Artificial Neural Networks and Expert Systems '95
November 20-23, 1995, Dunedin, New Zealand

Minimal Qualitative Topologic World Models for Mobile Robots

Uwe R. Zimmer

University of Kaiserslautern - Computer Science Department
67653 Kaiserslautern - Germany
e-mail: uzimmer@informatik.uni-kl.de
http://ag-vp-www.informatik.uni-kl.de/Leute/Uwe/

World models for mobile robots as introduced in many projects, are mostly redundant regarding similar situations detected in different places. The present paper proposes a method for dynamic generation of a minimal world model based on these redundancies. The technique is an extention of the qualitative topologic world modelling methods. As a central aspect the reliability regarding error-tolerance and stability will be emphasized. The proposed technique demands very low constraints on the kind and quality of the employed sensors as well as for the kinematic precision of the utilized mobile platform. Hard realtime constraints can be handled due to the low computational complexity. The principal discussions are supported by real-world experiments with the mobile robot "ALICE"[1].

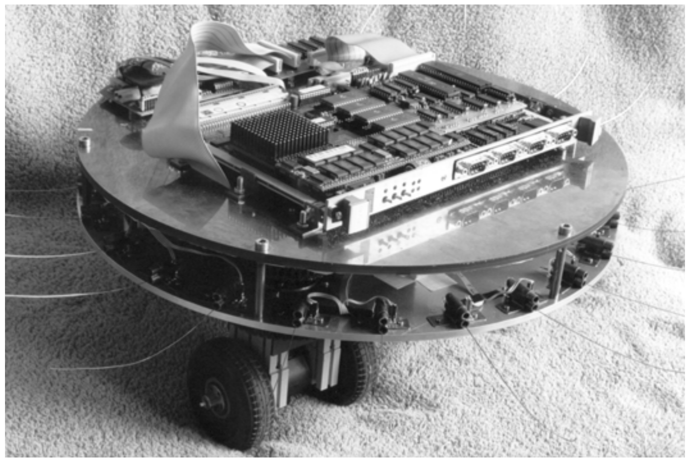

figure 1 : ALICE

Keywords: **artificial neural networks, mobile robots, self-localization, world-modelling**

1. Motivation

Based on the idea that a (really useful) mobile robot should be adaptive in its behaviour regarding its current environment, a dynamic world modelling method is introduced in this article. The "really useful" attribute includes sufficient simplicity, reliability, and stability, which are therefore considered basic demands for the proposed approach.

High precision metric approaches ([3] or [9]) demand very reliable and accurate sensor devices, as well as large computational power. Their applicability on small, and light weighted platforms is limited. During the last few years, "qualitative methods" have been proposed to overcome mainly problems regarding complexity and stability. Works utilizing qualitative modelling for self-localization and navigation include the basic article from Kuipers introducing the term "qualitative map" in [4], the work of Tani [6] based on local sensor-sequences rather than on explicit topology, and the adaptive, topological models introduced by Prescott [5].

In order to focus on the main issues on this field, the robot's world is designed to be simple, but still of practical relevance. The project as well as the mobile, experimental platform itself will be called *ALICE* in the following. This is not an abbreviation, but just a name.

The physical realization of *ALICE*, includes 24 whiskers and passive light sensors mounted together with one standard (CISC-) CPU on an omnidirectional platform. For an optical impression of *ALICE* please refer to figure 1. The included features are just sufficient for an autonomous mobile robot operating in realtime in a universe as described in [7]. The dead-reckoning disturbance for the internal position estimation is 20-25% at an operational speed of 25 cm/s. The angular resolution of the sensors is 20-30°. The term "realtime" is roughly and pragmatically approximated here by the demand that the machine should be able to move continuously at full speed where the world model is adapted without any time-jitter or delay.

The author would like to emphasize that the low reliability and resolution of the employed sensor devices together with the low relative position accuracy and the limited computer power is *not* a weakness of the system but is chosen *intentionally*. A low-preci-

1. The project ALICE is supported by the EU-project DG XII, F-5 (Teleman)

sion system like *ALICE* is an adequate experimental platform for any world modelling and control technique, which is intended to be stable and reliable in a real world. Any sensor and kinematic system with features superior compared to *ALICE* (i.e. almost any sensor system) promises a further improvement in terms of speed and precision but not with regard of the discussed, principal abilities.

