institutions' decentralized networks. Medical agent interfaces ([5], [23]) provide continuous and more direct access to the aforementioned information. Software agents are installed either on mobile devices (e.g., PDAs) or on interactive devices within the treatment center (e.g. PCs or LCD monitors, or smart walls [11]). Information retrieval and presentation can be either performed by user request or reactively (e.g, based on user's location or patient's state). Queries regarding patient data or medical information (e.g., medication procedures, diseases symptoms, etc.) are parsed through specific agents (i.e. query optimization agents) and forwarded to knowledge retrieval agents for research. The information retrieval can be performed either from the local hospital information system or remote medical knowledge repositories. Information retrieval, knowledge adaptation and presentation to the user are performed by related agents using medical ontologies for proper knowledge data representation [8].

Using such advanced knowledge representation and medical data retrieval methods, to access multiple healthcare information is feasible, even from mobile devices. Proper access restriction to sensitive information can be applied and direct access to important information in cases of emergency can be established [25].

4.2 Context Awareness

Context awareness is the capability of ehealth applications to be aware of the existence and characteristics of the patient's activities and environments. In rapidly changing scenarios, such as the ones considered in the fields of biomedical informatics, systems have to adapt their behaviour based on the current conditions and the dynamicity of the environment they are immersed in ([28]). A system is context-aware if it can extract, interpret and use context information and adapt its functionality to the current context of use. The challenge for such systems lies in the complexity of capturing, representing and processing contextual data. To capture context information generally some additional sensors and/or programs are required [22]. The main goal of context aware computing is to acquire and utilize information about the context of a medical device to provide services that are appropriate to particular people, place, time, events, etc. ([42]). According to the latter, the work presented in [40] describes a context-aware mobile system for inter-hospital communication taking into account patient's and physician's physical location for instant and efficient messaging regarding medical events. J. Bardram presents in [41] additional cases of context-awareness used within treatment centres and provides design principles for such systems. The project 'AWARENESS' (presented in [43]) provides a more general framework for enhanced telemedicine and telediagnosis services depending on patient status and location.

The way context-aware applications make use of context can be categorized into the three following classes: presenting information and services, executing a service, and tagging captured data.

Presenting information and services refers to applications that either present context information to the user, or use context to propose appropriate selections of actions to the user.

Automatically executing a service describes applications that trigger a command, or reconfigure the system on behalf of the user according to context changes.

Attaching context information for later retrieval refers to applications that tag captured data with relevant context information.

The patient state can be determined through a number of biosensors (i.e. heart rate and body temperature sensors) and corresponding vital signals. Defined threshold values in the latter signals determine the case of an immediate medical data transmission (alarm event) to the monitoring unit. In case of normal patient status, periodical summarized data transmission might occur at lower detail. Data coding and transmission can also vary according to network availability and quality: Context awareness can be used for instance in cases of remote assessment or telesurgery. According to the network interface used, appropriate video coding is applied to the transmitted medical data, avoiding thus possible transmission delays and optimizing a telemedicine procedure.

5 Discussion and Conclusions

As clinical machine intelligence techniques mature, it seems they can offer increasingly exciting prospects for improving the effectiveness and efficiency of patient care and the development of more reliable intelligent electronic healthcare systems. According to a recent review [71] published studies of clinical machine intelligence systems are increasing rapidly, and their quality is improving. It seems that they may enhance clinical performance for drug studies, preventive care, and other aspects of medical care, but not convincingly however in all cases for diagnosis and prognosis. The potential reason for this is that rigorous evaluations of MDSSs are usually more difficult to conduct than evaluations of drug studies, for instance, because clinical settings often preclude complete separation of the intervention and control groups. The studies of patient outcomes require also large numbers of participants and significant budgets, which are not always easy to find. Without the existence of such rigorous patient outcomes studies physicians may not be convinced to introduce the use of MDSSs in the routine practice of healthcare.

Clearly, the goal is to reach a stage where intelligent electronic healthcare systems are integrated in the process of everyday clinical work, but without being assigned roles they are not made for, such as the role of the actual clinician. It seems that a number of parameters will have an effect in this process, ranging from purely financial issues to degree of automation, from availability at the time and location it is needed to the ease of the user interface and from the adoption of standards in medical data acquisition components to the success of the system development and integration procedures. The areas in which intelligent electronic healthcare systems could make a difference are many. The following Table provides a summary of the most important ones in the author's view.

Table 3. Potential users and uses for intelligent electronic healthcare systems

User	Application
Pharmacists	Drug levels, drug/drug interactions, culture & sensitivity results, adverse drug events
Physicians	Advanced Medical Data Processing Tools, Extraction of Features, Quantification of Pathological Phenomena
Non-Expert Physician	Computer Supported Diagnosis
Remote Physician	Advanced Telemedicine Systems
Biologists	Simulation of pathogenetic mechanisms
Nurses	Critical lab results, drug/drug interactions
Dietary	Patient transfers, lab support for tube feedings
Epidemiology/infection control	Epidemiological results, reportable organisms
Homecare	Patient Monitoring at Home
Billing	Excessively expensive tests and treatments
Administration	Patient chart administration
Patient	Drug/drug interactions, drug dosing, missing tests

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