REAL-TIME INTELLIGENT DECISION SUPPORT IN INTENSIVE MEDICINE

Filipe Portela, Manuel Santos, Marta Vilas-Boas
Departamento de Sistemas de Informação, Universidade do Minho, Guimarães, Portugal

Fernando Rua, Álvaro Silva
Hospital de Santo António, Porto, Portugal

José Neves
Universidade do Minho, Departamento de Informática, Braga, Portugal

Keywords: Real-time, Knowledge Discovery in Databases, Intensive Care, INTCare, Intelligent Decision Support Systems.

Abstract: Daily, a great amount of data that is gathered in intensive care units, which makes intensive medicine a very attractive field for applying knowledge discovery in databases. Previously unknown knowledge can be extracted from that data in order to create prediction and decision models. The challenge is to perform those tasks in real-time, in order to assist the doctors in the decision making process. The Data Mining models should be continuously assessed and optimized, if necessary, to maintain a certain accuracy. In this paper we present the INTCare system, an intelligent decision support system for intensive medicine and the way it was adapted to the new requirements. Some preliminary results are analysed and discussed.

1 INTRODUCTION

Intensive care units (ICU) are a particular environment where a great amount of data related to the patients' condition is daily produced and collected. Physiological variables such as heart rate, blood pressure, temperature, ventilation and brain activity are constantly monitored on-line (Mahmoud 2003). Due to the complex condition of critical patients and the huge amount of data, it can be hard for physicians to decide about the best procedure to provide them the best health care possible. The human factor can lead to errors in the decision making process; frequently, there is not enough time to analyze the situation because of stressful circumstances; furthermore, it is not possible to continuously analyze and memorize all the data (Pereira et al. 2007) .

Care of the critically ill patients requires fast acquisition, registering and availability of data (Gardner et al. 1991). Accordingly, rapid interpretation of physiological time-series data and accurate assessment of patient state is crucial to patient monitoring in critical care. The data analysis allows supporting decision making through prediction and decision models. Algorithms that use Artificial Intelligence (AI) techniques have the potential to help achieve these tasks, but their development requires well- annotated patient data (Ying, Silvers and Randolph 2007, Morik 2003).

We are developing a real-time and situated intelligent decision support system, called INTCare[1], whose main goal is to improve the health care, allowing the physicians to take a pro-active attitude in the patients' best interest (Santos et al. 2006, Gago et al. 2006).

INTCare is capable of predicting organ failure probability, the outcome of the patient for the next hour, as well as the best suited treatment to apply.

[1] The INTCare project is financially supported by FTC (PTDC/EIA/72819/2006).

Portela F., Santos M., Vilas Boas M., Rua F., Silva Á. and Neves J..
REAL-TIME INTELLIGENT DECISION SUPPORT IN INTENSIVE MEDICINE.
DOI: 10.5220/0003098200440050
In *Proceedings of the International Conference on Knowledge Management and Information Sharing* (KMIS-2010), pages 44-50
ISBN: 978-989-8425-30-0

To achieve this, it includes models induced by means of Data Mining (DM) techniques (Santos et al. 2006), (Gago and Santos 2008, Gago, Silva and Santos 2007, Silva et al. 2003, Silva et al. 2004).

This paper is organized as follows. Section 2 presents some background relating to Intelligent Decision Support Systems (IDSS), Knowledge Discovery in Databases (KDD) and intensive medicine. In section 3 it is presented the INTCare system, focusing on its features, the information architecture and the latest DM models developed. Section 4 and 5 conclude this paper, presenting a discussion, a conclusion and pointing to future work.

2 BACKGROUND

2.1 Intelligent Decision Support Systems

According to Turban (Turban, Aronson and Liang 2005), a Decision Support System (DSS) is an interactive, flexible and adaptable information system, developed to support a problem solution and to improve the decision making. These systems usually use AI techniques and are based on prediction and decision models that analyze a vast amount of variables to answer a question.

