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Assessing the Clinical Uses of Fuzzy Detection Results in the Automated Detection of CVC-related Infections: A Preliminary Report

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Abstract. Central venous catheters (CVCs) play an essential role in the care of the critically ill, but their use comes at the risk of infection. By using fuzzy set theory and logic to model clinical linguistic CVC-related infection criteria, clinical detection systems can detect borderline infections where not all infection parameters have been (fully) met, also called fuzzy results. In this paper we analyzed the clinical use of these results. We used a fuzzy-logic-based computerized infection control system for the monitoring of healthcare-associated infections to uncover fuzzy results and periods, after which we classified them, and used these classifications together with knowledge of prior CVC-related infection episodes in temporal association rule mining. As a result, we uncovered several rules which can help with the early detection of re-occurring CVC-related infections.

Keywords. Infection control, Automated surveillance, Fuzzy logic, CVC-related infections, Infection prediction

Introduction

Central venous catheters (CVCs) are commonly used in critically ill patients admitted in intensive care units (ICUs). Despite their essential role in the care of the critically ill, the use of CVCs comes at the risk of a patient developing CVC-related infections (CRIs), such as catheter–related local infections (CRLIs) and catheter-related bloodstream infections (CRBSIs). These infections lead to an increase in morbidity [1], mortality [2], and added cost [3].

Several national and international infection reporting and prevention programs have been initiated, including the Hospitals in Europe Link for Infection Control through Surveillance (HELICS) program, which has been integrated in the European

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Centre for Disease Prevention and Control surveillance activities. Rules for the detection and prevention of CRIs are included in this program [4], which can be used in rule-based clinical detection and monitoring systems (CMSs) to automate the surveillance of healthcare-associated infections (HAIs), including CRIs.

A complicating factor in aforementioned automation process is that within medicine, data often contains inaccurate, contradictory, or unknown values. Fuzzy set theory and fuzzy logic can be used to model these complications, at least to a certain extent. In fuzzy set theory, linguistic medical concepts that are not sharply defined are represented as fuzzy sets, and each patient is assigned a value between 0 and 1 that represents to what extent a patient's situation is compatible with the medical concept. Fuzzy logic can be applied to reason about fuzzy sets by using inference mechanisms. Fuzzy set theory and logic are frequently used in a multitude of medical fields, as is shown in [5-7].

When using fuzzy set theory and logic to model to what extend a patient conforms to the definition of a certain CRI, fuzzy infection results can appear, where a patient shows signs of infection, but these signs do not meet or fully agree with all the criteria of the CRI rules. In this paper we investigate how these fuzzy results can be clinically interpreted, and to what extent they can serve the physicians in the detection and treatment of CRIs.

1. Methods

For the detection of HELICS-defined CRIs we used a fuzzy-based computerized infection control system for the monitoring of HAIs in adult patients of ICUs called MONI-ICU [8-10]. MONI-ICU monitors HAIs at the ICUs of the Vienna General Hospital (VGH), a 2133-bed tertiary care and teaching hospital, where it is used on a daily basis by its Clinical Institute of Hospital Hygiene.

Two ICUs were selected for this study, one at the Department of Gastroenterology and Hepatology and the other at the Department of Internal Medicine. All patients admitted in these ICUs who were hospitalized for a period longer than 48 hours between November 13, 2006 and February 7, 2007 were selected and subsequently evaluated according to HELICS-defined rules for CRIs.

1.1. Definitions

An ICU-acquired infections, is an infection that occurs later than 48 hours after the patient has been admitted in an ICU [7]. There are three types of CRIs defined:

- CRI1, a CLRI without a positive blood culture, partially identifiable by an infected insertion site,
- CRI2, a general CVC-related infection without a positive blood culture, partially identifiable by general clinical infection signs,
- CRI3, a microbiologically confirmed CRBSI.

For each of these CRI types we searched for established infections, as well as fuzzy results for CRI2. A *fuzzy result* is a score for a CRI type that falls between 0% and 100% on a day of a patient's stay. A *fuzzy period* constitutes two or more

consecutive days with fuzzy results. When a patient has a 100% score for a certain CRI type, that CRI is said to be *established*.

1.2. Data Collection and Processing

MONI-ICU uses two data sources in the VGH information infrastructure. For a patient's day-to-day laboratory and nursing data it accesses the patient data management systems of the ICUs; for microbiology data and microbiology data it accesses the laboratory information system of the Department of Microbiology of the VGH. Data from both sources are downloaded overnight for each patient admitted in the ICUs of the VGH on a daily basis.

