

Evidence-based Clinical Knowledge Assistance towards Supplementing Patient Referral Letters for Evidence Informed Decision Making

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ABSTRACT

Referral letters are common means by which healthcare practitioners exchange information relevant to patient care. It has been argued that information contained in letters of referral and reply often does not meet the information needs of letter receipting. GPs (general practitioners) and specialist require knowledge and information at point of care that is related to patient specification to narrow the information gap and to assist towards better interpretation of referral letters. Given this problem at hand we present, in this paper ECKA (Evidence based clinical knowledge assistance) framework that provides evidence based clinical knowledge assistance from clinical practice guidelines and medical explicit knowledge in terms of medical literature from Medline/Pubmed pertaining to referral letter. This will help narrow the information gap at point of care and to provide better interpretation of referral letters.

Keywords

Medical information processing; Medical query generation; Clinical guidelines computerization

1.0 INTRODUCTION

In healthcare setting patient care depends to great extent on adequate and timely information and knowledge exchange between treating doctors vis-à-vis GPs and specialists. Referral letters are common means by which healthcare practitioners exchange information relevant to patient care (Martin, Tattersall, Phyllis, Judith, and John, 2002). It has been argued that information contained in letters of referral and reply often does not meet the information needs of letter receipting, for example reply letters often are not equipped with proposed treatment, expected outcomes, and any psychosocial concern etc (Martin et al. 2002). Pringle (Pringle, 1991) stated the referral letter as "the most underexploited method to influence consultant attitudes" and the reply letter "the most neglected route of GP education".

We have consulted specialists and GPs and discovered the problem that persists during the interaction

through referral letters between both healthcare practitioners pertaining to information and knowledge needs at the point of care. GPs and specialist require knowledge and information at point of care that is related to patient specification to narrow the information gap and to assist towards better interpretation of referral letters.

On the other hand medical information and knowledge is growing with a rapid pace in heterogeneous knowledge sources located at different locations. Consequently, keeping updated from this knowledge searching, analyzing, extracting, finding, clinical knowledge and information from such heterogeneous sources for a patient specific conditions is a non-trivial task for medical practitioners (Cheah, and Abidi, 1999; Allan, et al., 2003; Abidi, Micheal, Evangelos, 2005). This scenario leads to a situation where most of the contextually relevant and useful knowledge and information, pertaining to patient specifications, are left unused that could make a significance impact at point of care. Furthermore, (i) time constraint, (ii) inexperience and inability to formulate the right search query, (iii) unawareness of online literature search facilities and (iv) subject specific filters, puts healthcare practitioner under pressure towards the usage of evidence-based heterogeneous medical knowledge at their decision points for specific patient (Abidi, et al. 2005).

Given the above described problem at hand, we have designed and developed a framework "ECKA" Evidence based clinical knowledge assistance that provides evidence based clinical knowledge assistance from clinical practice guidelines and medical explicit knowledge in terms of medical literature from Midline/pubmed pertaining to referral letter, to help narrow the information gap at point of care and to provide better interpretation of referral letters.

We present, in this paper, ECKA functional architecture and components workflow of its major phases which are 'Query optimization', 'clinical practice guidelines (CPG) knowledge Computerization', 'Extended knowledge component (Ex-KCs) retrieval module' 'Autonomous Query generator' from KCs and a working example showing the functionality and results of the ECKA.

2.0 FUNCTIONAL FLOW OF ECKA FRAMEWORK

ECKA framework functional architecture is shown in Figure 1. It has different phases that are operated at different stages. The query specifications from the referral letter are taken through “Query Specification module”. The query at this stage needs to be optimized, standardized and compatible with the internal system format. It is sent to query optimization phase that consists of two modules (i) Query modeling module and (ii) Medical term mining module. Query modeling module works with Medical term mining module to remove non-medical textual words and concepts, to identify and extract only medical terms and concepts, to standardize the medical concepts, to find the semantic types and UMLS score of each medical concept, to find the query type based on the semantic types and to finalize the query keywords which are sent to Ex-KCs retrieval module.

