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Validation of Fuzzy Sets in an Automated Detection System for Intensive-Care-Unit-Acquired Central-Venous-Catheter-Related Infections

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Abstract

Central venous catheters play an important role in patient care in intensive care units (ICUs), but their use comes at the risk of catheter-related infections (CRIs). Electronic surveillance systems can detect CRIs more accurately than manual surveillance, but these systems often omit patients that do not exhibit all infection signs to their full degree, the so-called borderline group. By extending an electronic surveillance system with fuzzy constructs, the borderline group can be identified. In this study, we examined the size of the borderline group for systemic CRIs (CRI2) by calculating the frequency of fuzzy values for CRI2 and related infection parameters in patient data involving ten ICUs (75 beds) over one year. We also validated the expert-defined fuzzy constructs by comparing overall and CRI2-specific support. The study showed that more than 86% of the data contained fuzzy values, and that the borderline group for CRI2 consisted of 2% of the study group. It was also confirmed that most fuzzy constructs were good representatives of the borderline CRI2 patient group.

Keywords:

Infection Control, Cross Infection, Intensive Care Units, Automatic Data Processing, Fuzzy Logic.

Introduction

Central venous catheters (CVCs) play an essential role in the care of critically ill patients admitted to intensive care units (ICUs). Estimates suggest that in the United States 15 million CVC days occur annually [1]. However, the frequent use of CVCs also puts a patient at risk of acquiring CVC-related infections (CRIs), which increases morbidity, length of hospital stay, and cost of care, especially in ICUs [2-5].

In response to the threat of CRIs and other healthcare-associated infections (HAIs), the US National Healthcare Safety Network and the European Centre for Disease Prevention and Control (ECDC) have developed infection surveillance programs to identify and document HAIs in ICUs, also known as ICU-acquired infections [6]. However, manual surveillance based on these programs requires a high amount of resources, and produces variable results [7, 8]. To reduce resource consumption and improve surveillance quality, electronic HAI surveillance systems have been developed [9-11].

In an effort to make surveillance rules less subjective to interpretation, involved medical concepts are often supplied with numerical cut-offs on underlying measurable raw data to classify a patient condition as either HAI or non-HAI. While this makes surveillance rules easier to interpret, the downside is that due to the simplified representation of the patient population, patients who adhere to at least some of the conditions in a surveillance rule (the so-called borderline patient group) are indistinguishable from patients with little or no infection signs. This limits the usefulness of surveillance systems as well as the recognition of starting infection episodes.

In order to identify the borderline patient group and distinguish them from the remaining patient population, we applied fuzzy set theory and fuzzy logic in an electronic HAI surveillance system [11-13]. Through fuzzy set theory, it is possible to quantify a patient's health status in a numerical spectrum between 0 and 1 rather than in a yes/no binary form, thus preserving information about borderline cases. For each clinical infection parameter, fuzzy sets and processing rules were defined by clinical and infection control experts.

In this paper, we assessed the frequency of fuzzy values for clinical infection parameters involved in the detection of CRIs in ICUs. Furthermore, we validated the established fuzzy sets by comparing overall and CRI-specific support of fuzzy results. If the difference between both metrics was statistically significant, this would indicate that the fuzzy set for that parameter would be an accurate representation of the borderline group compared to the overall patient population.

Materials and Methods

Study design and setting

Our retrospective data study included ten ICUs (comprising 75 beds) of the Vienna General Hospital, a 2,133-bed tertiary care and teaching hospital. Electronic surveillance was performed by the MONI-ICU system, which serves as a support tool for surveillance and epidemiology to the Clinical Institute of Hospital Hygiene.

Participants and study period

All patients admitted to or staying in the selected ten ICUs between January 1st, 2011 and December 31st, 2011 were eligible for this study. Conforming to the ECDC definition of

ICU-acquired infections, only patients staying longer than 48 hours in an ICU were included in the study. Furthermore, patients of age 17 and younger were excluded since MONI-ICU was established to monitor adult patients.

Electronic surveillance

Data sources

Electronic surveillance of HAIs is done by combining patient-specific data from three different types of data sources: clinical data, biochemistry laboratory data, and microbiology laboratory data. Clinical and biochemistry laboratory data are supplied by the Philips™ CareVue patient data management system, whereas microbiology results are provided by the laboratory information system of the Department of Microbiology. Data are combined through unique patient and admission identifiers registered in the hospital information system.

