

Fuzzy-Based Nosocomial Infection Control

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Abstract

Nosocomial, or hospital-acquired, infections (NIs) are a frequent complication affecting hospitalized patients. The growing availability of computerized patient records in hospitals allows automated identification and extended monitoring of the signs of NI for the purpose of reducing NI rates. A fuzzy- and knowledge-based system to identify and monitor NIs at intensive care units according to the European Surveillance System HELICS was developed. It was implemented into the information technology landscape of the Vienna General Hospital and is now in routine use.

1 Introduction

Nosocomial, or hospital-acquired, infections (NIs) are by far the most common complications affecting hospitalized patients. Currently, 5 to 10 percent of patients admitted to acute care hospitals acquire one or more infections. These adverse events affect approximately 2 million patients each year in the United States, result in some 90,000 deaths, and add an estimated \$ 4.5 to \$ 5.7 billion per year to the cost of patient care [1].

The growing availability of computerized patient records in hospitals allows extended monitoring of the signs of NIs for the purpose of reducing NI rates by early initiation of appropriate therapy. In addition, ward- and

institution-based surveillance data of NIs analyzed by infection control personnel are used as a basis to implement preventive measures.

2 Methods

Based on the methodological and practical results obtained from the development and application of CADIAG-II/RHEUMA (computer-assisted diagnosis, version 2, applied to rheumatology), a fuzzy-based differential diagnostic consultation system for rheumatology [2–5], the MONI system (cf., Fig. 1) was developed [6, 7]. MONI is a fuzzy- and knowledge-based system for the evaluation of definitions of NIs according to the European Surveillance System HELICS [8]. The definitions are derived from those issued by the Centers for Disease Control and Prevention (CDC) in Atlanta, USA [9, 10]. They are expressed as natural language text (see Fig. 2)

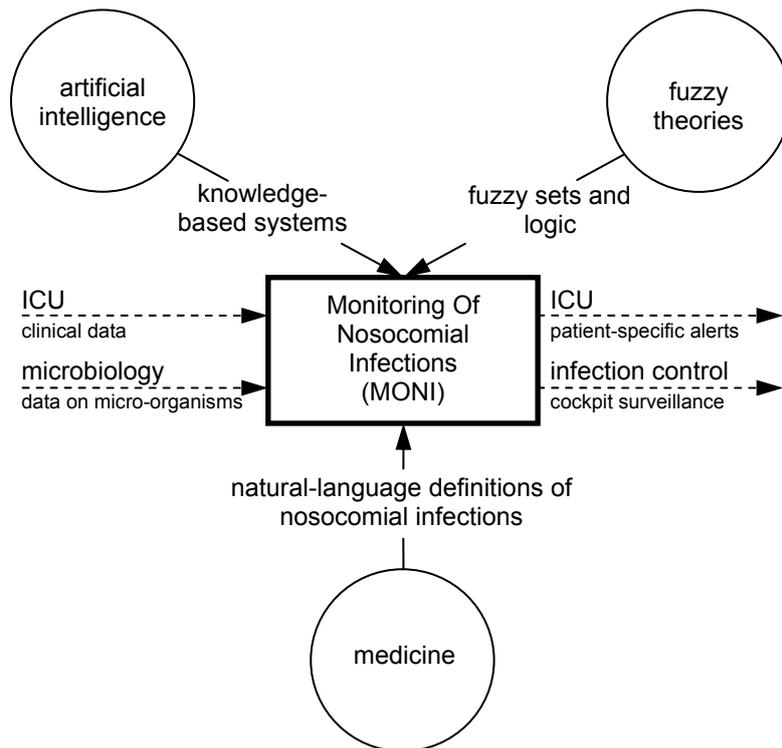


Fig. 1. Medical and formal areas that constitute the methodological basis of MONI.

