Qualitative Physics versus Fuzzy Sets Theory in Modeling and Control

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Abstract: *The purpose of this paper is to present a comparison between two modeling and control techniques of physical systems: qualitative physics based on symbolic manipulation and fuzzy logic. The first point to be determined is the main features of each approach. What are modeling and control using qualitative physics and fuzzy logic? To which specific domains of application are these approaches preferably devoted? Are they complementary? The concepts studied in this paper will be illustrated with an example of biological control.*

Introduction

It is widely accepted that human possibilities are largely distinct of conventional computer capabilities: while humans are very good in activities such as pattern recognition, learning by examples and several sorts of imprecise reasoning, conventional computers are very good in following orderly sets of instructions and manipulating great quantity of numbers. We claim that this characteristic of dealing with imprecise concepts is a main reason for the better performance of human beings over their electronic counterpart .

In fact, imprecision is pervasive of human reasoning. Imprecision, instead of being a course, can be considered as a blessing: characteristics associated with imprecision are robustness and flexibility. The great importance of imprecision gave birth to several approaches of dealing with it. In fact, if in the informal language imprecision and qualitative are used as synonyms, people with some knowledge on the domain tend to use particular expressions indicating not only the kind of problem treated, but also the approach used to deal with the problem. This leads to a terminology difficulty in making a comparison between two different approaches of dealing with qualitative, imprecise, approximate reasoning when these terms are considered synonyms. So, it is useful to precise the meaning of words that will be used in this work.

Informally quantitative refers to things that can be expressed by numbers, and qualitative refers to things that are not necessarily expressed by numbers : a quality is sufficient. So, when we say that the Everest is 8848 meters high, we have something quantitative and when we say that in Holland, there are regions under the see level we state a qualitative property to some parts of the country.

Further examples of quantitative are the coordinates of a point in a three dimensional space, the numerical value of a temperature at a definite instant, etc.

Examples of qualitative entities or characteristics are: the fact that a system is stable, the kind of singular point of a second order system , a color, the fact that a variable is expressed as positive, negative or null, and finally an emotional feeling that can only be expressed by linguistic values.

At this point we can introduce a comment: to many qualitative values such as great, average, low, etc, it is possible to associate numbers to express these values. In fact, when we say numbers, we refer to a precise structured set, for example, the set of real numbers is a set, with the structure of a completely ordered, complete, commutative field. Obviously such structure is too rich to deal with the values 'great', 'average' and 'low'.

The importance of imprecision has motivated the appearance of several conceptual models to exploit the advantages of imprecision. Here two models of imprecision will be compared with respect to modeling and control.

- The first one is "qualitative physics" (note the use of the word "qualitative" to denote one way of dealing with qualitative problems and so, motivating some confusion). It was born with the works of De Kleer, Brown, Kuipers, Forbus, etc. They were motivated by the desire of expressing in a language of symbol manipulation such as Lisp a way of reasoning about physical systems. In other terms the implementation of a reasoner about physical systems using "The "Physical Symbol System Hypothesis"[14].
- The second, very popular nowadays is the use of fuzzy sets[15] and fuzzy logic. This tool for dealing with qualitativeness is of mathematical nature. It can be considered as an answer to the difficulties imposed by the philosophical conjecture of "excluded middle" that implies two truth values: true and false.

These two tools, both well suited to deal with imprecision or qualitativeness, will be compared in modeling, simulation and control of physical systems. They will be referred by their usual names: qualitative physics and fuzzy approaches.

Modeling, Simulation and Control

In modeling, a system S is given and a second system S' is built using some of the available knowledge on S. S' is said to be a model of S. Simulation is the activity of experimenting with models.

Control is more complex than simulation in the sense that control often uses modeling and simulation as tools. Formally, a control

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problem can be characterized by a couple <S,G> where S is a system and G a goal. To solve a control problem is to find a system C, the controller in such a way that a composite system constituted by the systems S and C satisfies the goal G. Modeling and simulation are useful tools to solve control problems allowing, for example to verify if for a given candidate controller C_1, the goal is attained.

These conceptual differences between modeling, simulation and control are fundamental when comparing the two approaches of dealing with imprecision.

