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Detecting borderline infection in an automated monitoring system for healthcare-associated infection using fuzzy logic

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ABSTRACT

Background: Many electronic infection detection systems employ dichotomous classification methods, classifying patient data as pathological or normal with respect to one or several types of infection. An electronic monitoring and surveillance system for healthcare-associated infections (HAIs) known as Moni-ICU is being operated at the intensive care units (ICUs) of the Vienna General Hospital (VGH) in Austria. Instead of classifying patient data as pathological or normal, Moni-ICU introduces a third *borderline* class. Patient data classified as borderline with respect to an infection-related clinical concept or HAI surveillance definition signify that the data nearly or partly fulfill the definition for the respective concept or HAI, and are therefore neither fully pathological nor fully normal.
Objective: Using fuzzy sets and propositional fuzzy rules, we calculated how frequently patient data are classified as normal, borderline, or pathological with respect to infection-related clinical concepts and HAI definitions. In dichotomous classification methods, borderline classification results would be confounded by normal. Therefore, we also assessed whether the constructed fuzzy sets and rules employed by Moni-ICU classified patient data too often or too infrequently as borderline instead of normal.
Participants and methods: Electronic surveillance data were collected from adult patients (aged 18 years or older) at ten ICUs of the VGH. All adult patients admitted to these ICUs over a two-year period were reviewed. In all 5099 patient stays (4120 patients) comprising 49,394 patient days were evaluated. For classification, a part of Moni-ICU's knowledge base comprising fuzzy sets and rules for ten infection-related clinical concepts and four top-level HAI definitions was employed. Fuzzy sets were used for the classification of concepts directly related to patient data; fuzzy rules were employed for the classification of more abstract clinical concepts, and for top-level HAI surveillance definitions. Data for each clinical concept and HAI definition were classified as either normal, borderline, or pathological. For the assessment of fuzzy sets and rules, we compared how often a borderline value for a fuzzy set or rule would result in a borderline value versus a normal value for its associated HAI definition(s). The statistical significance of these comparisons was expressed in *p*-values calculated with Fisher's exact test.
Results: The results showed that, for clinical concepts represented by fuzzy sets, 1–17% of the data were classified as borderline. The number was substantially higher (20–81%) for fuzzy rules representing more abstract clinical concepts. A small body of data were found to be in the borderline range for the four top-level HAI definitions (0.02–2.35%). Seven of ten fuzzy sets and rules were associated significantly more often with borderline values than with normal values for their respective HAI definition(s) ($p < 0.001$).
Conclusion: The study showed that Moni-ICU was effective in classifying patient data as borderline for infection-related concepts and top-level HAI surveillance definitions.

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1. Introduction

Electronic systems for the detection and monitoring of healthcare-associated infections (HAIs) have become common in clinical routine over the last decade [1–3]. Electronic monitoring is considered superior to traditional surveillance because electronic systems are faster, require less human resources, and are not subject to inter-rater variability as manual surveillance is [3–6].

A common limitation of electronic infection monitoring systems is that they employ dichotomous "yes/no" classification methods, thereby classifying an infection as either present or absent. Consequently, *borderline* infection cases, i.e., patients who show vital signs and laboratory test results that nearly or partially fulfill the conditions defined in the infection surveillance rules are not explicitly recognized. Instead, they are confounded by patients whose vitals and test results are normal. Borderline infection cases are clinically relevant, as these patients are at a high risk of developing infection, need close monitoring and possibly interventions as well. As such, failing to identify borderline infection cases reduces the usefulness of electronic infection monitoring systems in predicting, alerting, and preventing infection.

One way of differentiating borderline infection cases from patients without signs of infection is through the integrated use of fuzzy sets and logic [7]. By using fuzzy sets for the formal representation of infection-related clinical concepts such as fever, hypertension, or leukocytosis, we extend the traditional dichotomous classification methods. An accurately defined fuzzy set can classify patient data as *not compatible* (normal), *fully compatible* (pathological), or expressing a *degree of compatibility* (nearly or partly pathological, or borderline) with respect to a clinical concept under consideration. In the latter case, a degree of compatibility between measured or observed patient data and the respective clinical concept represents a gradual transition from normal to pathological values for the respective concept. After the initial evaluation of clinical concepts using fuzzy sets, fuzzy logic is used to evaluate logical combinations of these concepts in order to draw conclusions about higher-level concepts, and ultimately infer the full or partial compatibility or non-compatibility of the top-level HAI terms with the underlying patient data.