2. Topological World-Modelling

The central motivation of **q**ualitative **t**opological world models (**QT**-Models) is the basic mobile robot task: "Recognize places you have seen before!". In this article this task will be approximated by extracting "situations" (i.e. recognized places) together with their topological neighbourhood from the current sequence of sensor-samples, rather than modelling the boundaries of the detected obstacles and objects in a metric manner. Assuming a stable situation-recognition-process and a technique for moving between distinct situations, the concept of a qualitative, topological world model suggests a human-motivated basis for a navigation. The main concept has already been proposed by Kuipers et al. [4], but there the construction process was carried out using explicit rules, not statistical techniques. Therefore, the real-world abilities of the Kuipers approach are, in the opinion of the author, limited.

The world model proposed in this article is based on clustering techniques introduced by Kohonen ("self-organizing-maps") and Fritzke ("growing cell structures", [1]) together with some previously proposed extensions by this research group [2]. Due to a couple of specific autonomous robots-constraints, these structures are modified to cope with realtime-aspects, lifelong learning, "local forgetting", and correlation.

3. Methods

This section will introduce the technical details of the proposed topological world model. The algorithms following are expressed in general terms ignoring computational details.

3-1. Pre-Processing

Following the idea of representing situations (consisting of readings from different kinds of sensors) in a way that they can be compared directly, the sensor-samples have to be preprocessed to form a vector of unified elements. In the current system, passive light and tactile sensors as well as an (x, y)-position produced by odometry are available. Considering the fact, that the angular resolution of the tactile sensors is very low, each vector of tactile readings is smoothed by applying gaussian functions. Finally the sensor samples from different types of sensors are weighted and concatenated to produce a "situation-vector", or more briefly a "situation" (consisting of 50 values in the example given).

In the following, sensor situations will be indicated as S; the position or x, y-component of such situations as p.

3-2. Adaptation

As a basis for the network model, the euclidian norm is applied to calculate distances between sensor situations, d, and distances between positions, g, respectively.

Consider a network N consisting of a number of cells c_i, which are connected with respect to the topological neighbourhood of the situations $S(c_i)$ attached to each cell. Then, at each adaptation step the cell c_{opt} with the smallest situation-distance d_{opt} to the new input situation S_x is determined according to:

$$\forall c_i \in N: d_{opt} = d(S(c_{opt}), S_x) \le d(S(c_i), S_x) \quad (1)$$

In order to limit the effort for this adaptation to a constant the search area is limited by the geometric distance g_{search}. In the current system, this is done by applying adequate data-structures to the network-management. The selected cell c_{opt} and all its topological neighbours are then adapted according to:

$$c_{opt}^{new} = c_{opt} - (\varepsilon_o \cdot d_{opt}) \quad (2)$$

$$\forall c_n^j \mid a(c_n^j, c_{opt}) > 0: \; c_{n_j}^{new} = c_{n_j} - (\varepsilon_n \cdot d_{n_j}) \quad (3)$$

where $a(\cdot, \cdot)$ is the adjacency-function of the network. The "classification error" d_{opt} is then added to a total classification error d_{total} attached to the cell c_{opt}.

$\forall c_i \in N$ (after n adaptation steps):

$$d_{total_i} = \sum_{t=1}^{n} hit_{i,t} \cdot d_{opt_t} \quad (4)$$

$$\text{where } hit_{i,t} = \begin{cases} 1 & ; c_i = c_{opt_t} \\ 0 & ; c_i \ne c_{opt_t} \end{cases} \quad (5)$$

In order to decrease the adaptation speed of a well adapted network, the parameters ε_o and ε_n are controlled by:

$$(\varepsilon_o^{new}, \varepsilon_n^{new}) = \begin{cases} (\varepsilon_o \cdot \varepsilon_\Delta, 0) & ; (d_{opt} \le d_{acc}) \\ (\varepsilon_o^{init}, \varepsilon_n^{init}) & ; (d_{opt} > d_{acc}) \end{cases} \quad (6)$$

where: $0 < \varepsilon_\Delta < 1$

and ε_o^{init} resp. ε_n^{init} are the initial values of the parameters ε_o and ε_n.

In each adaptation step, where d_{opt} is larger than a tolerated error d_{acc}, a global counter n_{miss} is incremented. This counter will be used as a measurement for the need for change in the network structure. An update-counter u_{opt} attached to c_{opt} is incremented and will be used as an indicator for the stability of this specific cell.

