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Interval sessions at NAFIPS/IFIS/NASA'94

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Интервальные секции на конференции NAFIPS/IFIS/NASA'94

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NAFIPS/IFIS/NASA'94, the First International Joint Conference of The North American Fuzzy Information Processing Society (NAFIPS) Biannual Conference, The Industrial Fuzzy Control and Intelligent Systems Conference (IFIS), and The NASA Joint Technology Workshop on Neural Networks and Fuzzy Logic was held in San Antonio, TX, USA, on December 18–21, 1994. The Proceedings of this conference were published by IEEE Press [7].

At the suggestion of Reza Langari and John Yen, we announced a special session devoted to applications of interval methods to expert systems and fuzzy control. The number of contributors exceed our expectations, so at the conference, we had three sessions (out of 24) devoted to fuzzy intervals. These sections were chaired by A. Esogbue, V. Kreinovich, H. Nguyen, and L. M. Rocha. Several interval-related papers were presented at other sessions. Totally, interval papers were authored by 27 authors from 8 countries: Australia (L. Reznik), Austria (A. Neumaier), Canada (M. H. Smith and I. B. Türkşen), France (B. Bouchon-Meunier), Japan (M. Nakamura), Morocco (D. Misane), Russia (G. N. Solopchenko), and the USA.

These sessions were attended by leading researchers in the field, and we hope that they further promoted the understanding between the interval and the expert system communities. A well-organized social program, that included a boat tour of the San Antonio Riverwalk, a walking tour of the Alamo (the "Shrine of Texas Freedom"), and a bus tour of the Old City, definitely helped researchers to make informal contacts.

Why fuzzy intervals? One of the main applications of expert knowledge is *intelligent control*. In many cases, we want to design an automated controller, but do not know the exact behavior of the controlled plant, and we cannot therefore use traditional control techniques. In such cases, we often have the expertise of human controllers who know how to control the plant (e.g., how to drive a car, how to ride a plane, etc). These experts cannot formulate how exactly they control in exact terms. Instead, they can formulate their expertise in terms of "if-then" rules of the type: "if the obstacle is nearby, and you are driving with a moderate speed, hit the breaks immediately".

There exists a methodology that transforms experts' rules, formulated in terms of words of a natural language, into a precise control strategy. This methodology is called *fuzzy control* (see, e.g., [9]). Fuzzy control technique starts with determining the values of the membership functions $\mu_A(x)$ that correspond to different words used in the rules. Namely, the value $\mu_A(x)$ represents the expert's degree of belief that a value x satisfies the property A. Then, it computes the degrees of belief in composite statements, and in particular, computes, for each possible values of control u, the degree of belief that this value u is reasonable in a given situation. Finally, one of these control values is chosen (the choice is called a *defuzzification*).

There exist several different methods of generating the degrees of belief (see, e.g., [5]). These methods give only an approximate value of the membership function. For example, we can estimate the desired degree of belief by asking an expert to estimate his degree of belief on a scale of, say, 0 to 10. If the expert picks, 8, then we say that his degree of belief is 0.8.

However, we cannot claim that his degree of belief is exactly equal to 0.8. Indeed, if we used another scale (e.g., from 0 to 8), we would have a multiple of 1/8, and never exactly 0.8. The only conclusion that we can make from the fact that an expert has chosen 8, is that his degree of belief is closer to 8 than to 7 or to 9. In other words, that his "actual" degree of belief belongs to the interval [0.75, 0.85]. It thus makes more sense not to attach a precise number 0.8 to the degree of belief, but instead, to use an *interval* as a value of the membership function. We thus arrive at the idea of what we called a *fuzzy interval* (a membership function with fuzzy values) as a more adequate description of expert's knowledge.

Examples that show that intervals are more adequate are given in [17].

A little bit of history. Intervals as description of degree of belief have been used in numerous publications by I. B. Türkşen and L. Kohout (see [10, 22, 23], and references therein). Their usage is also known under the name of "intuitionistic fuzzy logic".

In [12, 13, 16], it is shown how to use these intervals in fuzzy control (since we start with interval functions, at the end, we get an *interval* of possible control values).

The main idea of using fuzzy intervals. The *main idea* of using fuzzy intervals (i.e., interval-valued membership functions) instead of traditional fuzzy values (i.e., single-valued membership functions) is that we get a *larger set* of membership function, and therefore, a *larger set of control solutions* to choose from. And if we have a *larger* set to choose from, then we can expect to be able to find a *better* solution.

This is indeed the case in many applications. Let us describe these applications.

What are science and engineering about? Brief description of a scientific approach to real-life problems. To classify the applications of fuzzy intervals, let us briefly recall what science and engineering are about. Suppose that we have a goal (e.g., to build a power station, or to design a computer network), and it is not yet known how to do it. So, we do the following:

1) We make experiments and *measure* the results.

