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Using Custom-designed Vlsi Fuzzy Inferencing Chips For The Autonomous Navigation Of A Mobile Robot — Source link ⌄

François G. Pin, H. Watanabe, J. Symon, R.S. Pattay

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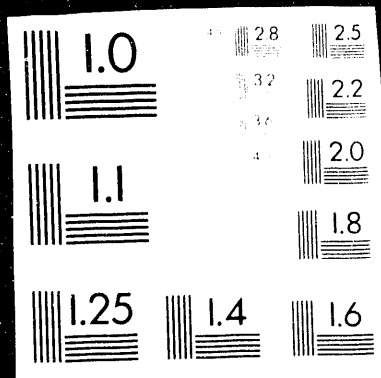**Topics:** Mobile robot navigation, Mobile robot, Qualitative reasoning, Fuzzy logic and Robot

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USING CUSTOM-DESIGNED VLSI FUZZY INFERENCING CHIPS FOR THE AUTONOMOUS NAVIGATION OF A MOBILE ROBOT*

François G. Pin, Hiroyuki Watanabe,* Jim Symon,* and Robert S. Pattay

Center for Engineering Systems Advanced Research
Oak Ridge National Laboratory
P.O. Box 2008
Oak Ridge, TN 37831-6364, U.S.A.

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Contact: Dr. François G. Pin, Oak Ridge National Laboratory, P.O. Box 2008, Building 6025, MS-6364, Oak Ridge, TN 37831-6364, U.S.A., Telephone: (615)574-6130, Fax: (615)574-7860, Email: pin@stc10.ctd.ornl.gov

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ABSTRACT

Two types of computer boards including custom-designed VLSI fuzzy inferencing chips have been developed to add a qualitative reasoning capability to the real-time control of autonomous mobile robots. The design and operation of these boards are first described and an example of their use for the autonomous navigation of a mobile robot is presented. The development of qualitative reasoning schemes emulating human-like navigation in a-priori unknown environments is discussed. An approach using superposition of elemental sensor-based behaviors is shown to allow easy development and testing of the inferencing rule base, while providing for progressive addition of behaviors to resolve situations of increasing complexity. The efficiency of such schemes, which can consist of as little as a dozen qualitative rules, is illustrated in experiments involving an autonomous mobile robot navigating on the basis of very sparse and inaccurate sensor data.

1. INTRODUCTION

One of the greatest challenges in the motion planning and control of autonomous mobile robots in a-priori unknown or dynamic environments is to provide the reasoning modules with methods for handling and/or coping with the many imprecisions, inaccuracies, and uncertainties present in the system. These typically are caused by: (1) errors in the sensor data (current sensor systems are far from perfect) which lead to inaccuracies and uncertainties in the representation of the environment, the robot's estimated position, etc., (2) imprecisions or lack of knowledge in our understanding of the system, i.e., we are unable to generate complete and exact (crisp) mathematical and/or numerical descriptions of all the phenomena contributing to the system's and environment's behavior, and (3) approximations and imprecisions in the information processing schemes

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* Department of Computer Science, University of North Carolina at Chapel Hill, Chapel Hill, NC 27599

(e.g., discretization, numerical truncation, convergence thresholds, etc.) that are used to generate decisions or control output signals.

Qualitative reasoning (also termed approximate reasoning) refers to a set of methodologies which have been developed to provide alternative solutions methods for decision-making problems when the uncertainties can not be fully engineered away from the system (e.g., there are limits on maximum sensor precision, predictability of the environment, etc.). The general approach underlying these methodologies consists in capturing some aspects of the reasoning methods typically exhibited by humans when controlling systems; in particular, by implicitly incorporating uncertainties in the information gathering and reasoning processes, rather than attempting to explicitly determine and propagate them through numerical calculations or representations. Several approximate reasoning theories and associated mathematical algebra have been developed over the past two decades [1], the most commonly used today for applications to control systems being Zadeh's Theory of Fuzzy Sets [2]–[5]. This theory is at the basis of very successful implementations varying from control of subway cars, elevators, cement kilns, washing machines, cameras and camcorders, inverted pendulums, to painting processes and color image reconstruction, to even ping-pong playing robots [6]–[12].

