Global spatial modeling based on dynamics identification according to discriminated static sensations

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Abstract— **This article focuses on the problem of identifying and discriminating trajectories (as sequences of situations connected by transition-dynamics) in a mobile robot setup. The continuous time dynamics are segmented and scaled by transition sensations between significantly different static situations. The complementary information out of static attractors and dynamical transitions is fused in a canonical way and under hard realtime constraints. Based on the generated and continuously adapted trajectory models, a global topological model is maintained and attributed suiting the needs of robust qualitative navigation tasks. Neither a global position nor any other global metrical description is generated or employed by this approach, thus it is not meant to fulfill global precision requirements. The presented results describe physical experiments with autonomous robots in unprepared environments.**

Keywords— **mobile robots, world modeling, dynamical environments, exploration, self-localization, self-organization**

I. Motivation

DUE to the various restrictions that the remoteness and the complex dynamics pose, spatial modeling of hostile environments is a very complex task [1], [2], [3], [4], [5]. The major borders of complexity are drawn from the impossibility to employ a global position or any other global metrical description of such an environment, its complex dynamics, and the uncertainty of the acquired sensor information.

All the restrictions which the environment poses predetermine that the modelling can be performed only by means of the information which the explorer itself obtains and provides, by deciding whether, how and with what degree of certainty to interpret it.

The egocentric perspective of the robot-explorer combines absolute (measured by magnetic compasses, active beacons, global positioning systems, landmark navigation, model matching) with relative (measured by gyroscopes, accelometers or wheel encoders) information. The absolute knowledge of the autonomous robot is constructed from a sequence of measurements, considered in the order of their appearance, and therefore they do not distinguish among dynamics of different origins (dynamics of the robot itself; dynamics of the environment, that does not affect the explorers movement; dynamical changes in the environment that change the explorers position and/or direction, etc.).

In previous work [6] that aimed at discrimination of local sceneries, all kinds of dynamical changes are considered as they are reflected in the explorers perceptions. This approach shows good results for local modeling. For building a global model of an environment with complex dynamics such an subjective (relative) perspective it is not sufficient. In addition, another, more 'objective' frame of reference is searched for. The remoteness of the environment presumes that neither a global observer is available, nor stable landmarks are known a-priory. Therefore, a solution for an alternative frame of reference can be searched in the measurements about the robot's position and movement, provided by the gyroscope, and thus the information that it supplies has absolute character.

At contemporarily, established approaches for combining an absolute with a relative positioning information are based on probabilistic combination methods [7], [8], [9]. This way, the uncertainties when fusing data from different sensors are naturally incorporated in the modeling process.

The probabilistic methods have shown good results in combining data from one type of sensors, but can not provide a theory for combining data from multimodal sensor sources. Bayesian networks has been applied with success to fuse sensors from different modalities [10] in a topological map building task. Alternatives such as occupancy grids [8] and evidence grids [11] representations have been suggested later on. The common approach in the mentioned works is to translate the information from different sensor streams to a common concept and to minimize the uncertainties in the different recordings by decreasing the error probability in a common representation. The different recording rates are equalized by either lowpass-filtering and downsampling the faster data stream or by interpolating the slower one.

Our critique on this general approach is, first, that by downsampling or lowpass-filtering a lot of substantial information can be lost. Second, by dealing with uncertainty in an error-averaging minimization method one can only tune the results, but never obtain a representation with new quality. The attempt to find an optimal representation of the available information, made in this paper is grounded on the idea that the environment and processes that are strongly dynamical in their nature can not be described effectively by combining static entities. Moreover, the dynamic features, encaptured by the sensors can not arise by chance, since they are extracted during a longer time span. Preserving the dynamic information by sources with different recording frequencies requires a different pattern of extracting and combining the information encoded in the different data streams.

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Following the global frame of work outlined in [6] movement models are derived, based on a comparison between the two dimensions of motion that reflect the dynamics of the transactions in between different situations. Attaching this models to the local models of the encountered situations, as defined in [6], is a major step for building a reliable global spatial model.