Knowledge base

Electronic surveillance of CRIs is based on ECDC guidelines for CRI surveillance [6]. Three types of CRI are defined:

- CRI1, a localized CRI, confirmed by a positive microbiology CVC culture, and pus or inflammation found at the CVC insertion site.
- CRI2, a systemic CRI, confirmed by a positive microbiology CVC culture and an improvement of clinical signs within 48 hours after catheter removal.
- CRI3, a microbiologically confirmed CVC-related bloodstream infection (BSI), confirmed by the occurrence of a BSI 48 hours before or after catheter removal, and a positive microbiology culture of both the CVC tip and a separately drawn blood specimen with the same microorganism.

A BSI is defined as follows [6]:

- A patient has at least one positive blood culture for a recognized pathogen, or
- A patient has at least one of the following signs or symptoms: fever (>38° C), chills, or hypotension, and two positive blood cultures for a common skin contaminant.

The MONI-ICU knowledge base is a structured adaptation of the ECDC rules implemented in Arden Syntax 2.7, whereby each clinical decision is performed in a medical logic module [14, 15]. Due to the binary representation of some data elements in the various data sources, only clinical parameters in the CRI2 definition could be extended with fuzzy sets, and thus fuzzy results may occur only for CRI2.

Selection and fuzzy set construction of CRI2-specific clinical infection parameters for the knowledge base was done by both clinical and infection control experts, and was based on aforementioned surveillance guidelines and medical literature. Each fuzzy parameter falls into one of three categories:

- Core parameters, which are parameters whose values are calculated by applying fuzzy sets to data stored in aforementioned data sources.
- Aggregate parameters, which are fuzzy parameters whose values are either calculated by using fuzzy logic operators such as fuzzy conjunction (min function) and disjunction (max function) on the values of other aggregate and core parameters, or are derived from fuzzy relations (algebraic product) on crisp or fuzzy values. It should be noted that all operator definitions also include "missing values".
- CRI2 surveillance definition, which is the aggregate parameter representing the final value for the CRI2 definition.

Table 1 shows all fuzzy infection parameters and relations for CRI2, divided into aforementioned categories. Relationships between core, aggregate, and CRI2 definition parameters are also listed. Note that non-fuzzy parameters are denoted with # and that fuzzy relations on parameters are denoted with *.

Table 1 - Fuzzy infection parameters and dependencies

Core parameters	
Increased body temperature, shock, drop in blood pressure, increased C-reactive protein, leukopenia, leukocytosis, hypotension	
Aggregate parameters	**Fuzzy parameter dependencies**
Fever	Elevated body temperature, *#thermoregulation
Hypotension	*Drop in blood pressure, *shock
Clinical signs of BSI	Fever, increased C-reactive protein, leukopenia, leukocytosis, hypotension
CRI2 definition	Clinical signs of BSI, #CVC presence

Outcome measures

In order to quantify the overall occurrence of fuzzy values in the data for each clinical infection parameter, we calculated the fuzzy support. Let P be the amount of patients, and N_i be the amount of patient days for patient i; furthermore, let x_{ij} be the value of the parameter of interest for patient i on day j. The fuzzy support $FSup$ for a specific infection parameter can then be calculated as follows:

$$FSup = \frac{\sum_{i=1}^{P}\sum_{j=1}^{N_i}\left\{1 \middle| 0 < x_{ij} < 1\right\}}{\sum_{i=1}^{P} N_i} \quad (1)$$

We also calculated the fuzzy conditional support to quantify how often fuzzy values for infection parameters occur given that the value for CRI2 definition is fuzzy. Let $CRI2_{ij}$ be the value of the CRI2 definition for patient i on day j, and again let x_{ij} be the value of a relevant infection parameter for patient i on day j. Given that parameter x is involved in the decision process of d, $FCSup_{CRI2}$ can be calculated as follows:

$$FSup_{CRI2} = \frac{\sum_{i=1}^{P}\sum_{j=1}^{N_i}\left\{1 \middle| 0 < x_{ij} < 1; 0 < CRI2_{ij} < 1\right\}}{\sum_{i=1}^{P}\sum_{j=1}^{N_i}\left\{1 \middle| 0 < CRI2_{ij} < 1\right\}} \quad (2)$$

Data collection and analysis

Data were collected from the MONI-ICU database. Empty and partial records were removed from the study data. Aforementioned outcome measures were programmed in Python. Patient and data filtering according to study inclusion guidelines was done in both Python and Microsoft Excel 2007. P-value calculation was done in R with Fisher's exact test. Results were defined as significantly different when $P < 0.05$.

