Industrial and Engineering Applications of Artificial Intelligence and Expert Systems

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Appendix 1: Structural scheme of the ISFBM

Intelligent Process Control by means of Expert Systems and Machine Vision

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Abstract. In this paper an architecture for Intelligent Process Control is proposed. The main components of the architecture are an inspection vision system to identify defects on products and an expert system to diagnose the process malfunction. The expert system architecture is based on the cooperation of two models, heuristic and causal. Both models are defined and their connection with the vision system is explained. An example on a TV flawcoating process exemplifies the features of the architecture and shows the possibilities of the approach achieving performances not reachable in current commercial on-line Process Control Systems.

1 Introduction

The use and integration of advanced information technologies in Control and Supervision are crucial for the improvement of the Productivity and Quality of any Manufacturing Process.

Higher level activities like supervision are difficult to carry out because there is a huge amount of information involved, processes are not well-understood and usually a lot of experience is needed in order to solve problems.

In this paper an architecture for Integrated Process Control incorporating Artificial intelligence and Machine Vision techniques is presented (See fig. 1).

Fig. 1 The IPCES architecture.

The IPCES project (Intelligent Process Control by means of Expert Systems) is aimed at extending process control with general human characteristics like vision and reasoning.

Thus IPCES like systems are intended to achieve performances not reached by current commercial on-line process control systems.

The process control domain includes several intelligent tasks like Vision, Monitoring, Diagnosis, Repair, Prognosis, Generation of control actions and Learning. In this paper we focus on the part of the Vision System and the Expert System concerning the Diagnosis task. A generic system for Diagnosis in the domain of Process Control is presented. Two knowledge representation models are defined: the first based on experiential knowledge and the second based on causal knowledge. The way they interact to get improved results is defined. A real application, including a TV tube flawcoating Diagnosis System, a Screen Inspection Vision System and the interaction between them is presented. In Figures 2-5 some illuminating photographs of correct and defective screens are showed. Discussion on this application is made in the last section.

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2 Diagnosis in Process Control

The Diagnosis of a system consists of determining those out-of-order elements -causes- that account for the observed abnormal behaviour [1]. Different kinds of knowledge can be used in a human expert does. On one hand the so-called shallow or heuristic knowledge that embodies the experience gained through solving problems for a long time. On the other hand the deep or fundamental knowledge that explains how the physical process actually works -causal relations-. The IPCES Diagnosis System incorporates both types of knowledge and takes advantage of their cooperation in order to get more accurate and complete solutions, and to increase the system robustness. It is the fundamental basis of the 2nd Generation Expert System [2, 3, 4, 6, 8]. In this section generic formalisations for both types of knowledge and their interaction are presented.

2.1 The Hypothesis Space

The Hypothesis Space model (HS) is a general approach to Diagnosis using heuristic knowledge [1] based on the idea of refinement of the set of possible causes. Evidences about them are propagated along a hypothesis hierarchy towards the most plausible causes.

To define this model several requirements of the Diagnosis task in a changing domain -as it is the case in Industrial Process- have been taken into account: Dealing with Uncertainty, Reasoning with Incomplete Information, Non-monotonicity, Efficiency and Adequacy for Knowledge Acquisition. The model definition is inspired on the results of a behavioral analysis of the human expert explained next.

2.1.1 The Expert’s Behavioural Analysis

The HS model has been derived from the results of the analysis of the expert’s behaviour while diagnosing the product defects due to process malfunctions [9]. It has been made over three functioning process control experts. The conclusions of this analysis are that the Diagnosis task can be defined as a RBS-like process of generation, refinement and pruning of hypotheses while case data is being gathered. Main knowledge components is a hypothesis-refinement relationships static structure on which Focussing and Testing knowledge is organised:

i) **Focussing knowledge** is used by the expert to focus on more specific causes in the absence of some findings.

ii) **Testing knowledge** is used by the expert to verify a particular hypothesis currently considered. Hypothesis are tested when a certain amount of evidence for them has been gathered. This test is based on the evidence about other hypothesis and findings from the problem. In the trivial case these tests are just the results of verifying the hypothesised cause in the reality.

2.1.2 The Hypothesis Space Model

A basic Hypothesis represents an atomic cause of the problem. Given a domain, the set of basic hypotheses is determined by the expert. Also a set of observable data, called Data, is defined. The elements of this set represent any information that can be obtained from the domain’s problem.

