Triage of Acute Abdominal Pain in Childhood: Clinical Use of a Palm Handheld in a Pediatric Emergency Department

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Abstract

The paper describes design and implementation of a mobile clinical triage support system for the evaluation of acute appendicitis in childhood.

The MET (Mobile Emergency Triage) system was developed according to the general principles of client-server architecture, with mobile clients running on Palm handhelds. Decision model implemented in MET follows the principles of evidence-based medicine based on retrospective data. We applied a hybrid methodological approach involving fuzzy measures and rough set theory to develop this model. In a randomized retrospective trial, the triage recommendation of the MET system had a sensitivity of 86.7% and a specificity of 85.7%.

MET is a fully functional mobile clinical triage support system that provides triage recommendation at the point of care, irrespective of the completeness of the clinical information. It also allows for data capture and interaction with the hospital’s information system.

Given mobility of MET and its easy-to-use features, we are proposing a system that can both support evidence-based emergency room patient care, and at the same time, streamline the bedside triage of a child with abdominal pain.

1. Introduction

Abdominal pain in childhood is a highly prevalent symptom caused by organic diseases, psychosocial disturbances and emotional disorders. Attending medical staff must focus on identifying the minority of cases requiring urgent treatment. Repeated physical examinations and investigations, including abdominal ultrasound, and conducted by different physicians, are time consuming and may be painful. In order to facilitate these investigations and arrive at an accurate triage, several studies advocate the use of a clinical scoring system [1, 2], while others argue that only an experienced member of a pediatric surgical team is capable of the reliable diagnosis of acute appendicitis [3]. It is well documented that most accepted pediatric surgical diagnostic methods are not founded on evidence-based medical research [4]. On one hand, there is a lack of well-designed randomized, controlled trials due to the relative rarity of many of the pediatric surgical diagnoses observed in a single institution, and on the other hand there are technical and ethical difficulties in randomizing surgical therapies. Therefore, over 95% of studies reported in the pediatric surgical literature involve case reports or retrospective studies [5]. Faced with such a situation, we decided to apply evidence-based principles to develop a decision model for the early triage of the abdominal pain patient. This paper describes the development of such a model and its implementation on a Palm handheld in the form of a clinical triage support system.

2. Methods

2.1. Triage of Abdominal Pain

The process of triaging a child complaining of abdominal pain in the emergency department’s (ER) is illustrated in Figure 1.

The ER triage nurse initially assesses the child and assigns her to a proper priority level according to severity of a complaint (this stage is also called prioritization). This assessment is followed by a detailed examination conducted by the ER physician (the time span between assessment and examination depends on the assigned priority – it may vary from minutes to hours). The possible outcomes of this evaluation are: discharge to family doctor (FD), surgical consult (consult), or continue investiga-
tion/observation (observation). FD indicates that no abnormality is detected, and the abdominal pain spontaneously subsides. Consult implies that acute appendicitis is suspected, and a surgeon is called. All other patients require further in-hospital clinical evaluation. The final (actual) diagnosis is recorded when the patient is discharged. The second phase of triage is also called disposition, however for simplicity we will refer to further in the text as the “triage”.

The MET (Mobile Emergency Triage) system is a clinical decision support system (clinical DSS) aimed at facilitating the rapid ER triage of children with abdominal pain. The system supports the disposition phase and is intended to be used by ER physicians and residents to help them in evaluating patients and making disposition decisions.

2.2. Development of the Decision Model

A retrospective chart review was done, using the records of 606 patients with abdominal pain, seen during the 1997 – 2002 period in the Emergency Department of the Children’s Hospital of Eastern Ontario (Ottawa, Ontario). The ER chart of each patient was reviewed with special reference to 12 clinical symptoms, signs, and tests (attributes) and the discharge diagnosis (see Table 1). Reliance on the discharge diagnosis guarantees that the actual clinical outcomes, not the decisions made by the ER staff, are used for developing and evaluating the decision model for early triage.

