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Embedding local metrical map patches in a globally consistent topological map

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This article considers some practical and theoretical issues in the trade-off between globally consistent navigation and local precision manoeuvring. Precise local metrical maps are the common base for docking, manipulation, or other exact trajectory planning and control tasks. Yet these models are not scaling fine in the total geometrical size, when handling real world sensory data, and drifts. Nevertheless there is a need for a globally consistent spatial model for long term navigation. The presented work proposes a method of embedding local metric area patches in a topologically consistent global structure suitable for qualitative, and robust navigation. A global positioning information is not required at any stage, which limits the global precision of the spatial model, but on the other hand recommends it for environments where this information is not available. Results from physical experiments with autonomous robots are presented to demonstrate the robustness and practicality of the approach.

Keywords: **mobile robots, world modelling, dynamical environments, exploration, self-localization, self-organization**

1. Motivation

The motivation for this article might be illuminated from two different perspectives. One is sketched by the actual robotics problem, where a concrete localization and navigation task is to be solved. The other perspective on the topic could be described as an abstract life-long, on-line learning problem, occurring in many actual setups. Both aspects will be briefly introduced in the remainder of this introducing chapter.

1-1. The robotics problem

Explorating and navigating at the same time, is a common problem for any autonomous vehicle without global correlations or predefined maps. While not solvable in the general case, its approximated solution is essential for the tasks of artificial creatures and the plain survival of most animals. Considering large areas and limited capabilities concerning storage and measurement precision (a realistic guess for artificial as well as biological creatures), a globally consistent, precise, and metrical map does not seem to be reasonable. On the other hand, highly precise trajectories are required or can be observed in specific situations (approaching the nest, or docking at a loading station). Obviously this cannot be supported by one unique spatial structure. Solutions are offered for locally precise manoeuvring (see e.g. [2]), or for globally consistent qualitative maps (see e.g. [8]). Combinations are suggested on a behavioural level by Gat [3] or Hertzberg et. al. [4] and on a geometrical level by Thrun [7]. The behavioural level approach assumes a precise knowledge about the artifacts capabilities (i.e. its 'command set') and the interpretation of the sensor data, while the geometrical suggestion introduces a topological map based on an earlier created metrical map, i.e. it requires an all covering metrical map. Both directions face severe limitations, when entering large, and unknown environments.

The method proposed in this article, assumes that the topological representation is the primary representation covering the global spatial environment, while precise geometrical maps are employed in local contexts. This implies that there is only a weak or no connection between the individual geometrical maps on a global scale. As shown in the results section the assumptions of the proposed method regarding the artifact itself, as well as about the environment are minimal, while the achieved spatial models are adequate for a global as well as a local variant of navigation.

Before describing the actual method, the theoretical constraints of life-long learning and on-line clustering methods need to be illuminated.

1-2. The life-long clustering problem

Opposed to off-line clustering methods on fixed data sets, constraints and expectation in life-long on-line setups are very different. Such a system, which is requested to find categories in a data stream of undetermined length where moreover no temporal storage of data is available (beside in the structures of the clustering system), meets the following problems. The first severe consequence is that the samples are available in a certain order only. In contrast to off-line systems which can replicate and mix the sample sets, the influence of individual samples on the clustering process will differ here depending on the sampling time. Expecting the exact same resulting clustering representation for any potentially occurring sequence of the input data stream can only be justified in rare cases. On the other hand, it should be expected to generate similar representations (beside symmetry) independent of the sequence of samples. But, since the original data is available only once and can therefore not influence later on adaptation steps with its full precision, even this expectation can only be approximated. Nevertheless, in some setups the unlimited data stream with its maximal number of different samples can even offer stochastical advantages over a small fixed data set, if the sampling trace is chosen adequately.

Although the potential statistical expectations are limited from the very beginning, the considered setup is nevertheless of great significance, because robust life-long on-line learning is (or should be) a central feature of the currently emerging artificial autonomous systems in physical operational environments.

Since the reaction and adaptation time of physical systems is considered a central quality, it is tried to approach spontaneous learning here, but keeping the touchy balance with overall robustness.

A further constraint is the tolerated computational complexity. Assuming a system which is forced to come up with critical control answers under all circumstances (as it is the case with any moving vehicle for instance), and which cannot limit the spatial opertional environment (and thus the spatial model) a-priori, the computational complexity could be constant only. In the presented approach, this does not hold under all conditions, thus it is tolerated to slow down the control loop in rare cases. This can be expected when the focus of attention in the internal spatio-temporal model is lost and a re-orientation requires some time.

