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Dynamical Situation and Trajectory Discrimination by Means of Clustering and Accumulation of Raw Range Measurements

Emilia Barakova & Uwe R. Zimmer

GMD - Japan Research Laboratory
AIM Building 8F, 3-8-1,
Asano, Kokurakita-ku
Kitakyushu-city, 802-0001, Japan

This article focuses on the problem of identifying and discriminating situations and trajectories (as sequences of situations) in an autonomous mobile robot setup. The static identification level of situations as well as the dynamical level of trajectories are based on egocentric measurements only. Adaptation to a specific operating environment is performed in an exploration phase and continuously during operation. Descriptions and classifications are based on statistical entities of the operating environment (in the geometrical space and in the space of dynamics). The recognition is performed in the sense of emitting the same signals in similar situations or on similar trajectories. Neither a global position nor any other global geometrical description is created or employed by this approach.

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

1. Motivation

Exploring hostile and previously unknown environments (as deep sea, space, etc.) is a challenging subject, investigated by a couple of different authors [3][7][11][22]. As a realistic presumption, characterizing such an environment, it is assumed that it is dynamical: it changes and causes changes in the position or the perception of the 'explorer' itself. Therefore, an increasing amount of robotics research focuses on motion tasks, which has to be completed autonomously by additionally taking into account their inherent dynamics [4][9][13][14].

The autonomous motion task implies two major assignments, which have to be performed concurrently: the construction of a representation which is useful for guiding robot movements and navigating according to the so created representation. Taking into account the remoteness of the environment, its exploration need to be performed without support of a global observer of any kind, i.e. the only information available is the subjective (egocentric) perspective of the autonomous robot, constructed from a sequence of measurements, considered as their observable dynamics (order and variability of their appearance).

Correspondingly, the task of creating a representation, suitable for navigation has to be addressed by reflecting both: the dynamical changes in the environment as well as the dynamics of the robot perceptions (as one of the few information sources). Furthermore, in real world environments it is to be expected that sensors occasionally will not detect situations (places) or not being able to distinguish among different locations (sensor aliasing). It is obvious that both types of dynamics as well as the sensor aliasing are reflected in the robot perspective, i.e. they are equivalent from the explorers point of view.

Our ultimate goal is to build an inherently dynamical representation, suitable for navigation, where this paper focuses on reliable discrimination of dynamical scenarios.

Since two aspects of the robot perceptivity needs to be persuaded simultaneously: the obscurity of the observations and the dynamics of its perceptions, the requirements they pose and the existing approaches to solve them are described in the following.

The former aspect requires that creating a spatial representation has to imply collection and memorisation of the robot observations in an effective way upon the environment it is to explore. Naïve gathering and storing of observations (measurements) will not meet the memory and computational limitations when a real world task has to be accomplished. A common way to overcome these limitations is to define two levels of abstraction when building an effective representation: global and local [4][8][17][19]. Global features are modelled in a topological like manner by recording the geometric or similarity relationships between the observations. The important details are shown in a straightforward manner with their absolute metrical relationships and form local representation. There is a range of known possibilities to combine these two levels of representation determined by the features of the environments to be described and the tasks to be accomplished [17][19][21].

The second aspect, dynamics of the environment, suggests that a straightforward metrical/topological division of the surrounding space is very difficult to achieve. Particularly, a suitable alternative of metric representation has to be found, that encodes local robot observations with respect to the variability of their appearance instead of absolute distances among them.

It has been suggested by neurophysiological and psyhological experiments that spatial information is represented in the brain as ordered pattern maps [1][5]. This is the reason for us to choose a neural solution, that forms a map-like representations. Models for short and long-term memory (STM, LTM, see [2][5][12][20]) that imply naturally information about the dynamics of the underlying processes have been particularly considered.

Related to the so defined research directions, our approach preserves the idea of constructing a topological representation, (for instance in a form of a dynamical graph $G = (V,E)$) as an 'ultimate' navigation setup. The nodes (vertices) V of this global topological graph contain sufficiently detailed interpretation of the local dynamical perception of the environment and the edges E have to give the most probable relation among this places.