Basic Hypothesis and Data are represented as events in the probabilistic sense, i.e. an expression $X = x_i$ where $X$ is a variable and $x_i$ is a value for it. Next the basic definitions of the HS model are presented:

- **The Basic Hypothesis Set of a given domain is defined as $BH = \{b_i | \forall b_i \in BH\}$ is a Basic Hypothesis.**

- **We define the Hypothesis Set of a given domain as $H \in B(D)$, for any $h \in H$, $h = (b_{h1},... b_{hn})$ means the expression $b_{h1} \land ... \land b_{hn}$. $P$ means power set.**

- **The set of Hypothesis Refinement Link, for short $L$, is $L \in H \times H \times \{0,1\}$, where for**
any \((a, b) \in L, bca, \) and \(a = p(ba),\) being \(p\) a probabilistic measure.

- **A Hypothesis Space** is a directed acyclic graph where nodes, \(H\), represent hypotheses, and links, \(L\), represent refinements. Relationships in the sense that \(a \rightarrow b\) means \(bca\).

- **A Validation function** on \(H\) is a function \(\psi: H \rightarrow \{0, 1\}\). The set of these functions is defined as \(\Psi = \{\psi: \psi(H) \rightarrow \{0, 1\}\}\). These functions represent the belief on the hypothesis.

- **A Heuristic Rule** is a quadruple \((h_1, h_2, h_3, c)\) where \(h_1, h_2 \in \{0, 1\}\) and \(c \in \text{COND} = \{\text{NS, LS, ES}\} \Rightarrow H\) \(\Rightarrow\) \(D\).

- **A Focusing Rule** is a heuristic rule \((h_1, h_2, h_3, c)\) where \(h_1\) is predecessor of \(h_2\).

- **A Testing Rule** is a heuristic rule \((h_1, h_2, h_3, c)\) where \(h_1 = D\).

Now we can define what a Hypothesis Space is.

**Def.** A Hypothesis Space is a quadruple \(H = (N, FR, TR, \sigma, \delta)\) where:

- \(N = (H_1, L)\) is an HSN.
- \(FR = \{FR, \psi\}\) is a focusing rule.
- \(TR = \{TR, \psi\}\) is a testing rule.
- \(\sigma, \delta\) are functions which transform the current validation function by the application of an heuristic rule.

**Def.** A Hypothesis Space State is the composite object \(HSS = (HS, \psi)\) where \(\psi \in \Psi\).

### 2.1.3 The Inference Control

The HSS as such is a static structure over which an inference control is defined. The reasoning is performed by applying the knowledge contained in the hypothesis space to the current case data and the HSS. The inference control algorithm defines an exploration of the hypothesis space that is determined by the hypothesis hypotheses and the relationships between them. The algorithm takes an HSS state which is transformed into a hypothesis space that best reflects the reality according to the diagnosis objectives and the problem at hand.

### 2.1.4 HS Evaluation

The HSS model offers a solution to the requirements stated at the beginning of the paper. Not all the relevant information is needed to provide solutions and the accuracy of the outcome suffers a graceful degradation when less information is available. The static hypothesis structure and the organization of the knowledge space among the hypotheses is invariant and allows a flexible new information by revising the existing hypothesis space and giving a refined solution.

The clear meaning of what a hypothesis and its links to other hypothesis represents leads to a natural and understandable knowledge representation even for experts that allows the knowledge engineers to follow a structured knowledge acquisition and to know at any moment what has been already obtained and what is still missing.

In [11] it is explained how the HSS model is related to the domain of Industrial Process Control. Among others the requirement of quick answers is mentioned.

#### 2.2 The Qualitative Causal Model

The fundamental knowledge about how the physical process works is useful for diagnosis. Basically we are interested in representing the elements that change in the process, the process parameters variables, and how these changes influence each other. The causal knowledge of the model, it is because of the physical process is not precisely known and (ii) human experts match acceptable performances explaining just qualitative information. We will propose a Qualitative model:

**Def.** The relevant parameters in a given process is represented by a set of Variables defined as \(V = \{\psi, \psi_i\}\) where \(\psi\) is a variable. Variables take values over a Quantitative Space \(Q\), a qualitative set which represent qualitative abstractions of real values of parameters.