The paper is organized as follows. In section II, a global framework for spatiotemporal modeling is given that determines the place and importance of the current work. The following section III describes the background and ideas behind. The relevant experimental setup is outlined in section IV followed by some results of experimenting with the described method. In perspective, we discuss the relevance of the current experimental work and aims in section V.

II. Global modeling as an interaction of two frames of reference

As discussed by many authors [7], [12], [4], and suggest as working approach in [6] a convenient way of world representation is a use of topological maps expressed by graphs. The vertices in the graph correspond to distinctive places while the edges (in the graph) between them give a probabilistic indication of reaching such a place from a recognised one. Such maps do not contain any metric (or geometric) information, but notions of proximity and order. Therefore they are robust to local movement errors. In addition, topological maps represent space very compactly since they only represent distinctive places. In the framework outlined in [6], the main goal of building an inherently dynamical representation, suitable for navigation is achieved by the dynamical trajectory method, which has been used for creating such a distinctive places. In this context the dynamical trajectories are stored in the vertices, and therefore will be considered in their final (static) form.

Here, the dynamics in the frame of the global representation will be taken into account, i.e. the transition dynamics between the vertices. As already discussed, the global modelling task requires a combination of at least two different reference methods, because of the potential misjudgment that every method can employ.

On the basis of the data, that the gyroscope provides, together with range data, movement models, representing the probable transactions to a new state are created. Since both: the relative measurements, that the gyroscope records as well as the measurements, provided by the range sensors stem for big accumulative or estimation errors, the metric information is not used directly.

An idea how to exploit the available information in a way that avoids accumulation of errors is based on the following. A term, widely associated with relative methods for position estimation is dead reckoning and refers to the process of updating one's estimate of its position on the basis of knowledge of how fast it has been moving, in what direction, and for how long. There is considerable evidence that this process plays a fundamental role in navigation in animals: from ants to humans [13]. Although humans (for instance) have dead reckoning abilities, they are not precise on a longer time span. For instance, humans can hardly fulfil a moderately complex navigation task by only counting on this ability. On the contrary, the knowledge about the instant movement contributes a lot to the short-time navigation, while in longer term humans use their perceptions of the surrounding world. Of course, to draw analogies between a human's feeling for space and robots gyroscope measurements is not a straightforward and easy task. Following the general idea only, it can be shown how the information about the instant movements of the robot are beneficial for the short term navigation.

III. Movement models

The combination of the absolute and the relative reference frames is accomplished on two levels: methodological, discussing how to build movement models, that contribute conceptually to the global modeling and technical, that accounts for the different nature of the information streams and the different frequencies of the recordings. To distinguish both aspects, two terms are used: multisensor integration (which refers to the synergistic use of the information provided by multiple sensory devices to assist in the accomplishment of a task by a system) and multisensor fusion (which refers to any stage in the integration process where there is actual combination of different sources of sensory information into one representational format).

In the framework of the global modeling task it was outlined, that the end representation on the node level, that the dynamic trajectory method provides is in a diagram form. Accordingly, there should be a compatibly compact way for representing informative transactions, among different situations or sceneries.

In consideration with our critique against the suitability of the established methods for fusing data from two different sensor modalities, the necessary information from both strings is taken in beneficial interaction: Initially, the range sensor data from long exploration is divided into clusters, that correspond to distinctive perceptions of the robot. The corresponding gyroscope records, characterizing the relative robot movement, are divided into intervals, defined by the so determined distinctive perceptions.

The gyroscope recordings between two situations (two distinctive perceptions) are used for the construction of velocity trajectories, characterizing the movement between this situations. As discussed before, the information for the instantaneous movement that the robot provides is used for close navigation goals (in our case between two situations) and the perceptions of the environment, that the range sensors record - for movement understanding, that accounts for environmental dynamics and can compensate for accumulative errors.

To extract the needed information about the type of the movement between two places, the trajectory type has to be distinguishable. Therefore, the transactions between two distinctive perceptions are divided on classes. The transactions, that belong to the same class describe specific type of movement, that we call movement model. In short, the process of movement model formation is shown in figure 1.

