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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-

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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".

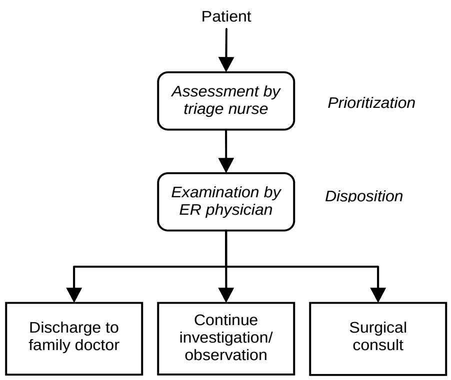

Figure 1. Emergency triage of child with abdominal pain

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 patents 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.

Table 1. Attributes and their value domains

Attribute	Domain
Age	0–5 years, ≥ 5 years
Sex	male, female
Duration of pain	≤ 24 hours, 1–7 days, > 7 days
Site of pain	right lower quadrant, lower abdomen, other
Type of pain	continuous, intermittent
Vomiting	yes, no
Previous visit	yes, no
Temperature	< 37 °C, 37–39 °C, ≥ 39 °C
Site of tenderness	right lower quadrant, lower abdomen, other
Localized guarding	absent, present
Rebound tenderness	absent, present
White blood cell count (WBC)	≤ 4000, 4000–12000, ≥ 12000

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

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the subsets we evaluated the classification accuracy of corresponding decision rules.

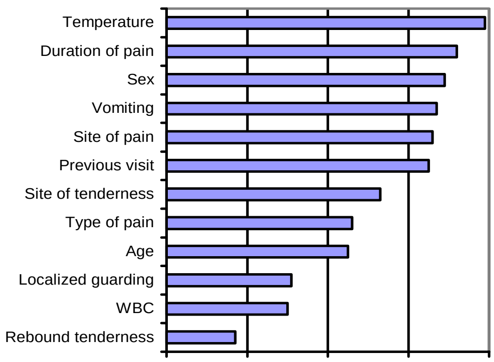

Figure 2. Shapley values

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

Triage	Conditions
FD	age is 5 years or older, and type of pain is intermittent, and temperature is below 37 °C
FD	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
consult	there was previous visit , and temperature is 39 °C or more, and site of tenderness is RLQ
consult	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
observation	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
observation	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

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

Outcome \ Triage	Negative	Positive
Absent	60	10
Present	4	26

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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 4. Retrospective evaluations

Measure	Value
Sensitivity	86.7%
Specificity	85.7%
Classification accuracy	86.0%

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.

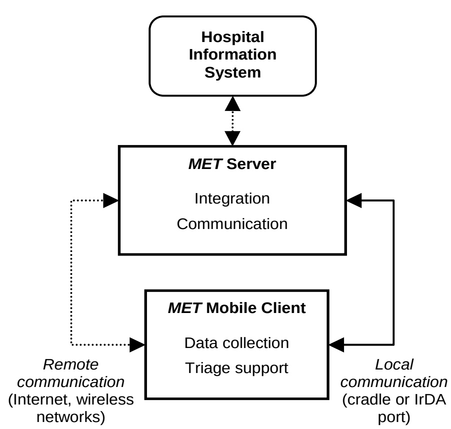

Figure 3. *MET* architecture

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].

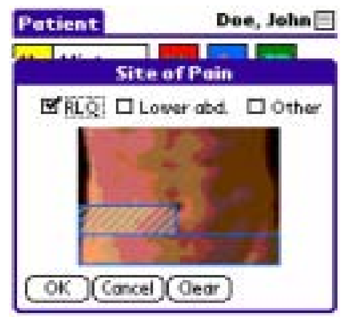

Figure 4. Graphical data capture using the pictogram

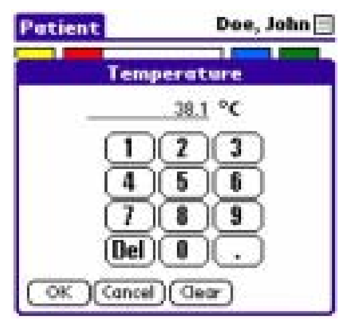

Figure 5. Numeric data capture using the numeric keypad

The system's triage function can be invoked at any time, and it uses the patient's most current data to provide a triage recommendation. The function is executed on the *MET* client, thus it gives real-time results without a need of connecting to the server. Depending on the information currently available to the caregiver, the *MET* system invokes the most suitable part of the decision model, that is, a subset of rules providing the best overall match. The system gives a triage recommendation by highlighting the outcome that according to the model represents the strongest triage recommendation. Even if the model does not have rules exactly matching the available data, the system will consult the most closely matching rules, but diminishing 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.

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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

[1] T.I. Anatol, Y. Holder, "A Scoring System for Use in the Diagnosis of Acute Abdominal Pain in Childhood", *Wisconsin Medical Journal*, vol. 44, 1995, pp. 67-69.