Table 2 - Overall and CRI2-specific fuzzy support for selected infection parameters

	Overall (N=24,487)		CRI2 (N=501)		
Infection Parameter	**#Fuzzy values**	**FSup**	**#Fuzzy values**	**$FCSup_{CRI2}$**	**P-value**
Increased body temperature	3,421	.141	100	.20	0.003
Shock	6,615	.272	188	.38	< 0.001
Drop in blood pressure	14	<.001	-	-	1
Increased C-reactive protein	5,841	.240	386	.77	< 0.001
Leukopenia	668	.027	34	.07	< 0.001
Leukocytosis	1,544	.063	44	.09	0.032
Fever	15,033	.618	450	.90	< 0.001
Hypotension	15,904	.654	339	.68	0.297
Clinical signs of BSI	5,015	.206	501	1	< 0.001
CRI2 definition	501	.021	N/A		N/A

Results

During the study period, 2,429 patient stays were recorded comprising 24,487 patient days. Stay duration ranged from two to 138 days, with a median of six. In total, 20,962 patient days contained fuzzy values. Furthermore, 1,752 patients had one or more CVCs during their stay (72%). Table 2 shows both overall support and CRI2-conditional support for the parameters listed in Table 1.

Overall support for core parameters ranged between smaller than 0.01% and 27.2%. Drop in blood pressure had the least fuzzy support, recording fuzzy values for only 14 patient days, while shock had the highest support, with fuzzy values recorded for 6,615 patient days. For aggregate parameters, hypotension had the highest support with fuzzy values recorded for 15,904 patient days (65.4%), followed by fever with 15,033 patient days (61.8%) and clinical indication of BSI with 5,015 patient days (20.6%). Finally, fuzzy values for the CRI definition were recorded for 501 patient days (2.1%).

When we compare fuzzy conditional support for CRI2 with overall support for core parameters, we see that except for the drop in blood pressure parameter (<.001 vs. 0), conditional support is generally higher than overall support and that differences between both support metrics are statistically significant. For aggregate parameters, conditional support is also significantly higher for fever and clinical indication of BSI; no significant differences were found between the two support metrics for hypotension (.645 vs. .68).

Discussion

This study showed that when an electronic ICU-associated CRI surveillance system is extended with expert-defined fuzzy sets and logic, more than 86% of the data is affected, and a borderline patient group for CRI2 is uncovered comprising more than 2% of the data. The study also showed that most of the fuzzy infection parameters represented the CRI2 borderline patient group significantly better than the general patient population.

Overall support of infection parameters showed that the parameter drop in blood pressure had an almost negligible support, with fuzzy values recorded for 14 patient days. Further analysis of the study data showed that there were 48 cases where drop in blood pressure fully applied, and that regardless of its value, it did not have an impact on the value of the CRI2 definition. This indicates that the fuzzy set definition for this parameter should be changed or that this parameter is not representative for the CRI2 condition and supposedly could be omitted.

Comparison between overall and CRI2-conditional support revealed no significant difference for hypotension, indicating that the fuzzy logic rules used to derive the value of this aggregate parameter are too unspecific. Part of the problem could be its dependence on the drop in blood pressure parameter, but that would not account for the high overall support. One solution would be to calculate its value using more restrictive fuzzy logic. Alternatively, instead of combining the parameters drop in blood pressure and shock in a fuzzy relation, the parameter shock could be used as a substitution for hypotension, since statistically it's proven to be a better representative of the borderline CRI2 patient population ($P < .001$).

One of the main strengths of this study is that it is based on almost 2,500 patient stays, which yielded nearly 25,000 patient days for analysis. In addition, the data come directly from systems used in clinical routine. A limitation of the study is the relatively low number of fuzzy parameters.

Other studies have also described electronic HAI surveillance systems specifically for ICUs [9, 10], but these systems did not engage fuzzy sets to represent linguistic uncertainty in clinical terms, nor did they employ fuzzy logic to process those data; the studies focused solely on the detection of cases where HAIs were fully established. We extended our system with fuzzy set theory and fuzzy logic to retain information on the patient group that shows infection signs, but not strong enough to adhere to the surveillance definition of an HAI. This enables infection control specialists to distinguish between the patient group without signs of infection and the borderline patient group, and allows for better prediction of reoccurring CRI2 episodes [16].

Fine-tuning and validation of fuzzy sets in an electronic HAI monitoring system is important for both infection control experts and system developers. If too many patients are attributed with fuzzy values for a specific medial concept, as was the case for the hypotension parameter, the borderline patient group is overrepresented. On the other hand, if there are too few patients represented by a fuzzy set, the fuzzy set should be changed or replaced by a non-fuzzy set to improve system performance.

Conclusion

This study shows that extending an electronic HAI surveillance system with methods to identify the borderline patient population, in this case fuzzy set theory and logic, affects the majority of the data and uncovers a substantial borderline patient group. Statistical validation also showed that most of the expert-defined fuzzy sets and logical constructs currently present in the knowledge base are an accurate representation of the CRI2 borderline patient population.

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