Architecture and Systems for Monitoring Hospital Acquired Infections inside a Hospital Information Workflow

Denys Proux[1], Caroline Hagège[1], Quentin Gicquel[2], Suzanne Pereira[3], Stefan Darmoni[4], Frédérique Segond[1], Marie-Hélène Metzger[2]

(1) XRCE, 6 Chemin de Maupertuis, 38240 Meylan, France
(2) UCBL-CNRS, UMR 5558 Lyon, France
(3) CISMEF, Rouen, France
(4) VIDAL, Issy les Moulineaux, France
Denys.Proux@xrce.xerox.com, Caroline.Hagege@xrce.xerox.com,
Quentin.Gicquel@chu-lyon.fr, Suzanne.Pereira@vidal.fr,
Stefan.Darmoni@cismef.fr, Frederique.Segond@xrce.xerox.com,
Marie-Helene.Metzger@chu-lyon.fr

Abstract

This paper describes the latest developments in the design of a tool to monitor Patient Discharge Summaries to detected pieces of evidences related to Hospital Acquired Infections. Anonymization, Named Entity detection, Temporal Expressions analysis and Causality detection methods have been developed and evaluated. They are embedded in a tool designed to work in a Hospital Information Workflow.

1 Information and Communication Technologies to Improve Patient Safety

Managing information related to Patient Records (PR) is something complex. Treating a patient is not like fixing a tire; it is a long process that involves many medical disciplines. For each analysis, each treatment, each diagnosis, fragmented information is produced by different people, different medical units. Information and Communication Technologies (ICT) appears to be a good opportunity to make use of this information to offer monitoring and alert services which contribute in the end to patient safety. Among these opportunities Hospital Acquired Infections is a domain where ICT can bring a lot to help experts.

1.1 The problem

Hospital Acquired Infections (HAI) can be defined as: *An infection occurring in a patient in a hospital or other health care facility in whom the infection was not present or incubating at the time of admission. This includes infections acquired in the hospital but appearing after discharge, and also occupational infections among staff of the facility.* (Garner 1988). This problem occurs because hospitals are special places concentrating both weak people and various types of diseases and infections. Not all HAI have the same effect but they all jeopardize patient safety and increase the time spent in hospitals.

1.2 Attempt to address the problem

In order to address this issue several efforts have been made mainly through the creation of a strict health protocol for the medical staff and appropriate training provided to this staff. Furthermore experts have been appointed to monitor these risks and a strict reporting process has been setup. However these efforts are not completely successful or at least could be improved. This is mainly due to both the way information is managed inside hospitals, and the inherent complexity of HAI.

To perform their analysis experts need to have access to many data / reports to make a decision about the causality of an infection. This is difficult to obtain for experts not only because information is spread out into various databases but also because, as they are dealing with constantly evolving information. Therefore they need a tool to automate report monitoring. Such tool does not exist as one of the major issues is

that information, most of the time, remains in an unstructured free text format.

This conclusion has pushed for the development of a research project bringing together HAI experts, medical terminology experts and Natural Language Processing experts to design a monitoring tool for patient records. The ultimate goal is to automate detection of HAI events from patient records.

2 A Natural Language Processing Approach to Monitor Patient Records

This 3 year project, started in January 2009, is conducted in collaboration with 3 University hospitals providing 1500 patient discharge summaries (half of them dealing with HAI). These reports have been manually analyzed 3 times by 3 different HAI experts to identify and annotate all pertinent elements. These elements have been indexed using a custom made tool connected with the FMTI multi-terminology server provided by project partners. These annotated documents are spitted into 3 sets used for designing the HAI detection rules, and to serve as a gold standard for 2 rounds of evaluation

2.1 Terminologies

Based on discussions between HAI experts and Terminology experts it has been decided (Metzger 2009) that only the following terminologies are necessary to reach our objective which is the detection of HAI events from reports:
- symptoms/diagnosis: CIM10, SNOMED3.5, MeSH
- bacteriological exams : SNOMED3.5, MeSH
- type of microorganisms : SNOMED3.5
- biological exams : SNOMED3.5, MeSH
- radiological exams : SNOMED 3.5, MeSH, CCAM
- Antibiotics : ATC, MeSH
- Type of surgical intervention: CCAM, MeSH

These terminologies are used to index pertinent named entities inside input reports. However after a first set of experiments we came to the conclusion that using as it is all the vocabulary contained in these terminologies generate noise and ambiguities for the detection of very specific information. Indeed, indexing is designed to maximize recall, but in our case we need to maximize precision. Therefore, based on the result of the annotation step we have decided to build our own HAI terminology which is a sub-part of these terminologies.