The decision making process can be divided in five phases: Intelligence, design, choice, implementation and monitoring (Turban et al. 2005). Usually it is used in the development of rule based DSS (Arnott and Pervan 2004). However, these DSS are not adaptable to the environment in which they operate. To address this fault, Michalewicz (Michalewicz et al. 2007) introduced the concept of Adaptive Business Intelligence (ABI). The main difference between this and a regular DSS is that it includes optimization that enables adaptability. An ABI system can be defined as "the discipline of using prediction and optimization techniques to build self-learning decisioning systems. ABI systems include elements of data mining, predictive modelling, forecasting, optimization, and adaptability, and are used to make better decisions." (Michalewicz et al. 2007).

As it is known, predictive models' performance tends to degrade over time, so it is advantageous to include model re-evaluating on a regular basis so as to identify loss of accuracy (Gago and Santos 2008) and enable their optimization.

There is a particular type of DSS, the real-time DSS. Ideally, the later includes adaptive behaviour, supporting the decision making in real-time.

To achieve real-time DSS, there is a need for a continuous data monitoring and acquisition systems. It should also be able to update the models in real time without human intervention (Santos et al. 2006). In medicine, most systems only use data monitoring to support its activities, without predictive behaviour and with poor integration with other clinical information.

2.2 Knowledge Discovery from Databases

KDD is one of the approaches used in Business Intelligence (BI). According to Negash (Negash and Gray), BI systems combine data gathering, data storage, and knowledge management with analytical tools to present complex and competitive information to planners and decision makers. KDD is an interactive and nontrivial process of extracting implicit and previously unknown and potentially useful and understandable information from data (Frawley, Piatetsky-Shapiro and Matheus 1992).

The KDD process is divided in 5 steps: Selection, pre-processing, transformation, data mining and interpretation/evaluation (Fayyad, Piatetsky-Shapiro and Smyth 1996). This process starts with raw data and ends with knowledge.

The automation of the knowledge acquisition process is desirable and it is achieved by using methods of several areas of expertise, like machine learning (Gago et al.). The knowledge acquisition takes advantage of KDD techniques, simplifying the process of decision support (Gago and Santos).

Knowledge discovery is a priority, constantly demanding for new, better suited efforts. Systems or tools capable of dealing with the steadily growing amount of data presented by information system, are in order (Lourenco and Belo 2003).

2.3 Intensive Medicine

Intensive medicine can be defined as a multidisciplinary field of the medical sciences that deals with prevention, diagnosis and treatment of acute situations potentially reversible, in patients with failure of one or more vital functions (Silva 2007). These can be grouped into six organic systems: Liver, respiratory, cardiovascular, coagulation, central nervous and renal (Hall, Schmidt and Wood 2005).

ICU are hospital services whose main goal is to provide health care to patients in critical situations and whose survival depends on the intensive care (Ramon et al. 2007), (Rao and T. 2003). In the ICU, the patients' vital signs are continuously monitored and their vital functions can be supported by medication or mechanical devices, until the patient is able to do it autonomously (Ramon et al. 2007).

Clinical intervention is based on the degree of severity scores like the SOFA (Sequential Organ Failure Assessment) score, that allow the evaluation of the patient's condition according to a predefined set of values (Vincent et al. 1996).

The assessment of these severity scores are based on several medical data acquired from bedside monitors, lab results and clinical records.

2.4 Real-time

A system that aims to support decision making must analyze many parameters and output in short real-time and consider online monitoring (Morik, Brockhausen and Joachims). It is known that in the ICU setting, there is a huge amount of noisy, high dimensional numerical time series data describing patients. Consequently, such systems must go beyond classical medical knowledge acquisition, since they have to handle with high dimensional data in real-time.

Data acquisition in real-time implies the need for a system responsible for collecting the relevant data to the DSS. This process can be divided in two phases: monitoring and acquisition and storage. Initially, the required data (variables) for the project is identified for further being monitored by sensors or other technology. Subsequently, data is acquired and stored in DB. This is a critical phase, for technical, human and environment factors are involved and may condition the quality of the data acquired by a gateway, for example, and its storage on a DB. Usually, the monitoring is continuous and there is a small percentage of failures. Although they may occur, they are relatively easy to correct. The biggest problem occurs in the communication between the monitoring system and the storage system.

In conclusion, monitoring in real-time is relatively easy; usually, problems arise in the data storage process.

