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# Fuzzy Decision Tree for the Objective Explanation of Subjective Functional Evaluation: Application to the Upper Limb

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# **IDAMAP 2002:**

## **Intelligent Data Analysis in Medicine and Pharmacology 2002**

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Working notes of workshop **W21**, held during  
The *European Conference on Artificial  
Intelligence*, ECAI 2002  
Lyon, France, 23rd July, 2002



***Peter Lucas, Lars Asker, Silvia Miksch***  
**(Editors)**

## Preface

These are the working notes of the IDAMAP 2002 workshop, which was held during the *European Conference on Artificial Intelligence, ECAI 2002*, on 23rd July, 2002, in Lyon, France. The workshop brought together various theoretical and practical approaches to using data-analysis and machine-learning approaches tackling biomedical and health-care problems.

The IDAMAP workshop series is devoted to computational methods for data analysis in medicine, biology and pharmacology that somehow exploit expert knowledge of the problem domain. Such knowledge may be available at different stages of the data analysis and model-building process.

Nowadays, machine-learning tools provide an effective means to derive understandable diagnostic and prognostic rules; Bayesian structure and parameter learning methods are capable of capturing the (in)dependence structure hidden in data and of learning and updating the model's parameters; clustering and instance-based learning methods, like case-based reasoning, may represent a crucial help to physicians in their decision making process; the interpretation of time-ordered data through the derivation and revision of temporal trends and other types of temporal data abstraction provides a powerful instrument for event detection and prognosis; data visualisation is increasingly becoming an essential element in the overall process of knowledge discovery in databases.

In the workshop series, special attention is given to systems that aim at integrating the above mentioned techniques to promote the construction of effective decision models to support medical decision making, the discovery of meaningful patterns and structures in biomolecules and bioassays, the design of new drug compounds, discovery of drugs, etc. In addition, issues related to automated data collection in modern hospitals, such as analysis of computer-based patient records (CPR), data warehousing tools, outcomes analysis, intelligent alarming, effective and efficient monitoring, and so on are covered.

We are grateful to our colleagues who served on the programme committee of the IDAMAP 2002 workshop. They carefully read and reviewed each submission. Each paper was reviewed by at least two members, and in some cases by three members. It is now up to the reader to judge whether we succeeded in achieving our aims!

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28th May, 2002

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# Fuzzy Decision Tree for the Objective Explanation of Subjective Functional Evaluation: Application to the Upper Limb

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**Abstract.** The purpose of this paper is to contribute to the kinematics data interpretation in the domain of the shoulder arthroplasty and the associated rehabilitation process. Indeed this practice suffers from a lack of hindsight and from a lack of objective evaluation of its results.

At first, the measurement protocol is briefly described and the data characterizing and coding methods are presented. An objective explanation of the functional evaluation of the upper limb is derived from the fuzzy rules generated by fuzzy decision trees. Then the method is evaluated.

**Keywords.** Machine learning, reuse of knowledge, fuzzy decision trees.

## 1 INTRODUCTION

The number of shoulder prosthesis implantations has been considerably increasing for the last decade. This practice suffers from a lack of objective evaluation of its functional results and from a lack of hindsight. Moreover the shoulder is a complex joint and its kinematics behaviour is not well known. Physicians must also face new demands that come from patients, laws and society. They have to inform patients not only about their current health state but also about the evolution of it. They have to justify their acts in front of unsatisfied patients, health assurances and justice.

An objective evaluation of the functional results of the surgical intervention would help physicians to improve and complete their knowledge in order to improve their practice. New tools are available to provide objective data. Clinicians are often not able to interpret these data and to integrate them in their daily practice.

The solutions proposed in this paper are:

- A measurement method of the upper limb kinematics;
- A help for the measurements interpretation by fusion of objective and subjective data.