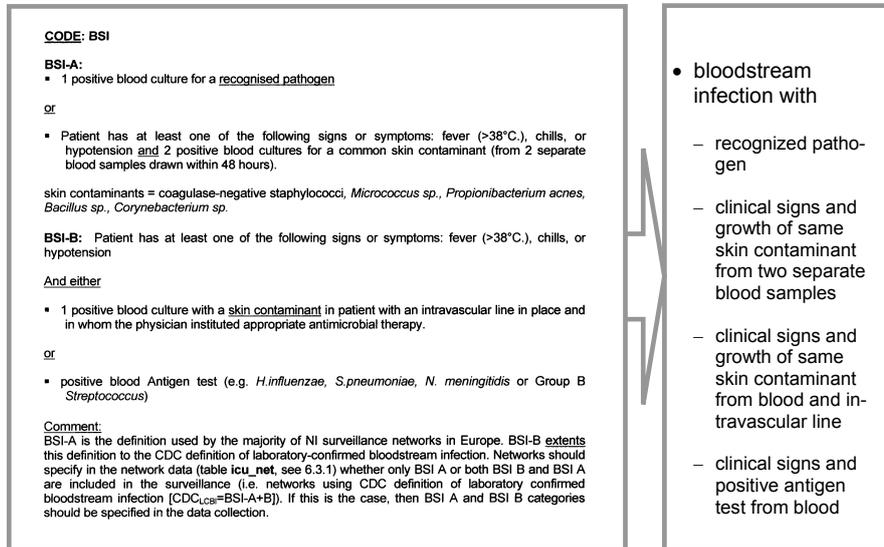


Fig. 2. Natural language definition for BSIs (left part) from which four different entities of BSIs are derived (right part); excerpt from [8].

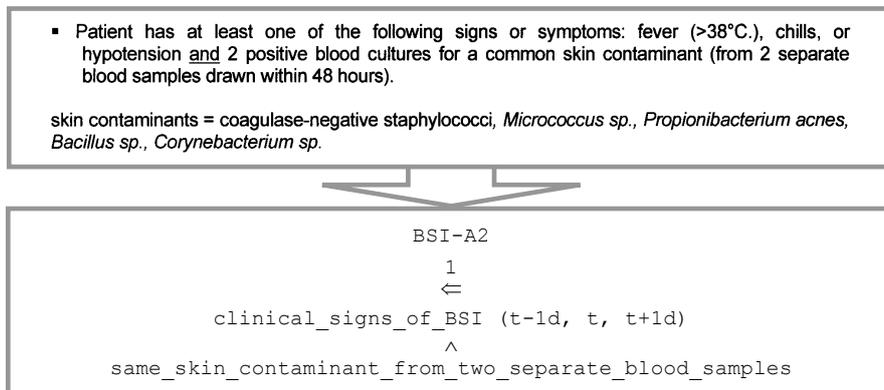


Fig. 3. Example of one BSI definition (\wedge denotes fuzzy logical and, \Leftrightarrow denotes full implication if the premise on the right side is definitely fulfilled); each of the two conjuncts will be decomposed to less aggregated entities.

and are analyzed and transferred into a fuzzy-rule-based representation with a step-wise decomposition of major medical concepts (such as “clinical signs of bloodstream infection (BSI)”) to subconcepts (such as “CRP (C-reactive protein) increased”) until data items from the patient records in the hospital can be mapped into these definitions (see Fig. 3, Fig. 4, and Fig. 5). MONI applies fuzzy sets to formally represent all medical entities

such as symptoms, signs, laboratory test results (see Fig. 5), clinical findings, intermediate medical concepts, and diseases. Fuzzy logic, then, is the method of knowledge processing in MONI.

The rules and the fuzzy sets were formed in a dialogue between a medical knowledge engineer and an expert of the infection control unit. The rules are based on the natural language definitions in [8]; the fuzzy sets allow for gradual transition from one medical concept to an adjacent concept such as “CRP normal” to “CRP increased”. Common sense knowledge and clinical experience tell how “stretchable” the respective medical concepts are, i.e., how far the gradual transition area must extend in order to capture early and slight forms of NIs.

