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Full-text Automated Detection of Surgical Site Infections Secondary to Neurosurgery in Rennes, France

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Abstract

The surveillance of Surgical Site Infections (SSI) contributes to the management of risk in French hospitals. Manual identification of infections is costly, time-consuming and limits the promotion of preventive procedures by the dedicated teams. The introduction of alternative methods using automated detection strategies is promising to improve this surveillance. The present study describes an automated detection strategy for SSI in neurosurgery, based on textual analysis of medical reports stored in a clinical data warehouse. The method consists firstly, of enrichment and concept extraction from full-text reports using NOMINDEX, and secondly, text similarity measurement using a vector space model. The text detection was compared to the conventional strategy based on self-declaration and to the automated detection using the diagnosis-related group database. The text-mining approach showed the best detection accuracy, with recall and precision equal to 92% and 40% respectively, and confirmed the interest of reusing full-text medical reports to perform automated detection of SSI.

Keywords:

Surgical site infection, information retrieval, vector space model, text mining.

Introduction

The French Health Authority recommends routine surveillance of Surgical Site Infections (SSI) in the broader context of risk management of Healthcare-Associated Infections (HAI). It is part of the national standardized surveillance, coordinated by RAISIN (Réseau Alerte Investigation Surveillance des Infections Nosocomiales) and the West regional coordinating center for nosocomial infection prevention (CCLIN Ouest).

The HAI surveillance aims to identify clusters of infections and risk factors, to provide comparisons between institutions and surgical specialties. This allows evaluation of control measures. The positive impact of HAI surveillance on health and healthcare efficiency has been shown. Currently, the identification of infections is mostly manually performed by local hospital hygienists or directly by practitioners. Thus, surveillance is both costly and time-consuming for heath institutions or infection control teams, and usually most resources are focused on counting infections rather than elaborating and monitoring prevention procedures [1,2].

Alternative methods based on electronic and automated detection procedures have been experimented in different facilities. This used hospital information systems detailing microbiology results, antibiotic prescriptions, or the hospital's diagnosis-related group (DRG) database [3]. Few encounters of detecting HAI by textual approaches have been reported in the literature, but the first results using natural language processing on medical reports showed promising perspectives [4,5].

The first milestone for a textual approach, regardless of the methodology used, is recognition of patterns that are actionable for infection surveillance. This task in the SSI detection context may be quite difficult because SSI concepts are very rarely reported by clinicians. Medical reports mostly mention terms indirectly related to HAI (e.g, wound infection, dehiscence of scar, reoperation, etc.) where the vocabulary used varies according to practitioner habits, surgical procedures, outcomes and SSI disclosure. The present paper describes an original approach for the automated learning of specific SSI patterns using semantic enrichment of French medical documents. The identified patterns were used to build a vector space model [6] to detect SSI secondary to neurosurgery, and results were compared to those of both the conventional surveillance approach and the DRG database approach.

Materials and Methods

Study population and materials

Patients

The study population was composed of patients admitted to the Department of Neurosurgery, at the University Hospital of Rennes, France in 2008 (n=1798), 2009 (n=1987) and 2010 (n=1225). All patients aged greater than 18 years old treated by neurosurgery were included in the study.

The medical records of all included patients were extracted from the hospital information system and stored in a Clinical Data Warehouse (CDW) [7]. They were divided into a learning set (for patients admitted in 2008 and 2009) and an evaluation set (for patients admitted in 2010).

The documents of the learning set were further divided into documents from patients without SSI and documents from patients with SSI. All medical records of patients operated in 2008 and 2009 were manually reviewed by a hospital hygienist physician, and the detected SSI validated by a neurosurgeon. Additional SSI were detected in a retrospective study of the 1798 and 1987 neurosurgery admissions in 2008 and 2009, 25 and 17 cases respectively.

Electronic support for SSI detection

The CDW contained full-text documents such as medical reports (interpretation of radiology exams, anatomic pathology reports, hospital discharge summaries, consultation notes, etc.), as well as structured documents linked to thesauri, such as the 10th international classification of diseases (ICD-10) and the French classification of procedures (CCAM) used for encoding the DRG database.