CPG computerization is carried out before the system is made available to be used by healthcare practitioner or when new CPG is to be added as a knowledge resource during system maintenance. This phase consists of three module (i) CPG-modeling, (ii) Ex-KCs instance creator and (iii) UMLS-MMTX manager. It converts the textual form of CPG in knowledge components (small knowledge entities from CPG) which are computer understandable and rich in context sensitivity and semantics relevancy. These Ex-KCs are indexed and stored in Ex-KC knowledge base.

‘Ex-KCs Retrieval Module’ takes the optimized query and uses Ex-KCs knowledge base to retrieve related knowledge components using our algorithm and developed technique. It retrieves those knowledge components which are contextually and semantically related to the optimized query. Each retrieved Ex-KC is then processed by ‘Autonomous query generator’ to generate medical search query and query type autonomously for Pubmed using our search strategy. The query for each KC is then sent to ‘SOA Enabler’ that converts the query in a Pubmed E-utilities compatible format and connect to Pubmed to retrieve relevant medical literature pertaining to that knowledge component. ‘Visualizer Module’ is then take the retrieved Ex-KC and related medical literature from Pubmed and embed them together according to the defined presentation scheme and results are presented to healthcare practitioner.

2.1 Query optimization components workflow

Query optimization is carried out for two options (i) To process the entire or selected referral letter or (ii) to process the query words entered or selected by healthcare practitioner. Figure 2 depicts the internal functionality of query optimization. In case of first

scenario, entire or selected letter is taken as query specification. It is processed to identify the medical concepts using UMLS. We used two thesauri MESH and SNOMEDCT for our work. All identified medical concepts are sent to redundant filter. It filters the redundant medical concepts on sentence basis. Remaining medical concepts are then processed to find semantic types and UMLS score. Here those words are also filtered whose semantic types belong to our filtered semantic type list. Frequency counter is used to identify the high frequency medical concepts. Next, semantic type relation is found between two words if two words are semantically related, these words become more strong candidates for final query. Following equation is used to select the final query candidates.

$$S.K = H.F + SMR + \text{High UMLS Score} \quad (1)$$

In equation 1, S.K is selected keyword, H.F is high frequency, SMR is semantically related, and UMLS score indicates strength/confidence of the mapping of the original phrase to the corresponding MeSH or SNOMEDCT term. Based on these keywords, query type is found. Query type are from Pubmed clinical filter which are (i) therapy, (ii) diagnosis, (iii) etiology and (iv) prognosis. Query type is found by matching the query words against the trigger words of the semantic types which are related to each query type. For instance, if the medical concept is “Reperfusion” then its semantic type is “Therapeutic or Preventive Procedure”. This semantic type is a representative of query type ‘therapy’. After determining the query type, final query is sent to Ex-KC Retrieval Module.

In second scenario, where only some keywords are entered and query type is not specified for query specification then same above described procedure is done for only those keywords. In case if healthcare practitioner specifies the query type then determining query type automatically is not performed.

2.2 CPG Knowledge Computerization

CPG-Knowledge Computerization phase is depicted in Figure 1. In essence, functionality of this phase could be divided in three stages. In the first stage CPGs are marked up using our CPG-Encoding strategy via GEM Schema (Hashmi and Zrimec, 2008) to have GEM-Encoded CPGs, In the second stage Ex-KCs Instances (Extended knowledge components instances) are created using our Ex-KC Ontology along with C.W (contextual weight) module and Element-Id module. In the third stage, KCs instance creator works with UMLS-MMTX manager for Medical terms, semantic types and other meta-information mining and retrieval.