Qualitative Physics

Hayes[8,9] presented a classical discussion on the possibilities of qualitative reasoning about physical systems. Later, De Kleer and Brown[4] start with a quantitative description of the physical system and by introducing the 'confluence', deduces the qualitative description. Forbus[6] develops a theory of qualitative process, by considering the notion of active processes from which the constraint equations are derived. Considering mainly the medical physiology field, Kuipers[10] introduces the influence of commonsense reasoning in qualitative modeling. He considers the importance of system structure in deducing the behavior of the system. To do so, he treats constraint equations as given, either by textbook or experimental results. Later[11], he presents a formalization of the approach where the set of qualitative values are derived using the concept of 'landmark' values. The time in qualitative models was also studied, in particular by Allen & Kautz[1] who used an interval based model for time, which can be extended to include psychological aspects of the experimenter[2].

The use of qualitative physics in approximate reasoning deals with concepts, mainly motivated by interpreting the physical world. The main points are: qualitative variables and values, 'rules', inference mechanism.

- Qualitative variables assume a finite set of values. Sometimes these values belongs to an ordered set of values. The most current qualitative values are elements of the set {+, 0, -}. While they mention the possibility of more complex sets of qualitative values the definitions of addition and multiplication over these qualitative values become intricate and motivate the constant use of these three values. When the qualitative values have a correspondence with values of real variables, it is useful to introduce the concept of landmark value separating qualitative values.

- Rules allow to represent the knowledge available about the system. These 'rules' can assume several forms: confluences (qualitative equations), constraints (arithmetic, functional, derivative,...), production rules,...

- Inference mechanism allows from current values of the qualitative variables to infer their future values. It can be described for instance by propagation and prediction rules. It must be remarked that most of time in qualitative physics it is assumed that there is a time set, parameter of all descriptions, so that only dynamic systems can be dealt with.

Note: Kuipers[11] introduces the notion of 'landmark value' as values separating qualitative values. They must be chosen considering a quantitative model of the system, and can represent critical points of functioning. These landmark values allow to define a quantity space richer than the simple {+, 0, -} set, starting from a quantitative model. To each landmark value corresponds a distinguished time point. For example, if we are interested in studying the system during the time interval [a, b], there is a finite set of distinguished time points:

$$a = t_0 < t_1 < t_2 < t_3 \dots < t_n = b$$

to which corresponds (not necessarily in order, so to a t_i corresponds a l_j) the set of landmark values:

$$l_1 < l_2 < l_3 <\dots < l_p$$

A qualitative simulation is an episode generator that infers qualitative behavior from a qualitative model. Usually, the behavior is completed by some causal explanations. Begining with some initial values of the variables of the model, future values are inferred step by step, each step consisting in a propagation/prediction cycle. First, values at the current time-point are propagated through the 'rules' to create a more complete description of the episode. The description is complete when the direction of change (and the amplitude) for each variable is known. Then, next qualitative values of the variables are inferred from the current ones and their direction (and amplitude) of change. A new time-point is defined. With systems described by production rules, propagation and prediction cannot be distinguished . The result of the qualitative simulation of a model is a set of behaviors, a behavior being itself a set of qualitative values ordered with respect to the independent variable (for instance, time).

This approach has found broad use in simulation of systems to predict and explain the behavior of physical systems. However the use of such simulation model for control purposes did not follow the same pattern.

Fuzzy Approach

The fuzzy approach has its roots in the work of Zadeh[15] on fuzzy sets as a mathematical model for imprecision. Since then, fuzzy sets have been largely used as a framework to deal with approximate reasoning[16]. The pioneering work of Mamdani & Assilian[13] started the interest of using the fuzzy approach in control. The main motivations are:

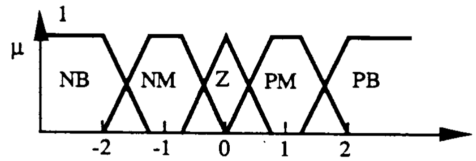
- the possibility of implementing the controller without use of an explicit knowledge of the mathematical model of the plant to be controlled,

- the use of qualitative (or approximate) reasoning, imitating a human operator, and in this sense following the same approach as the design of an expert system, where the behavior of an expert is imitated to solve a problem - in the present case the knowledge of the expert is the knowledge on how to control a plant.