**Def.** \(Q \in \text{QN}\) is a possible qualitative value of a variable \(V\) with a total order relation \(\triangleleft\) and a central value denoted by \(C\).

**Def.** For a certain process, given a \(Q\), a set of Influence functions is defined as \(IF = (\psi, \psi_i, \psi_j)\).

**Def.** Given a certain process, a Causal Model is defined as a finite, acyclic, directed and labeled graph where nodes are Variables and arcs are Causal Relations labeled with influence functions. \(CM = (V, Q, C)\) where \(V\) is a set of Variables, \(Q\) is the Qualitative Space over which the variables take values and a set of Causal Relations \(C \subseteq V \times (IF, V)\), where \(\psi\) influences the parameter represented by \(\psi_{ij}\) influences the parameters represented by \(\psi_{ij}\) according to the \(\psi_{ij}\) function.

In a CM the variables in \(V\) are classified according to the influence received and sent:

- **Initial:** \(V\) is an Initial variable iff there is no influence on it, i.e. \(\psi, \psi_i, \psi_j\) \(\psi\) \(\in\) \(Q\).
- **End:** \(V\) is an End variable iff \(\psi, \psi_i, \psi_j\) \(\psi\) \(\in\) \(Q\).
- **Intermediate:** \(V\) is an Intermediate variable iff it is neither an Initial nor an End variable.

The value of the process specifies the values of the parameters. In the model this state is described by assigning values to the variables.

**Def.** An state of a CM is a function \(v: V \rightarrow Q\) where \(L\) represents the undefined value and \(a = \psi_{ij}\) is the value of \(\psi_{ij}\).

In order to compute the value of each variable \(\psi_{ij}\) is computed from

**Fig. 6.** The Brick, the basic building block of a Causal Model.

**Def.** The brick of a CM related to the variable \(\psi_{ij}\) is defined as \(\psi_{ij} = \psi_{ij}(\psi, \psi_i, \psi_j)\) \(\in\) \(C\).

The \(\psi_{ij}\) are called causing variables and the \(\psi_{ij}\) is called explained variable.

It is assumed that the influence on a variable from its causing variables are independent and that the final behaviour of the explained variable can be computed from a combination of the effects that would induce each causing variable separately, namely the additive assumption. Let's see how the value of the explained variable of a brick is computed from
an state over the causing variables:

First, by the M function, it is computed the marginal influence that every causing variable induces on the explained variable through the influence function:

\[ M: QS \times I^F \rightarrow QS \]

\[ M(v_i, I^F) = m_i = f_i(v_i) \]

Then the explained variable value is computed combining the marginal influences:

\[ F: QS^N \rightarrow \Phi(QS) \]

\[ F(m_1, m_2, ..., m_N) = \psi(v) \]

\( F \) is defined as a recurrent application of a binary function called \( f_i \). So \( F(m_1, m_2, ..., m_N) = f_i(m_i, f_i(m_{i+1}, ..., f_i(m_N) = \psi(v)) \). Given that QS is finite, only a finite number of such binary functions exist. The set of possible functions is reduced by determining some properties that the function has to satisfy. Among them, next properties are stressed: Associativity, Commutativity and Non-decreasing respect to any variable (See [12] for further details). To define the functionalities to be provided by the Causal Model and their algorithms it is introduced the condition of consistency of a given valuation over the variables.

A valuation function \( \psi \) on a Causal Model \( CM = (V, QS, C) \) is said to be consistent iff \( \forall \) brick \( = \{(v_i, v, v_i, v, v) \in C \}: \psi(v) \in F(M(\psi(v))) \), ... 

Let's now define the functionality of the tasks we perform upon the Causal Model. A cause means a disturbance on an initial variable, a compound cause a set of them, an effect a disturbance on an end variable and a compound effect a set of them. The complexity of the algorithms for these tasks is exponential in the general case but for Causal Models where i) the number of disturbances is limited and ii) the number of different paths between parameters is small\(^1\), the combinatorial explosion is kept under control.

\[ 2.2.1 \text{ Causal Simulation} \]

Given a set of disturbances on one or more variables \( \{v_i, v_q\} \), simulation on a Causal Model CM consists in generating every possible set of effects consistent with it \( \{v_i\} \):

\[ S_{CM}: \{v\} \rightarrow \{v_i^\}
\]

\[ S_{CM}(\{v, v_q\}) = \{v_i\} \]