Beside the mentioned principal and practical limitations (as shown in the results), the proposed methods enables robust life-long on-line clustering with no temporal storage in high dimensional and fast sensor data streams (720 dimensions and 4.7 Hz are chosen as the basic bandwidth/throughput for the data being analysed in the result section).

2. Clustering technique

Let

$$\begin{aligned} Net = (C, E, R, N, \alpha) = \; & (\{c_i\}, \\ & \{(c_j, c_k) \in [0, 1]\}, \\ & R(c_i) \in \Re^n, \\ & N(c_i) \in \Re^n, \\ & \alpha(c_i) \in [0, 1]), i \in 1 \ldots n \end{aligned} \tag{1}$$

be a network consisting of n cells C, edges E, representatives R (the 'centres' of the data space represented by each cell), snapshots N (an actual sensor sample close to the representative of a cell), and individual adaptation parameters α. Let α_0, λ, p, ε, h_α, h_E, t_E be the parameters controlling the network adaptation process as introduced in the following.

Assuming an empty network in the beginning, the first sensor sample S_1 is employed to generate the first cell c_1, with

$$\begin{aligned} R(c_1) &= S_1 \\ N(c_1) &= S_1 \\ \alpha(c_1) &= \alpha_0 \approx 1/10 \end{aligned} \tag{2}$$

In each subsequent step k, the new sensor sample S_k is compared to all existing cells $\{c_i\}$, employing an metrics $\|\bullet,\bullet\|$, resulting in a distance vector D_k:

$$D_k = (d_i) = (\|R(c_i), S_k\|)\forall i \tag{3}$$

Ordering the cells in the network according to D_k, leads to a set of cells $\{c_i\}$ where

$$\|R(c_i), S_k\| \le \|R(c_{i+1}), S_k\| \forall i \tag{4}$$

Since the process is bound to realtime constraints, the already ordered set of cells is only compared and reordered up to a certain depth, controlled by the precision parameter p, assuring for every sensor sample S_k to be at least one cell c_i with

$$\exists i;(\|R(c_i), S_k\| \le p) \tag{5}$$

Accordingly the set of neurons is checked and reordered only up to a depth, in which a certain number m of cells can be found with

$$\exists i_1 \ldots i_m;(\|R(c_{i_j}), S_k\| \le p \cdot \varepsilon) \; ; \; \varepsilon \approx 3/2 \tag{6}$$

If none close enough cell can be found in the network, i.e.

$$\neg\exists i;(\|R(c_i), S_k\| \le p) \tag{7}$$

then a new cell is inserted:

$$\begin{aligned} R(c_{n+1}) &= S_k \\ N(c_{n+1}) &= S_k \\ \alpha(c_{n+1}) &= \alpha_0 \end{aligned} \tag{8}$$

and placed in the very beginning of the ordered set of cells. In the course of this insertion, the adaptation parameter α is increased for all neighbouring cells also

$$\alpha(c_i) = \alpha(c_i) + (\alpha_0 - \alpha(c_i)) \cdot \sqrt[4]{\left(e^{-\frac{i}{\lambda}}\right)};\ \lambda \approx 1 \qquad (9)$$

where (4) still holds. In the other case ((5) is fulfilled), the representatives are adapted according to

$$R(c_i) = R(c_i) - e^{-\frac{i}{\lambda}}\alpha(c_i)d_i \qquad (10)$$

and all α_i are decreased according to their ranking

$$\alpha(c_i) = \alpha(c_i) - e^{-\frac{i}{\lambda}}\left(\alpha(c_i) - \left(e^{\frac{\log(1/2)}{h_\alpha}} \cdot \alpha(c_i)\right)\right) \qquad (11)$$

with h_α determining the number of steps to halve α. After having the individual cells adapted to the most recent element of the continuous input stream, the snapshot of the closest cell needs to be checked and occasionally updated, the edge-weights of the network are updated and as the result of this, cells could vanish. First, it is checked, whether the current sensor sample could serve as a better snapshot

$$\|R(c_1), S_k\| < \|R(c_1), N(c_1)\| \qquad (12)$$

If this is the case, the current sensor sample is considered the new snapshot model for the cell c_1:

$$N(c_1) = S_k \qquad (13)$$

Next, the edge-weights of the *previously* closest cell c_{1_p} are adapted, if the previously closest cell differs from the current one c_1:

$$(c_{1_p}, c_i) = \begin{cases} \sqrt[n_E]{e^{\frac{\log(1/2)}{h_E}}} \cdot (c_{1_p}, c_i) & \forall i \neq 1 \\ 1 & \forall i = 1 \end{cases} \qquad (14)$$

with h_E determining the number of steps to halve the edge weights and n_E the number of edges emerging from the cell c_{1_p} (note that the edges are directed). All edges with a weight dropping below a threshold value t_E are considered none existent. Finally and based on the potential recent edge elimination, cells c_i without a directed path to c_1 (criteria (15)) or without any incoming edges (criteria (16)) are deleted.