SSI definition

Surgical Site Infection was defined according to the CDC/NHSN recommendations [7]. SSI secondary to neurosurgery consisted of infections that appeared to be related to the operative procedure, occurring within 30 days after the operation for non-implant procedures, or within one year if implant was in place.

According to this definition, neurosurgery procedure and SSI diagnosis could be reported at different times. Thus, every detected and validated SSI are said to be linked to the first neurosurgical procedure.

For the equivalent reason, a neurosurgical event begins with the patient's admission for the originally planned neurosurgery and includes all documents produced by the neurosurgery department from admission to one year after the surgery.

Strategies for detection

Conventional surveillance

SSI surveillance at Rennes hospital is based on reviewing of patients' medical records for whom a neurosurgeon has signaled an infection. SSI validation is carried out during weekly meetings between hospital hygienist physicians and neurosurgeons.

Strategy based on the DRG database

The strategy based on the DRG database uses ICD-10 codes for querying the medico-administrative database.

ICD-10 codes were initially defined from codes selected for unspecific SSI detection by the Southwest regional coordinating center for nosocomial infection prevention [8]. ICD-10 codes specific to neurosurgery were then added. Finally, codes were validated during a session involving both neurosurgeons and hospital hygiene physicians. The complete list of extended ICD-10 codes for SSI detection in the present study is shown in appendix 1.

Strategy based on full-text medical reports

The first step was devoted to concept extraction and semantic enrichment of full-text medical reports, using NOMINDEX: a natural language processing tool that extracts MeSH concepts from full-text documents and is based on a French medical lexicon and the UMLS [9,10].

This task was independently performed on the two learning sets of documents (documents from patients with a validated SSI and documents from patients without SSI).

Document frequency per each extracted concept was independently calculated in each learning set, calculated as the number of documents containing the concept divided by the total number of documents. The most frequently used concepts identifying the SSI set were kept according to the semantic relationship with concepts from the non-SSI sets (see Figure 1).

In the text-mining analysis, two conceptual groups were extracted to specifically define patterns of the SSI set. The first group consisted of concepts related to the bacteriology domain with terms like staphylococcus, antibiotics, or sepsis; while the second group consisted of concepts related to the surgery domain and to the surgical site complications e.g. wound suppuration, abscess, accumulation, etc.

Finally, the selected concepts that defined an SSI specific "conceptual space" upon document retrieval was generated using a vector space model and its cosine similarity measure (6).

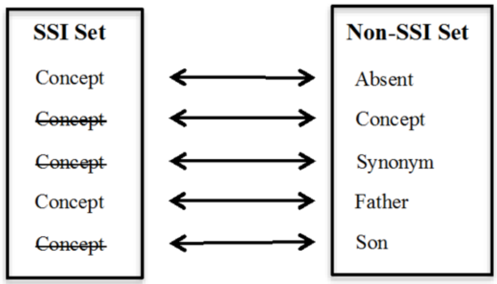

Figure 1 – Rules for the selection of concepts, according to the semantic relationships between concepts that were most frequently relevant in full-text medical reports of patients with surgical site infection (SSI set) or without infection (non-SSI set)

Evaluation and performance metrics

The detection strategies were evaluated using recall, precision and F-measure on an independent validation set of full-text documents. As no reference method was available, our own Gold Standard was defined as follows:

A medical report was said to be a True Positive if at least one of the three detection strategies had identified SSI secondary to neurosurgery for that patient, and if it was confirmed by a physician.

Finally, in order to estimate the work overload implied by each detection strategy, an overload index (OI) was calculated by the following equation 1:

$$OI = \frac{Number\ of\ SSI}{Number\ of\ non\ SSI} \times \frac{False\ Positive}{True\ Positive} \quad (1)$$

Results

In 2010, 1225 admissions with a neurosurgical intervention were reported. Overall, 13 SSI secondary to neurosurgery were found by at least one of the three detection strategies. Three infections after surgery were detected by the conventional surveillance procedure, 11 by the DRG database approach with extended ICD-10 codes for neurosurgery, and 12 by the vector space model approach associated to the semantic analysis of full-text medical reports.