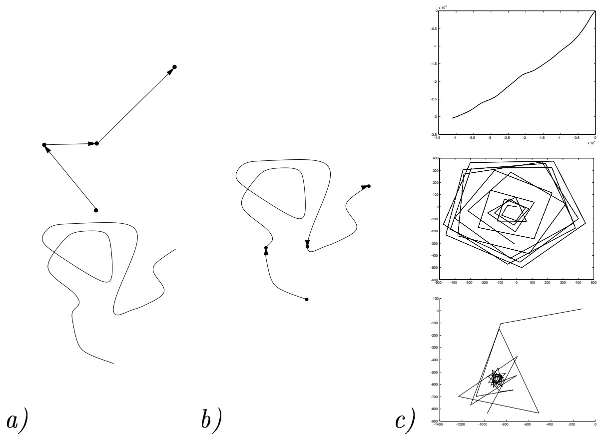

Fig. 1. Stages of motion model formation. From the graph representation of the discriminated perceptions and the gyroscope data *a)* is created the velocity trajectory *b)*, that is a basis for the movement models *c)*.

On the basis of the graph that represents the distinctive perceptions and the recorded by the gyroscope velocity data (shown in the left part of figure 1) are build diagrams, characterizing the transaction between every two nodes, which we call velocity trajectories. Their classification is a complex task that might imply different processing steps. Aiming to give a freedom to the classification process to define itself the pattern of the underlying movement, the only processing over the extracted velocity trajectories between two encountered distinctive situations we take is to equalize their length. Therefore after their formation they are resampled (interpolated or undersampled).

After clustering the data from a long exploration, and classifying additionally recorded trajectories that are made to carry out a specific route, different paths has been distinguished to describe the same type of movement. The distinguished in this way trajectory type determines distinctive movement models, correspondingly for straight, rotational and combined movements, characterizing transactions between different places (figure 2).

IV. Exploration in changing environments

As outlined in the introduction, the modeling task approached in our research has to meet the restrictions that changing environments pose. The representation, made in [6] reflects the robot perceptions about its own dynamics and the dynamics in the surrounding environment, as they are encoded by its range sensors. Because the range sensors provide relative type of information, the additional knowledge about the overall dynamics, provided by the gyroscope, (i.e. the absolute knowledge about its movement) helps distinguishing robot's motion in diferent environments. Therefore, the contribution of the created motion models is that they account for specificity of the environmental dynamics.

There are different taxonomies possible, that structurize the types of dynamical changes in the environment. The

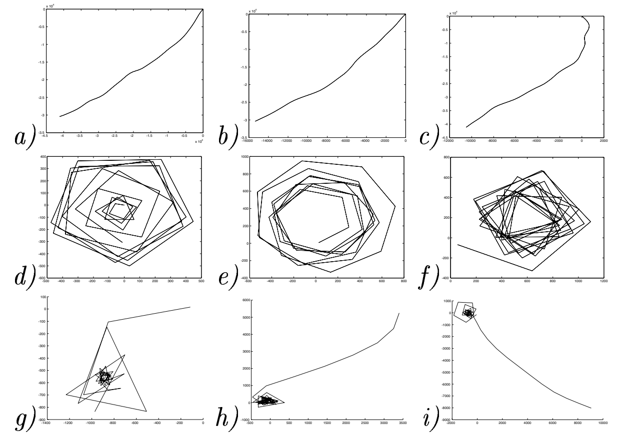

Fig. 2. Classes of trajectories. The clustering algorithm has assigned the trajectories from subplots *a)-c)* from *d)-f)* and from *g)-i)* to the classes of correspondingly straight, rotational and combined movement.

taxonomy, suggested in [4], is summarized in figure 3. In agreement with it, it can be shown, that the constructed movement models account for lasting environmental changes, that affect robot perceptions. Since the spatial model is build on the basis of the subjective perspective of the robot only, having understanding over it helps creating an objective orientation model.