One of the important factors which have prevented the wide-spread utilization of approximate reasoning in real-time systems has been the unavailability of computer hardware allowing processing and inferencing directly in terms of approximate or linguistic, or "fuzzy" variables (e.g., far, fast, slow, left, faster, etc.) and approximate rules (e.g., if obstacle is close, then go slower; if temperature is high and pressure is increasing, then decrease power a lot, etc.). Prospective implementations thus had to rely on simulation of the approximate reasoning schemes on conventional hardware and computers based on "crisp" processing, with a resulting significant penalty in speed of operation, prohibiting applications in most "hard real-time" systems.

In cooperation with Micro Electronics, Inc., unique computer boards have recently been developed using custom-designed VLSI chips [13],[14] which can be programmed to directly communicate and interface in terms of qualitative variables and rules. Additionally, the boards' architecture is reconfigurable on-line to allow several levels of reasoning (meta level, non monotonic, etc.) and to allow full inferences with up to 350 rules and 28 input channels to take place in 30 μ sec, i.e., at a rate of 30,000 Hz (at least two orders of magnitude faster than video frame rate). This paper provides an overview of the design and operation of these boards and discusses their first implementation in the development of approximate reasoning methodologies and schemes for CESAR's series of HERMIES (Hostile Environments Robotic Machine Intelligence Experiments) test-bed robots.

2. QUALITATIVE REASONING ON A VLSI CHIP

The qualitative reasoning methodology utilized for the VLSI implementation is inspired from the Theory of Fuzzy Sets, in which the functions $\mu_X(x)$ defining the membership of an element x to a subset X of a universe of discourse U can take any value in the interval $[0, 1]$, rather than only the discrete $\{0, 1\}$ values (0 for does not belong, 1 for belongs) used in conventional (crisp) Set Theory. The function $\mu_X(x)$ thus defines the *degree* of membership of the element x in X. Such a subset X of U is termed a qualitative (or approximate, conceptual, or fuzzy) variable for reasoning on the universe of discourse U.

For the current VLSI implementation, reasoning is embodied in programmable "production rules" operating on four sets of qualitative input variables and two sets of output qualitative variables, as in

$$\text{IF } (A \text{ is } A_1 \text{ and } B \text{ is } B_1 \text{ and } C \text{ is } C_1 \text{ and } D \text{ is } D_1) \text{ THEN } (E \text{ is } F, \text{ and } F \text{ is } F_1), \quad (1)$$

where $A_1, B_1, \ldots F_1$ are qualitative variables whose representative membership functions define the rule, and $A, B, C \ldots F$ are the time-varying qualitative input and output variables analogous to memory elements in conventional production systems.

With the above representation, the Fuzzy Set Theoretic Operations can be directly applied to the qualitative variables on their universe of discourse: given two subsets A and B of U,

$$\mu_{A \cap B}(x) = \min(\mu_A(x), \mu_B(x)) \quad (2)$$

$$\mu_{A \cup B}(x) = \max(\mu_A(x), \mu_B(x)) \quad (3)$$

The laws of logical inferences including modus ponens, cartesian product, projection and compositional inferences (e.g., see [3] and [4] for detailed description of these laws of inferencing) can also be applied to multivariable systems. In particular, the extension principle [3],[4] is used in the mapping between a set A of the input universe of discourse U and its extension through F to the output universe of discourse V, as:

$$\mu_{F(A)}(v) = \underset{u}{Sup}\, \mu_A(u) \quad (4)$$

where $v = F(u)$, $u \epsilon U$, $v \epsilon V$.