It is usual that data collected as part of a retrospective chart review contains a significant number of missing values. The analysis of those clinical symptoms and signs that have missing values is very important. Clearly, they should not be discarded (a common approach in other studies was to remove from further analysis the clinical symptoms and signs with a number of missing values above a certain threshold), as their importance depends on the context in which they are evaluated. The WBC data is a very good example of such a situation. It had 44% missing values for the FD class, but less than 3% for the consult class. One can conclude that the triage of almost half of the patients (FD class) was clear, and did not require any further investigations, thus indicating that the WBC in this particular context was not an important attribute. On the other hand, when a patient is triaged as a consult, the WBC results are very important for that patient’s management, and a minimal number of missing values (less than 3%) could be attributed to the incorrect entry of the WBC information on the patient’s chart in the ER.

In this study, the data set created from the patients’ charts was studied for regularities using knowledge discovery methods – namely, rough sets theory and fuzzy measures. (The basic notions behind rough sets theory and the fuzzy measure are described in the Appendix.) It is a novel approach to the treatment of clinical data that considers missing values during the analysis.

The medical data set was analyzed using ROSE software [6]. The information richness of each attribute for the triage of abdominal pain was established using a Shapley value [7] based on a fuzzy measure. Shapley values are presented in Figure 2 (the greater the value, the more information an attribute carries). At this point physicians involved in the emergency management of children with abdominal pain were consulted and asked to validate the obtained results.

The information about importance of signs, symptoms and tests as indicated by respective Shapley values was considered in the process of generating decision rules [8]. In order to check if all clinical attributes should be used to create sound rules, we iteratively tested subsets of attributes distinguished according to Shapley values, starting with six top ones and ending with all twelve. For each of

### Table 1. Attributes and their value domains

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Domain</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>0–5 years, ≥ 5 years</td>
</tr>
<tr>
<td>Sex</td>
<td>male, female</td>
</tr>
<tr>
<td>Duration of pain</td>
<td>≤ 24 hours, 1–7 days, &gt; 7 days</td>
</tr>
<tr>
<td>Site of pain</td>
<td>right lower quadrant, lower abdomen, other</td>
</tr>
<tr>
<td>Type of pain</td>
<td>continuous, intermittent</td>
</tr>
<tr>
<td>Vomiting</td>
<td>yes, no</td>
</tr>
<tr>
<td>Previous visit</td>
<td>yes, no</td>
</tr>
<tr>
<td>Temperature</td>
<td>&lt; 37 °C, 37–39 °C, ≥ 39 °C</td>
</tr>
<tr>
<td>Site of tenderness</td>
<td>right lower quadrant, lower abdomen, other</td>
</tr>
<tr>
<td>Localized guarding</td>
<td>absent, present</td>
</tr>
<tr>
<td>Rebound tenderness</td>
<td>absent, present</td>
</tr>
<tr>
<td>White blood cell count (WBC)</td>
<td>≤ 4000, 4000–12000, ≥ 12000</td>
</tr>
</tbody>
</table>
the subsets we evaluated the classification accuracy of corresponding decision rules.

2.3. Implementation of the Decision Model

There was no clear evidence in the literature with regards to the form, depth, and method of implementing a decision model for clinical triage. After consulting with Division of General Surgery we created a model based on all generated decision rules – and embedded it in the MET system. Due to a proposed way of evaluating the rules comprising this model (the set of rules most appropriate from the point of view of available data is selected, i.e., the more information about a patient’s condition that is available, the more specific rules are used), the system will always derive a triage recommendation, irrespective of the amount of clinical information available. Because of the use of triage strength factors for each triage recommendation, it will present triage possibilities, together with the associated strengths of a given recommendation. The triage class that acquired the highest strength factor is then labeled the “suggested triage”.