2.2 Event detection

The heart of this project is an Incremental Parser (XIP), which performs text mining. This parser is robust that is to say it has already been used in various projects to process large collections of unrestricted documents (web pages, news, encyclopedias, etc.) It has been designed to follow strict incremental strategies when applying parsing rules. The system never backtracks on rules to avoid falling into combinational explosion traps which makes it very appropriate to parse real long sentences from scientific texts for example (Aït-Mokhtar 1997). The analysis is relying on three processing layers which are: Part of Speech Disambiguation, Dependency Extractions between words on the basis of sub-tree patterns over chunk sequences, and a combination of those dependencies with Boolean operators to generate new dependencies or to modify or delete existing dependencies.

Named Entity detection and Event detection is performed using a standard French grammar that have been customized for medical language. As introduced in the previous section the issue with the scope of all selected terminologies forced us to develop and new terminology dedicated to HAI. To be more specific the system focuses on some very specific Named Entities and Events to perform the analysis. These elements are the following:
- Infectious germ: Bacteria, Virus, Yeast,
- Antiseptic : products used to clean or kill infectious germs
- Temperature : elements that indicate a fever or an abnormal change in body temperature
- Invasive devices: to perform measure or to cure. These devices can be an open gate for infectious germs.
- Exams: Such as bacteriologic, radiologic that could be the indication of a problem
- Treatments: all possible treatment that can be related or lead to an HAI (e.g. surgery)
- Diagnostic can also be used to take a decision (e.g. if it is explicitly said that an HAI occurred).

Furthermore, negation is also something to be taken into account for appropriate decision making. For example "no evolution on patient tem-

perature" is a completely different statement compared to "the patient gets fever". Therefore appropriate negation management rules related to pertinent medical terms have been added to enrich the level of information extracted by the parser.

2.3   Temporality

HAI detection in Patient Discharge Summary (PDS) requires also an additional level of information to allow an accurate decision making process: temporality. HAI is not just about detecting isolated elements inside a report, it is also about matching the occurrence of these events with respect to a scenario. Detecting the right time stamp for these events is crucial as according to the time lap between two events (e.g. a knee surgery and an unexpected fever) is crucial to valid a possible HAI hypothesis.

Time detection rules have been designed and added to the parser. Time stamps are computed according to a reference date T0. The algorithm used for temporal indexing is detailed in (Hagège et. al., 2010).

2.4   Causality and decision heuristics

Among all challenges to detect an HAI event inside patient discharge summaries one of the most prominent is the fact that, most of the time, it does not appear explicitly inside texts. The only clue is a sequence of events occurring in a given time frame. This can be compared to a criminal investigation collecting pieces of evidence, searching for specific links between events, evaluating alibi, etc. Furthermore generally only few elements, separated in the text are present in the patient discharge summaries (Horan et al. 2008).

Therefore several discussions have brought together HAI experts and linguists to define which elements are necessary and what kind of relations are mandatory to come to a decision. There is a subtle difference between the official HAI definition and the type of information appearing in a patient record (PR).

A 1st set of heuristics have been designed to evaluate the ability of our system to detect HAI events inside patient records. These heuristics have been designed to maximize the recall. This means that not all the official rules have been encoded. These heuristics have therefore been created based on both formal definition and an empirical approach based on annotated samples.

To summarize this work, what is considered as a "smoking gun" in a patient records is:

- For Intensive Care Unit (ICU) at least one of the following criteria should be valid:
  o If there is an explicit sentence speaking of a HAI
  o If in close sentences we have at least 1 occurrence of both an Infection (e.g. germ) and an Antibiotic drug with time stamps at least equal to 2 days after T0 (T0+2), and no Infection event is described before T0 and the patient is alive.
  o If the patient is already infected at T0 or if he has died during his stay and if at least 2 occurrences of either Infection, Antibiotic drug, Temperature, or an Invasive Device can be found with time stamps superior or equal to T0+2
- For a stay in an Surgery Unit at least one of the following criteria should be valid:
  o If there is an explicit sentence speaking of a Surgery Site Infection
  o If 1 of the following event can be detected with a time stamp superior to T0 : Infection, Antibiotic, Antiseptic, Germ, Bacteriological Exam.

These heuristics have been evaluated to estimate the level of improvement necessary to reach performance objectives expected by medical experts.

3   First Results

A preliminary experiment has been performed by our medical experts on 205 patient records. Results are presented in (Berrouane et al., 2011). The goal of this 1st experiment was to evaluate the efficiency and more specifically the recall of our heuristics to separate patient discharge summaries that deal with HAI and those that don't. On the evaluation corpus 128 patient records over 205 was dealing about HAI. The following table shows a brief overview of the results (details about the protocol are presented in (Hagege et al, 2011)). Here the recall is computed as True positive / (True Positive + False Negative), and Specificity is computed as True negative / (True Negative + False Positive).