For their VLSI interpretation, each qualitative variable is represented by its membership function discretized over a (64×16) array of $(x, \mu(x))$ values. Equations (1), (2), (3), and (4) can thus be easily implemented using series of min. and max. gates as shown in Fig. 1 for one rule. Figure 2 schematically represents an inference with two rules

of the form IF $(A$ is A^1 and B is $B^1)$ THEN $(E$ is $E^1)$ operating on two input A and B and producing a composite membership function for E.
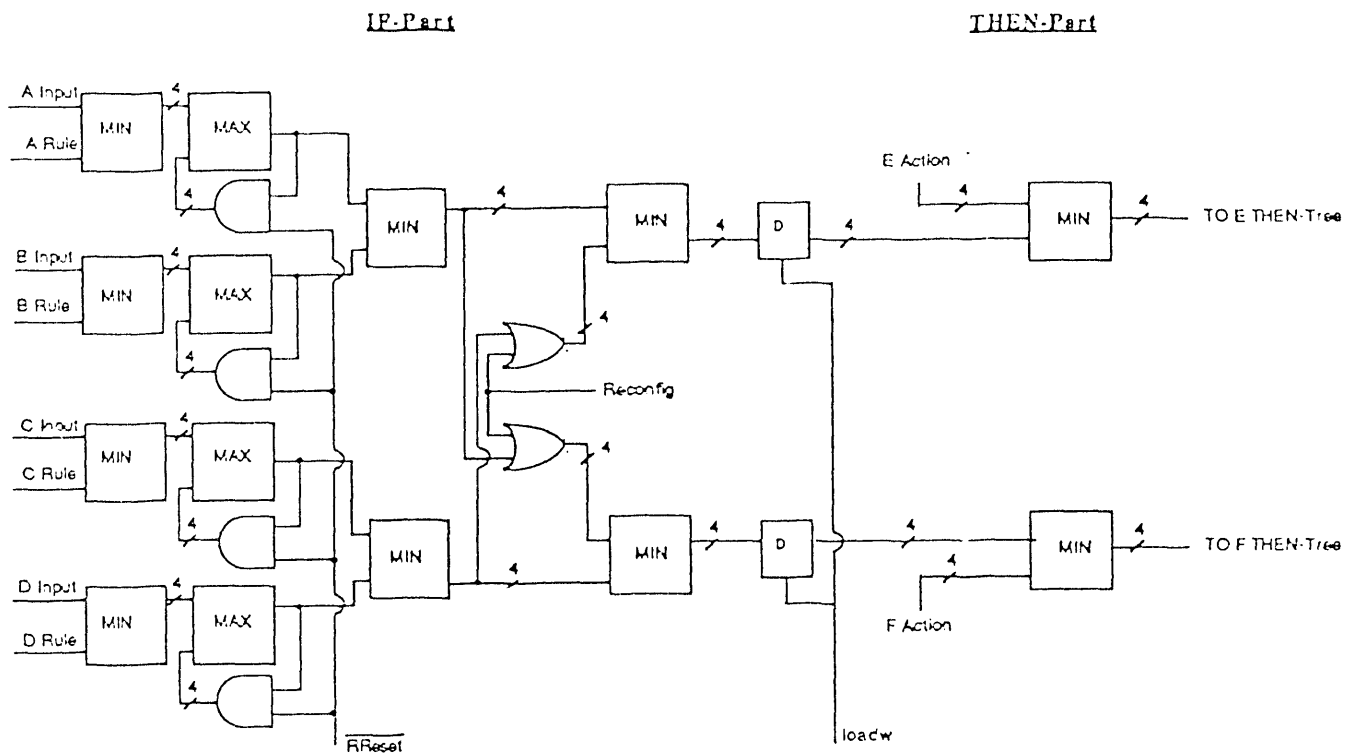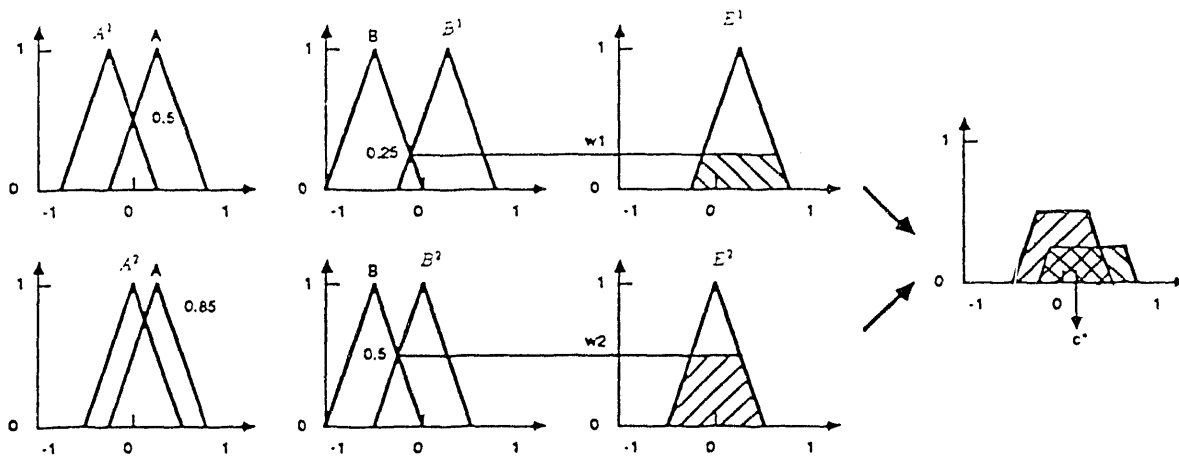
Fig. 1. Data path for rule execution.

