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A framework for a prototype of an intuitionistic fuzzy expert system

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Abstract

Today only a relatively simple or intentionally simplified real-world system could be modeled and precisely analyzed by application of the conventional mathematical and analytical methods. Most complex systems include the uncertainty as a characteristic of a variety of their parameters or attributes. To analyze such inherent ambiguity it is most natural to incorporate fuzzy or intuitionistic fuzzy logic (IFL) into the model. Due to the ability of IFL to handle the uncertainty, we suggest in this paper a framework for development of a prototype of an intuitionistic fuzzy expert system (IFES) that has to be able to capture, model and manage fuzzy data or the uncertainty of human or system behavior. As the contemporary systems usually have to deal with a great amount of data, the suggested framework does not rely on experts who will determine the IF degrees for each individual input object, but recommend that an IFES prototype should have automatic determination of the membership and non-membership degrees.

Keywords: Expert systems; Intuitionistic fuzzy analyses; Membership functions; Intuitionistic fuzzy inference; Intuitionistic fuzzy databases.

1. Introduction

A sophisticated analysis of the most complex relationships that arise in the different scientific and economy fields requires application of contemporary scientific approaches like fuzzy or intuitionistic fuzzy systems, neural networks, probabilistic reasoning and other soft computing techniques. The fuzzy logic inference systems have combined fuzzy logic with other machine learning techniques in order to model the uncertainty, to do some fuzzy reasoning and to produce a crisp decision. The literature overview revealed that there are studies on the notion of intuitionistic fuzzy expert systems (IFES) [8,9,10,11,12,13], and some prototypes are suggested or exist [6,7,27], but to the best knowledge of the author there is no clearly exposed common framework revealing what are the components of an IFES and how the construction of these components could be based on different types of algorithms, according to the kind of the problem area. The main components of an IFES are like those of a conventional expert system – a database where the data that represent the analyzed problem, plus the accumulated rules are stored and also an inference engine. The components of an IFES however should be enabled to apply IFL and also to manage the data and the degree of its belonging to any IF sets. Components that bring the source data into IF representation, as well as the result data – into crisp form are also necessary. In this paper we do not discuss the user interface of the different components, which is usually considered as an important feature of an expert system. We focus on the IF properties of an IFES and the various types of algorithms that could be employed for the application of the IFL. The database component should be a relational database management system (RDBMS) enabled to represent and manipulate intuitionistic fuzzy data. We suggest usage of the Intuitionistic Fuzzy Postgre (IFPG) [22,23], as we are not aware of another software packages that expand the traditional relational database functionality to store and manage intuitionistic fuzzy relations. For an initial prototype of IFES as user interface could be considered the one of the IFPG as it provides good interaction of the user with the system. Next our discussion is focused on the usage of IF methods for representation of the problem and IF inference reasoning over the data.

In most current IFL models it is assumed that the membership grades of the elements are assigned employing expert knowledge [2,3,26]. However we could not always have experts on our disposal and when they are not available, the membership grades could not be set accurately. Moreover most of the contemporary real-world problems require handling of enormous amount of data that should not be manipulated manually – on a record-by-record basis, whatever the goal is – including the assignment of membership grades. Like in the case of a fuzzy expert system [20,25], the framework of an IFES should include preliminary definition of the intuitionistic fuzzy sets, the associated membership functions and the inference rules in order to be able to automatically map numerical data into linguistic variable terms and produce decisions based on intuitionistic fuzzy reasoning.