$$\neg\exists k;\forall i;(c_{k_i}, c_{k_{i+1}}) > 0$$
$$\text{where } c_{k_1} = c_i \text{ and } c_{k_n} = c_1 \qquad (15)$$

$$\neg\exists j;(c_j, c_i) > 0 \qquad (16)$$

3. Method discussion

As long as the number of neurons remains constant, the algorithm is a neural gas [5] derivate, where the neighbourhood parameter λ is kept constant and the adaptation parameter α is handled individually for each node. It can nevertheless be expected that the algorithm performs with the same constraints and benefits as the neural gas algorithm in this case. In the case of dynamic number of neurons, the situation is quite different. The overall behaviour of the algorithm optimizes for an equal distribution of representatives in the assumed data space. With the insertion of a new neuron the representative density in this area is abruptly increased together with an ascend of flexibility in the local α. A local reorganization of the further on locally equally distributed representatives is the immediate response. Since the flexibility of the network is different in different areas after growing or shrinking the network, an overall equal distribution is not guaranteed. Nevertheless, a local reorganization will result in a slight change in neighbouring regions, what could in return result in further reorganizations. The probability of drastic reorganisations (the cells are moved symmetrically by the half mean distance between the cells), is reduced with the distance to the insertion (or deletion) point, although situations in which a total reorganization is triggered can be constructed. A total reorganization (a cascade like shift over the network) is the best approximation to a global equal distribution, whereas a plainly local adaptation improves the robustness of the method against slight changes. The parameters λ and α_0 control the trade-off between these two behaviours.

4. Experimental setup

The chosen experimental setup employs the following components:

- an on-line implementation of the life-long clustering method described above.
- a mobile robot, equipped with a laser range finder a three axis gyroscope, encoders, linear accelerometers, and ultrasonic sensors. The individual characteristics are given or set to:
  - *Laser range finder*: measuring on a horizontal plane approximately 20 cm above ground in front of the vehicle; opening cone: 180°; angular resolution: 0.5°; maximal range: 8.12 m; range resolution: 1 cm, sampling frequency: 4.7 Hz (180° scan).
  - 17 ultrasonic sensors: opening cone: ≈ 20°; maximal range: 2 m; minimal range: 0.1 m; sampling frequency: ≈ 10 Hz (all sensors).
  - *3-axis gyroscope*: stability: ≈ 1 °/s; sampling frequency: 178 Hz.
  - *3 linear accelerometers*: resolution: 5 mG; sampling frequency: 178 Hz.
  - *2 Encoders*: resolution: ≈ 86000 ticks per wheel revolution.

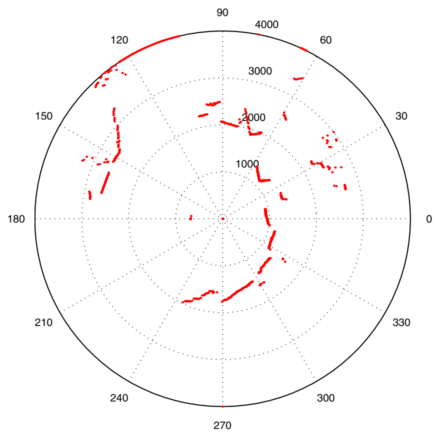

figure 1 : A sensor sample
(720 samples per 360° at 4.7 Hz; distances in mm)