At first the objective measurement method is briefly described and the data characterisation and coding are presented. A space-time windowing of the kinematics data is chosen. The fusion method of objective and subjective data is then developed. It is based on the explanation of the subjective self-evaluation of the patients by the movement characteristics. The space-time windowing allows to generate decision trees and rules whose premises contain a qualitative representation of the movement. The evaluation of the satisfiability between the kinematics characteristics of a given patient and the premises of the rules is used to provide an explanation of the functional deficiency of this patient.

## 2 KINEMATICS DATA

### 2.1 Upper limb kinematics measurement

A 6 cameras optoelectronic system is used to measure the three dimensional (3D) positions of reflective markers fixed on patients skin [1]. Movement is measured during three different tasks (gestures) realisation: the elevation of the arm in the scapular plane (SP), the hand to the nape (HN) and the elevation of a light load initially put on a table (LE). These tasks are considered as representative of every day activities. Each movement is repeated at least three times and at best five times, depending of the patient's health state. Patients are seated and are told to realise the movements as naturally as possible. Instructions concern the beginning and the end of the movements. At these instants the subject looks ahead with the two arms vertically outstretched and the palms turned medially. For each patient, kinematics measurements are performed before the surgical procedure, then at three, six and twelve months after the prosthesis implantation, then annually.

### 2.2 Kinematics data characterisation

The data characterisation summarises the initial data and makes them interpretable by transforming measurement variables (3D positions of markers) into analysis variables [2].

Upper limb kinematics is expressed in terms of movement of body segment relative to another or to the laboratory frame. The considered body segments are the head, the trunk, the arm, the

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forearm, the hand and the “shoulder girdle”, corresponding to a segment that links the trunk at the level of the 7<sup>th</sup> cervical vertebra to the acromion.

Euler’s angles have been chosen to describe the relative movement of the body segments as they are easily interpretable by clinicians.  $N_V=20$  analysis variables have been retained to describe the kinematics. The set of variables has been chosen with the medical team and is not the result of a preliminary data analysis. These variables are the relative orientations of the studied body segments, the angular velocities and accelerations of the flexion of the shoulder and of the elbow and the linear velocity and acceleration of the hand.

### 2.3 Kinematics data coding

The data coding makes each analysis variable compatible with another and with a specific method of data analysis [2].

Humans have the natural ability to deal with vague, inaccurate, erroneous and uncertain data. A large part of medical data presents these characteristics. The human movement measurement with the previously described method is also very sensitive to measurement artefacts [1] and to the poor reliability of human movement.

Moreover the human reasoning is also approximate even if decision is often precise, particularly in medicine.

The fuzzy sets theory is an adequate tool to deal with these measurements and human reasoning characteristics.

#### 2.3.1 Space-time windows

For each trial, particular instants define significant periods of movement: the beginning, the instant of task achievement (maximal elevation of the arm or of the load, hand in contact with the nape) and the return to initial position. Two more instants are identified for the LE movement: the hold and the putting of the load on the table. All half period instants are then computed. SP and HN movements present five characteristic instants and LE movement nine instants. Note that these instants are defined from a functional point of view, i.e. in relation with a task realisation, and not from the data characteristics.

Analysis variables are coded using  $N_T$  ( $N_T \in \{5, 9\}$ ) fuzzy triangular windows centred on characteristic instants. So there are as many time windows as characteristic instants (see Figure 1). Note that time duration of the movement is eliminated with such a coding. However movement velocity is characterized by analysis variables and implicitly contains duration.

Each analysis variable comprises characteristic values in the space domain. For instance the variable “head incline relative to the trunk” is neutral when the amplitude is zero degree. Characteristic values are established by the specific variables properties, by statistical properties of a data set or with the help of clinicians when they consider that particular values are significant.

All analysis variables are coded using  $N_S=3$  space windows defined by characteristic values.



Figure 1. Fuzzy time windowing for SP and HN movements

#### 2.3.2 Membership values computation

Let  $Vn(tk)$  be the value taken by the  $n^{th}$  analysis variable at time unit  $tk$ .