For the detection of CRIs, MONI-ICU uses a knowledge base (KB) in which the HELICS-defined CRI rules and linguistic concepts are implemented in Arden Syntax using fuzzy set theory and logic [11-13]. A significant portion of these intermediate concepts, such as "fever" and "increased C-reactive protein" are represented as fuzzy sets. Using fuzzy logic, these concepts are then aggregated into a higher-level linguistic medical concept, also represented as fuzzy sets, such as "general clinical infection signs", which is in turn used to partially diagnose CRI2 with; CRI2 is therefore also represented as a fuzzy set.

1.3. Outcome Measures

Fuzzy CRI2 results were determined and grouped into fuzzy periods. These periods were then classified into one of three classes, which were defined by medical experts. Table 1 shows these classes, together with a short description.

Table 1. Fuzzy period classes and their descriptions

Class	Description
Inceptive	The fuzzy period started without prior or currently established CRI episodes.
Remissive	The fuzzy period follows after an established CRI infection. There is no established co-occurring CRI of another type.
Co-occurring	A fuzzy period for one type of CRI that co-occurs with an established infection of another CRI type.

Based on the time of appearance and classification of these fuzzy periods, as well as established CRI episodes that had occurred earlier within a patient's stay, we uncovered rules for the prediction and reappearance of CRI episodes for each CRI type using association rule learning. Given $n \geq 1$ rule antecedents, these rules are of the following form:

IF antecedent_1 AND ... AND antecedent_n THEN CRI_type

Each rule is evaluated using the following metrics:

- *Support*, which indicates the proportion of the entire dataset where the antecedents and the target CRI type in a rule occur together.
- *Confidence*, which indicates the probability of finding the CRI type in a dataset item, given that the item also contains the antecedents.
- *Lift*, which indicates the prediction ability of the rule compared to random chance. A value of 1 indicates a random chance, while values greater than one indicate an increased prediction ability.

These metrics were used to give an indication if a certain rule was predictive for a specific type of CRI.

1.4. Data Analysis

Algorithms for the detection and extraction of CRI detection results as well as the classification of fuzzy CRI2 results, their subsequent combination into periods, and rule mining were programmed in the Python programming language. For association rule learning, a modified version of the APRIORI-algorithm was used [14].

2. Results

Within the study period, 93 patient stays with a combined length of 800 days were analyzed for CRI episodes. Twenty-seven CRI episodes were established by both the MONI-ICU system and infection control specialists; fifteen CRI1 episodes comprising a total of 75 days, and twelve CRI2 episodes comprising a total of 40 days. The system also recorded 53 days of fuzzy results for CRI2, spread over 16 episodes; one inceptive, four remissive, and eleven co-occurrence periods were found and confirmed by medical experts.

After analysis of the generated rules, remissive periods were determined to be reasonable indicators for the reappearance of CRIs. For CRI1, the following rule had the highest lift:

IF period= remissive AND prior=CRI1 THEN CRI1

This rule had a support of .13, a confidence of .67, and a lift of 3.56. Mutatis mutandis, a similar rule was also valid for CRI2, which had a support of .06, a confidence of .5, and a lift of 2. However, when this rule was extended with an extra antecedent where it states that a patient had both types of CRI as priors, then CRI2 had the same support, but confidence rose to .50 and lift to 4. For CRI2, co-occurring fuzzy periods together with a prior CRI2 episode also have a lift above 1:

IF period=co-occurring AND prior=CRI2 THEN CRI2

This rule had a support of .13, a confidence of 1, and a lift of 1.6. Since fuzzy results were not detected for CRI1 within the study period, co-occurrence did not take place, and no comparison could be made.

3. Discussion

In this study, we showed that fuzziness can be useful for early recognition of recurring CVC-related infections. By classifying fuzzy periods, rules with reasonable support and an elevated ability to predict CRI infections (sometimes by as much as two days in advance) could be uncovered for two out of three classes.

This method has its limitations. As it is, the resolution of the dataset is not good enough yet to uncover accurate predictive rules. Data is retrieved on a daily basis, a time span in which an infection can easily manifest itself fully. If the data used to calculate fuzzy linguistic concepts would be updated in shorter intervals, more fuzzy

results and periods would appear in the data set, and more elaborate patterns are expected to emerge.

Another limitation of the current approach is that rules for fuzzy periods were based on the "general clinical infection signs" concept, which is an aggregation of several other fuzzy concepts. By using these concepts separately for prediction, more accurate rules can be uncovered.

As future work, individual fuzzy concepts need to be explored as antecedents of predictive rules for CRI episodes and re-occurrences. Furthermore, apart from the classification of fuzziness, the trend of fuzziness, which indicates if infection symptoms become clearer, less clear or remain equal, will also be a topic of interest, paving the way for more advanced temporal analysis methods.

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