For this experiment we compute Specificity instead of Precision (True Positive/(True Positive + False Positive)) as the distribution of the available corpus do not reflect the reality. In our

corpus the number of positive and negative document are equal and the number of document per medical unit (Intensive Care Stomach Unit, Surgery, Orthopedic Surgery, Neuro-surgery) also do not reflect the same exact distribution as in a hospital.

	Patient Discharge Summaries	Recall	Specificity
All	205	87.6 %	97.4 %
ICU	29	62,5%	92.3%
Stomach Surgery	67	89,7%	100%
Orthopedic Surgery	21	87,5%	80%
Neuro-Surgery	88	93,1%	100%

Table 1: 1ˢᵗ results for automatic HAI detection

These results give only a flavor of the potential efficiency of the system. However this gives us good hope for the overall efficiency of the system as the global recall on our evaluation set reach 87.6 % with a Specificity of 97.4% before any improvement.

After some improvement a new experiment will take place at the end of 2011 on a final set of 800 Patient Discharge Summaries. But the success of this first evaluation campaign as pushed us to start developing an evolution of the prototype to plug it directly in a hospital information workflow for live evaluation.

4 Architecture for a Deployment in a real Hospital Information Workflow

The result of this 1ˢᵗ evaluation has demonstrated the potential of the detection system, however several assumptions have been made in the context of the research project and the evaluation is done on a set of ad-hoc documents prepared by medical experts participating to the project.

Therefore medical experts have asked for a special version of the system that could be directly plugged inside the hospital workflow to evaluate its performance in real life. Discussions have taken place to define the specifications and to prepare the delivery of such tool.

4.1 The patient record

After discussions it appears that the way information is managed inside an hospital information workflow is much more complex than simple collections of coherent patient discharge summaries. In fact in our case, each medical unit inside the hospital generates its own set of data when a treatment/analysis is performed. This information is both structured (for parts that can be structured) and unstructured (for free text comments, diagnosis, or summaries). However, even in a free text format, this information is always stored in text fields inside a database.

Furthermore patient information is very fragmented inside the database. Indeed, a patient can enter and leave the hospital several times in a given time frame, for different pathologies, and can travel across different medical units. This means that the global patient record evolve in time. So several questions have to be addressed:

- When the HAI detection system should be applied ?
- How to regroup coherent information related to a given patient (e.g. a left knee surgery, then 1 month later a right knee surgery, then after a new right knee surgery, etc)
- When can we decide that it is no more necessary to process new information?

In order to solve these questions we have defined with people managing the information system inside the hospital a specific architecture and HAI monitoring process for our system.

4.2 Architecture

It has been decided not to plug the HAI monitoring system directly inside the hospital information system (HIS) but rather to set it aside and to develop an ad-hoc standardization interface to allow further compatibility with potentially different types of hospital information systems. The process that is developed consists in:

- Each time new data is recorded inside the HIS for a given patient then a specific module is activated to gather all previous data recorded over a given time frame (currently over 1 year).
- A Custom Patient Record (CPR) is generated by the Data Gathering Module (DGM). This custom patient record is an XML document. Its structure is detailed in the next section. This document is pushed into a predefined temporary input repository.
- The HAI monitoring system browses the input repository and parses the content of

all custom patient records that are dropped in.

- If a HAI event is detected then related information is recorded in a specific database dedicated to HAI. This database allows expert to go back to the patient and to all documents they need to analyze the problem.

This architecture is designed so that it could easily fit with any other hospital information system infrastructure and organization. To do so a data gathering and formatting module (DGM) has to be designed to capture each new update of the patient record.

4.3 A Custom Patient Record for HAI monitoring

The initial research project to create a HAI detection system has made some assumptions with respect to the input format of the documents to be parsed among which we can notice: amonymization, time standardization, content coherence, etc. However the organization of data extracted from the hospital information system by the ad-hoc data gathering module is not so "clean". Therefore the gathering module has to generate a Custom Patient Record (CPR) compatible with what is expected by our HAI monitoring prototype.

This means that for one patient several collections of data are grouped together in one single custom patient record. This structure has the advantage to allow an analysis with specific content parsing rules and decisions rules for each type of treatment. Indeed elements presented in section "3.4 Causality" and "4 Results" show that there are differences between reports produced by different medical units.

The structure proposed for the custom patient records is the following:

- Patient ID
- Patient birth date
- List of files (coherent set of data for one specific treatment)
  - File ID
  - Date T0H provided by the hospital
  - Date T0D detected from texts
  - Reference Date T0
  - List of Documents
    - Document ID
    - Document type (e.g. medial unit)
    - Document Content (text)

4.4 Date of the origin

Another problem to be addressed is the proper detection of the reference date: T0. This is important as temporality management and reasoning for hypothesis validation is based on this reference date.