The use of fuzzy sets in approximate reasoning deals with several different concepts - here we will consider mainly the following (useful for our purposes): fuzzy values and variables, rules, inference mechanism.

- Fuzzy values are qualitative values described by membership functions (Figure 1). These values are labels of fuzzy sets.

Transition from a fuzzy value to another is usually not sharply defined but it is gradual. There is no crisp landmark. If these values have a linguistic meaning they are called linguistic values.



N = negative Z = zero
M=medium B = big

Figure 1: Membership functions of fuzzy values

- A model is described by a set of fuzzy rules (knowledge base) manipulating its fuzzy variables, usually expressed as "If situation then action". An example of rule is:

If error_is_A_i **then** do_action_B_i

(Note that this is not the same as "**If** error_is_A_i **then** action_is_B_i" this last being a sentence in first order predicate logic, that can be true or false, depending on the particular interpretation of A_i and B_i).

- The inference engine selects the rules that satisfy a situation (precondition) and specifies the action to be performed (postcondition), manipulating the values of membership functions obtained from the fuzzification.

This computational formalism is an instance of a "production system" in artificial intelligence (AI) terminology. In AI terminology the major elements of an production system are a "database" (note the word database here has a different meaning from the usual "data base" in computer science), a set of "production rules", and a "control system". The production rules operate on the database. Each rule has a "precondition" that is either satisfied or not by the database. If the precondition is satisfied, the rule can be applied. There are cases where several rules can be applied at the same moment. The "control" chooses which applicable rule will be effectively applied. Application of the rule transforms the database into an other one.

The following correspondences of concepts between fuzzy and production system can be established:

databases	→	fuzzy values of inputs and outputs
production rule	→	a set of fuzzy rules
precondition	→	fuzzy interpretation of input, result of fuzzification
postcondition	→	fuzzy output to be defuzzified
control	→	trivial (there is only one set of fuzzy rules that is active at each moment)

Fuzzy control is an application of approximate reasoning as described above. In fact, in a system controlled using a fuzzy controller (Figure 2), two kinds of signals are involved:

- quantitative signals: signals input and output of the plant, the reference signal,

- fuzzy signals: input and output of the fuzzy controller, characterized by their membership functions.

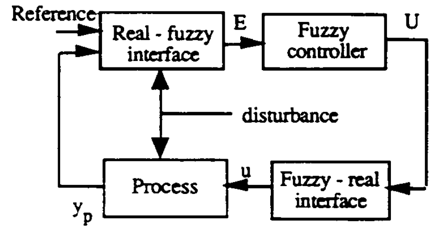


Figure 2: Plant and fuzzy controller

The interface between these two kinds of signals is assured by two types of modules, performing the functions of fuzzification (real to fuzzy interface) and defuzzification (fuzzy to real interface).

Fuzzification is performed by functional units called fuzzifiers that must accomplish the functions:

- sampling input signals,

- transforming the sampled signals into linguistic values; to do so, the fuzzifier must have access to the membership functions characterizing the linguistic values,

- holding the linguistic value during the sampling interval.

Complementary functions are performed by the defuzzifier that performs defuzzification:

- transforming the output of the fuzzy controller into quantitative values to be used by the actuator to the plant,

- holding the quantitative value, output of the defuzzifier, until a new output of the fuzzy controller is available.

Finally, the fuzzy controller uses a fuzzy knowledge base and an inference engine.

The fuzzy knowledge base stores the knowledge about how to control the process. This knowledge can be extracted from a human operator or created in order to satisfy some performance criteria of the controlled system. In the first case, the controller tries to reproduce the reactions of this human operator. Self organizing fuzzy controllers (SOC)[5] can be considered as belonging to the second category, where performance table extracted from a desired transient behavior allows creating a suitable knowledge base.

Fuzzy control has been widely used in concrete cases. However the same principles are not so widely used neither in modeling physical process nor in simulation. The situation is exactly opposite to the case of qualitative physics. Why?

That is the subject of the rest of this paper.