2) From these experimental results, we try to *find the dependency* between the data.

3) When we know the dependency, we can formulate our problem in precise terms. Depending on what we are looking for, we can have three types of problems:

   a) The simplest case is when we have finitely many (two or more) choices, and we need to choose between them. This is called *decision-making*.

   b) If we have one or two *continuous parameters* to choose, then this is called *optimization*.

   c) If we must find a *function* (e.g., the function that described how to press the accelerator depending on the current position and velocity of a car), then we have a *control* problem.

4) On all these stages, we need computers to process data.

Fuzzy intervals help on all the stages of real-life problem solving. Papers presented on interval sessions show that fuzzy intervals can help on all these stages. Namely, fuzzy intervals lead:

1) to a more adequate description of *measurements* [19];

2) to a better way of *finding the dependencies* from experimental data:

   a) [21], on the example of computations on the Internet;

   b) for Positron Emission Tomography (unpublished talk by A. Neumaier, Linda Kaufmann, and V. Kreinovich);

   c) in combination with neural network techniques [2].

3) a) to better *decision making* ([8], on the example of solder joint inspection);

   b) to more reliable *optimization* techniques [1];

   c) to better *control* strategies:

   - more *reliable* ([3], on the example of a bike control);
   - more *efficient* ([24], on the robot example).

4) In *data processing*:

   a) to better software testing [6];

   b) to better congestion control of computer networks [20].

Computation problems of fuzzy interval computations. Three papers deal with *computational problems* of fuzzy interval computations themselves:

- *Software* problems are discussed in [4], where it is shown that a new language can reasonably speed up fuzzy interval computations.

- *Hardware* problems are discussed in [15], where it is shown that in order to make fuzzy interval computations really fast, it is desirable to hardware support not only traditional operations (with one and two fuzzy interval operands), but also operations with three or more fuzzy intervals.

- In [18], the explicit use of *fuzzy intervals* is *compared with* two *other approaches* (with respect to their relative computational complexity); the approaches that also take into consideration that membership functions are only approximately known:

  – uncertainty in &- and $\vee$-operations, and

  – uncertainty in defuzzification.

  The last approach turns out to be the most computationally simple.

Fuzzy intervals explain the existing form of fuzzy control. Finally, in [14], fuzzy intervals are used to justify the prevailing form of fuzzy control, when rules are of the type "if x_1 is A_1, and x_2 is $A_2, \ldots$, then u is B" (i.e., when the condition of the rules consists of several "sub-conditions", each containing only one input variable).

Outline. A brief outline of the presented papers is given in [11].

Open problem: it is necessary to combine these results with additional sources of interval uncertainty. All these results are mainly based on the fact that it is difficult to express the expert's degree of belief by a precise number: an interval (of possible degrees of belief) is a more adequate representation. In addition to this fact, there are at least two other sources of interval uncertainty [10, 22, 23]:

- In fuzzy control, fuzzy expert systems, and in other applications of fuzzy logic, we must estimate the expert's degree of belief in a composite statement (e.g., $A\&B$) based on our knowledge of his degrees of belief $d(A)$ and $d(B)$ in the statements A and B. Traditionally, in applications of fuzzy logic, we choose a single value $f_\&\big(d(A), d(B)\big)$ as the desired estimate for the degree of belief $d(A\&B)$; the algorithm $f_\&(a,b)$ is called an *&-operation*, or a *t-norm* (it can be min, product, etc). In reality, however, the values of $d(A)$ and $d(B)$ do not determine $d(A\&B)$ uniquely. Therefore, for fixed degrees of belief $d(A)$ and $d(B)$, instead of a single value $d(A\&B)$, we have an *interval* of possible expert's degrees of belief in $A\&B$. In other words, we must consider &- and $\vee$-operations with *interval* values.
- For more complicated statements, e.g., for $S = A\&(B \vee C)$, there is an additional problem: Indeed, suppose that we know $d(A)$, $d(B)$, and $d(C)$. Then, there are at least two different ways to estimate the degree of belief $d(S)$ in C:
  - First, we can simply follow the construction of the desired statement S. In our example, this means that we:
    - apply an $\vee$-operation to $d(B)$ and $d(C)$, and then
    - apply an &-operation to the result and $d(A)$.

    As a result, we will get $f_\&\big(d(A)\big), f_\vee\big(d(B), d(C)\big)$.
  - Instead of that, we can first transform our statement into a logically equivalent form, e.g., $(A\&B) \vee (A\&C)$, and apply the same procedure to this new statement.

  The resulting estimates for $d(S)$ can be different. If we consider all possible logically equivalent forms, then even for fixed &- and $\vee$-operations, we will thus not get a single value of $d(S)$, but an *interval* of possible values.

All three sources of interval uncertainty make sense. It is desirable to *combine* these interval uncertainties into a *general* fuzzy interval formalism.

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