2. Definition of the concept of an Intuitionistic Fuzzy Set

In [5] Atanassov defines an intuitionistic fuzzy set (IFS) A over a finite universal set E as an object having the following form:

$A = \{<x, \mu_A(x), \nu_A(x)>|x\in E\}$, where the functions μ_A: $E \rightarrow [0, 1]$ and ν_A: $E \rightarrow [0, 1]$ define the degree of membership and the degree of non-membership of the element $x \in E$ to the IFS A, and holds the following condition

$0 \leq \mu_A(x) + \nu_A(x) \leq 1$

Larger values of μ denote higher degree of set membership while larger values of ν denote lower degree of set membership. The set E is called universe of disclosure. The value of $\pi_A(x) = 1- \mu_A(x) - \nu_A(x)$ represents the degree of hesitation (or uncertainty) associated with the membership of an element $x\in E$ in the IFS A. We call this value intuitionistic fuzzy index (or degree of non-determinacy/uncertainty) of the element x to the IFS A. If $\pi_A(x) = 0$, for all $x\in E$, then the IFS A is reduced to a fuzzy set.

The membership degree and non-membership degree of an IFS themselves are crisp values - μ is the exact lower boundary of all estimates for the belonging of an element x to the IFS A and ν is the exact upper boundary of all estimates that the element x does not belong to the IFS A. These membership functions are more or less independent, with the only constraint that the sum of the two degrees does not exceed one. In other words, an intuitionistic fuzzy set is a generalization of a fuzzy set which defines another degree of freedom into the set description. This possibility to represent formally an additional aspect of the imperfect knowledge could be used to describe many real-world problems in a more adequate way – by specification of both - advantages and disadvantages, pros and cons for each variable in the model.

3. Architecture of an intuitionistic fuzzy expert system

The basic components of the architecture of an IFES are represented on the Fig.1. They are the components for assignment of linguistic labels and membership/non-membership functions, the database that stores the IF data as well as the IF inference rules, the IF inference engine, the defuzzification component.

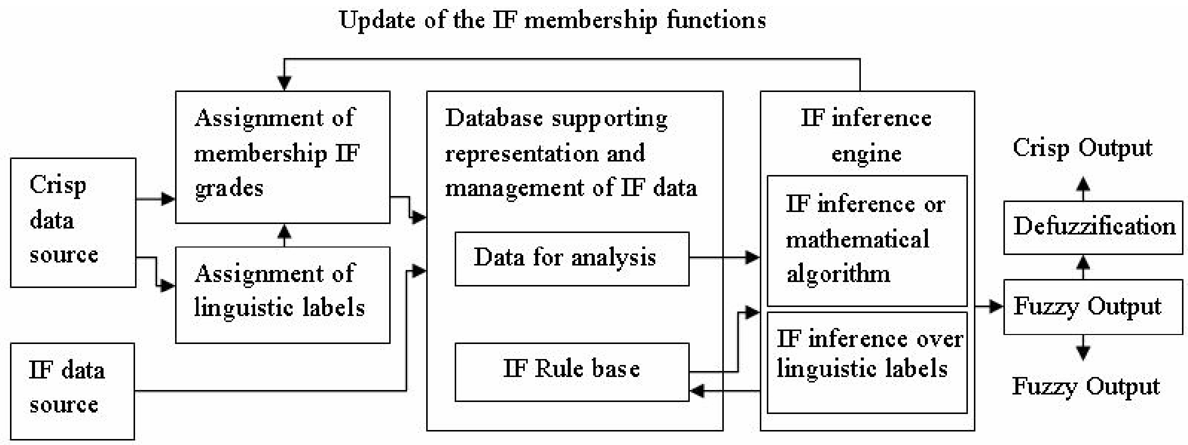

Fig. 1: Main components of an IFES.

The actions described in the following steps represent the main points of the research and development that should be part of an implementation and usage of an IFES:

1. Using experts, accurately analyze the problem that is to be modeled by the IFES as well as the data that are currently available or that will be fed into the system on some regular schedule. Determine the variables of the model, which of them and how will represent the uncertain information.
2. Through the user interface represent into the IFES the initial expert model developed in the first step – i.e. define the linguistic labels, the membership and non-membership functions, the initial IF inference rules and approach to derive new ones as well as if/how the membership and non-membership functions will be adjusted automatically from training instances.
3. Load the source data into the IFPG database – if the source data has already assigned membership and non-membership degrees, just feed the records to the respective tables. When we speak next for membership and non-membership degrees that are stored as values in the IFPG we will utilize the terminology introduced in [22] and will call them MSHIP and NSHIP. In the case when the source data are crisp, first calculate the MSHIP and NSHIP values, according to the pre-defined linguistic labels A_i and the respective membership functions $\mu_{A_i}(x)$ and $\nu_{A_i}(x)$. The notion of a linguistic label is discussed later on.
4. Assign the respective linguistic label to each of the records or some of their attributes. Eventually duplicate the crisp records in order to represent their membership grades to more than one IF set.
5. Let the inference engine work on the fuzzified data by applying the intuitionistic fuzzy rules in order to produce some intuitionistic fuzzy result.

6. The IF result could be directly presented to the user or it could be defuzzified to a crisp value. Which of these types will be delivered as an output from the IFES is up to the specific task, the user requirements and users' acquaintance with the IFL subject.
7. The inference result in its IF form should be stored in the rule base and used eventually for some tuning of the $\mu_{A_i}(x)$ and $\nu_{A_i}(x)$ functions or of the inference algorithm.

Modification in the third and omission of the fourth of the suggested steps would occur when the experts utilize IFL mathematical model that computes the result not by making inference with the help of the rule base but works directly over the data and its associated MSHIP and NSHIP grades. Samples for such IFL based models are those presented in [4,29]. In such cases the mapping to linguistic labels is usually not necessary. Upon a user request it could be done over the IF result from the system.

Let us analyze in more detail the phases where the data fuzziness is determined and assigned in the form of IF degrees and labels as well as how the IF inference machine works.

4. Intuitionistic fuzzy representation of the source information

The domains of the different problems that are modeled could be non-homogeneous or with different granularity and thus the source information could bring different type of associated uncertainty. Such cases require initial application of algorithms that transform the data into a common representation [19]. We consider that we deal with homogeneous information.

In order to construct the membership and non-membership functions, first have to determine the intuitionistic fuzzy sets to be used in the model. The number of the fuzzy sets that are needed is equal to the number of the linguistic labels. The notion "linguistic label" was introduced first by Zadeh in [30]. We will use the same notion however possessing IF properties – i.e. under linguistic label we will understand a human-language word, that implies some intuitionistic fuzzy perception and thus represents an intuitionistic fuzzy set [17]. When we represent phenomena related to human perception it is usually easy to determine the linguistic labels that qualify the information – for example as "bad"/"good", or ''poor''/"middle-class"/"rich", or "very slow"/"slow"/ "fast"/"very fast". We could have as many labels as we need – with the requirement that they cover the domain of the variable. In most of the cases the number and names of the labels could be defined preliminary by the nature of the data domain. However for some domains, where the context is not a human perception but a technical indicator (measurement, state, estimation, etc.) a preliminary analysis of the domain values should occur and next – the number and names of the linguistic labels are revealed.

Under each linguistic variable is the universe of disclosure of an IFS. So if one fuzzy concept E has to be modeled and it is described by tree linguistic labels, say A_1, A_2 and A_3, then tree membership functions have to be determined:

$$\mu_{A_1}(x),\ \mu_{A_2}(x) \text{ and } \mu_{A_3}(x),$$

as well as tree non-membership functions:

$$\nu_{A_1}(x),\ \nu_{A_2}(x) \text{ and } \nu_{A_3}(x).$$

The form of these membership functions could vary a lot from case to case. For some domains they could be continuous functions (linear or of a higher order), for other – they could have discontinuous form. In any case they have to be defined over the whole universe of disclosure for the respective IFS. Different methods could be employed also for the construction of those functions - similarity measures [21,24] or clustering techniques [28], etc.

5. Intuitionistic fuzzy inference engine

The inference engine of an IFES could be of two main types. According to the source data and to the way the IF indexes are assigned to them, the inference engine could work over the IF indexes (i.e. the MSHIP and NSHIP numbers) or over the linguistic labels, utilizing the respective associated rule base. These two types of inference engines are different although both follow the rules of IFL.