Comparison between the two approaches

To compare techniques that deal with different problems and that were created with different primary goals is a difficult task. Here we adopted the style of asking questions, and follow the questions not by the answer but a comment.

- Qualitative physics included in fuzzy ?

Suppose a choice of membership functions as shown in Fig.3 representing the linguistic values "negative", "near zero", "positive". In this case, for any value of fuzzifier input corresponds only one linguistic value. The value separating the concepts has the same role as the "landmark values" in qualitative physics. From this point of view, we can say that the values used in qualitative physics is a particular case of those used in fuzzy approach for a particular choice of membership functions, of crisp nature.

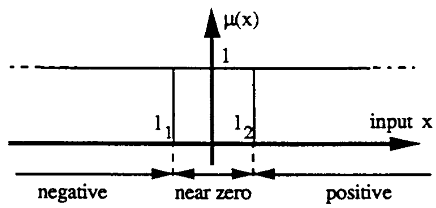


Figure 3: Case of membership functions with crisp boundaries

On the other hand, qualitative physics deals with several concepts that are not present in the fuzzy approach:. Examples are: episodes, history,...

- Does the fuzzy approach solve the problem of combinatorial explosion in qualitative physics ?

It is true that in the fuzzy approach there is no combinatorial explosion of paths to examine. But for more complex systems described by several interconnected subsystems, each of them being characterized by a set of fuzzy rules, a correspondent problem can appear. Often the support set of the consequence value of a set of rules is larger than the support set of the input value so that if this consequence value in turn is the input of an other subsystem, the resulting value can have a support set still larger. Thus output becomes more and more fuzzy if several inference steps in chain are achieved. This increase in fuzziness, when it exists, is due to the fact that several rules are triggered in parallel. On the other hand, this last fact ensures a limited lost of information.

- How arbitrary is the choice of the landmark values ?

Landmark values are often difficult to choose and their choice is often artificial. However in the fuzzy approach the choice of membership function is most of the time arbitrary.

- Qualitative physics approach in control ?

The major problem is the branching. It is due to a lack of information about the value of a variable or to a value space too simple. If the number of branching increases, finding a control value becomes intractable. An other characteristic is that a variable can only take a limited number of discrete values. So a good control performance in term of small steady state error will not always reached.

- Is it easy to predict behavior with the fuzzy approach ?

Behavior prediction needs the generation of a sequence of descriptions and thus the execution of a sequence of inference steps. As mentioned above, the tendency will be in general to increase fuzziness at each step. Moreover explanation generation of the behavior is also difficult (several rules relating the same variables of the model are triggered in parallel).

- Does qualitative physics lead to simpler implementations ?

In qualitative physics, there is no need neither for defuzzification nor for linguistic approximation, and the generation of dialogues and explanations is easier. On the other hand, branching or case joint are not easily dealt with.

At this state of the art, it seems that fuzzy approach oriented rule is suited for describing shallow knowledge and qualitative physic approach for deep knowledge taking into account the structural information about the system.

Biological example: eye-head coordination and control

The illustrative example taken from physiology concerns control of coordinated eye-head movement in the orientation of the visual axis in space (i.e. gaze). The oculomotor system is particularly well suited to this study. Indeed, its simplicity (compared to much more complex peripheral limb control systems) makes it easier to understand and model. However, the gaze control system involves the coordination of two platforms (eye and head) and thus is a good testing bench for studying multiple limb systems.

Anatomical structures involved

Eye and head movements rely on both cortical and subcortical processes. However, one could schematize in saying that cortical processes are mostly implied in voluntary or complex movements, while the subcortical processes are at a lower level (reflex). Indeed, for reflex movements (like express saccades), the latencies observed indicate that the subcortical pathway is probably used independently of any online cortical interaction.

Subcortical structures

Sensory signals from the retina project straight to the Superior Colliculus (SC), a structure organized in a retinotopic map and playing a major role in generation and control of all fast orienting movements (saccades).

The SC projects then to the premotor areas in the brain stem (reticular formation and vestibular complex), which are connected to the motor areas (motoneurons of eye and head). All these subcortical structures are highly interconnected through control loops and adaptive learning processes (proprioception, cerebellum ...)[3, 7].