Fig. 2. Schematic of a qualitative inference using two rules operating on two input and one output channels.

Because conventional sensors typically provide data in "crisp" form (i.e., they provide a single number which does not reflect the uncertainty involved in the measuring process), it is desirable to add this uncertainty on the measurement, effectively mapping it to a qualitative variable, prior to processing through approximate reasoning. This step (which has been termed fuzzification) is of course not necessary if the data is already in the form of a qualitative variable, such as in interchip communications, and therefore has been implemented as a programmable optional data path on the VLSI chip. Similarly, an optional defuzzying step which calculates the "center of weight" of the output composite membership function (see Fig. 2), can be used to send "crisp" data to conventional actuators if these are used in the process control hardware as depicted on Fig. 3. To provide added flexibility, the chip architecture is reconfigurable, allowing either 50 rules operating on four input and two output channels or 100 rules operating on two input and one output channels. Since all rules are processed in parallel, the speed of operation of the chip is independent of the configuration or the number of rules involved in the inferencing, and reaches 30,000 FFIPS (Full Fuzzy Inferences Per Second) [13],[14]. In other words, full qualitative data processing and inferencing schemes can take place at 30 KHz, (i.e., at least two orders of magnitude faster than the sampling rate of typical sensors) making feasible the control of very fast systems or motions, such as those involved in reflex behaviors based on very approximate or uncertain informations.
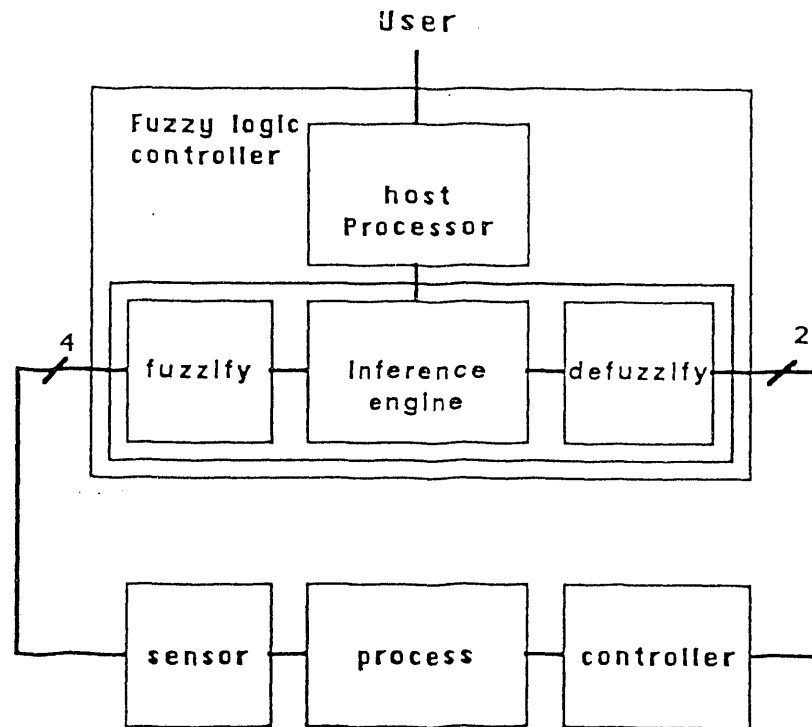