One solution could be to use the recording date that is associated with all information pushed in the hospital information system. However, after discussions it seems that this date cannot be trusted as a report is not immediately written and recorded after a given treatment. Therefore we have decided identify automatically the date of origin T0. For a given file (coherent set of data for one specific treatment for a given patient):

- A date T0H is provided by the data gathering module (DGM). This date is either the date of the main treatment (e.g. the surgery) if it is recorded in the hospital database, or the date when these documents have been recorded in the system.
- A date T0D is provided by an evolution of the anonymization tool designed for the research project. This tool parses the text content of the CPR to detect all dates or time reference. A date T0 is defined either through the detection of an explicit link between an event and a date (e.g. "… a knee surgery has been done on patient Mr X on June 6th 2011…") or through the comparison between the document redaction date and the closest date mentioned in the document.
- Then a separated decision module assign to the patient file the reference date T0. The decision can be taken according to the level of confidence assigned to each T0H and T0D date.

The decision algorithm should be tuned according to experiments performed on real patient records from the hospital information system.

4.5 Scalability and workflow

Another factor to be considered when delivering a monitoring system in a real hospital information workflow is the amount of information to be processed, the capacity of the system to handle the flow, and the amount of result data generated.

After discussions with people managing the hospital information system, we can anticipate a workload of 300 patient records updated per day

with an average size of 30 KB per patient record. This makes approximately 9 to 10 MB of data to be processed per day. This can be easily processed by our system which is able to parse more than 2000 words per second, and even if it was not the case, the process is easily parallelizable. Therefore scalability is not an issue.

4.6 The decision module

The final aspect to be considered is the evolution of the monitoring system in a live environment. Decision heuristics have already been defined and evaluated on our research project. These rules are currently being improved to face the second and final evaluation. However this is done to cover the requirements of our initial project (orthopedic and surgery reports). In the context of a deployment in a real hospital the system should be customizable enough to allow its modification to address new types of bacteria, or new antibiotic drugs or even a modification of HAI classification criteria, but it raises some problems.

Terminologies can be easily updated if added expressions remain at the level of simple words. As soon as more complex expressions are concerned it implies a more important modification of the Part of Speech tagger that requires the expertise of a linguist. Furthermore adding new entity types will implies modification of the decision rules and a good understanding of their structure to avoid unpleasant side effects.

Finally modifying decision rules implies that results can change with respect to previous analysis. It is important to evaluate and control the impact.

5 Conclusion and Next Steps

We have presented in this paper the latest achievements on a research work to develop a Hospital Acquired Infection detection system from patient discharge summaries. Results of the 1st real evaluation of the system have demonstrated very interesting performances which has conducted us to consider an evolution of the system to plug it inside a real hospital information workflow.

This is a great opportunity to prove that an NLP based monitoring system can be used inside a hospital information workflow to improve patient safety.

References

Aït-Mokhtar S., Chanod J.P., (1997) *Incremental Finite-State Parsing.* In Proceedings of the Fifth Conference on Applied Natural Language Processing (ANLP'97), Washington March 31st to April 3rd, 1997, pp.72-79

Berrouane Y, Hagège C, Gicquel Q, Kergoulay I, Pereira S, Proux D, Darmoni S, Segond F, Metzger MH. *Preliminary evaluation of an automated detection tool for healthcare-associated infections, based on screening natural language medical reports.* Poster at the 21st European Congress of Clinical Microbiology and Infectious Diseases and the 27th International Congress of Chemotherapy. Milan from 7 - 10 May 2011.

Garner JS, Jarvis WR, Emori TG et al. *CDC definitions for nosocomial infections*,1988. Am J infect Control 1988;16 : 128-40

Hagège C; Marchal P; Gicquel, Q; Darmoni, S; Pereira S, Metzger MH. Linguistic and Temporal Processing for Discovering Hospital Acquired Infection from Patient Records. In the 2nd International Workshop on Knowledge Representation for Health Care (KR4HC-2010) - Workshop ECAI 2010, Lisbon, Portugal, August, 2010

Hagège C; Proux D; Gicquel, Q; Darmoni, S; Pereira S, Segond F. Metzger MH. *Développement d'un système de détection des infections associées aux soins à partir de l analyse de comptes-rendus d'hospitalisation.* In Proceedings of *TALN, Montpellier, France, June 27-July 1, 2011.*

H, S. E. Humphreys. *Prevalence surveys of healthcare-associated infections : what do they tell us, if anything?* Clin Microbiol Infect 2006; 12: 2-4

Marie-Hélène Metzger, Quentin Gicquel, Denys Proux, Suzanne Pereira, Ivan Kergourlay, Elisabeth Serrot, Frédérique Segond, Stéphan Darmoni. *Development of an Automated Detection Tool for Healthcare-Associated Infections Based on Screening Natural Language Medical Reports.* In American Medical Informatics Association conference, San Francisco CA, November 2009.