In order to use the high speed of this adaptation process to achieve better adaptation, each situation is presented several times k to the network. A constant delay of l sensor-sample-time-slots before the current sensor situation affects the network is also found useful (see section "Correlation" below). Accordingly a learning set holding $(k \cdot (l+1)) - 1$ situations is implemented.

3-3. Growing & Shrinking

At start-up time of the system, there are no cells; the network is empty. So the common problem finding a "good" initial state of the network is avoided, but there is a need for some growing strategy. In the present system, two growing strategies are applied. The first is called "**spontaneous insertion**", the second "**statistical insertion**". In the first, new cells representing the current sensor situation, are inserted when the distance between the current sensor situation and c_{opt} exceeds a certain limit ρ_s (in the special case of an empty network this strategy produces the first cell). In the second strategy a new cell is inserted in the middle between the cell with the highest "degree of movement" c_{runner} (measured by the cell attribute d_{total}) and its farthest topological neighbour c_{far} every n_{insert} "miss-classifications" (measured by the global counter n_{miss}). The new cell is instantiated with mean-values of c_{runner} and c_{far} for position and light-intensity, but with minimal values for touch-information.

Another aspect of growing relates to the topological connections between cells. Assuming that c_{opt} has just changed from c_{opt}^{old} to c_{opt}^{new} in two consecutive adaptation steps, and that the cell c_{opt}^{new} has m other neighbours c_j ($a(c_{opt}^{new}, c_j) > 0$), the following changes in connection weights are imposed:

$$a(c_{opt}^{new}, c_{opt}^{old}) = 1 \tag{7}$$

$$\forall j, (1 \le j \le m):$$

$$a^{new}(c_{opt}^{new}, c_j) = a(c_{opt}^{new}, c_j) - (a_{red}/m) \tag{8}$$

$$\text{with } 0 < a_{red} \le 1$$

A connection with a weight ≤ 0 is regarded as non existent. Thus the deletion of cells is now straight forward. A cell or a cell-cluster with no connection is removed.

3-4. Correlation

Three degrees of freedom out of the internal representation (*(x, y)*-position and orientation) are corrupted by drift effects or other errors and have to be continuously corrected according to the world model. The correlation of current and former sensor impressions from the operational environment is an essential task for all mobile robots, which have no access to global positioning or predefined global landmarks. The correlation process in the case of qualitative topologic maps is discussed in [7].

3-5. Eliminating Redundancy

The representation as introduced up to here handles every situation completely individually (connected by topological links only). Due to the assumption that similar situations occur in multiple locations, it is tried to eliminate this redundancy.

In the special case of *ALICE*, the touch information is an obvious example for this kind of redundancy. The number of different wall or corner situations is between 10 and 30 in most environments. Nevertheless, the touch information is stored separately in each situation according to the QT-maps. The following concept, called **non-spatial mapping**, will eliminate most of the redundancy while keeping some basic features of the introduced qualitative topologic maps.

Based on the three different kinds of sensor information gathered on the *ALICE* platform, three separated self-organizing maps are constructed: the **geometry-network** (N^g), the **light-network** (N^l), and the **touch-network** (N^t), representing the distribution of the cartesian coordinates, the light-, and the whisker-information respectively. While the network N^g is built according to the introduced rules of the qualitative topologic maps (but based on the position information only), the networks N^l and N^t can be implemented emplyoing standard self organizing maps or growing cell structures [1]. Assuming that the total number of different situations cannot be estimated in advance (although it is assumed that they are limited), the growing cell structures will show superior behaviour and are chosen therefore in the present case.

A new input situation S_x is divided into the situations S_x^g, S_x^l, and S_x^t, representing the different kinds of sensor information. Following the usual adaptation process, the cells c_{opt}^g, c_{opt}^l, and c_{opt}^t are determined according to:

$$\forall c_i^g \in N^g: d_{opt}^g = d(S(c_{opt}^g), S_x^g) \le d(S(c_i^g), S_x^g) \tag{9}$$

$$\forall c_i^l \in N^l: d_{opt}^l = d(S(c_{opt}^l), S_x^l) \le d(S(c_i^l), S_x^l) \tag{10}$$

$$\forall c_i^t \in N^t: d_{opt}^t = d(S(c_{opt}^t), S_x^t) \le d(S(c_i^t), S_x^t). \tag{11}$$