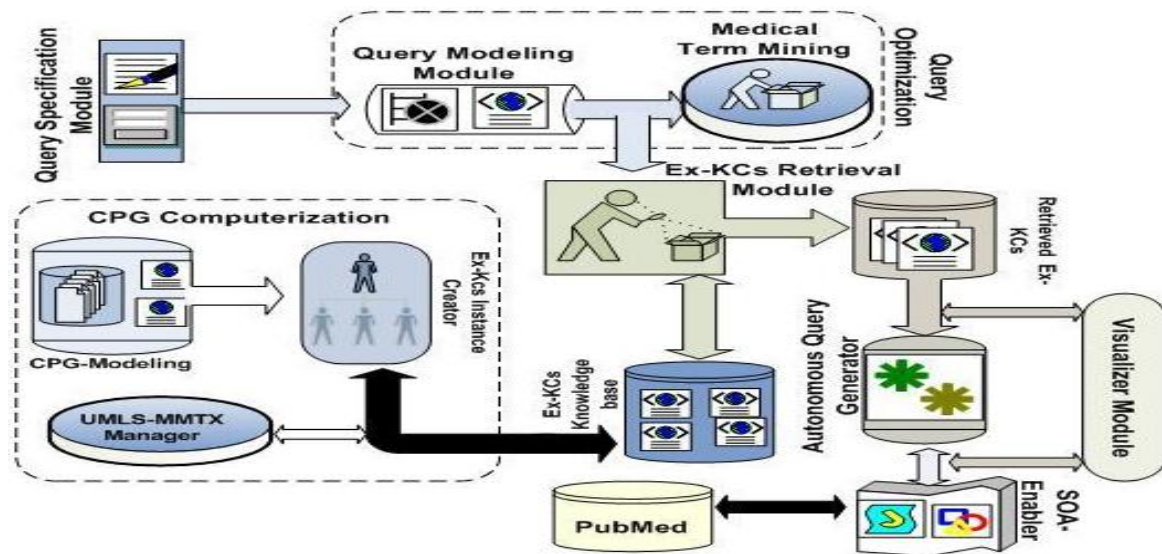


Figure 1: Functional Architecture of ECKA Framework

Created Ex-KCs instances represent CPG knowledge that is enhanced with context sensitivity, semantic relevancy and other important meta-information. Detailed functionality of each module can be found in (Hashmi, Zrimec, and Hopkins, 2009).

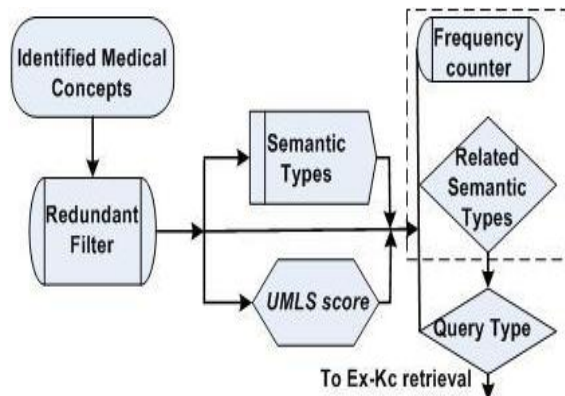


Figure 2: Query optimization Strategy

2.3 Extended Knowledge component retrieval Module

Our CPG-knowledge computerization process does not transform CPG knowledge in “If-then-With” rules rather it adds medical context, semantics and related meta-information to the CPG contents, structures and transforms them in knowledge components. Lets CPG is represented by C and extended knowledge components by Ex-KC so CPG can be represented by the following equation.

$$C = \{ \text{Ex-KC1}, \text{Ex-KC2} \dots \text{Ex-KCn} \} \quad (2)$$

So search space of knowledge retrieval is

$$S = \{ C1 + C2, \dots, Cn \} \quad (3)$$

That means

$$S = \{ \text{Ex-KC1}, \text{Ex-KC2} \dots \text{Ex-KCn} \} \quad (4)$$

For the retrieval of Ex-KC, we use vector space model with contextual weight factor. Every medical word in a Ex-Kc has contextual weight. See (Hashmi, and Zrimec, 2008 b) for details.