3 THE INTCARE SYSTEM

INTCare is an IDSS for intensive medicine that is being developed in the ICU of the Hospital Santo António (HSA) in Porto, Portugal. It makes use of intelligent agents (M. F. Santos M.F.) (Abelha et al.) that are capable of autonomous actions in order to meet its goals (Gago et al. 2006), (Jennings 2000).

3.1 System Features

In order to model the information for KDD processing, the system attends some requirements:

Online Learning. The system acts online, i.e., the DM models are induced using online data in opposition of an offline approach, where the data is gathered and processed afterwards;

Real-time. The system actuates in real-time, for the data acquisition and storing is made immediately after the events take place to allow that decisions are taken whenever an event occurs;

Adaptability. The system has the ability to, automatically, optimize the models with new data when needed. This information is obtained from their evaluation results;

Data Mining Models. The success of IDSS depends, among others, on the acuity of the DM models, i.e., the prediction models must be reliable. These models make it possible to predict events and avert some clinical complications to the patients;

Decision Models. The achievement of the best solutions depend heavily on the decision models created. Those are based in factors like differentiation and decision that are applied on prediction models and can help the doctors to choose the better solution on the decision making process;

Optimization. The DM models are optimized over time. With this, their algorithms are in continuous training so that increasingly accurate and reliable solutions are returned, improving the models acuity;

Intelligent Agents. This type of agents makes the system work through autonomous actions that execute some essential tasks. Those tasks support some modules of the system: Data acquisition, data entry, knowledge management, inference and interface. The flexibility and efficiency of this kind of system emerges from the intelligent agents and their interaction (Gago et al. 2006).

In order to accomplish these features, the system has some requirements:

- Fault tolerance capacities;
- Processing to remove null and noisy data;
- Continuous data acquisition process;
- Time restrictions for the data acquisition and storage;
- Online learning mode;

- Digital data archive in order to promote the dematerialization of paper based processes (e.g., nursing records);
- Database extension to accommodate the data structures;
- Correct usage of the equipment that collects the vital signs.

3.2 Information Architecture

Patient management is supported by complex information systems, which brings the need for integration of the various types and sources of data (Fonseca, Ribeiro and Granja 2009).

In order to follow the requirements enumerated above, an information model was drawn, regarding the data acquisition module which includes three types of information sources:

- Bedside Monitors (BM);
- Lab Results (LR); and
- Electronic Nursing Records (ENR).

All sources can produce information to the system and that information can be used to develop predicting models in Intensive Care (knowledge). The development of an automated information system for ICU has to be in harmony with the whole information system and activities within the unit and the hospital (Fonseca et al. 2009).

The first type of sources relates to data acquisition from BM. This acquisition is in real-time, the data is received by a gateway, and it is stored on a DB table by an agent. Automatic acquisition eliminates transcription errors, improves the quality of records and allows the assembly of large electronic archives of vital sign data (Fonseca et al. 2009)

The second type of sources (LR) is the one that contains the less frequent observations, because the patient normally does this type of clinical analysis once or twice per day, except in extraordinary situations. With this method we can collect the data related with some clinical analysis, such as: number of blood platelets, creatinine, billirubin, SOFA scores, partial pressure of oxygen in arterial blood and fraction of inspired oxygen.

3.3 INTCare Sub-systems Functionality

The INTCare System (Gago et al. 2006, Santos et al. 2006) is divided into five subsystems, represented in Figure 1: data acquisition, data entry, knowledge management, inference and interface. Figure 1 shows a model that is a part of INTCare system and represents an evolution of two subsystems: data acquisition and data entry.

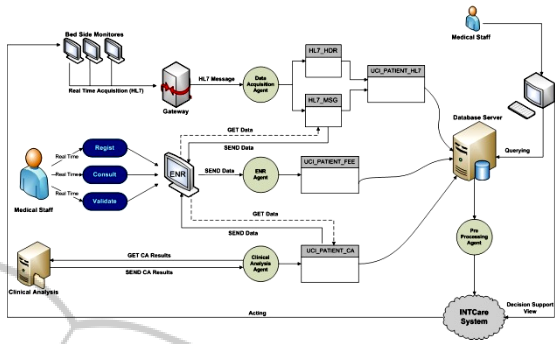

Figure 1: The INTCare system.