Let  $\mu_{Tj}(tk)$  (respectively  $\mu_{S_{i,n}}(Vn(tk))$ ) be the membership value of the  $k^{th}$  time unit to the  $j^{th}$  time window  $Tj$  (resp. of the  $Vn(tk)$  value to the  $i^{th}$  space window  $S_{i,n}$ ).

The membership value of a given signal to the space-time window  $W_{j,i}^n$  is defined as [2]:

$$\mu_{W_{j,i}^n} = \frac{1}{\sum_{k=1}^K \mu_{Tj}(tk)} \sum_{k=1}^K \mu_{Tj}(tk) \times \mu_{S_{i,n}}(Vn(tk)) \quad (1)$$

Where  $K$  is the number of time units.

$\forall j \in [1, N_T]$  and  $\forall n \in [1, N_V]$ , i.e. for each time window and each variable, we have:

$$\sum_{i=1}^{N_S} \mu_{W_{j,i}^n} = 1 \quad (2)$$

The universe of objects is described by  $N_L = N_V \times N_T$  linguistic variables or attributes  $L^{(l)}$  ( $l \in [1, N_L]$ ). Each attribute  $L^{(l)}$  being divided into  $N_S$  fuzzy subsets  $S_i^{(l)}$  ( $i \in [1, N_S]$ ) corresponding to the space windows.

## 3 SUBJECTIVE DATA

Subjective data result from the ASES<sup>1</sup> [3] score. The ASES score is a pure functional evaluation. It is composed of ten questions on the ability to perform every days tasks: “to put a coat on”, “to do one’s hair”, “to sleep on the shoulder”, “to wash one’s back”, “to get washed”, “to reach a high shelf”, “to lift 500g above the shoulder”, “to throw a ball”, “the professional practice” and “the practice of a sport”. Patients answer by choosing the appropriate modality among the following four: “Impossible”, “Very difficult”, “Quite difficult” and “Easy”.

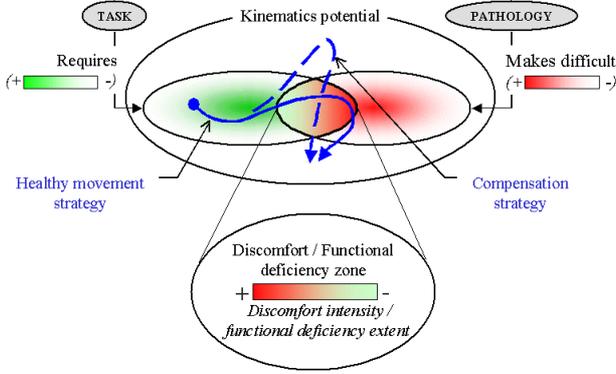
## 4 OBJECTIVE AND SUBJECTIVE DATA FUSION

### 4.1 Movement strategy and functional deficiency

Kinematics data result from an objective measurement of a movement, for a given task and a pathology. They comprise information on healthy movement and on compensations strategies. The compensations strategies attempt to make the task feasible if the extensive of the functional deficiencies

<sup>1</sup> ASES: American Shoulder and Elbow Surgeons

prevents to perform it and attempt to decrease discomfort during task realisation. So the patient's functional deficiencies and discomfort depend on the combination of the following factors: the task, the pathology, the movement strategy and especially the compensations strategies developed. Figure 2 represents these factors and their relations.



**Figure 2.** Relation between functional deficiencies/discomfort, task, pathology and movement strategy

A task requires a certain part of the kinematics potential which can be represented by an area. Some subparts are essential to perform the task. For instance “to reach a high shelf” will require a minimal range of motion of the shoulder in the sagittal plane. The pathology makes difficult or impossible the progress in some parts of the area. The overlap of the zone required by the task and the one affected by the pathology represents a zone of discomfort or of functional deficiency. The compensatory movement strategies are developed to reduce the discomfort or/and the functional deficiency by finding an appropriate path in the overlap zone.