The MET system went through a limited retrospective evaluation using ER charts from the Children’s Hospital of Eastern Ontario, collected for 100 randomly selected patients admitted to the ER with abdominal pain between 1997 and 2002 (those charts were not used for developing the decision model). The purpose of this evaluation was to establish how well suited MET is to triage those patients that require an urgent surgical consult. In order to compute the basic statistics for such an evaluation, the consult class was labeled as positive (it represents an acute situation), and the remaining two categories (FD and observation) were combined into a negative class (they represent patients that do not require urgent attention). The overall triage accuracy of the MET (with discharge diagnosis used as a gold standard) was 86.0% (see Table 3). The sensitivity of the MET triage recommendation was 86.7%, and its specificity was 85.7%, confirming the good value of a MET triage recommendation. The system exhibited classification accuracy of 35% while evaluating patients from the observation class (combined together with FD into the negative category). Nevertheless, such result is in line with other research [12], reporting that differentiation between non-specific abdominal pain (one of the most common complaints among the discharged patients) and other surgical or gynecological diseases (common for patients from the observation class) is difficult on the basis of regularly evaluated symptoms and signs. Complete results of the retrospective evaluation are given in Table 4.

Table 3. MET triage

<table>
<thead>
<tr>
<th>Triage</th>
<th>Negative</th>
<th>Positive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absent</td>
<td>60</td>
<td>10</td>
</tr>
<tr>
<td>Present</td>
<td>4</td>
<td>26</td>
</tr>
</tbody>
</table>

Figure 2. Shapley values

The rules were tested retrospectively on how well they could classify a patient presenting with an abdominal pain. The classification accuracy was estimated through the validation tests commonly used in data analysis with rough sets theory and other techniques based on a machine learning approach [9]. Results of the validation tests suggested that rules based on all twelve attributes give the highest classification accuracy. Robustness of these rules confirms our earlier findings [10, 11] concerning the evaluation of alternative knowledge discovery methodologies. Generated decision rules (sample decision rules are presented in Table 2) were used to develop a decision model that reflects the physician’s clinical thinking while evaluating a child with abdominal pain.

Table 2. Sample decision rules

<table>
<thead>
<tr>
<th>Triage</th>
<th>Conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>FD</td>
<td>age is 5 years or older, and type of pain is intermittent, and temperature is below 37 °C</td>
</tr>
<tr>
<td>FD</td>
<td>sex is female, and site of pain is other, and there was no vomiting, and there was previous visit, and temperature is below 37 °C</td>
</tr>
<tr>
<td>consult</td>
<td>there was previous visit, and temperature is 39 °C or more, and site of tenderness is RLQ</td>
</tr>
<tr>
<td>consult</td>
<td>sex is male, and site of pain is RLQ, and vomiting occurred, and there was no previous visit, and temperature is between 37 and 39 °C, and rebound tenderness is present</td>
</tr>
<tr>
<td>observation</td>
<td>sex is female, and duration of pain is 7 days or more, and vomiting occurred, and temperature is below 37 °C, and WBC is between 4.000 and 12.000</td>
</tr>
<tr>
<td>observation</td>
<td>age is under 5 years, and vomiting occurred, and there was no previous visit, and temperature is between 37 and 39 °C, and site of tenderness is RLQ, and rebound tenderness is absent</td>
</tr>
</tbody>
</table>
In the literature, reported accuracy of computer-aided initial diagnosis is around 60% [12]. Higher accuracy was reported in [13], for a multi-centre trial of a clinical DSS. The system evaluated in such a way relied on a database of past cases while making initial diagnosis. Reported accuracy of clinicians was 61.0% (sensitivity – 77.3%, specificity – 52.7%), and accuracy of the system was 77.1% (sensitivity – 77.3%, specificity – 70.0%). Considering these results the MET performance as given in Table 4 is comparable or better.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensitivity</td>
<td>86.7%</td>
</tr>
<tr>
<td>Specificity</td>
<td>85.7%</td>
</tr>
<tr>
<td>Classification accuracy</td>
<td>86.0%</td>
</tr>
</tbody>
</table>

### Table 4. Retrospective evaluations

3. Results

The decision model described in the previous section forms the core of the MET system. The system’s design, illustrated in Figure 3, follows the principles of client-server architecture [14]. The client module runs on a handheld under PalmOS 3.5 (or later), and the server is implemented on a PC running Windows NT/2000. The desired functionality of the MET system is accomplished through a clear division of the tasks and functions to be performed on the server and on the client side. The server performs two functions: it provides integration with a hospital information system, and it communicates with mobile clients. The mobile client is used for clinical data entry and triaging a patient.