This subsystem is responsible for all activities of data acquisition and data store and will gather all required data into a data warehouse (Santos M.F. and J. 2009, Santos 2009, Santos et al. 2009). The evolution of this architecture is prominent. Formerly, most of the data was registered in paper format, and it was necessary to manually put it in electronic format, i.e., the information was rarely stored in computers, except the information from the BM, which was automatically collected and stored in electronic format.

The new architecture (Santos M.F. and J. 2009, Santos 2009, Santos et al. 2009) contemplates the data acquisition from three sources and, regarding the information input, it is done either automatically (BM, LR) or automatically and manually (nursing records). The adjustment made to the system was the addition of one more data source and the creation of two more agents that enable storing information in the database (DB).

This modification is in course and it is the most important, because it makes possible the data acquisition in electronic and automatic mode for all data sources through multi-agent system. Whit this change, we will have all the necessary information in electronic format for the DM models and the decision support process, addressing the timing requirements of critical tasks.

How These Subsystems Work. The first type of data sources is the BM, which collects the patients' vital signs (VS). The gateway is connected to the monitors, reads the information and stores it on a DB through the data acquisition agent. This agent splits a HL7 (Hooda, Dogdu and Sunderraman) message in two, one with the header information and another with patient data. The second source is the ENR (Santos M.F. and J. 2009). It was developed with the objective of registering electronically the paper-based nursing records. With the ENR, the medical and nursing staff can register various types of data, like confirming if some therapeutic was performed or not, and they may consult all the present and past data about the patients. The last type of data sources is the LR, which is controlled by the clinical analyses agent that automatically stores all the LB from the patients.

All the data is stored in one DB and it can be accessed by the medical staff through a computer. The integrated data will be used by the INTCare system to create prevision and decision models.

The DM agent belongs to the sub-system knowledge management and it is in charge of retrieving the required data to feed the DM models and to train new models whenever their performance becomes unsatisfactory.

3.4 Data Mining Models

3.4.1 Data Description

The data used to generate the DM models originates from three distributed and heterogeneous sources: LR, BM and paper-based nursing records, presented and explained previously. Additionally, variables containing the case mix (information that remains unchanged during the patient's stay - age, admission from, admission type) were also considered. It was also included some calculated variables: Critical Events (CE), SOFA scores and a set of ratios relating the previous variables to the patients' length of stay. The data was gathered in the ICU of HSA and it was collected in the first five days of stay of thirty two patients. The construction of the dataset was not automatically, the data from the LB and nursing records was manually registered, for the new adjustments of the system regarding the data acquisition and data entry were not developed at the time the models were generated

3.4.2 Features Selection

For the prediction of the dysfunction/failure of each organic system and outcome, three scenarios were explored regarding the inclusion of the variables mentioned above – M1, M2, and M3 – where

M1 = {Hour, Case Mix, CE}
M2 = {Hour, Case Mix, CE, Ratios}
M3 = {Hour, Case Mix, CE, SOFA}.

For each model, the techniques applied were Artificial Neural Networks, Decision Trees, Regression and Ensemble methods.

3.4.3 Results

Table 1 shows the best results achieved for cardiovascular, respiratory, renal, liver, coagulation and neurological systems and outcome in terms of sensibility (i.e. percentage of failure and death correctly classified as such) as well as the scenario that produced the best results. The models were developed for hourly prediction with the intent to make predictions as fast as possible, in the patients best interest.

Table 1: Sensibility of the DM models by system and outcome.

System	Sensibility (%)	Scenario
Cardiovascular	93.4	M3
Respiratory	96.2	M2
Renal	98.1	M3
Coagulation	97.5	M2

4 DISCUSSION

In this paper we presented the INTCare system, which is an IDSS for intensive medicine. It relies on the KDD process and AI algorithms to apply DM techniques for predicting outcomes that might support the course of action of doctors' decision.

Relying on intelligent agents, the system in divided into five sub-systems (data acquisition, data entry, knowledge management, inference and interface) that guarantee its functionality.

Since its beginning, INTCare has evolved towards using real-time and online clinical data so that the predictions can be as accurate and as soon as possible. As an IDSS, INTCare uses continuous data monitoring and acquisition systems that make possible for all information being available at the right time. This allows doctors to have a proactive attitude in patients' care.