Building the local dynamical perceptions that attribute the nodes of the topological graph is the focus of this paper. Since the nodes of the topological graph has to be defined as a locally distinctive places the authors suggest to identify discernible structures of real environments. Discernability does not require, that from one situation (static state) the scenery can uniquely be discriminated, but rather that there exists a sequence of situations, that can be used to separate any two scenarios.

Practically, the scenarios are expressed as a sequence of distinguishable states (situations). This sequence is defined as a dynamical trajectory and encodes the history and the variability of robot perceptions.

2. Spatiotemporal modelling

The frame of the work presented in this paper is a general understanding of spatiotemporal learning processes suitable for robust navigation tasks. This schema can be divided by means of timing. A *preprocessing and correlation* phase processed with every sensor data sample, a *'focus of attention' - correction* phase processed with some delay to the sensor data sampling time and finally a *spatiotemporal model update phase* processed with a significant delay. These general phases are discussed briefly in the following.

Preprocessing and correlation

The most recently sampled sensordata (left in figure 1), which is possibly compound of different sensor modalities is preprocessed (e.g. removing what is obviously noise) to a so called 'situation', describing the most recent perceptions of the robot. The situation can include (accumulate) some part of the recent history also. At the some time and based on a formerly set focus of attention, a certain part of the spatiotemporal memory is extracted and called the 'local model'. The final and main task of this first stage is the correlation between the local model and the current situation. The degree of correlation reflects the degree of being embedded/adapted/ in/to/ the current operating environment.

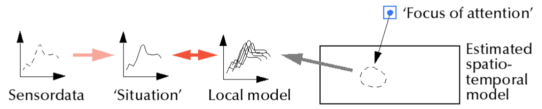

figure 1 : prococessing and compression

'Focus of attention' - correction

In this second phase which is done on a slower timepiece than the first one, the spatiotemporal internal model it is still considered static. Based on the accumulated outcome of the preprocessing and correlation phase, only the focus of attention as a pointer to the most active part of the current internal model is corrected in order to reflect changes in the state of the robot (which will be in the easiest case a change in the position of the robot, but can also refer to changes in the environment, which are represented in the internal model already). Still the intention at this timescale is only to keep the internal model as close as possible in correlation with the flow of sensor data without changing the internal model itself.

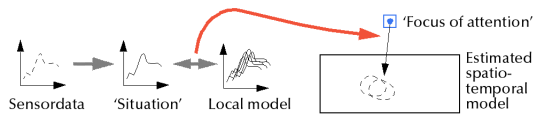

figure 2 : 'Focus of attention' - correction

Spatiotemporal model update

According to biological observations (see e.g. Pöppel et. al. [15]) the internal model is updated significantly slower and with a certain delay to the signal sampling time. This makes sense, because the robot can-

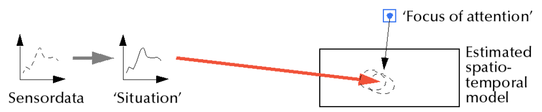

figure 3 : Spatiotemporal model update

not make use of its internal models and change them at the same time. Thus the update of the spatiotemporal model and the usage of it is decoupled. Nevertheless all mentioned phases are processed in parallel and all the time, but they are operating on different areas of the model. While for instance the spatiotemporal model update is integrating the sensor data being perceived some seconds ago, the preprocessing and correlation phase is concerned with the most recent sensor data and at an already advanced focus of attention.

In the present paper only the first and the third phase are discussed in terms of a physical experiment.

3. Dynamical trajectory formation

Within the framework of establishing a general spatiotemporal learning model (section 2), this paper focuses mainly on creating of distinguishable local representations. With respect to the timing division made so far, our experimental setup concerns formation of situations by coupling the current data flow with the already existing situation space and adaptation of the overall spatiotemporal model.

As discussed in the introduction, distinguishing among the local representations is possible only if they are considered together with their dynamics.

First, a discernable structure has to be constructed: the obscurity of the environment, the similarities caused either by the range of detected objects or by the clustering method presume that a sequence of observations are needed to reliably discriminate among two scenarios.

Attempting to encode the local features of the environment without using metric (spatial) references, a qualitative positional model is chosen also for the local representations. Among the possibilities to express the spatial knowledge a survey type (a view from above on a spatial situation) or route type (giving the order between the encountered landmarks) description can be distinguished. Obviously, the nature of the information stream (egocentric view of the autonomous robot, that is constructed from sets of measurements, recorded in their variability and order of appearance) and obscurity of the environments to be explored, suggests that route information is more stable as positional and spatial qualifier. This establishes the second aspect of our dynamical model.