The input variable-value pairs fix values for some variables in the Causal Model i.e. partially define the valuation function. By a Closed-World Assumption every undefined predecessor to those defined variables are set to the undefined value (2). Then, simulation propagates the variable disturbances forward through the causal links maintaining the consistence condition. If this disturbances are not inconsistent this computation produces a set of partially defined valuation functions \( \{v_i\} \) corresponding to the different possible behaviors. The projection of these functions on the end variables is the result of the simulation task, a set of sets of effects.

\[ 2.2.2 \text{ Causal Diagnosis} \]

Given a set of disturbances in one or more variables \( \{v_i, v_q\} \), diagnosis on a Causal Model CM consists of generating every possible set of causes consistent with it \( \{v_i\} \):

\[ D_{CM}: \{v\} \rightarrow \{v_i^\}
\]

\[ D_{CM}(\{v, v_q\}) = \{v_i\} \]

The diagnosis computes all the possible value combinations of influencing variables affecting explained variables related with the disturbed variables through a forward

\[ 2.3 \text{ Explaining} \]

Given a set of disturbances on one or more initial variables and a rather set of them over a set of end variables \( \{v_i, v_q\} \), explaining in a Causal Model CM consists in generating every possible explanation-causal chain from effects to causes, consistent with the set of observations \( \{v_i\} \), that justify the effects from the causes, and it can be described by the function:

\[ E_{CM}: \{v\} \rightarrow \{v^e\}
\]

\[ E_{CM}(\{v, v_q\}) = \{v_i\} \]

\[ 2.3 \text{ Interaction between the Heuristic and the Causal models} \]

Up to this point two models have been presented based on different types of knowledge. In general heuristic knowledge is used first to generate solutions efficiently. But this efficiency is obtained in return for no guarantee about feasibility among solutions or completeness of the solution. Thus when heuristic solutions are not satisfactory fundamental knowledge is applied. The heuristic results can be improved in several ways using the causal knowledge: i) to complete them, ii) to validate them, and iii) to provide sound explanations of them (See [11]). Besides, it, the heuristic knowledge also embodies efficient strategies for determining which is the most interesting knowledge to be obtained. So the subsequent application of causal knowledge will take advantage of the information made available during the heuristic process.

\[ 3 \text{ An example: The Flowcooling Application} \]

The flowcooling process consists of coating the TV screen glass with a phosphorescent suspension in order to get a periodic sequence of streaks of colour lines (red, green and blue) by letting several input materials like the screen glass, the mask, the phosphorescent powder, through a sequence of physical and chemical processes like processing, suspension flowcooling, suspension, exposure, developing.

\[ 3.1 \text{ The Flowcooling Diagnostic System} \]

The flowcooling hypothesis hierarchy the known hypothesis represents that there is a problem without specifying in the flowcooling process. Sub-hypothesis of it are defects. A classification of such problems in the screen (stained during the production has been done and is identified by a pattern on the screen. For instance in the figure 5 you can see screens with patterns similar to it. Basic Hypothesis are either a deviation on a process (e.g. too high suspension Temperature), deviation on an environment parameter material out of specifications (e.g. phosphorescent powder is old, glass roughness out of spec), according to our Structured Process Description [10].

The Data set defined in the HIS model in this case is composed of information about the product or any intermediate product feature and previous actions taken by the operators on the process (e.g. field maintenance, change of exposure table).

The general inference control algorithms defined generically for the HIS model has been particularised. Once an hypothesis is selected it is reduced to many rules that are applicable till the set of rules is exhausted. The rule selection is simplified to the current hypothesis in the following order: first try the testing rules and afterwards the focusing rules.
A Causal Model has been built that represents the process and product parameters of the flowcoating process and the influence links between them. The leftmost side variables represent input material parameters and process parameters. The middle side variables represent product parameters. Intermediate variables represent subproduct parameters. A three-value Quantity Space has been defined, with [−1, 0, +1] representing a smaller, normal and greater value with respect to the right specified value. Also a five-value QS has been studied [12]. Four influence functions have been defined (See Fig. 7).

Fig. 7. These are the influence functions defined in our application: Direct, Inverse, Extreme positive and Extreme negative. A and b represent the domain values and a by b the range values.