Electronic HAI monitoring systems using fuzzy sets and logic remain as effective as their non-fuzzy counterparts in the detection of pathological infection cases [8]. However, they possess the additional ability to permit a distinction between patients with a suspected borderline infection and normal patients. This ability offers the following advantages: (a) more accurate feedback on the patients' status to the attending physicians and the infection control experts, and (b) identifying incipient and recurring infections [9], which allows early therapeutic intervention.

The goal of the present study was to separate borderline infection cases from patients without signs of infection, and assess the size of the newly created patient group with respect to the aforementioned two patient classes (normal and pathological). Using the electronic HAI surveillance and monitoring system Moni-ICU [10–12], we calculated the frequencies of patient data in the categories of normal, borderline, or pathological for all of the incorporated fuzzy sets. The results of the application of fuzzy rules for higher-level clinical concepts and HAI surveillance definitions were calculated in the same manner. We also analyzed the present definitions of fuzzy sets and rules to ensure they did not classify patient data too often or too infrequently as borderline rather than normal. To this end, we postulated the hypothesis that borderline values for a clinical sign or symptom should more often result in a borderline value than in a normal value for its associated HAI definition(s). By constructing contingency tables for each fuzzy set and fuzzy rule and their associated HAI definition(s), we were able to express the ability of a fuzzy set or fuzzy rule in separating borderline infection cases from normal patients with the aid of *p*-values.

2. Background

2.1. Fuzzy set theory and fuzzy logic

Fuzzy set theory and fuzzy logic are being developed since 1965. Fuzzy sets have been introduced to express partial membership of objects to classes, which are usually characterized by their linguistic terms. A so-called *degree of membership* [13] indicates the degree to which the linguistic term is present; it expresses the degree of compatibility between the measured underlying value and the concept under consideration. Subjectively interpretable linguistic clinical concepts are commonly used in medical definitions, protocols, and guidelines. Fuzzy sets can be employed to model the unsharpness of clinical terms when trying to diagnose a patient's condition on the basis of his/her medical data [14,15]. This process includes the calculation of compatibility between measured patient data and the linguistic clinical concept under consideration (Fig. 1).

Fuzzy logic can be used to evaluate logical combinations of concepts that are assigned a degree of membership [16]. In the present study, we employed propositional fuzzy logic, a many-valued logic used to reason and make inferences about one or more evaluated fuzzy sets (including the results of the evaluation of crisp sets as a specialization of fuzzy sets). We employed three propositional fuzzy operators throughout this report: conjunction, disjunction, and negation.

Conjunction is commonly interpreted by a t-norm $\odot$: $[0,1]^2 \to [0,1]$. Any t-norm is associative, commutative, neutral with respect to 1, and isotone in both arguments [17]. Disjunction is usually interpreted by the corresponding t-conorm $\oplus$: $[0,1]^2 \to [0,1]$. For the present study we used the Gödel t-norm $\odot_G$, the associated Gödel t-conorm $\oplus_G$, and the standard negation function $\neg$: $[0,1] \to [0,1]$. Given $x, y \in [0,1]$, these are defined as follows:

$$x \odot_G y = \min(x, y)$$

$$x \oplus_G y = \max(x, y)$$

$$\neg x = 1 - x$$

Fuzzy set theory and fuzzy logic have become increasingly popular in medicine over the last thirty years, especially in the areas of fuzzy classification and inference [18,19]. Abbod et al. [20] provide an overview of applications using fuzzy sets and/or fuzzy logic in many specialties disciplines of medicine while Mahfouf et al. [21] present a comprehensive survey on applications in medicine that use fuzzy logic for monitoring and control.

2.2. Healthcare-associated infections

An ICU-based HAI is defined as an infection manifested in a patient later than 48 h after admission to the ICU. Electronic HAI monitoring is based on the ICU surveillance rules defined by the European Centre for Disease Prevention and Control (ECDC) surveillance program. Several definitions of infection are included therein [22]:

- Blood stream infection (BSI),
- Pneumonia (PN1-5),
- Central venous catheter-related infection (CRI1-2),
- Urinary tract infection (UTI-A and -B).