It seems natural to try to explain functional deficiencies and discomfort sensation expressed by the patients by kinematics data. We restrict the problem by assuming that functional deficiencies and discomfort sensations expressed by a patient can be explained by kinematics data measured during the realisation of the three basic tasks described in section 2.

## 4.2 Induction of fuzzy decision trees

In order to explain subjective responses of the patients to the questions of the functional evaluation, we propose to use a set of data training pairs and to perform rules induction. Each data pair is built up for a given patient and a given gesture by kinematics data coded according to section 2.3 and by the response to a given question of the functional evaluation. A data training pair is also called an example. Fuzzy decision trees and corresponding fuzzy rules are then induced. A patient's answer to a given question is interpreted as a membership or a non-membership of a class. Rules generated by a fuzzy decision tree are incomplete and considered as easily interpretable [4]. Moreover the main advantage of fuzzy rules is to underscore non-linear relationship between inputs and outputs.

Since Quinlan [5] has described ID3 algorithm to induce decision tree, several methods have been proposed to adapt it to fuzzy data [6-9]. All the methods are based on the same principle.

1. A discrimination measure is used to determine which variable better explains the repartition of the patients among the classes and a node is created;
2. The data set is partitioned to build as many subsets as modalities of the variable previously chosen;
3. A termination condition is verified with the help of a termination criterion;
4. If the termination condition is verified, then the subset is considered as a leaf. If it is not verified, then stages 1 to 4 are repeated.

The most popular discrimination measure, which we adopt, is based on the information entropy defined by Shannon, adapted to the fuzzy case and renamed fuzzy entropy:

$$\forall i \in [1, 3], H_i^{(l)} = \sum_{c=1}^C -p^{N/S_i^{(l)}} \log p^{N/S_i^{(l)}} \quad (3)$$

Occurrences of the examples are assumed to be equiprobable. So  $p^{N/S_i^{(l)}}$  can be considered as the fuzzy conditional probability [10, 11] to belong to the class  $c$  given the fuzzy restriction  $S_i^{(l)}$  at the node  $N$ .

$$p^{N/S_i^{(l)}}(c) = \frac{M(\chi^{N/S_i^{(l)}} \times C_c)}{M(\chi^{N/S_i^{(l)}})} \quad (4)$$

$$\chi^{N/S_i^{(l)}} = \min(\chi^N, \mu_{S_i^{(l)}}) \quad (5)$$

$\chi^N$  represents the set of fuzzy restrictions from the root of the tree to the node  $N$ . The  $\min$  operator realises the logical conjunction *AND*. At the root level  $\chi^0(k) = 1 \forall k \in [1, K]$ .

$\mu_{S_i^{(l)}}(k)$  is the membership value of the  $k^{\text{th}}$  patient to the fuzzy subset  $S_i^{(l)}$ .

$C_c$  is the set of membership values of the patients to the class  $c$ .

$M(S_i^{(l)})$  is the cardinality of the fuzzy set  $S_i^{(l)}$ , i.e.:

$$M(S_i^{(l)}) = \sum_{k=1}^K \mu_{S_i^{(l)}}(k) \quad (6)$$

The variable chosen to split the observations of the training set at a node is the one that minimizes the following expression:

$$E^{(l)} = \sum_{i=1}^{NS} \frac{M(\chi^{N/S_i^{(l)}})}{\sum_{j=1}^{NS} M(\chi^{N/S_j^{(l)}})} H_i^{(l)} \quad (7)$$

This measure is especially adapted to the case of two classes [9]. So for each question of the functional evaluation and for each gesture, as many decision trees as modalities (classes) are induced and each tree concludes on the membership or the non-membership of a class. So to each functional question corresponds a “forest” of decision trees [9].