Combining the trajectory perspective with the discernability of the observations suggests to 'scan' differing observations of the robot in the sequence of their occurrences. In agreement with theories about spatial information coding in the mammal brain [1][6], the authors suggest to distinguish according to some criteria the observations, that the robot makes in a short term in a sequence of maps (figure 4). Since neural algorithms perform particularly well on clustering uncertain data and can give a solution in a map like form, a neural model has been chosen. Moreover, it is tried to give a high degree of freedom to the ways a discrimination of varying perceptions is to be performed. This requirement specifies the choice of self-organising neural algorithm. Particularly, the neural gas (NG) algorithm [10] has been selected as a clustering technique for the result presented here, due to its high stochastical stability. The clustering actually employed on the robot itself, is an on-line, life-long learning, method, applicable for real setups, but with (naturally) weaker stochastical assurances.

Figure 4 shows a schematic trajectory passed by the mobile robot. The places, where the robot perceptions are to be distinguished are marked with circles at the left sub-figure. The middle sub-figure depicts the map-like representations of different encountered clusters they are assigned to. Furthermore, the so created sequence of static cluster scans have to be combined in a way that they imply the history and the dynamics of this short exploration path. A hint of how to encode the information from different situations, forming a distinguishable route in a suitable and compact representation are found in the theories, featuring the memorising process: The new observations are strongly influenced by the previous once, and the strength of the previous impressions fades with time.

Encoding of time history in the new representation is studied by various authors. First, the *decay theory of forgetting* has been established. The earliest models within this theory suggest, that older patterns are fading with time in an exponential manner. Correspondingly, a common methodology to describe various memory architectures is to represent the short-term memory as a convolution of the input sequence with a kernel function (1):

$$\bar{x}_i(t) = \sum_{\tau=1}^{t} f_i(t-\tau)x(\tau) \tag{1}$$

where $x(t)$ is the input and $f_i(t)$ is the convoluting function.

Tank & Hopfield [18] proposed a set of exponential kernels (2) to sample the signal history.

$$f_k(t) = (t/k)^{\alpha}(e^{\alpha(1-\frac{t}{k})}) \quad k = 1, \ldots, K \tag{2}$$

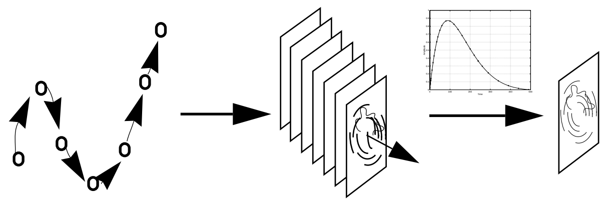

figure 4 : Trajectory as a sequence of encoded route maps

In this model, each unit samples within a certain period, peaked at a specific time step $t = k$. De Vries and Principe [16] propose *gamma* kernels instead of exponentially decaying ones. The advantages of this model are, that N-step history may be sampled by less then N kernels. Moreover, the gamma kernels can be computed recursivelly, whereas by the exponential kernels the convolution must be computed between the kernel function and the activity history.

In the models described so far each symbol is traced independently from other input symbols in the Short-Term Memory (STM). Instead, the *interference theory of forgetting* (Wang and Arbib [20]) offers a flexible time traces for storing input symbols, depending on how often later symbols enter the STM.

Further understanding of the human retination leads to models, that in addition to receintcy imply also a primacy factor, whereby the beginning items in a sequence are less prone to forgetting [2].

For our initial exploration a simple model from the decay theory of forgetting has been chosen. The distinguished patterns from the sequence shown at the middle plot of figure 4 are convoluted with an exponential function, as determined in equation (1). The resulting encoding implies one single map for a trajectory, considered to be quite compact as a local representation. Schematically this is shown with the right subplot.

A so defined and encoded sequence is defined a dynamical trajectory, although no global spatial metrics is applied to the sequence of passed states.