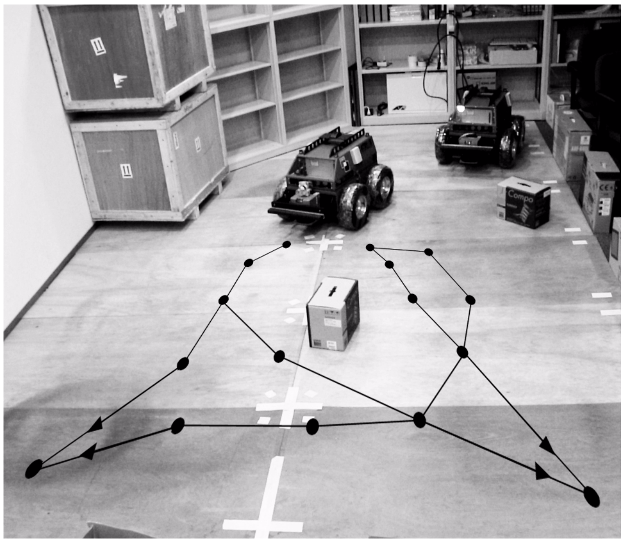

figure 2 : Clustering network

Note that no global position information is supplied and all measurements are subject to drift effects and other systematic disturbances. The laser range image taken during movement for instance is bend and shifted according to the sequential scanning process. The ultrasound sensors are detecting signals not necessarily stemming from physical obstacles in their opening cone, the gyroscopes are naturally drifting, and the odometry is subject to wheel slip.

The resolution and precision of all these sensor systems is much higher than what would be required by the suggested method. A couple of experiments are currently being done, in order to identify some lower borders for the required sensor systems. What can be observed up to now, is that the robustness of the system is not touched by significant sensor disturbances.

By reducing the sensor dimensionality, the process will also become suitable for µcontroller systems, whereas the current implementation utilizes up to 40% of a 300 MHz Linux computer (which can be carried on-board on even small vehicles, but consumes a relatively large amount of energy, which makes these systems critical for long term tasks).

In order to gain a stabilized local range image of the environment, the gyroscope, the linear accelerometers, the sonar system and the laser range system are combined to produce a 360° polar map of the environment. For safety and speed reasons all new detections are immediately included in this model, thus the it reflects the subjective condition of the local environment with at least 4.7 Hz (the speed of the slowest component). A sample snapshot of this local model is shown in figure 1.

For the experiment, the robot is furthermore equipped with a ‘curiosity algorithm’, sending the vehicle around exploring, ‘inspecting’ outstanding objects in the local environment and trying to cover as much open space as can be done on a reflexive basis. The algorithm itself is of no interest for the experiment, it only suits the need for the vehicle to explore the space, which should be reflected in the internal models. An exploration algorithm, which is mutually connected to the spatio-temporal modelling itself, is currently under investigation.

The vehicle is operated in this experiment with up to 0.8 m/s in a continuous closed-loop tracking style, i.e. the control process is not suggesting implicitly any way of dividing the environment, by stopping regularly at certain points in space or similar singular behaviours. The exploration was continued, until no further structural change in the clustering network structure could be observed.

5. Results

After exploring a closed environment for approximately 13 minutes (3767 local polar maps generated), the clustering network was considered stable, i.e. all occurring data in the range of the representatives and the α values near to zero. A plot of the resulting network is shown in figure 3, where the full circles showing the representatives (red/dark means more frequently accessed), and the empty circles representing the attached snapshots. The diagram need to be interpreted with care, since out of 720 dimensions only three are arbitrary chosen and plotted. The actual representatives are equally distributed in the full 720 dimensional data space.

In figure 4, six snapshots of the representatives are plotted at their approximate cartesian recording positions. By finding the maximal correlation of these snapshots in x, y and orientation, the approximate relative recording positions (in green) can be calculated. The reliable (i.e. frequently used) oriented con-

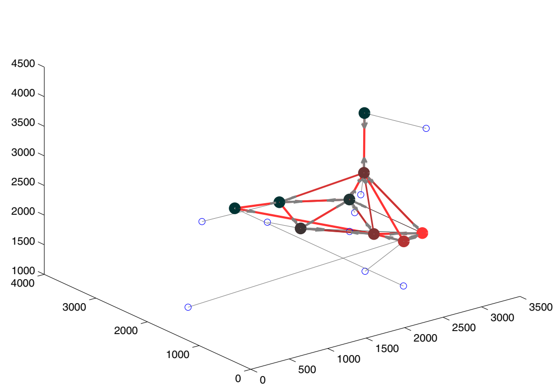

figure 3 : Clustering network

nections extracted from the generated network are drawn between the estimated positions, leading to another more illustrative plot of the actual internally build spatial structure (figure 5). The observed trajectories (the physical realisations of the logical edges in the topological graph) can be further classified and distinguished, in order to exploit all local sensations in their full content. Note that the actual representatives are not bound to a closed area in the real environment. They can be addressed by spatially separated areas characterized by the same or similar sensations. The context given by the sensation sequences is required to distinguish all individual spots or different trajectories [1].