Fig. 3. Schematic of a typical qualitative control system for a real-time process.

Two types of VMEbus-compatible printed boards and associated software were developed to allow interfacing of the chips with sensors and actuator data channels for application to "intelligent machines" and, in particular, to autonomous mobile robots. The first type of board includes one chip and is therefore limited to inferencing involving only 4 input and 2 output channels. The second type of board includes 7 chips and some multiplexer circuits which allow on-line reconfiguration of the input, output and interchip communication paths [14]. This provides the capability to implement qualitative reasoning schemes with up to 350 rules and 28 input channels (with all chips in parallel), multi-level reasoning schemes (e.g., 4 chips in a first layer feeding into 2 chips in the second layer feeding into 1 chip in the third layer), or non-monotonic reasoning (e.g., with feedback of the output of some of the downstream chips into the input of some of the upstream chips, in a series or "cascade" of chips). The speed of operation of each layer of parallel chips remains the same than on the single chip board, with the multi-layer configurations reaching rates in the KHz order of magnitude.

3. TEST IMPLEMENTATION FOR MOBILE ROBOTS NAVIGATION

The problem of autonomous mobile robots navigating in a-priori unknown and unpredictable environments was selected for initial testing of the qualitative reasoning systems because its characteristics rank very high on the list of criteria that typically indicate suitability of a reasoning problem for representation and resolution using qualitative logic: the input to the control system, particularly when provided by sonar range finders and odometry wheel encoders, is extremely inaccurate, sparse, uncertain and/or unreliable; there exist no complete mathematical and/or numerical representation of the behavior termed navigation, although, as demonstrated by humans, a logic for this behavior exists which can typically be represented and successfully processed in terms of linguistic variables; by its given nature the behavior of the environment is unpredictable, leading to large uncertainties in its representation; the approximations involved in the numerical representation of the system and its environment (e.g., geometric representations, map discretization in grid, etc.) are significant.

The single chip board and a recently designed omnidirectional mobile platform [15],[16] were used for these initial experiments. Because of the limitations to 4 input channels using this board, data from only 3 frontal sonars were used for perception of the environment, while the fourth channel produced information on angular direction to the given navigation goal based on odometry sensor data. The output channels provided translational speed and steering velocity commands to be sent to the motor controls. No

a-priori environmental data or maps were input to the system, nor were any generated during motion, and in this sense, the initial investigations focussed on reactive navigation. The development and testing of the first series of qualitative rule-bases led to empirical findings providing significant insights for efficient implementation of qualitative reasoning schemes in autonomous robots:

- Modularity and consistency of the rule-base can best be achieved through decomposition of the decision-making scheme into elemental and independent "behaviors."

- Independence of these elemental behaviors is assured if each can be formulated as a direct mapping between a subset of the input and a subset of the output, with no redundancy in the qualitative values spanned by the input variables of various behaviors.

- Independent behaviors can be singly developed and tested, and their independence experimentally verified prior to merging with other behaviors.

- Once developed, tested and verified, each behavior can be assigned a normalized "weight" (in [0,1]) corresponding to its relative importance with respect to other behaviors with which it is to be merged, (e.g., safety from obstacle vs. speed of operation, etc.). The weighting is implemented by a direct scaling of the membership functions of either the input or the output variables.