The development of an ENR allows the integration of all necessary information regarding the patients' condition to be collected and integrated in just one application, which is a great gain in time and performance for the medical staff operating in the ICU. In addition to the patients' vital signs, data regarding their LR, procedures, medication, is also available by the time it is generated.

Moreover, the INTCare system is designed to address know issues of the ICU setting, such as noisy, high dimensional numerical time series data in real-time (Morik et al.), as well as the data acquisition in real-time, storage, integration and rapid availability of all clinical information.

5 CONCLUSIONS AND FUTURE WORK

The main concern in ICU is to avoid or reverse organ failure, in order to preserve the patients' lives. The INTCare system is being developed for hourly prediction of the patients' clinical condition, i.e. the prediction of dysfunction/failure of the organ systems (cardiovascular, respiratory, renal, coagulation and liver systems) and outcome. We believe that, with this fine grained prediction, it will be possible for the healthcare professionals to have a timely intervention and a proactive attitude so that worst complications for the patients may be avoided. Further work will encompass the test of the DM models generated so far, with online and real-time data from the ICU of HSA, in order to guarantee their accuracy or, in case their performance decays, to optimize them. The models presented used data manually entered and the next step is to use them with the new adjustments of the system, i.e., online and in real-time. Prediction, optimization and adaptability are features that make INTCare an ABI system, whose maid goal it to allow the medical staff to make better decisions, at the right time and place, improving quality in health care.

The integration with the various data sources and with the rest information systems of the hospital has been supported by the development of an ENR and further related work include its test in the ICU and subsequently, its optimization.

REFERENCES

Abelha, A., J. Machado, M. Santos, S. Allegro, F. Rua, M. Paiva & J. Neves. Agency for Integration, Diffusion and Archive of Medical Information.

Arnott, D. & G. Pervan. 2004. A critical analysis of decision support systems research. In *Conference on Decision Support Systems*, 67-87. Prato, ITALY: Palgrave Publishers Ltd.

Fayyad, U. M., G. Piatetsky-Shapiro & P. Smyth (1996) From data mining to knowledge discovery: an overview.

Fonseca, T., C. Ribeiro & C. Granja (2009) Vital Signs in Intensive Care: Automatic Acquisition and Consolidation into Electronic Patient Records. *Journal of Medical Systems,* 33**,** 47-57.

Frawley, W. J., G. Piatetsky-Shapiro & C. J. Matheus (1992) Knowledge Discovery in Databases: An Overview. *AI Magazine,* 13**,** 57-70.

Gago, P. & M. F. Santos. 2008. Towards an Intelligent Decision Support System for Intensive Care Units. In *18th European Conference on Artificial Intelligence*. Greece.

Gago, P., M. F. Santos, Á. Silva, P. Cortez, J. Neves & L. Gomes (2006) INTCare: a knowledge discovery based intelligent decision support system for intensive care medicine. *Journal of Decision Systems*.

Gago, P., A. Silva & M. F. Santos. 2007. Adaptive decision support for intensive care. In *13th Portuguese Conference on Artificial Intelligence,* ed. J. S. M. F. M. J. M. Neves, 415-425. Guimaraes, PORTUGAL: Springer-Verlag Berlin.

Gardner, R. M., W. L. Hawley, T. D. East, T. A. Oniki & H. F. W. Young (1991) Real time data acquisition: recommendations for the Medical Information Bus (MIB). *International journal of clinical monitoring and computing,* 8**,** 251-258.

Hall, J. B., G. A. Schmidt & L. D. H. Wood. 2005. *Principles of Critical Care*. McGraw-Hill's AccessMedicine.

Hooda, J. S., E. Dogdu & R. Sunderraman. Health Level-7 compliant clinical patient records system. 259-263. ACM.

Jennings, N. R. (2000) On agent-based software engineering. *Artificial Intelligence,* 117**,** 277-296.

Lourenco, A. & O. Belo (2003) Promoting agent-based knowledge discovery in medical intensive care units. *WSEAS Transactions on Computers,* 2**,** 403-408.

M. F. Santos M.F., V.-B. M., Machado and A. A. J., Neves J., Silva A., Rua F., Salazar M., Quintas C., Cabral A.F. Intelligent Decision Support in Intensive Care Units - Nursing Information Requirements.