The defined functionalities of the Causal Model, their algorithms and the interaction between the heuristic and the causal model has been implemented following the general ideas described previously.

3.2 The Interface SIVS - FDS

The communication between the Screen Inspection Vision System (SIVS) and the Flowcoating Diagnostic System (FDS) is performed through the Monitoring System (See Fig. 1). The SIVS delivers a list of the defects that match with the currently detected defects on the flowcoating screen. It is the initial input of the Flowcoating Diagnostic System (FDS). It includes information about features general in all defects and other specific to each defect that has been specified in the defect definition. Inside it, the SIVS provides data about other features of the product not directly concerning the defect. Also a statistical treatment on these informations is performed in order to assess the pattern of occurrence of the defects and trends of specific product parameters (e.g. the trend of the line width).

3.3 The Screen Inspection Vision System (SIVS)

3.4 SIVS Constrains

The aim of the Screen Inspection Vision System (SIVS) is to 100% check each screen to detect any defect and to analyze it, in order to deliver the information to the Diagnosic Expert System. The customer's requirements of checking the whole screen area in 12 seconds with a resolution of 50 μm is a major determining factor for the whole visual inspection system. It means an information flow rate of about

\[ \frac{(1.6 \times 0.45) \text{ m}^2 \text{screen} \times 8 \text{ bits/pixel}}{(50.1 \times 10^{-6})^2 \text{ m}^2 \text{pixel} \times 12 \text{s}} = 72 \text{ M bytes/s screen} \]

It is not easy to deal with this enormous amount of data. Solving it by software is prohibitive because of time constraints. To manage all this data it is imperative to preprocess it in order to achieve two objectives: first, to reduce the flow data without losing information and second, to extract the most relevant characteristics from the raw data.

There are different types of defect. They can appear at macro level, where a general view is necessary to detect them (See figure 5) and at micro level where a closer view is necessary (See figures 3 and 4). They are grouped into similar kinds, the different kinds must be treated with tailored pre-processors which have to work in parallel to fit the time constraints.

3.4.2 Surface Scanning of the Screen

All the needed information about the defects to be detected will be gathered by an image scanner consisting in a galvano-mirror system which has a colour TV camera associated (See

Fig. 8. The image scanner is controlled by a X and a Y signal which deflect the horizontal and vertical mirrors giving the coordinates to scan the optical system. There are also a focusing signal and a zooming signal.

![Image Scanner](image)

In order to get the desired resolution, the screen is scanned by small area. A resolution of 50 μm means about 7 pixels per phosphor line (a phosphor line is about 2800 μm wide). For a screen with 1800 phosphor lines and a colour screen with 512 horizontal pixels, this implies

\[ \frac{1800 \text{ pixels}}{7 \text{ pixels/line}} \times \frac{1}{12} \text{ frame} = \frac{1}{256} \text{ area}, \]

\[ \frac{512 \text{ pixels/width} \times 600 \text{ mm}}{1800 \text{ pixels}} = 24 \text{ mm/width} \]

and

\[ 24 \text{ mm/width} \times \frac{3}{4} \text{ width/height} = 18 \text{ mm, high} \]

3.4.3 Screen Inspection Vision System Architecture

The figure 9 shows the final SIVS Architecture. We are in mind the currently produced commercial hardware [7]. This can save designing and developing time allowing us to concentrate in the specific problems for which there are no existing solutions because of time constrains. We can say that the choice of either commercial or specific hardware depends on the time constrains. For the detection and location of defects we have decided on specific hardware. For classification and characterization of defects we have decided on commercial hardware and is shown.

![SIVS Architecture](image)

Fig. 9. The Screen Inspection Vision System Architecture.
The IVS architecture has four main functions: the microdefect detection, the microdefect analysis and the microdefect detection and analysis.

The information to be used by the whole SIVS comes from the Image Scanner. So the obtained video signal is send to the microdefect detector that consists of several preprocessors specialized in each kind of defect. When a microdefect is detected an interrupt preprocesses prepares for this defect. Then, signal is given to the controller which captures the x,y coordinates of this defect. These coordinates are used to zoom-in on the defect. Once the zooming-in has been realized, the coordinates are used to zoom-in the defect image to the image processor unit and transferred to the new enlarged image of the defect is imput to the image processor unit and transferred to the image processor unit. Later, on, the image processor will analyze the defect image with several algorithms which, using the information of the preprocessors allow the characterization of the defect.