The final weight of every medical concept is determined by the combination of statistical weight and contextual weight. This contextual weight addition has shown quite significance in retrieval performance in terms of recall, precision and contextual relevancy.

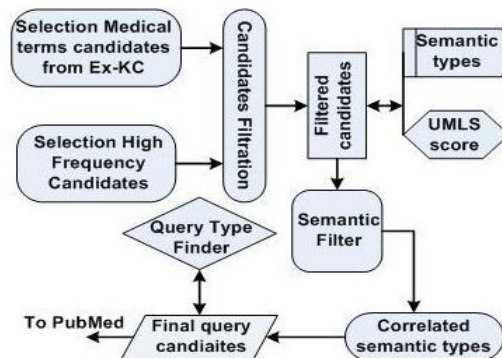


Figure 3. Autonomous Query Generator

Thank you for your note concerning Mrs ---, whom I saw today the 18th April, 2008. She was recently admitted to St. George Hospital with a history of chest discomfort, which she described as a rather sharp discomfort radiating to the left arm and associated with dyspnoea. In hospital there were no ECG changes of ischaemia and the Troponins were negative. A CTPO was performed to exclude pulmonary embolism which was negative and an exercise Sestamibi scan was performed looking for ischaemia, which suggested there was a small area of inferoapical ischaemia and she was only able to exercise for three minutes on the treadmill. It maybe that this was a false positive, but given her history today of gradually decreasing effort tolerance with dyspnoea and chest discomfort, along with also chest discomfort at rest and given her risk factors, it seems likely she would have some coronary disease.

Figure 4. Referral Letter Excerpt for Query Specification

2.4 Autonomous Query Generator

Autonomous query generator functional flow is shown in Figure 3. It generates the query so that pubmed medical literature related to this particular Ex-KC could be retrieved. Here selection of medical terms candidates is done for certain types of context in Ex-KC, which are (i) medical words representing the knowledge component element (Ex-KC is in xml form), (ii) medical words representing recommendation element, (iii) medical words representing decision variable elements under conditional element and (iv) medical terms representing imperative element.

In second step those words are found that have high frequency in full Ex-KC. Candidate filtration process is done to filter out those words that have high frequency and are representative of any of the above described four elements. Filtered candidates' semantic type and UMLS score are taken into account. These candidates are passed through another filter that is semantic type filter. It removes all those candidates which belong to filtered semantic types. Correlation between different medical terms is determined based on the semantic types (same as described above) and based on equation 1 final candidates, for query, are selected. Query type is determined using these medical terms. This query is sent to SOA-Enabler so that medical literature from Pubmed can be retrieved.

3.0 WORKING EXAMPLE AND RESULTS

We present a simple example for the ECKA framework functionality. Figure 4 shows the excerpt of a referral letter. GP selects some of the medical terms from the letter to find evidence based information. Following keywords are selected as query specification and query type is not defined.

“chest discomfort, sharp discomfort, ischaemia, Troponins, dyspnoea, inferoapical”

As GP selected the Keywords, so, high frequency factor is not taken into account. These keywords are processed to identify medical terms based on

UMLS thesauri. The words which are not identified as medical term candidates are (i) sharp discomfort and (ii) inferoapical. After redundant filter, semantic types of the candidate terms are found which are : (i) { Chest discomfort : Sign or Symptom }, (ii) { dyspnoea : Sign or Symptom }, (iii) { ischaemia : Disease or Syndrome }, and (iv) { Troponins : Biologically Active Substance }. Semantic type filtration is done and “Biologically Active Substance” semantic type term is filtered out. Semantic correlation is determined among the terms and UMLS score is taken into account.

Table 1: Table Retrieved Medical Literature from Pubmed.