Mahmoud, M. 2003. Real-time data acquisition system for monitoring patients in intensive care unit., 320-326. Multisensor, Multisource Information Fusion: Architectures, Algorithms and Applications.

Michalewicz, Z., M. Schmidt, M. Michalewicz & C. Chiriac. 2007. *Adaptive Business Intelligence*. Springer.

Morik, K. (2003) Data analysis and knowledge validation in intensive care monitoring.

Morik, K., P. Brockhausen & T. Joachims. Combining statistical learning with a knowledge-based approach-a case study in intensive care monitoring. 268-277. Citeseer.

Negash, S. & P. Gray Business intelligence. *Handbook on Decision Support Systems 2*, 175-193.

Pereira, M., A. Curra, R. Rivas, J. Pereira, G. Banos, J. Teueiro & A. Pazos (2007) Computer aided monitoring system of intensive care unit patients. *WSEAS Transactions on Information Science and Applications,* 4**,** 78-84.

Ramon, J., D. Fierens, F. Güiza, G. Meyfroidt, H. Blockeel, M. Bruynooghe & G. Van Den Berghe (2007) Mining data from intensive care patients. *Advanced Engineering Informatics,* 21**,** 243-256.

Rao, S. M. & S. T. (2003) Organization of intensive care unit and predicting outcome of critical illness. *Indian J. Anaesth,* 47 (5)**,** 328-337.

Santos M.F., P. F., Vilas-Boas M., Machado & A. A. J., Neves J., Silva A., Rua F., Salazar M., Quintas C., Cabral A.F.,. 2009. Intelligent Decision Support in Intensive Care Units - Nursing Information Requirements. In *WSEAS Transactions on INFORMATICS,* ed. Springer.

Santos, M. F., P. Cortez, P. Gago, Á. Silva & F. Rua. 2006. Intelligent decision support in Intensive Care Medicine. In *2nd International Conference on Knowledge Engineering and Decision Support*, 401-405. Lisbon, Portugal.

Santos, M. F., F. Portela, M. Vilas-Boas, J. Machado, A. Abelha, J. Neves, A. Silva & F. Rua. 2009. Information Modeling for Real-Time Decision Support in Intensive Medicine. In *Proceedings of the 8th Wseas International Conference on Applied Computer and Applied Computational Science - Applied Computer and Applied Computational Science,* eds. S. Y. Chen & Q. Li, 360-365. Athens: World Scientific and Engineering Acad and Soc.

Santos, M. F., Portela, F., Vilas-Boas, M., Machado, J., Abelha, A., Neves, J. 2009. Information Architecture for Intelligent Decision Support in Intensive Medicine. In *8th WSEAS International Conference on APPLIED COMPUTER & APPLIED COMPUTATIONAL SCIENCE (ACACOS '09)*. Hangzhou, China,: WSEAS.

Silva, A. 2007. Modelos de Inteligência Artificial na análise da monitorização de eventos clínicos adversos, Disfunção/Falência de órgãos e prognóstico do doente critico. Tese de doutoramento, ciências médicas, universidade do Porto.

Silva, Á., P. Cortez, M. F. Santos, L. Gomes & J. Neves. 2004. Multiple organ failure diagnosis using adverse events and neural networks. In *6 th International Conference on Enterprise Information Systems*, 401-408. Springer.

Silva, Á., J. Pereira, M. Santos, L. Gomes & J. Neves. 2003. Organ failure prediction based on clinical adverse events: a cluster model approach. 3th International Conference on Artificial Intelligence and Applications: ACTA Press.

Turban, E., J. E. Aronson & T.-P. Liang. 2005. *Decision Support Systems and Intelligent Systems*. Prentice Hall.

Vincent, J. L., R. Moreno, J. Takala, S. Willatts, A. De Mendonca, H. Bruining, C. K. Reinhart, P. M. Suter & L. G. Thijs (1996) The SOFA (Sepsis-related Organ Failure Assessment) score to describe organ dysfunction/failure. *Intensive care medicine,* 22**,** 707-710.

Ying, Z., C. T. Silvers & A. G. Randolph. 2007. Real-Time Evaluation of Patient Monitoring Algorithms for Critical Care at the Bedside. In *Engineering in Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE*, 2783-2786.