4. Experimental setup

Summarising, our initial experiments are performed by utilizing the following features of the outlined memory and computational models. First, it exploits the idea of encoding the incoming patterns in a sequence of ordered pattern-like maps. This idea is brought to a practical realization by the self-organizing NG algorithm, that finds distinguishable observations and encodes them as memory patterns. The second idea, incorporated in our model is based on the assumption that the most recent patterns have the greatest impact on building an orientation picture in a scenary. Therefore, the incoming input patterns are convoluted with an exponential function, as shown at figure 4.

The empirical prove of the consistency of the so proposed dynamical trajectory model is to be made for the environments or signals, that provide for ambiguities in the situation interpretations, if considered in their static form. For instance, similarities in the environment are a potential drawback for static discrimination of situation vectors.

Because of that an exploration of an environment was performed in terms of either reaching two obser-

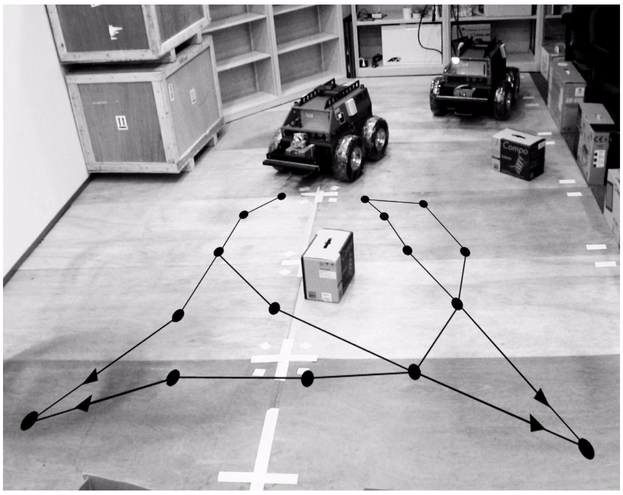

figure 5 : Experimental environment

vation points with high degree of similarity (the same from the observers point of view) or passing different, but overlapping to a certain extend routes, or routes formed by situations, that can be interpreted by the sensor system as the same.

In contrast, invariances of the sensor readings to slight transition require complex noise models, if the situation formation process does not deliberate them. The situation formation process has to find the trade-off between both constraints.

The first constraint is resolved directly by applying the dynamical trajectory concept.

Through a long exploration in a static environment the robot collects information about it. The collected information is used for learning of the environment which implies clustering the observations to a recognizable states (situations).

For the testing phase various trajectories are constructed. All of them are finishing at either of two points, which are constructed to give the same sensor output i.e. there is a similarity in the last perception. Some of the trajectories are partially overlapping (that brings another degree of similarity - in the number of observations that form the dynamical prospective). The so designed trajectories are suitable for testing the discriminatory abilities of the dynamic trajectory method with respect to both types of similarity.

The second requirement for invariance with respect to slight translations of the robot assumes, that the description of a particular situation is robust against them. The employed clustering (learning) algorithm is insensitive to translations of the vehicle - up until a certain range. The lower precision - the smaller number of distinguished situations increases this invariance insensitivity, but the trade-offs with the accuracy of the identification process has to be considered also. The method used so far is not invariant to rotation.