After the selection of an attribute, examples are shared out in the sub nodes. The membership value of an example to the sub node corresponds to the fuzzy restriction  $S_i^{(l)}$  and is defined as followed:

$$\begin{cases} \chi^{N/S_i^{(l)}}(k) = \min(\chi^N(k), \mu_{S_i^{(l)}}(k)) & \text{if } \mu_{S_i^{(l)}}(k) = \max_{j \in [1, NS]} (\mu_{S_j^{(l)}}(k)) \\ \chi^{N/S_i^{(l)}}(k) = 0 & \text{otherwise} \end{cases} \quad (8)$$

This definition implies that an example belongs to only one sub node. This is not an essential property for the fuzzy decision trees [9, 12] but the computation time is significantly reduced.

The termination criterion  $\beta$  is a given value of the conditional probability  $p^{N/S_i^{(l)}}$ , which corresponds to the rule fire strength  $F$  at the leaf level. Each path of branches from root to leaf is converted into a rule. Fuzzy conditions of a rule are the fuzzy modalities of the attributes along the path. The conclusion of the rule is the membership or the non-membership of the class at the leaf level.

### 4.3 Fuzzy decision tree pruning

Each rule is simplified by removing all fuzzy conditions that make the rule fire strength decrease. Each condition is removed from the *IF* part of the rule and the new fire strength  $F'$  is computed. If  $F' \geq F$  the condition is definitely removed. This leads to shorter and more general rules with higher fire strengths and consequently better prediction capacities. However the main goal of the rule base is not to perform prediction but to act as a knowledge depository in order to explain new situations.

### 4.4 Objective explanation of functional deficiencies

The aim is to explain a given positive or negative answer of a patient to the ASES score with the help of the kinematics data of this patient and thanks to an abductive reasoning on the rule base. A positive answer is of the form “to do this task IS impossible (or very difficult ...)” and a negative answer is of the form “to do this task IS NOT impossible (or very difficult ...)”. For this purpose we have at our disposal the fuzzy rules that conclude positively or negatively to each level of handicap of each question of the ASES functional evaluation. So we propose to explain a given patient’s handicap by editing the rules that conclude to this functional deficiency and whose the fuzzy conditions (*IF* part) are the most satisfied by the kinematics data of this patient.

Let  $R = \{R_1, R_2, \dots, R_N\}$  be the set of fuzzy restriction of the rule  $\mathcal{R}$ .

$\forall j \in [1, N]$ ,  $\mu^{R_j}(k)$  and  $s_{\mathcal{R}}(k)$  represent in what extend the kinematics data of the  $k^{\text{th}}$  patient satisfy  $R_j$  and the premises of the rule  $\mathcal{R}$  respectively:

$$s_{\mathcal{R}}(k) = \min_{j \in [1, N]} (\mu^{R_j}(k)) \quad (9)$$

So the rules that can explain a given functional deficiency are these to which the kinematics data satisfy the more.

## 5 RESULTS

The initial termination criterion was  $\beta=0.7$  but this criterion was too low for some functional evaluations. Indeed this criterion controls the generality of the knowledge represented by the rules inferred from the trees. The specificity of the knowledge increases with  $\beta$ . When one class is preponderant in comparison with the other, the tree can produce leaves that explain only this class if the termination criterion is too low. So we chose to increase the termination criterion up to the two classes were explained by at least one leaf of the tree.

A training set of 61 examples was used to induce the fuzzy decision trees. Due to the small number of examples, the data set is not split into a training set and a test set and all the examples are used as training examples. The “*professional practice*” and the “*practice of a sport*” have not been studied as these two questions have been rarely given by the patients of the training set (respectively 17/61 and 15/61). So 96 fuzzy decision trees were induced, representing 1087 rules.

Without pruning, the average of the number of conditions of the rules is 9.37, with a minimum of 1 and a max of 46 conditions. 95% of the rules have less than 28 conditions and 46% less than 6 conditions.