The adaptation as well as the growing and shrinking procedures as introduced in the sections 3-2 and 3-3 are applied. The resulting clustering will represent the distributions in the current environment regarding the different kinds of sensor information, but the relation between places and sensor impressions is missing. Therefore two links between the nets are introduced. In case of stable classifications (i.e. $d^g_{opt} \le d^g_{acc}$, $d^l_{opt} \le d^l_{acc}$, and $d^t_{opt} \le d^t_{acc}$), the links should be set to:

$$L^l(c^g_{opt}) = c^l_{opt} \quad (12)$$

$$L^t(c^g_{opt}) = c^t_{opt} \quad (13)$$

Unfortunately it is not sufficient to establish these connections after each adaptation step, because the densities (regarding the geometric space) in the several networks differ significantly. Using the cells of the geometric network as an index for the whole model (by following the attached links), it has to represent each situation-border in every network. Therefore, an additional "**spontaneous insertion**" is introduced in N^g, triggered by the networks N^l and N^t. After each adaptation step fulfilling the demanded amount of accuracy, the conditions (12) and (13) are checked. In case that the links are correct, nothing has to be done. If the geometric cell c^g_{opt} has not yet any link attached, the demanded links are instantiated. But in the critical case that links are already established but pointing to different cells, the resolution of the network N^g or the accuracy of the internal position is too low. Ensuring that small errors in the position measurement will not lead to new and redundant cells, the topological neighbours of c^g_{opt} in a spherical geometrical neighbourhood of radius ε_{jitter} are checked. If one of these direct neighbours fulfil the demanded conditions (12) and (13), no further processing is required. In case that such a cell cannot be found, a new cell is inserted in N^g immediately, and instantiated with the correct links.

Thus, the restriction that one place should not be linked to multiple situations is considered. The counter direction is of course intended, namely that multiple places are linked to the same light or tough situation.

Applying the non-spatial mapping technique, a couple of effects are obtained:

• *Compact World Model*
In a first phase, all three networks grow linear with the exploration/manoeuvring/navigation time. After establishing a sufficient set of light and touch situations, the growing rates of N^l and N^t slow down significantly. Nevertheless a complete saturation could not be observed (regarding exploration of unlimited, unknown terrain). In the performed tests N^l reaches approximately 20% whereas N^t stays at 5% of the size of the geometric network N^g.

• *Smaller Accuracy*
Due to the more compact world model, some details of specific situations will be lost. This effect potentially increases the required accuracy of the position measurement, because the correlation radius (denoting the spherical, geometrical area, within a proper correlation can be performed) will be decreased. On the other hand, the correlation radius can be manipulated by the network parameters of N^l and N^t directly. Thus, the smaller accuracy regarding the non-spatial mapping is a less critical effect.

• *Global Adaptation*
The non-spatial mapping results in global adaptation of the world model in every adaptation step, i.e. the concept of a corner will be learned employing several examples found at different places in the real environment. The order of adaptation steps is very critical in this context, because the global models of situations can "drift away" when the robot leaves a specific area for some time. Thus, the global situation models can be completely inadequate when returning to an area of the operational environment which was not visited for some time.

A potential but not satisfying solution for the problems of global adaptation would be an introduction of a small influence of the cartesian coordinates in the networks N^l and N^t. This would be a compromise between the qualitative topological maps and the non-spatial mapping, but once again almost identical situations at different areas in the environments will be stored separately, which does not mean any principal improvement regarding the QT-maps. Therefore this solution is not evaluated here, but perhaps it is worth to keep this possibility in mind considering concrete, practical applications.

4. Experiment

In this section, the author tries to emphasize the real world aspect of the *ALICE* project, i.e. the world modelling should be stable regarding the assumed world. The behaviour of *ALICE* is documented under a couple of critical conditions, like inadequate parameters, certain sensor weights, lost correlation, and dynamic environments in [7].

The results shown depend critically on the strategy and order of gathering sensor readings from the actual environment. The set of strategies (called "exploration") applied in these experiments is discussed in [8].

In a static environment, the world model reaches an equilibrium state after sufficient exploration of all available features. *ALICE* needs approximately 15 to 20 minutes to build up a QT-map of the static test environment. The final state (after gathering 5000 sensor situations) represents the geometric features, the light distribution as well as a network graph well suited for the navigator. As introduced in section 3, the network holds much more information than shown in the following figures. The cells contain complete sensor situations together with statistical values about their history, while the connections are attributed by degrees of confidence. All this information is employed in the planning and execution (driving) phase of the navigator.

