WESIC'98
Workshop on European Scientific and Industrial Collaboration on promoting

Advanced Technologies in Manufacturing

Girona, Spain June 10, 11 and 12, 1998

Organized by the Institute of Informatics and Applications University of Girona

Universitat de Girona
Imprecision and Intelligent Systems in Manufacturing

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Abstract

Some thoughts on the use of imprecision in intelligent systems are presented. Examples from knowledge-based systems, robotics and manufacturing are used to illustrate several methods that artificial intelligence proposes in order to model imprecision.

1 Introduction

The quest for precision has been a constant in the technological development of civilised societies. Recently, Professor Bradford Parkinson from the University of Stanford presented a prototype of tractor controlled by GPS showing a precision of a few centimeters, much better than the most trained tractorists.

The need for modelling imprecision is a meeting point between computer science, artificial intelligence and manufacturing. A paramount example in computer science can be Sir Charles Babbage, who was obsessed by the huge quantity of errors that could be found in the logarithmic tables published up to and during the XVIIIth Century—he was indeed a well-known collector of such books. The first computer in History, his "difference engine", was devised as a mechanical tool to compute logarithmic tables avoiding most potential sources of errors. One mistake that specially annoyed him, were the transcription errors introduced by humans when copying numbers. This is the reason why his design included, as an essential piece, a printer at the bottom of the huge computer body. He never finished the printer, and only recently the Science Museum in London has made public his project of building it to complete the construction of the difference engine made in 1991. It is then not strange the coincidence in eliminating the human intervention in the computer science genesis and by the robotization and automatization of so many industrial processes.

Imprecision is, of course, strongly related to measuring instruments. A well known example of precision in manufacturing was the success of John Harrison when he built the first chronometer in 1737, and won the prize awarded by
the British Parliament to the first who devised a mechanism that deviated less that 8 seconds in a travel from England to Jamaica on board of a ship. He won the price in 1762. After 3 months of travel his chronometer deviated only 5 seconds. He developed new mechanisms to compensate the errors introduced by dilatations of the material due to temperature changes and strong movements as those produced on board. He succeeded in hand-manufacturing with sufficient precision (expending all his life indeed) the components of the chronometer. Babbage, on the other hand, was not so lucky, the thousands of "identical" components necessary to build his difference engine could not be manufactured in the mid-XIX Century. He died without having completed his engine.

Resolution and precision are two sides of the same coin. Resolution is how close can two measures be of the measurand to be distinguished by an instrument. And precision is the capacity of an instrument to discriminate between two values of the measurand. Of course high precision entails high resolution. It is argued in artificial intelligence that human beings are not very 'precise' neither in their sensing capabilities nor in many cognitive processes such as reasoning. From the point of view of intelligent system construction we can find two types of them: systems based on measures of low resolution and systems based on imprecise measures. In particular, we will present cases of knowledge-based systems for both cases, and an example on robotics and manufacturing for the second type.

2 The case of knowledge-based systems

Knowledge based applications have been usually facing the problem of imprecision. Take for instance the case of identification in Biology. In [2] a system for the identification of sponges is presented. It is a very paradigmatical example of a real domain where imprecision is inherent. There are three basic reasons for this: (1) genetic variability, (2) adaptive variability, and (3) imprecision in the ‘linguistic’ description made by experts in the field. I. e. each specimen of a species shows a set of characters whose morphology depends on its particular genetic code — which is different from specimen to specimen —; hence a ‘precise’ definition of the characters cannot be made at the level of species. Second, individuals of a species adapt to the environment, so aspects of the morphology depend on the ‘history’ of the individual; for instance, if a sponge grows in a narrow space between two rocks it will present a very different external aspect than that of a sponge growing on a flat rock. And finally, human experts when describing observations do not always use measures given by instruments but plain natural language, with its known ambiguities and imprecisions. This means that when representing the identification knowledge to build an intelligent system, a model for imprecision must be developed. In the above mentioned system, fuzzy sets were used to model the intervals of morphological measures and imprecise classification rules were used to relate the antecedents with the identified classes appearing in the consequents.

In artificial intelligence applied to medicine, a classical approach diagnosis
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Introduction

In order to model Impression,  etc.

Abstract

In the field of Intelligent Systems, etc.
The case of knowledge-based systems

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Knowledge-based applications have been usually faced the problem of imprecise or uncertain data. In order to handle this problem, a class of models has been developed, known as knowledge-based systems. These systems are designed to reason under uncertainty and make decisions based on incomplete or uncertain information. They are used in many domains where traditional computational approaches are not sufficient.

In the mid-XIX Century, the idea of a machine that could perform logical reasoning and problem-solving tasks was first proposed. However, the development of practical knowledge-based systems required significant advances in computer science and artificial intelligence. The first successful application of a knowledge-based system was the Logic Theorem Prover, developed by Nils Nilsson in the early 1960s. This system was able to prove mathematical theorems, and it laid the foundation for the development of more advanced systems.

In the late 1970s, the first practical knowledge-based system was the MYCIN system, developed by Edward Feigenbaum and his team. MYCIN was designed to help doctors diagnose and treat patients with meningitis. It used a knowledge base of rules and heuristics to make decisions, and it was able to provide accurate and reliable advice to doctors.

Since then, knowledge-based systems have been applied in many fields, including medicine, finance, and manufacturing. They are used to automate complex tasks, improve decision-making, and provide insights into complex systems. As technology continues to advance, knowledge-based systems are likely to become even more important in many areas of our lives.
The case of robots

The production system of the firm

In the context of manufacturing, I would press the development of a system for

the automatic control of manufacturing processes. This is a development of know-how

that has been in several applications of knowledge-based systems, among other

reasons. The model of reasoning has

to increase the precision of the firm's result. This model of reasoning has

not been directly applied in the area of question. However, the reasoning in the

area of decision support is applicable to a large extent.

In many cases, the problem of decision support is not

decided on the basis of a single rule. Therefore, it is necessary to
develop new decision support systems. In this context, the

knowledge-based approach is recommended. However, this approach

requires a high level of precision. Therefore, it is necessary to

develop new decision support systems. In this context, the

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Discussion

Modeling techniques [6] that allow for different interpretations allow for different interpretations. The model of the interpretation is obtained in the model in any good sense and in the context of the model in any good sense. Building a model in any good sense is very expensive, so a good process that will be generated by a model, being expensive is difficult to ensure. The constraints of the global process are very obvious. The constraints of the global process are the constraints of the global process. A project called MOLLE in which my laparotomies were building.

The constraints of the global process are very obvious. The constraints of the global process are very obvious. These models are based on qualitative relations between qualitative relations between qualitative relations between qualitative relations. The use of qualitative models in modeling is very common. These models are based on qualitative relations between qualitative relations between qualitative relations.
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