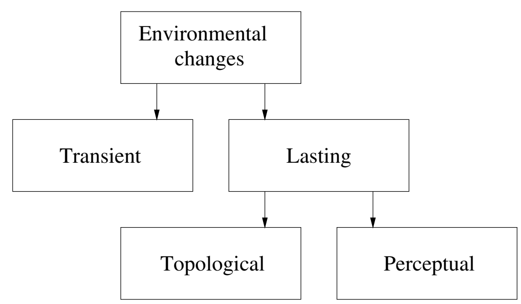

Fig. 3. Taxonomy for environmental dynamics.

The relevance of the developed movement models for global modeling of dynamical spatial environments is shown with the following setup. The experimental robot is made to wander on floors with different friction characteristics (figure 4. The robot is guided to surpass very close itineraries and to encounter the same distinctive places. As a result, the robot has different perceptions about the speed and correspondingly the distance it has passed, as the recordings, made by the gyroscope detect, while the range sensors encounter the same environmental features.

The difference in the perception of its movement is clearly seen in the plots of the velocity curves, build on the basis of the gyroscope measurements, as shown in figure 5. Correspondingly the movement models, characterizing the connections between the encountered distinctive sceneries in the environment differ, as it is straightforward to be shown.

This experiment illustrates the contribution of robot's knowledge about the characteristics of the environment, expressed in its perceptions about its own motion, to the accuracy of the spatial model it creates. The data from the sensors with either relative or absolute nature are a basis for creating objective local models about the dynamical perceptions of the robot about the topology and changeability of the surrounding environment or about the perceptions of its own movement with respect to the (changing) environment. The combination of both types of information in one model encodes the environmental features together with the robot motion in a compact way, that allows the informative dynamical features to be restored when the same sequence of sceneries or transitional dynamics are encountered.

Fig. 4. The experimental environment.

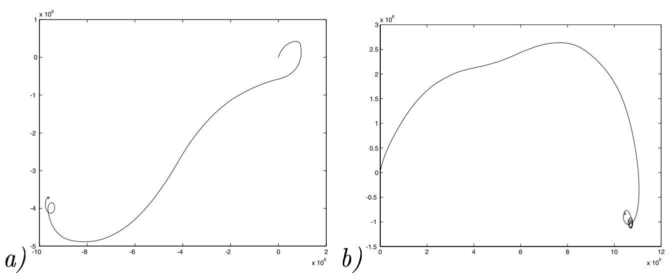

Fig. 5. Velocity curves when exploring environments with different dynamics.

V. Towards a global model

This paper features building of a qualitative description of the motion between two distinctive situations in a beneficial for a global spatial modeling way. The dead reckoning data recorded by a gyroscope are used together with a dynamical trajectories to form models of the movement, that help distinguishing among moving and static (stability belonging to the environment) entities.

The combined model is based on the coherence of the perceptions from different groups of sensors. The sensors that determine the robot's dynamical view about its surrounding environment divide the time intervals, according to which the recordings, accounting for the robot motion can reliably be integrated in a usable model.

The method does not try to interpret the data from different sensor modalities and fuse them because they express the same measurable characteristics. The need of exploration by means of uninterpreted data has been elaborated earlier in [5].

Moreover, it does not try to minimize the combined error function, constructed on the basis of the probable errors, that the separate sensor modalities make. Instead, the developed method takes into account the measurements of one sensor source on intervals, that does not allow accumulation of errors, that will affect the modeling process. Next, it takes information from the other type sensors and corrects the spatial estimation. Switching back to the first sensor source, the estimation error is "initialized" and starts accumulating from zero, while the error from the previous type of sensor is corrected by the alternative position estimating source.

The main contribution of the method is in its dynamical way of coding the transitions between the distinguished perceptions. Many recent works attempt to incorporate the dynamics of the robot's perceptions into the spatial mapping process. Additionally to the perceptions, which in analogy to those in the biological systems are formed on the basis of their variability in time, this paper outlines a way to represent also transitions between this perceptions in their absolute dynamics. In representing the global spatial modeling as inherently dynamical process we see a promising direction for solving complex navigation tasks.

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