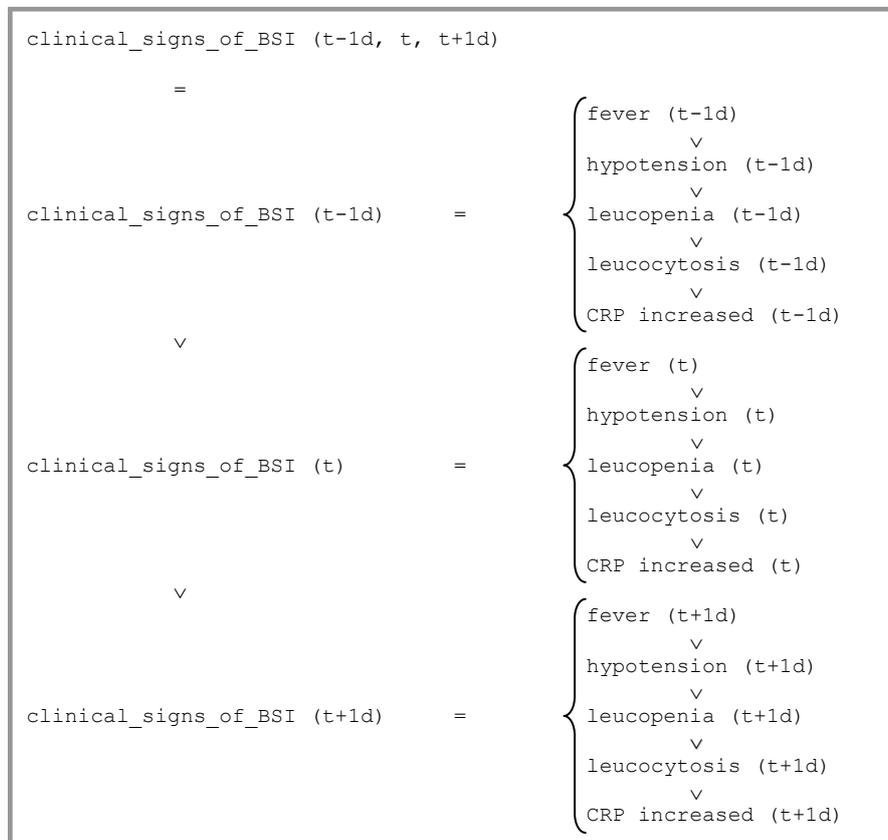


Fig. 4. Decomposition of the concept “clinical signs of BSI” (\vee denotes fuzzy logical OR; t-1d, t, and t+1d denote yesterday, today, and tomorrow, respectively); this concept can be used for both prospective and retrospective monitoring.

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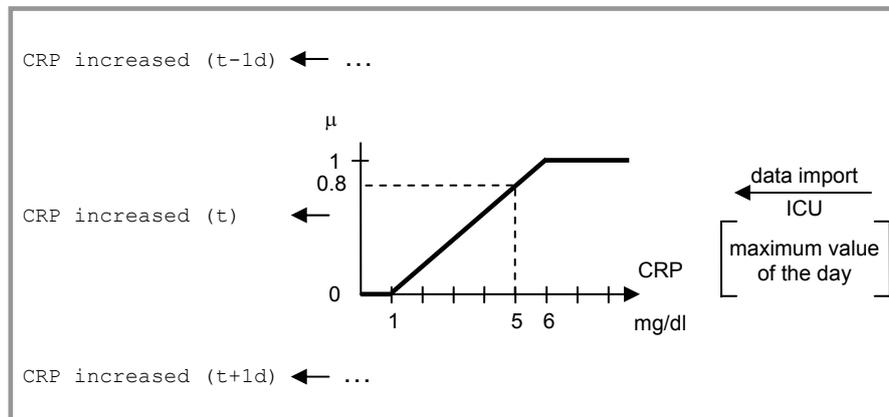


Fig. 5. Example of the definition of a fuzzy set; a measured CRP value of 5 mg/dl, for example, is compatible with the linguistic term “CRP increased” with a degree of 0.8, this degree of compatibility μ is then propagated through the rule-based inference network of MONI via fuzzy logic.

3 Results

MONI is operated in 12 adult intensive care units (ICUs) accommodating a total of up to 96 beds at the Vienna General Hospital, a 2,200-bed university hospital and the main teaching hospital of the Medical University of Vienna. It is fully integrated into the information technology (IT) landscape of the university hospital. Twenty-four definitions of NIs were implemented in MONI. They cover BSIs, ICU-acquired pneumonias, urinary tract infections, and central venous catheter-related infections.

The recognition and monitoring of NIs according to the HELICS definitions for ICUs can be viewed in the following screenshots (see Figs. 6–8).