Table 1 shows complete results of the 3 detection strategies.

Globally, the text-mining strategy showed the best detection accuracy with an F-measure close to 56% and a very low reviewing overload compared to the DRG strategy. This last observation was confirmed by an overload index measured to 1.6% for full-text detection, as opposed to 21% for the DRG strategy.

Considering the text-mining approach, 8 of the 18 false positives were confirmed non-surgical site infections after review by the neurosurgeon. It is interesting to note that they were all healthcare-associated infections. Of the ten remaining false positives, 9 were related to either an infection event concomitant to the admission in neurosurgery, or to an infection motivating the neurosurgical intervention. One false positive was due to the mentioning of the "absence of infection complications" after surgery in the medical record.

Table 1 - Results of surgical site infection detection secondary to neurosurgery interventions, per each evaluation set (year 2010)

	Conventional surveillance	**DRG database**	**Full-text medical reports**
True positive	3	11	12
False positive	0	219	18
False negative	10	2	1
True negative	1212	993	1194
Recall	23.1%	84.6%	92.3%
Precision	100.0%	4.8%	40.0%
F-measure	37.5%	9.1%	55.8%
Overload Index	-	21.4%	1.6%

DRG: Diagnosis-Related Group.

Discussion

The study confirmed the insufficiency of surveillance based on the self-declaration method to report SSI secondary to neurosurgery. SSI surveillance and HAI still need trans-sectional and retrospective studies, as well as prospective, ongoing surveillance.
Prospective surveillance is the method of choice, but it is hardly humanly feasible at a hospital level. Automated detection strategies can be viewed as credible alternative methods for performing routine surveillance and improving HAI surveillance [11-13] .

The text-mining approach in the present study found very interesting characteristic patterns for detection in such a low prevalence context as SSI in neurosurgery. With a recall evaluated greater than 90%, the text-mining strategy showed equivalent performance metrics for SSI detection when compared to other various strategies of automated HAI detection published in a recent study [3].
In addition, the text-mining strategy could be consistent with routine surveillance, as it does not involve overload work that would otherwise burden infection control teams.

Our evaluation results could be limited by the use of a non-independent gold standard for defining SSI in 2010. It was likely that few SSI remained simultaneously hidden to the 3 detection strategies. It could lead to the underestimation of false negatives. Nevertheless, the SSI frequency found in the 2010 evaluation set was close to SSI frequencies calculated on the learning sets (2008 and 2009). SSI prevalence remained fairly stable over the 3 years of the study.

The text detection in the present study was based on a quantitative approach using natural language processing. No concept association rules or syntactic rules were implemented to detect SSI on full-text medical reports. This could be an advantage in medicine, because it could ensure the method's adaptability to heterogeneous domains. The flexibility of the text-mining approach should be tested in future works, evaluating the SSI detection in larger samples and combining several types of surgeries, further evaluating the text-mining approach in varying conditions.

Finally, a recent published evaluation shows that combination of detection strategies using diagnosis codes, microbiological analysis results, and/or antimicrobial dispensing, can identify HAI with performance metrics that match or surpass those of conventional surveillance [3].

It appears natural to evaluate the benefit of text detection compared to other automated methods, and to test combination of such strategies. This is especially true with the emergence of electronic medical records, which represents a unique opportunity for infection control practitioners to integrate HAI surveillance directly within care delivery.

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Appendix 1

Complete list of extended ICD-10 codes for detection of surgical site infections secondary to neurosurgery

A40, A41, A48.8, A49, B37.5, B37.7, B37.8, B37.9, B95, B96, G00, G02.1, G02.8, G05.2, G06, G07, G93.0, G93.8, G93.9, G94.0, G94.8, G96, G97.1, G97.8, G97.9, R50, T81.3, T81.4, T81.8, T85.7, T85.8, T85.9, T88.8, T88.9, Z09.0, Z09.7, Z09.8, Z09.9, Z48.0, Z48.8, Z48.9

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