[2] S. Hallan, T. Edna, "Estimating the Probability of Acute Appendicitis using Clinical Criteria of a Structured Record Sheet: The Physician Against the Computer", *European Journal of Surgery*, vol. 163, 1997, pp. 427-432.

[3] E.T. Simpson, A. Smith, "The Management of Acute Abdominal Pain in Children", *Journal of Paediatrics and Child Health*, vol. 32, 1996, pp. 110-112.

[4] M. Blakely, K. Lally, "Using Evidence-based Medicine Principles to Improve Quality of Patient Care in Pediatric Surgery", *Seminars in Pediatric Surgery*, vol. 11, 2002, pp. 42-45.

[5] W. Hardin, S. Stylianos, K. Lally, "Evidence-based Practice in Pediatric Surgery", *Journal of Pediatric Surgery*, vol. 34, 1999, pp. 908-912.

[6] B. Predki, Sz. Wilk, "Rough Set Based Data Exploration Using ROSE System", in *Foundations of Intelligent Systems*, Z.W. Ras, A. Skowron A, Eds., Springer-Verlag, 1999, pp. 172-180.

[7] L.S. Shapley, "A Value for n-Person Games", in *Contributions to the Theory of Games II*, H.W. Kuhn, A.W. Tucker, Eds., Princeton University Press, 1953, pp. 307-317.

[8] J. Stefanowski, "On rough set based approaches to induction of decision rules", in *Rough Sets in Knowledge Discovery Vol. 1*,

A. Skowron, L. Polkowski, Eds., Physica Verlag, Heidelberg, 1998, pp. 500-529.
[9] T. Mitchell, *Machine Learning*, McGraw Hill, 1997.
[10] W. Michalowski, S. Rubin, R. Slowinski, Sz. Wilk, "Triage of the Child With Abdominal Pain: A Clinical Algorithm for Emergency Patient Management", *Journal of Paediatrics and Child Health*, vol. 6, 2001, pp. 23-28.
[11] S. Rubin, W. Michalowski, R. Slowinski, Sz. Wilk, "Computer-assisted Triage of Abdominal Pain in Childhood: A Suggested Clinical Algorithm", in *Proc. Conference on Simulation in Health Sciences*, San Diego, Society for Computer Simulations, 2000, pp. 19-24.
[12] B. Puppe, C. Ohmann, K. Goos, F. Puppe, O. Mootz, "Evaluating Four Diagnostic Methods with Acute Abdominal Pain Cases", *Methods of Information in Medicine*, vol. 34, no. 4, 1995, pp. 361-368.
[13] J.A.S. Dickson, A. Jones, S. Telfer, F.T. de Dombal, "Acute Abdominal Pain in Children", *Scandinavian Journal of Gastroenterology.*, vol. 23, 1988, pp. 43-46.
[14] J. Jing, A. Helal, A. Elmagarmid, "Client-Server Computing in Mobile Environments", *ACM Computing Surveys*, vol. 32, no. 2, 1999, pp. 117-157.
[15] H. Korner, K. Sondenaa, J.A. Soreide, "Structured Data Collection Improves the Diagnosis of Acute Appendicitis", *British Journal of Surgery*, vol. 85, 1998, pp. 341-344.
[16] A.S. Gertner, B.L. Webber, "TraumaTIQ: Online Decision Support for Trauma Management", *IEEE Intelligent Systems*, vol. 13, no. 1, 1998, pp. 32-39.
[17] Z. Pawlak, *Rough Sets: Theoretical Aspects of Reasoning about Data*, Kluwer Academic Publishers, 1991.
[18] Z. Pawlak, R. Slowinski, "Rough Set Approach to Multiattribute Decision Analysis", *European Journal of Operational Research*, vol. 72, 1994, pp. 443-459.
[19] R. Slowinski, "Rough Sets Approach to Decision Analysis", *AI Expert Magazine*, vol. 10, 1995, pp. 8-25.
[20] S. Greco, B. Matarazzo, R. Slowinski, "Rough Sets Theory for Multicriteria Decision Analysis", *European Journal of Operational Research*, vol. 129, 2001, pp. 1-47.
[21] T. Lin, N. Cercone, Eds., *Rough Sets and Data Mining*, Kluwer Academic Publishers, 1997.
[22] S. Greco, B. Matarazzo, R. Slowinski, "Dealing with Missing Data in Rough Set Analysis of Multi-Attribute and Multi-Criteria Decision Problems", in *Decision Making: Recent Developments and Worldwide Applications*, S.H. Zanakis, G. Doukidis, C. Zopounidis, Eds., Kluwer Academic Publishers, 2000, pp. 295-316.
[23] M. Grabisch, "k-Order Additive Discrete Fuzzy Measures and Their Representation", *Fuzzy Sets and Systems*, vol. 89, 1997, pp. 445-456.
[24] S. Greco, B. Matarazzo, R. Slowinski, "Fuzzy Measures as a Technique for Rough Set Analysis", in *Proc. 6th European Congress on Intelligent Techniques and Soft Computing (EUFIT'98)*, Aachen, 1998, pp. 99-103.