- Merging of the behaviors is handled directly and continuously through the laws of combinatorial inferencing, therefore providing a formal resolution to one of the major problems with which the "behaviorist" community (e.g., see [17] and [18] and references therein) has struggled: the real-time selection and/or conflict resolution in multi-behavior systems.

Building upon the experience and empirical results gained during the development of the first series of rule-bases, a new rule-base conforming with the observations listed above was developed for the single chip board and the CESAR's omnidirectional platform pictured in Fig. 4. The photograph in the figure shows the ring of accoustic range sensors at the edge of the platform deck (only frontal sensors are used) and the disk drive unit, the battery pack (rear right) and the seven-slot VME-bus (rear left) which hosts the qualitative inferencing board. The control system of the platform (detailed in [15] and [16]) includes a velocity loop servoing at 100 Hz on the commanded translational and rotational velocities, which will be hereafter referred to as speed control and turn control, respectively. Thus, behaviors corresponding to speed control (S.C.) and turn control (T.C.) as functions of goal orientation (G.O.) and obstacle proximity (O.P.) where developed as follows:

$$
\begin{array}{rcll}
\text{G.O.} & \longrightarrow & \text{S.C.} & \text{(1 rule)} \\
\text{O.P.} & \longrightarrow & \text{S.C.} & \text{(4 rules)} \\
\text{G.O.} & \longrightarrow & \text{T.C.} & \text{(2 rules)} \\
\text{``far''} \quad \text{O.P.} & \longrightarrow & \text{T.C.} & \text{(2 rules)} \\
\text{``near''} \quad \text{O.P.} & \longrightarrow & \text{T.C.} & \text{(2 rules)} \\
\text{``very close''} \quad \text{O.P.} & \longrightarrow & \text{T.C.} & \text{(3 rules)}
\end{array}
$$