The video signal also goes to the micro image synthesizer unit. In it an averaging system obtains an equivalent, small resolution image of the entire view that will be scanned and sent to the micro image storage board. This micro screen image is microscopically scaled and sent to the micro image storage board. This entire process is repeated in the synthesize unit. This unit performs an analysis over this information, which detects, locates and classifies the possible micro-defects. The information about any micro defect is given to the Defect Definition Frame.

4 Conclusions

The integration of advanced information technologies are leading to fully automated and higher performances in Process Control and Supervision. Vision Systems are able to inspect the product and deliver information about it. On this and other informations from the process, Expert Systems reason to identify, diagnose and repair a critical problem.

On the hand of the Knowledge-Based system, the combination of two different kinds of knowledge permits to achieve a more correct, robust and reliable system. A general model of knowledge base used for diagnostic purposes has been defined, the Hypothesis Space model. It is based in the hypothesis that experience has been defined, the Hypothesis Space. A Model has also been defined to represent the experiential knowledge for process diagnosis and very well-suited for representing the experiential knowledge for process diagnosis and repair. Among its properties the ability to reason under incomplete knowledge, the repair. Among its properties the ability to reason under incomplete knowledge, the repair. Among its properties the ability to reason under incomplete knowledge, the repair. Among its properties the ability to reason under incomplete knowledge, the repair. Among its properties the ability to reason under incomplete knowledge, the repair. Among its properties the ability to reason under incomplete knowledge, the repair. Among its properties the ability to reason under incomplete knowledge, the repair. Among its properties the ability to reason under incomplete knowledge, the repair. Among its properties the ability to reason under incomplete knowledge, the repair. Among its properties the ability to reason under incomplete knowledge. A Canonical Model has also been defined to complement the heuristic one. It has been shown how deep models can refine and complete the heuristic results, but further work is required to reduce the computational complexity of the algorithms in general cases.

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References


Tracking and Grasping of Moving Objects — A Behaviour-Based Approach

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Abstract: Behaviour-based robotics (cf. Brooks [2]) has mainly been applied to the type of autonomous systems and mobile robots. We present here our approach to robot programming that is based on the concept of a flexible and robust controller for a five degrees of freedom (DOF) robot arm. The implementation of the robot controller to be presented features the sensor and motor patterns necessary to tackle a problem we consider to be hard to solve for traditional controllers. These sensor and motor patterns are linked together forming various behaviours. The global control structure based on Brooks' subsumption architecture will be outlined. It coordinates the individual behaviours into goal-directed behaviour of the robot without the necessity to program this emerging global behaviour explicitly and in advance. To conclude, some shortcomings of the current implementation are discussed and future work, especially in the field of reinforcement learning of individual behaviours, is sketched.

1 Introduction

By the end of the sixties and the early seventies robotics was considered to be the most important field of Artificial Intelligence research. It was expected that a successful robot system would feature the main constituents of intelligent behaviour. Later on, the interest in robotics has declined considerably. In the following, we will shortly discuss why this (from our point of view) seems to be the case.

Knowledge-based systems were used to develop various functional modules for different aspects of world-interaction such as perception, planning, and control. These modules should enable a robot to act intelligently in the real world. As a result, these modules suffered from the same limitations as any other knowledge-based system (e.g., expert systems).

On the one hand, this is the qualification problem, i.e., the question of what aspect of the real world should be considered when building the knowledge base. On the other hand, it is the frame problem, i.e., the question which changes to the knowledge base should be made due to real world interactions. The unpredictability of the real world, which is reflected in these problems, limits the accuracy of the domain model as represented by the knowledge base. Unpredictable events will lead to system failures. In limited (closed world) domains pragmatic considerations of these problems can actually help to build properly working knowledge-based systems. But this is not possible for the field of robotics applications, where the real world has to be dealt with.

1Knowledge-based systems are mainly characterized by the use of an explicit world model, i.e., the knowledge base, as well as adequate state transition operators. These operators are used to modify the knowledge base and to maintain the implications of system activity in the real world. Hence, maintaining a complete and accurate world model in the knowledge base.