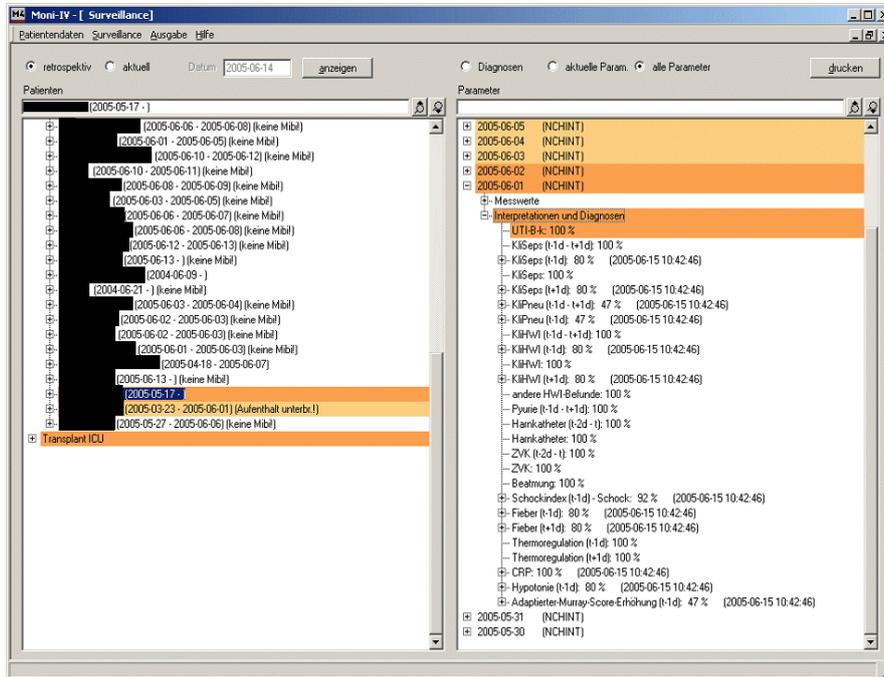


Fig. 6. In one patient, the definition of a catheter-associated symptomatic urinary tract infection (see above UTI-B-k) was completely fulfilled (100%): the underlying patient data and the interpreted symptoms derived from these data are shown.

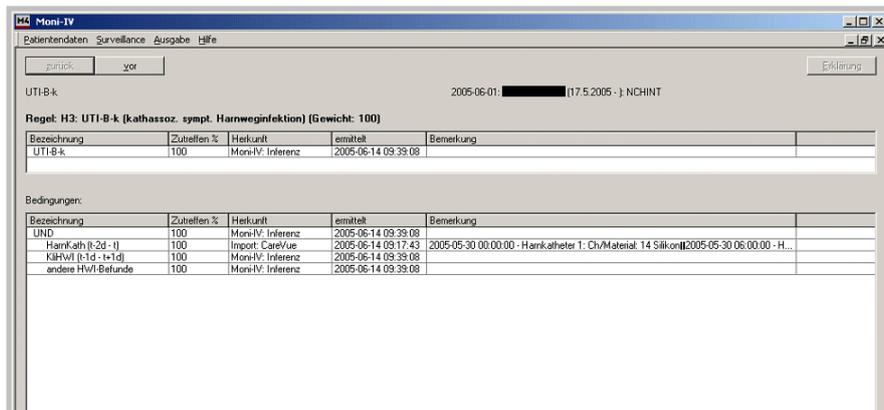


Fig. 7. Backtracking of the logical chain of reasoning shows that the patient has a urinary catheter; this data element was documented in the respective patient data management system (PDMS) and passed on to the MONI system through several intermediate steps of abstraction.

The screenshot shows the 'Moni-IV' software interface. At the top, there are menu options: 'Patientendaten', 'Surveillance', 'Ausgabe', and 'Hilfe'. Below the menu, there are navigation buttons: 'zurück', 'vor', and 'Erklärung'. The main display area shows 'CRP' with a date '2005-06-01' and a patient ID '[17.5.2005 -] NCHINT'. Below this, a section titled 'Daten-Symbol-Konversion: Fuzzy-Set: CRPErh' contains a table with the following data:

Bezeichnung	Zutreffen %	Herkunft	ermittelt	Bemerkung
CRP	100	Moni-IV: Daten-Symb.	2005-06-14 09:39:08	

Below this table, there is a section for 'quantitativer Wert:' with another table:

Bezeichnung	Wert	Herkunft	ermittelt	Bemerkung
CRP	6 mg/dl	Import: CareVue	2005-06-14 09:17:43	2005-06-01 07:00:00 - Serum: CRP: 6 mg/dl

Fig. 8. A CRP value of 6 mg/dl signifies that an elevated CRP is present with a fuzzy compatibility of 100%; therefore, a clinical sign necessary to fulfill the definition of symptomatic urinary tract infection is given.

At present, the system is being fine-tuned by physicians and infection control personnel. The preliminary results confirm the technical appropriateness of the system. The medical results are convincing, and a refined scientific study measuring the clinical correctness and potential impact on patient care and health care costs is under way. Besides, the medical results already allow a large number of NIs to be identified; these numbers of infection were considered impossible to identify in the past.

4 Conclusions

Medical knowledge is usually produced by human medical researchers for other human beings, who, as a rule, are practicing physicians. Natural language is used to document this knowledge, as is done with the definitions of NIs.

To automate and thus support the medical decision-making process, these texts have to be converted into a formal representation. The latter then allows application of this knowledge to medical data of specific patients through several layers of data abstraction. With the methodological framework of fuzzy theories, this is performed successfully and applied in clinical real-world settings.

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