where the three latter behaviors embody the fact that different navigation behaviors are utilized depending on whether all obstacles are still "far," "near," or "very close," thus reflecting differences in safety concerns (i.e., priority of the behavior) implemented using different weights. For each sampling period and decision, several behaviors are typically triggered and merged through the Fuzzy Set Theoretic laws of Combinatorial Inferencing, resulting in a smooth and continuous sensor-based navigation control.
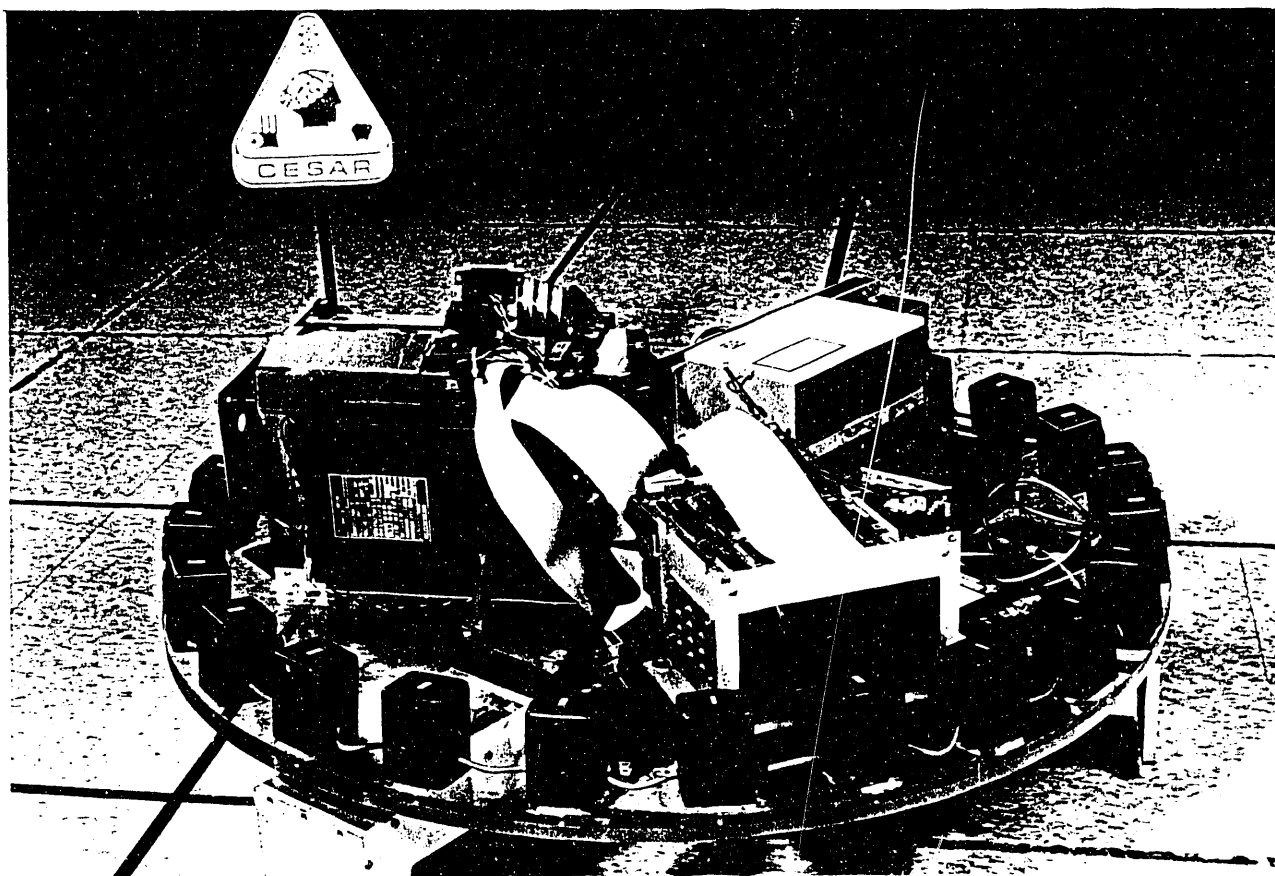
Fig. 4. The CESAR omnidirectional robotic platform prototype.

The rules for TC and SC as a function of GO express the very intuitive fact that if the goal is to the left (respectively right), then a small increment of turn to the left (respectively right) needs to be made during the loop rate cycle; and when the direction of the goal increases from $0°$ (front) to $\pm 180°$, then the speed is correspondingly decreased. The rules for SC as a function of OP express that when the distances to any obstacles (i.e., the sensor

returns in all three directions) are increasing, then the speed can be increased toward its maximum value (one rule), while when distance to an obstacle (sonar return) in any of the three sonar directions (thus, three rules) decreases toward a safety threshold (here selected as 30 cm), then the speed needs to be decreased, down to zero at or below that threshold.

Once these speed control and goal tracking behaviors were designed, they were merged and tested in environments with no obstacles. Since the chip used for this initial implementation allowed only four input channels, no information related to distance to the goal could be provided to the qualitative reasoning scheme in order to make the robot stop when reaching the goal. This was easily remedied in these tests by using the odometry data in the master program to stop both the reasoning scheme and the robot when it approached to within a given radius (2.5 cm) of the goal. In future implementations using the seven-chip board allowing up to 28 input channels, the distance to the goal could be input to the qualitative inference scheme and the stopping at the goal could be simply implemented as an additional behavior in the reasoning scheme.