The resulting topological graph is applicable to a standard global graph search navigation system, whereas the local area maps are representing the full available precision suitable for local manoeuvring planning. The structure does not represent any kind

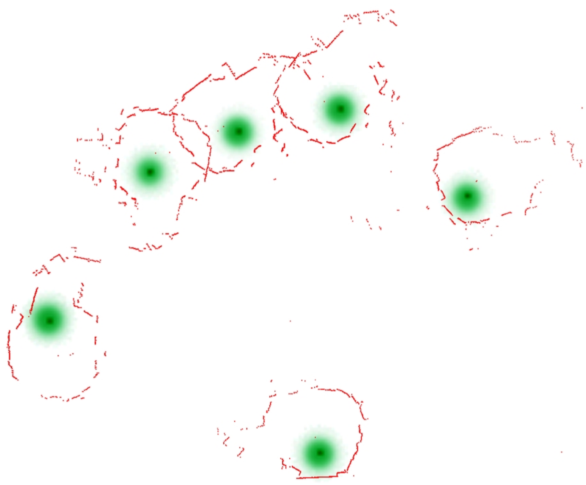

figure 4 : Individual snapshots

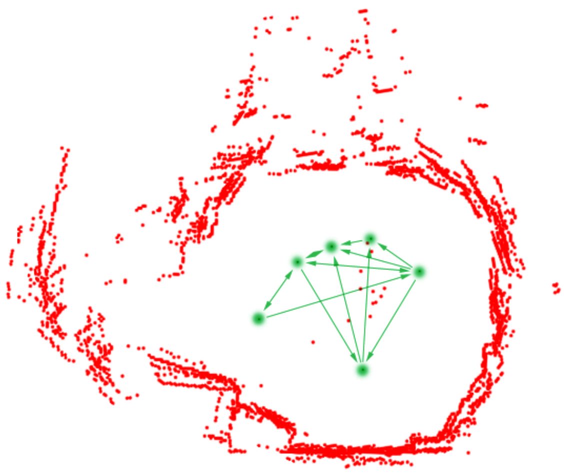

figure 5 : Correlated snapshots

of position explicitly, but the relative positions can be extracted robustly by correlating nightboured cells in the graph [6].

6. Conclusions

The results shown in this article are gained without any specific consideration of the actual environment. The mounting position for the laser range finder or the sonar systems for instance are chosen by chance. These sensor systems can be turned upside down or mounted in any other configuration as long as singularities are avoided. The exploration algorithm was developed before the actual modelling process was designed.

It is very aware to the author, that the morphology and the dynamics of any creature are essential for its success. The work presented here seem nevertheless widely independent from the local geometrical configuration (and of course from a global positioning). A conclusion from this observation could be to further investigate the actual relation between assumed basic underlying principles and instantiations suitable for specific environmental niches. Future work will try to consider this aspect.

References

[1] Emilia Barakova, Uwe R. Zimmer
Dynamical situation and trajectory discrimination by means of clustering and accumulation of raw range measurements
Proc. of the Intl. Conf. on Advances in Intelligent Systems, Canberra, Australia, February 2000

[2] A. Elfes
Sonar-based real-world mapping and navigation
IEEE Journal of Robotics and Automation, RA-3(3):249-265, June 1987

[3] Erann Gat
Integrating Planning and Reacting in a Heterogeneous Asynchronous Architecture for Controlling a Real-world Mobile Robot
In Proc. AAAI-92, San Mateo, CA, 1992. Morgan Kaufmann

[4] J. Hertzberg, H. Jaeger, P. Morignot, U. R. Zimmer
A Framework for Plan Execution in Behaviour-Based Robots
ISIC/CIRA/ISAS '98, September 14-17, 1998, Gaithersburg, Maryland, U.S.A.

[5] T.M. Martinetz, S.G. Berkovich, K.J. Schulten,
'Neural-Gas' Network for Vector Quantization and its Application to Time-Series Prediction,
IEEE Transactions on Neural Networks, Vol. 4, No. 4, July 1993, pp. 558-569.

[6] Franiois Tièche, Heinz Hügli
From topological knowledge to geometrical map
Control Engineering Practice 7 (1999) 797}802

[7] Sebastian Thrun, 1998.
Learning Metric-Topological Maps Maps for Indoor Mobile Robot Navigation.
Artificial Intelligence 99(1), 21--71.

[8] Uwe R. Zimmer
Robust world-modelling and navigation in a real world
Neurocomputing 13 (1996) 247-260