Use of the system begins with the entry of the patient’s information (including a unique PIN) at the moment of the patient’s admission to the ER. One of the unique features of the system is its adaptability to different end-user needs while capturing the patient’s clinical information. For example, the results of the physical examination of the abdomen are entered, using the pictograms (see Figure 4), while the temperature is entered using a numeric keypad to minimize the amount of data typed-in manually (see Figure 5). For most of the clinical symptoms and signs, the system allows also for the free entry of any additional comments about the patient’s condition. There is reported evidence that such structured data collection should contribute to the improved triage and diagnosis of a patient [15].

![Figure 4. Graphical data capture using the pictogram](image1)

![Figure 5. Numeric data capture using the numeric keypad](image2)
ing at the same time the value of the strength factor associated with the resulting recommendation.

When collection of information about the patient’s condition is completed, and care of the patient has been transferred to another caregiver, all the information gathered to date can be transferred to a MET database (if the triage phase is not completed) for use by other caregivers, thus either creating or updating the patient’s record, or moved to the hospital’s patients’ data repository (if the triage phase is completed). When new information about a patient becomes available during a triage phase, the triage function of MET might be invoked again, and the system will use the most recent information to re-evaluate the triage recommendation.

4. Discussion

The management of a patient with abdominal pain in the ER requires an initial assessment of his/her condition, repeated evaluation of the patient’s history, physical findings and laboratory and radiological tests. On the basis of such an assessment, an appropriate management is selected. Thus, any clinical triage support system needs to have the ability to mimic this process by having information-gathering facilities, the ability to give the triage recommendation, and to be available “on demand” at the patient’s bedside. The MET system has all these features.

The analyzed abdominal pain data set had a large number of missing values for some of the clinical symptoms and signs and tests. It would not have been possible to create the clinical algorithm without a hybrid approach involving knowledge discovery and a fuzzy measure that enabled us to consider the differential information content of the attributes, taking into account the number of missing values, and their distribution among the triage classes. Following consultations with physicians, the decision model was developed and incorporated into the MET system. The client module installed on the Palm handheld allows the medical personnel to gather pertinent patient information, and to triage the child appropriately in the hospital ER.

We believe that the development of a model using Class III data (i.e. data from retrospective case series and case studies) as reported here, and its implementation in the MET system, constitute a positive example of applying evidence-based principles in pediatric surgery. This was also demonstrated in a prospective evaluation conducted in one center. Clearly, the limitations of this evaluation are associated with the fact that cases and a model were confined to one teaching hospital. However, even if some variations in regimen may be appropriate for other locations, it is likely that the principles applied in developing MET will be valid elsewhere.

The MET system is designed to support early triage of acute condition in the ER, thus its interactions framework is created with this goal in mind. Taking advantage of the specific features of this framework (interface design and use of mobile clients), we were able to increase MET’s functionality by:

- Allowing for structured data capture, storage, and transmission;
- Providing triage support anytime and anywhere at the patient’s point of care.

5. Conclusion

Currently, we are in a process of the comprehensive clinical testing of the complete MET system in a teaching hospital. We are also expanding the system’s clinical function to cover the management of scrotal pain and hip pain in childhood.

The experience gained during MET’s clinical testing will allow us to develop appropriate procedures for evaluating and updating the decision model implemented in the system. This can happen only when a sufficient number of new records with verified discharge diagnoses is collected, however as outlined in section 2, the process is not automatic and has to be controlled and validated by the physicians.

Implementing MET’s client on a mobile device allows physicians to collect clinical data and ask for triage support directly at the point of care. In [16] it was reported that physicians perceived as a hindrance a need to leave the point of care in order to consult a computer system. Such setup also discouraged timely data entry. Therefore, it is clear that use of mobile devices that allow for support at the patient’s point of care is of paramount importance for system’s acceptance by the physicians and its successful implementation in a clinical setting.