Once these behaviors were tested, the rules for the TC as a function of OP behaviors were developed. When all sonar returns are "far" (further away than 2 m), the turn should be away from the closest obstacle. However, the weight on that behavior must be less than that for the TC as a function of GO, to ensure that when it is far away from any obstacles, the robot's priority is still to move in the general direction of the goal. When at least one of the sonar returns is "near" (between 30 cm and 2 m), the turn is away from the obstacle, increasing in magnitude with decreasing distance, such that at the lowest distance of 30 cm, this obstacle avoidance behavior has more weight on TC than the goal tracking behavior. Finally when any sonar return is less than 30 cm (the robot is stopped as required by the behavior on SC as a function of OP), the turn is always to the right. Note that setting the turn away from the closest obstacle in this latter behavior would often result in the dead-lock situations in which the robot reaches a limit cycle, and continuously oscillates between two orientations. This type of situation constitutes one of the very serious drawbacks of the reactive navigation methods using potential field techniques, and has been alleviated here using the TC as a function of "very close" OP behavior. Also note that this behavior allows the robot to travel to the end of dead-end corridors, turn around, and backtrack to a more open area, a situation which would lead to a (local minimum) dead-end point in potential field techniques.

Figures 5 and 6 show plots of sample runs made with the robot to illustrate the overall reactive navigation using the qualitative inferencing scheme and, in particular, the two characteristics just discussed. In the figures, the lightly shaded areas represent the obstacles which were placed in the room, while the path of the robot is illustrated using the dark succession of circles. In Fig. 5, the robot initially moves along a first wall toward the goal and passes the point directly opposite to the goal on the perpendicular to the wall (at

which a dead-lock would be encountered using potential field techniques). It then continues until it reaches the end of the wall where it can turn toward the goal, and encounters a second wall. The robot also passes a point opposite the goal on the perpendicular to the second wall, and continues in the corridor until it can turn. It then avoids the small obstacles and reaches the goal. In Fig. 6, the robot starts toward the goal and, when facing obstacle A head-on, moves in the opening on its right which is closest to the goal direction. When reaching the end of this blocked corridor, the robot turns around (using the TC as a function of "very close" OP behavior), exit the corridor, turns in a direction closest to the goal direction, avoids the small obstacles and then moves to the goal.

4. SUMMARY AND CONCLUDING REMARKS

Autonomous robot control in a-priori unknown, unpredictable, and dynamic environments requires many calculational and reasoning schemes to operate on the basis of very imprecise, incomplete, sparse or unreliable data, knowledge or information. In such systems, for which engineering all the uncertainties away from the hardware is not currently fully feasible, approximate reasoning may provide an alternative to the complexity and computer requirements of conventional uncertainty analysis and propagation techniques.

Two types of computer boards including custom-designed VLSI chips have been developed to investigate the implementation and real-time use of approximate reasoning in autonomous robotic systems. The methodologies embodied on the VLSI hardware utilize the Fuzzy Set Theoretic operations to implement a production rule type of inferencing on input and output variables that can directly be specified as qualitative variables through membership functions. All rules on a chip are processed in parallel, allowing full inferences to take place in about 30 μsec. This speed of operation makes real-time reasoning feasible at rates much faster than sensor data acquisition, therefore, making control of "reflex-type" of motions envisionable.

One of the qualitative inferencing boards, incorporating one chip with four input channels and two output channels, was installed on a test-bed platform to investigate the use of qualitative reasoning schemes for the autonomous navigation of a mobile robot in a-priori unknown environments on the basis of sparse and imprecise data. Experiments in which the robot uses only three accoustic range (sonar) sensors have demonstrated the feasibility of basic reactive navigation with a scheme including six elemental behaviors represented in fourteen-qualitative-rules. The approach using superposition of behaviors allows to progressively merge additional behaviors into the scheme to resolve any specific additional situation which may be encountered in particular environments of increasing complexity. Our ongoing work focusses on this area, utilizing the recently completed multi-chip board (which allows up to 28 inputs and 14 outputs) to investigate schemes with

additional input variables and greater numbers of behaviors, for which we were limited in this first series of experiments by the four-input-only restriction of the single-chip board.

Fig. 5. Sample run of the platform illustrating basic obstacle avoidance, wall following, and no "trapping" in local minima. S and G denote the start and goal locations.

Fig. 6. Sample run of the platform illustrating obstacle avoidance in more complex environments, motion in corridors, and no "trapping" in the local minimum at the end of the blocked corridor.

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