No.	Retrieved Medical Documents from PubMed
1	<i>The utility of gestures in patients with chest discomfort. Marcus GM, Cohen J, Varosy PD, Vessey J, Rose E, Massie BM, Chatterjee K, Waters D. Am J Med. 2007 Jan;120(1):83-9.</i>
2	<i>Detection of coronary stenoses by stress echocardiography using a previously implanted pacemaker for ventricular pacing: preliminary report of a new method. Benchimol D, Mazanof M, Dubroca B, Benchimol H, Bernard V, Couffinhal T, Dartigues JF, Roudaut R, Pillois X, Bonnet J. Clin Cardiol. 2000 Nov;23(11):842-8.</i>
3	<i>Improved detection of posterior myocardial wall ischemia with the 15-lead electrocardiogram. Khaw K, Moreyra AE, Tannenbaum AK, Hosler MN, Brewer TJ, Agarwal JB. Am Heart J. 1999 Nov;138(5 Pt 1):934-40.</i>

Three remaining terms are found semantically associated. As ‘disease and syndrome’ are

associated with 'sign and symptoms' according to UMLS semantic network. These terms are used to find the query type based on their semantic types. The query type "diagnosis" is selected as all of the semantic types belong to diagnosis query type.

Retrieval process is initiated and Ex-KC is retrieved. Query from retrieved Ex-KC is generated and the following query words are selected.

“myocardial infarction, chest discomfort, ischaemia, chest pain”.

These keywords are submitted to PubMed along with the query type “diagnosis”. Based on this query, medical literature documents are retrieved. Some of them are shown in Table 1.

4.0 CONCLUSION

We have described the functionality of our ECKA framework that provides the knowledge assistance from clinical practice guidelines knowledge source and PubMed. We have discussed our technique of query modeling for query optimization and autonomous query generation. CPG computerization and Ex-Kc retrieval techniques have been described. A working example for ECKA functionality has been put forward to provide practical understanding and results of the ECKA framework.

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REFERENCES

- Abidi, S.S.R., Micheal, K., Evangelos, E. M. (2005). BiRD: A Strategy to Autonomously Supplement Clinical Practice Guidelines with Related Clinical Studies. *HICSS*.
- Allan, J. et al., (2003, September 2002). Challenges in Information Retrieval and Language Modeling. Report of a Workshop held in the Center for Intelligent Information Retrieval, University of Massachusetts Amherst. *ACM SIGIR Forum*, 37(1) 31-47.
- Cheah, Y.-N. and Abidi, S.S.R. (1999). The Efficacy of Ontology-Based Knowledge Acquisition in Healthcare Enterprises. *International Medical Imaging & Instrumentation Technology Conference & Exhibition (IMIIT '99)*, Kuala Lumpur, Malaysia.

Hashmi, Z.I., Zrimec, T. (2008 a). Ontology-driven Modeling of Clinical Practice Guidelines (CPG) Towards Computerization of CPG knowledge sources via GEM Model. *IEEE International Symposium on Information Technology, ITSIM*, 26th -29th August, Malaysia..

Hashmi, Z.I., Zrimec, T. (2008 b). Context and Semantic based Knowledge Retrieval from Clinical guidelines Knowledge Bases. *IEEE International Symposium on Information Technology, ITSIM '08*, 26th -29th August, Malaysia.

Hashmi, Z.I., Zrimec, T., Hopkins, A. (2009). CPG-Knowledge Computerization Framework towards Augmenting Context and Semantic from UMLS via Ontology-Based-Extension of GEM Model, *The XXII International Conference of The European Federation For Medical Informatics, MIE 2009*, Sarajevo.

Martin, H. N., Tattersall, Phyllis, N. B., Judith, E. B. and John, F. T. (2002) Improving doctors' letters. *eMJA The Medical Journal of Australia, MJA*, 177 (9) 516-520.

Pringle, M. (1991). Referral letters — ensuring quality. *Practitioner*, 235, 507-510. <PubMed>.