After the tree pruning, the average of the number of conditions of the rules is 7.44 with the same minimum and maximum. 95% of the rules have less than 25 conditions and 58% less than 6 conditions.

For each patient  $k$  of the training set we determine which rule can better explain his functional self-evaluation.

As an illustration: here is the explanation, thanks to the gesture “*Hand to the Nape (HN)*”, of the answer “*to sleep on the shoulder is impossible*” given by a patient: *The rotation of the head is (nearly) null near the beginning of the movement AND the linear velocity of the hand is null during the elevation of the arm AND the pro-supination of the forearm is neutral during the descending phase of the arm AND the flexion of the head is null near the end of the movement. (Rule fire strength = 0.75)*

## 6 EVALUATION OF THE EXPLANATION

### 6.1 Method

The whole training set is used as a test set to evaluate the method. The quality of the explanation is evaluated by the percentage of fuzzy restrictions of the rule chosen for the explanation that are verified by the kinematics data. A condition [ $V_i$  is  $S_i^{(l)}$ ] is verified by the kinematics data if:

$\max_{j \in [1, NS]} \mu_{S_j^{(l)}}(k) = \mu_{S_i^{(l)}}(k)$ .  $V_i$  being the variable that corresponds to the fuzzy restriction  $S_i^{(l)}$ .

For each patient of the training set, we compute the explanation quality for his response to each question of the ASES score.

For each gesture, the mean quality of explanation is then computed over subjects that have chosen the same modality for each question of the ASES score.

## 6.2 Results

Almost all the modalities of all the questions are explained with a quality greater than 90 by at least one gesture. The modalities that are not explained with such a quality are: “impossible” and “quite difficult” to “lift 500 g above the shoulder” (respectively 25 and 0), “very difficult” to “reach a high shelf” (0), “very difficult”, “quite difficult” and “easy” to “wash one’s back” (80.6, 89.6 and 0) and “quite difficult” to “sleep on the shoulder” (85.4).

## 7 DISCUSSION AND CONCLUSION

The null explanation qualities previously mentioned are due to the fact that no rule concludes to the considered answers. Indeed only one or two patients of the training set have given these answers. The quality quoted at 25, 80.6, 85.4 and 89.6 correspond respectively to a frequency of answers equal to 4/61, 9/61, 3/61 and 12/61. This remark points out the problem of the completeness of the training set, i.e. the fact that the training set represents more or less the set of possible situations. Fuzzy decision trees have to be induced with a larger training set and the evaluation has to be performed on examples that were not used for the learning phase. This will be allowed by the important kinematics database that is available at the laboratory of movement investigation.

The explanation provided by the method previously described is evaluated by simply counting the number of fuzzy conditions of the explanation rule that are satisfied by the kinematics data. A second evaluation must be done by means of the expertise of D. Bouttens, orthopaedic surgeon and co-author of this paper. This expertise will evaluate the quality of the explanation with subjective criteria as clarity, conciseness and understandability of the explanation provided. It will try to establish the parameters that improve or affect this explanation: number of conditions, formulation of the result, etc. It is expected that the induction of the fuzzy rules with a larger training set will provide more general rules with less conditions.

This method for the objective explanation of the subjective functional evaluation is a step towards the taking into account of the objective measurements of human movements in the medical practice and especially in orthopaedics. By connecting kinematics data with easily intelligible functional evaluation, this method provides a support to the movement characteristics interpretation. Functional deficiencies would be reduced or eliminated by acting on the movement characteristics likely to explain these deficiencies. Rules obtained with decision trees can be viewed as classification rules and the generalised modus-ponens can be used. It would result on a functional evaluation from the only kinematics data and would provide a support to the clinicians who can not access to the subjective answers of the patients. The method presented in this paper participates to the improvement of the quality of the medical practice and to the objective evaluation of it. To be used and efficient, it has to be inserted in a user-friendly support system and be interfaced with a prognosis module.

Eventually, it can be adapted to any domain where an objective explanation of subjective data is required.

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