The second example of a developed world model (shown in figure 2a and figure 2b) demonstrates the ability to adapt to a changing world. In order to make the effect obvious, the formerly closed circle in the environment is cut off at the lower end until the gathering of sensor situation 3500 (figure 2a). Up to this situation, the world model shows a clear gap in the lower part. Although the absolute position error between the two sides of the gap is larger than it would be without the splitting wall, then gap is closed smoothly after another 1500 training steps (and of course, after removing the introduced obstacle). Due to the careful and smooth removal routines, the two worlds coexist for a certain time, until the world with the gap is completely "washed-out". The navigator may take advantage from the fact that the confidence values of the connections distinguish between most recent and established information.

5. Conclusion

Eliminating redundancies by applying the non-spatial mapping methods, memory requirements could be significantly reduced. This is of special interest in applications, where the available computational power or the memory capacity is strictly limited, e.g. in robots equipped with micro-controllers. On the other hand, the reader should keep some critical effects concerning the non-spatial mapping in mind.

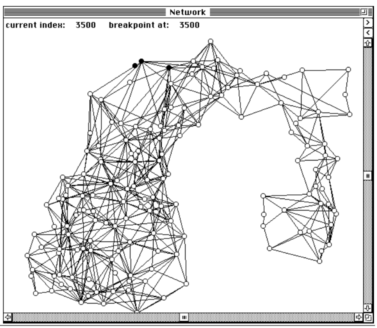

Figure 2a: 3500 samples

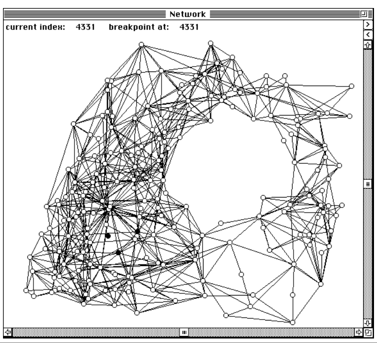

Figure 2b: 4331 samples

The limitation regarding global adaptation will be a major drawback in some applications. Although the original method of qualitative topologic method as introduced in [7] and [8] can be easily handled in using one standard CPU only, the further reduction introduced in the present paper could open up a wide range of applications, where only micro-controller configurations can be employed.

Moreover, both methods (qualitative topologic world modelling and its extention: non-spatial mapping) show superior results, if the main focus is on simplicity, stability or qualitative aspects of the task. Especially the small requirements for sensor equipment together with a high degree of robustness is an unique feature. The experiments have shown real world abilities offering sufficient information for navigation purposes as well as a stable self-localization method.

References

[1] Bernd Fritzke
Growing Cell Structures - A Self-organizing Network for Unsupervised and Supervised Learning
Technical Report 93-026, International Computer Science Institute, Berkeley, California

[2] Herman Keuchel, Ewald von Puttkamer, Uwe R. Zimmer
SPIN - Learning and Forgetting Surface Classifications with Dynamic Neural Networks
Proceedings of the ICANN '93, Amsterdam, The Netherlands

[3] D. Kuan, J.C. Zamiska, R.A. Brooks
Natural Decomposition of Free Space for Path Planning
IEEE International Conference on Robotics and Automation, St. Louis, Missouri, 1985, pp. 168-173

[4] Benjamin J. Kuipers, Yung-Tai Byun
A Robust, Qualitative Method for Robot Spatial Learning
Proceedings of the AAAI 1988

[5] Anthony Prescott
Explorations in Reinforcement and Model-based Learning
PhD-thesis, Department of Psychology, University of Sheffield, GB, 1994

[6] Jun Tani, Naohiro Fukumura
Learning Goal-Directed Sensory-Based Navigation of a Mobile Robot
Neural Networks, Vol. 7, No. 3, pp. 553-563, 1994

[7] Uwe R. Zimmer
Self-Localization in Dynamic Environments
Proc. of the IEEE/SOFT Workshop BIES '95, May 30-31, Tokyo, Japan

[8] Uwe R. Zimmer
Robust World-Modelling and Navigation in a Real World
submitted for publication

[9] Uwe R. Zimmer
Connectionist Decision Systems for a Visual Search Problem
Proc. of the IIZUKA ´94, Fukuoka, Japan, August 1-7, 1994, Invited paper