6. Acknowledgments

The research reported in this paper was supported by the grants from the Natural Sciences and Engineering Research Council of Canada and the Polish Committee for Scientific Research. The authors would like to thank Eric Payne for assistance in developing a data set from the ER admission charts, and Anne Burgess for editorial assistance.

The MET system was created using AppForge MobileVB and Sybase iAnywhere Studio.

7. Appendix

The clinical data set created from the patients’ charts was analyzed for regularities, using rough sets analysis
and fuzzy measures. Due to the novelty of our approach for clinical research, we decided to include a short description of the basic notions behind rough sets theory and fuzzy measure [7, 17, 18, 19].

Rough sets theory [17, 18, 20] proved to be a very useful data mining tool [21] for the analysis of data where objects are described by means of disjoint subsets of condition and decision attributes (for example, if the objects are the ER charts of patients with abdominal pain, then the clinical signs and symptoms and tests are condition attributes, and the triage outcome becomes a decision attribute). The rough sets approach can be applied to process both quantitative and qualitative data, and data inconsistencies need not be removed prior to the analysis. Recent extensions [22] of the rough set methodology allow us to deal with incomplete data (i.e., data containing missing values, such as lack of information about the WBC, for most of the patients who were discharged home to the care of the FD).

The rough sets analysis answers two important questions:

- Which condition attributes are most relevant for the quality of classification (the term is defined below)?
- What are the relationships between the condition and decision attributes?

The relationships between condition and decision attributes are presented in form of “if..., then...” decision rules, so they are easy to interpret. The rules are logical statements (implications), where the antecedent (“if” part of a the rule) is a conjunction of elementary tests on certain condition attributes (e.g., “if location of pain is RLQ and rebound tenderness is present...”), and the consequence (decision part) is a disjunction of the possible assignment to particular decision classes (e.g., “...then the triage recommendation is a surgical consult”).

The key idea of rough sets is to describe any subset of objects \( X \) (i.e., patients with the same triage outcome) by two sets called lower and upper approximation. The lower approximation of \( X \) contains all objects that certainly belong to \( X \), (i.e., the patients who certainly need a surgical consult) while the upper approximation includes all objects that may belong to \( X \) (i.e., the patients who might need a surgical consult). The difference between the upper and the lower approximation constitutes the boundary region, containing all objects that cannot be characterized with certainty as belonging to \( X \) or not (i.e., it represents a “grey area” where it is not possible to state with reasonable accuracy that a patient requires a surgical consult). Together, the approximations define a rough set \( X \) that can be described as separating certain knowledge from that which is doubtful.

The quality of classification is the basic measure that characterizes the crispness of classification of all objects into decision classes (triage outcomes). It is defined as the ratio of the number of objects in the lower approximations of considered decision classes to the number of all objects in the data set (i.e., the ratio of the patients who certainly are triaged as FD, consult, and observation to all the patients). Thus, the quality of classification of the MET system reflects how good it is in providing a triage recommendation.

Fuzzy measure was another tool that was used in this study. Within game theory, the fuzzy measure, called the characteristic function, represents the payoff obtained by the coalition of players in a cooperative game [7]; in a multi-attribute classification, fuzzy measure can be interpreted as measuring the conjoint importance of the attributes for describing patterns in a data set [23].

The quality of classification in a rough set can be considered a fuzzy measure [24], and thus can be used to assess the relative value of the information supplied by each attribute, and to analyze the interactions between the attributes. Such an analysis can be conducted using specific indices. One of the most important of these is an index that originates from the theory of cooperative games – the Shapley value [7].

The Shapley value, when used in conjunction with the rough sets, can be used to assess the contribution of a single attribute (i.e., particular sign, symptom or test) to the quality of classification (i.e., patients with abdominal pain to specific triage class). Those attributes with a higher Shapley value are considered to better explain the relationships in a data set.

8. References