Cortical structures

This level cannot be schematized as easily as the subcortical one, because it involves many cortical areas (frontal, visual, parietal... cortices), performing very complex and distributed computations. But one can say that these cortical areas play a role mainly in the generation of voluntary and complex movements as well as in decision making (remembered targets, target selection). Nevertheless, even if the cortex principally deals with strategy (computed before the movement onset), it is very likely that it also plays an important role in interacting on-line with the progress of the movement.

Links with qualitative physics and fuzzy approach

In this part the comparison between the two approaches will be illustrated by the example described in the previous paragraph.

Several points of view are considered.

Paths to examine

Unlike qualitative physics, fuzzy approach does not involve an examination of a combinatorial explosion of paths. This makes the fuzzy approach more appropriate than the qualitative physics, for the modelling and control of fast processes (low level, like on-line subcortical control of gaze).

Implementation

Qualitative physics often leads to much simpler implementations than fuzzy ones. This is a good reason for choosing qualitative physics models when appropriate (very high level processes): for instance, in image analysis, in cortical processes related to decision making, in complex motor programs elaboration, in cognitive processes ...

Landmark values and fuzzy linguistic values

In qualitative physics models, landmark values are often difficult to choose (and even artificial). But imprecision in this choice is not a real problem if one thinks about very high level processes, close to human reasoning. For instance, a subject is more interested in his right hemifield if he heard something from his right; a visual target being preferentially selected in this direction. Another example of such a process, is when a subject is asked to think to his nose during vestibular nystagmus in the dark (no visual feedback !); vestibular quick phases clearly end in the midline zone in this condition. These examples show that a qualitative physics model (based on imprecision) is very well adapted to high level processes.

Whereas landmark values are fixed values, fuzzy linguistic values have smooth boundaries, corresponding to usual meaning in natural language. This means that fuzzy can also model quite well high level processes (human reasoning). In any case, it is worth remembering that the fuzzy values include the qualitative physics values and can thus model cortical strategies as well as the qualitative physics does. However, when qualitative physics models better suit the problem they will be prefered for their easy implementation (as one prefers to program in Lisp rather than machine language, when possible).

Membership functions and defuzzification

The choice of membership functions and of defuzzification algorithms often introduces a degree of arbitrariness in the manipulations. First, learning should probably deal with selection of the appropriate membership function for each particular task (for instance, one could reproduce a 'fovea effect' in a fuzzy model in introducing higher resolution in certain zones of the colliculus, which are more often explored during a learning period)[12]. Second, the problem of defuzzification is only present at the interface between the fuzzy model and the 'real world'. If a fuzzy eye-head coordination model is built, the defuzzification at the interface would be realized automatically if one remembers that any biological process is done by a 'population of neurons' (e.g. at the motor level, pool of neurons driving plant muscles and yielding a quantitative position of the driven segment).

Concurrent rule activation

In fuzzy logic, more than one rule can be activated at the same time (unlike qualitative physics models). If one takes the example of the control of coordinated eye-head movements by deep collicular output cells, many cells are activated at the same time and are controlling one movement (with different weighted contributions). This corresponds well to a fuzzy model. On the contrary, the selection of a given target among several potential ones, as well as the selection of a particular motor program among a series (specially for orienting movements involving peripheral limbs), seems to be closer to a qualitative physics implementation (strategy, decision making).

Conclusions and perspectives

A comparison between qualitative physics and fuzzy sets approaches by means of a concrete example gives a good idea of what are the differences and the best fields of application for both techniques. An interesting conclusion is that these approaches seem to be complementary, even if their application areas obviously overlap. Within the scope of the eye-head coordination system, this study clearly shows that both qualitative physics and fuzzy sets are relevant techniques for modelling different aspects of this biological system. A very promising field to investigate would be to build a hierarchical model of the eye-head coordination system, using together the complementary characteristics of classical models (transfer function oriented), neural networks, fuzzy and qualitative physics models for the different processing levels participating in this biological system. This hierarchical approach should also apply to the modelling of other complex systems involving very different computation levels (high level strategical decisions as well as low level fast control systems).

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