The first type of inference is used when:

- the source data have already assigned MSHIP and NSHIP indexes (for example they are fed from another IF database or are preliminary assigned by experts) or
- the problem could be modeled just by one IFS over a given universe of disclosure or
- the problem could be modeled by several IFS but each over different universes of disclosure

When the data from the problem area fall under any of these cases, the experts could construct membership and non-membership functions without the utilization of any linguistic labels. The respective inference engine should actually be a computerized model that represents a mathematical algorithm based on IFL – for example IF least squares method, or intuitionistic fuzzy preference models [5,15,18] , or IF decision trees, etc. Whatever intuitionistic fuzzy inference method is applied, the common requirement is that it has to consider the membership $\mu_{A_i}(x)$ as well as the non-membership $\nu_{A_i}(x)$ grades and to apply different operators from the IFL in order to produce some result.

The second type of inference is used when the problem under analysis is a complex one and in order to represent it as an IF model we need to construct several IF sets over a common universe of disclosure or even in a more complex situation – when we have several IF variables whose representation needs several universes of disclosure and over each of them we need several IF sets. Such complex models are more easily analyzed when first for each universe of disclosure are defined linguistic labels, next – the input data are mapped to these linguistic labels and the IF reasoning is made over the linguistic values. This means that when this type of inference engine is used, the rules in the accumulated IF rule base should also be in the form of linguistic labels.

Next we will point out the main typical characteristics for an IF inference that do not have corresponding analogs in the crisp or fuzzy case.

The main type of rules in an IF rule base have the following form [16]:
$[\langle M_H, N_H\rangle\ H{:}-\ e\ (B_1, B_2,\ldots,B_n)\ \langle M_B, N_B\rangle]$, where $M_H, N_H, M_B, N_B \subset [0,1]$ and $\sup M_H + \sup N_H \leq 1$ and $\sup M_B + \sup N_B \leq 1$ and $e\ (B_1, B_2,\ldots,B_n)$ is a logical expression for the variables $B_1, B_2,\ldots,B_n$.

M_B and N_B represent the intervals where the IF grades of each of the variables should fall in order to consider the variable as true and to assign the consequent. Formaly represented:

$$M_B = [\mu_i^B, \mu_s^B],$$
$$N_B = [\nu_i^B, \nu_s^B],$$

where the index "i" stays for "infinimum" and the index "s" stays for "supremum". So if for all B_i the membership degree falls into $[\mu_i^B, \mu_s^B]$ and the non-membership degree falls into $[\nu_i^B, \nu_s^B]$, then the consequent H has membership degree μ_H that falls into $M_H = [\mu_i^H, \mu_s^H]$ and non-membership degree ν_H that falls into $N_H = [\nu_i^H, \nu_s^H]$.

Having this common form of an IF inference rule, should be noted the following IF characteristics that could be used in the inference process:

1) In contrast to the crisp case where the logical expression e $(B_1, B_2,\ldots,B_n)$ could contain only the Boolean operations "&", "v", "¬" and the quantifiers "∃" and "∀", in the IF case they could be much more complex and expressive because they could contain also the different operators and operations from the IFL [5,14] (like for example necessity "□", or possibility "◊",etc.)
2) For all or some of the variables B_i we could apply some IF operators to transform their membership and non-membership degrees. For example:
$$< \mu_{B_i}, \nu_{B_i} > \xrightarrow{D_\alpha} < \mu'_{B_i}, \nu'_{B_i} >$$
3) In a crisp case a given consequent H should be inferred just by a single logical expression e $(B_1, B_2,\ldots,B_n)$. In an IF rule base we could have also the case when a given statement H is a consequent of more than one logical expression. The calculation of the membership and non-membership degrees of the consequent in each of these cases is done by a different method.
   a. When there is a single occurrence of the consequent in the rule base, could be used the following method:
   $$\mu_H = \mu_i^H + \alpha_\mu.(\mu_s^H - \mu_i^H),$$
   $$\nu_H = \nu_i^H + \alpha_\nu.(\nu_s^H - \nu_i^H),$$
   where
   $$\alpha_\mu = \frac{\mu_B - \mu_i^B}{\mu_s^B - \mu_i^B}$$, if $\mu_s^B > \mu_i^B$ and $\alpha_\mu = 0.5$ in the other case, i.e. $\mu_i^B = \mu_s^B$
   $$\alpha_\nu = \frac{\nu_B - \nu_i^B}{\nu_s^B - \nu_i^B}$$, if $\nu_s^B < \nu_i^B$ and $\alpha_\nu = 0.5$ in the other case, i.e. $\nu_s^B = \nu_i^B$
   b. When there are multiple occurrences of the consequent H in the IF rule base, let us represent them as:
   H: – e_1 $(B_1, B_2,\ldots,B_l)$ $<M_B, N_B>$,
   H: – e_2 $(C_1, C_2,\ldots,C_m)$ $<M_C, N_C>$,
   …
   H: – e_p $(D_1, D_2,\ldots,D_n)$ $<M_D, N_D>$,
   where some or all of the variables B_i, C_j, D_k , for $1\le i \le l$, $1\le j \le m$, $1\le k \le n$ could coincide.
   Then if for given data the concrete truth and falsity degrees of the up-mentioned logical expressions are $< \mu_B, \nu_B >$, $< \mu_C, \nu_C >$, …,$< \mu_D, \nu_D >$, one of the

following methods could be used to calculate the membership and non-membership degrees for the consequent H:

- optimistic method:
  $\mu_H = \max(\mu_B, \mu_C, \ldots, \mu_D)$
  $\nu_H = \min(\nu_B, \nu_C, \ldots, \nu_D)$
- average estimation method:
  $\mu_H = (\mu_B + \mu_C + \ldots + \mu_D)/p$
  $\nu_H = (\nu_B + \nu_C + \ldots + \nu_D)/p$, where p is the number of the logical expressions, whose consequent is H.
- pessimistic method:
  $\mu_H = \min(\mu_B, \mu_C, \ldots, \mu_D)$
  $\nu_H = \max(\nu_B, \nu_C, \ldots, \nu_D)$

6. Representation of the inference result to the user

The output of the inference engine is in IF form – i.e. according to the type of the engine it has MSHIP and NSHIP degrees or linguistic labels. If the final user of the IFES is familiar with the basic principles of IFL then the output result could be directly presented to him in its IF form.

Another design option should be considered when the user requires crisp answer from the IFES. In this case different methods for de-fuzzification could be applied [1]. For example to obtain a crisp value, the conclusion of the inference engine could be next processed by calculation of some linear combination of the MSHIP and NSHIP degrees. If linguistic labels are used, first a reverse mapping should occur – i.e. the linguistic label in the result should be first mapped to his MSHIP and NSHIP degrees.

Conclusion

The paper discussed the main issues that have to be carefully analyzed when an IFES is designed and build. Following the framework suggested in this paper a prototype of IFES could be built in a straightforward way. A conventional, a fuzzy or intuitionistic fuzzy expert system, or even all three taken in common could not be just built once and next used for whatever problem has to be analyzed. Each new analytical task should be modeled separately, the model should be represented into the respective expert system and tuned before an “expert” answer from the expert system is expected. So the points for a high-level analysis that were presented here could be used as a template or reference not only when a prototype is build but also during the development of each next draft of the expert system. The author does not insist that all the design options and prospective algorithms are covered in this text however the discussion stressed the main ones that should be considered and also noted that variety of options exist for most of the architectural components. This variety gives flexibility and bigger capacity for modeling but at the same time usually brings great complexity thus the construction even of a simple prototype requires careful work in each of the design, development, training and production phases.

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