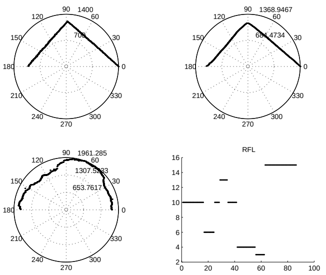

figure 6a: RFL

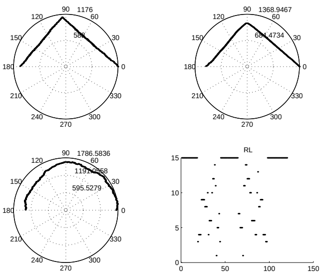

figure 6b: RL

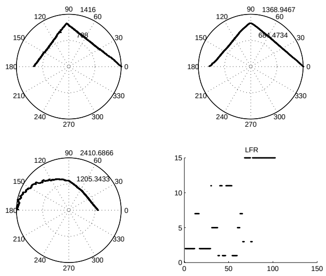

figure 6c: LFR

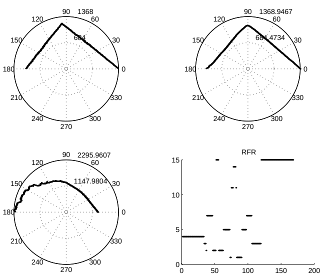

figure 6d: RFR

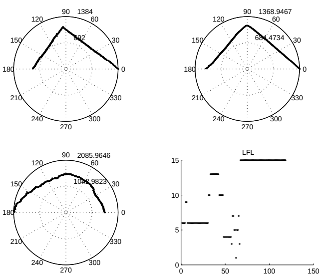

figure 6e: LFL

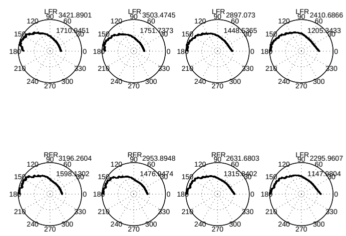

figure 6f: comparison RFR LFR

5. Results

In order to estimate the relevance of the obtained results easily, let us remind once more the main aim of this paper: to discriminate scenarios, that look similar with respect to one or more local perceptions without losing the invariance to slight transitions.

The suggested dynamic trajectory method discriminates various scenarios by considering the subsequence and variability of observations within certain time period. For the goals persuaded by this paper it is sufficient to accomplish the exploration of the created environment by predetermining the number of clusters, corresponding to different situations. After an exploration of approximately 8 minutes and collecting ≈2500 samples, 15 different situations are found sufficient to distinguish various places. 6 test trajectories have been constructed to contain all types of similarities to be distinguished. More precisely, the test trajectories are constructed to check whether the created method can discriminate:

Two places that look the same.

Due to the various routes, the similarly looking places have been reached, it can be easily concluded (from the differing dynamical trajectories) that there are different scenarios observed. It is logical to expect that similar outcomes of the dynamical trajectory representation will be detected, if the same place is reached in different ways. In real life scenarios this problem will be naturally resolved, by comparing the current maps from the time history, that will differ in the first case and be equivalent in the second.

From figure 6a to 6f it can be seen, that the final sensor readings look all the same (the upper left figure of every subplot. The NG algorithm has assigned them in the same class (class #15) and the output of the neuron for this class is visualised at the right upper figure of the subplots. Although the last encountered situation is the same the dynamical trajectory vector differs for the various tests.

Trajectories, that are partially overlapping.

Basically, the method is able to discriminate among scenarios, captured in their dynamics if they differ in some of the percepted situations. If the overlapping comes in later stages of the situation formation, the outcomes from the dynamical trajectory method are very similar. This effect is observed by the trajectories from figure 6c and figure 6d where the actual route passes the same places at its last fragment. Correspondingly the few latest observed situations are very similar as shown at figure 6f.

For resolving the appearing ambiguities in such a case the final observations can be compared in addition. The authors are looking forward to compare the results with another way of coding STM.

The classification algorithm assigns the so discovered dynamical trajectories in different classes, except those from figure 6c,d.

6. Discussion and following work

To distinguish among similarly looking places in the environment as well as to address the sensor aliasing problem, a highly symmetrical (i.e. hard to distinguish locally) experimental setup was created. The constructed situations can be distinguished only after considering the dynamics of the scenario, expressed as a trajectory of situations and probabilities of transitions between them. The obtained results show that trajectories, ending in the same local sensor perception are easily distinguishable, due to the differing previous situations, influencing the resulting dynamical trajectory representation. The dynamical trajectory approach distinguishes also the same place, if it has been reached in a different way.

The self-organizing method, used to discriminate between similar trajectories performs off-line classification of the existing states. The number of classes has been determined a-priory. Currently, an on-line, and life-long learning clustering is employed on the robot itself, and the stochastical characteristics are obviously different from off-line methods.

The dynamical trajectory as constructed in this paper does not give any topological relations between the detected situations and scenarios, since the NG algorithm does not have topology preserving features. Topological relations are currently handled in the online clustering implementation on the physical robot as relations between subsequent situations in the sensor-data space.

Analysing the (in the meantime implemented) online principles together with the topology preserving strategy is an immediate goal of our current work. More interesting perspectives are also expected in deepening the knowledge about STM possibilities for coding information in both: their biological grounds and engineering implementations.

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