Self-Localization of Autonomous Robots by Hidden Representations

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Abstract. We present a framework for constructing representations of space in an autonomous agent which does not obtain any direct information about its location. Instead the algorithm relies exclusively on inputs from its sensors. Activations within a neural network are propagated in time depending on the input from receptors which signal the agent's own actions. The connections of the network to receptors for external stimuli are adapted according to a Hebbian learning rule derived from the prediction error on sensory inputs one time step ahead. During exploration of the environment the respective cells become selectively activated by particular locations and directions even when relying on highly ambiguous stimuli.

Keywords: autonomous agents, place fields, self-localization, hidden Markov model, internal representations

1. Introduction

Placed in an unknown environment humans, animals, and robots receive only incomplete information about their current location via their senses. Nevertheless, we and many other animals very quickly develop a sufficiently precise knowledge of where we are and at which direction we are heading. Analogous abilities can be achieved in autonomous robots, e.g., by using specific sensors such as distance meters or compasses or by exploiting prior knowledge on identifiable landmarks, cf. (Franz and Mallot, 1998) for an overview. The present contribution studies the self-localization problem under weaker assumptions on sensory information and prior knowledge. In particular we exclude the presence of a map or other spatial information about the environment and the existence of external guidance.

Instead, the agent studied in the present experiments relies solely on sensory inputs and information about its own motor actions. These two sources of information are the only ones available in many animals.

Internal sensations of actions performed by the robot reveal the main causes for changes in position and, hence, in sensory input. Thus, sensory input being the only source of information about the environment is interpretable only when the transformations of sensory input due to self-motion can be tracked.

Given a model of the robot's hardware it is possible to perform path integration, which relies on integrating local positional increments. In this way small though unavoidable biases accumulate and may grow rapidly if the vehicle follows complex trajectories. Such biases can be minimized by calibrating the self-model, but still need to be corrected relying on external

information. Concerning rotational drift errors, which are particularly problematic, it has been judged (Duckett and Nehmzow, 1997; Oore et al., 1997) that specific "compass senses" are necessary for calibration. Another way to reduce odometry errors is to assume a specific behavior such as following walls or hallways (Duckett and Nehmzow, 1997; Mallot et al., 1995), such that the environment appears essentially one dimensional except at special places such as intersections. The latter can be considered as elements in a high-level description of the environment which is of sufficient simplicity to be represented as a hidden-Markov model (Shatkay and Kaelbling, 1997). Another approach is to learn association between sensor readings and position provided by a teacher in an initial learning phase (Thrun, 1997). Generally, however, external input can be ambiguous and of low information content. It is, therefore, necessary to use external information in an efficient way and to reconstruct missing input features from an internal representation.

In order to resolve the dilemma between sensor-based correction of path-integration and odometry-based sensor interpretation it has been suggested (Kaelbling et al., 1996; Oore et al., 1997; Shatkay and Kaelbling, 1997) to require merely consistency of the internal position estimates with the information about the environment which is available by external sensors. In other words, to any particular position estimation a prediction of a sensory state is to be assigned. The reliability of the estimate can be evaluated by the correctness of the prediction. A single prediction does not provide any information if it is incorrect and if no distance is defined in the space of sensory inputs. One should rather allow for a number of predictions by several parallel estimator units. Those estimates which incorrectly predict the inputs are considered to be less relevant. Expressing the relevance by the probability of correct prediction, it is possible to average individual estimates according to their relative correctness.

Finally, external sensory input and internal motion information have to be combined such that it is possible for the robot to both disambiguate the external sensations and to calibrate path integration. Our approach is to assume a process of self-organization, which should be sufficiently general in order to require only minimal assumptions and to allow for specific tasks to be solved without interference with the basic ability of self-localization. We assume a neural activity dynamics which depends on internal estimations of movements and which is modulated by external sensory input. The parameters are adapted in a self-supervised manner

such that expected observations maximally match the sensory input. At no point the "objective" location is mapped into the neuronal activities. Instead, an observer can deduce that the agent appears to "know" its location because after adaptation particular neurons are active only when the agent is at certain locations. Interestingly, neurons in the hippocampus of rats exhibit exactly these response properties (Wilson and McNaughton, 1993).

A previous attempt to approach the problem of self-localization on the basis of external stimuli has been taken up by Oore et al. (1997). There the basic idea consisted in applying Bayes' formula to arrive at predictions of the current position conditioned on sensory inputs from conditioned predictions of inputs. In contrast to (Oore et al., 1997), where specific information was obtained from long range sensors, our agent is equipped only with sensors that merely indicate the existence of an obstacle immediately in front, left or right of the robot. In our approach no direct information whatsoever about the actual position and allocentric orientation of the agent is taken into account. Further, our agent is not equipped with a compass which had to be used in (Duckett and Nehmzow, 1997; Oore et al., 1997). Because the model in (Oore et al., 1997) depends on explicit direction information it cannot be considered as a true hidden Markov model, whereas this theoretical framework can be directly applied in the more general setting presented here.

The present approach to the problem of self-localization is detailed in the following section. The third section of the present paper is devoted to experiments with a robot simulator (Michel, 1996) and a Khepera robot. The discussion briefly addresses applications of the present approach in robotics and possible neuronal implementations of the algorithm.

2. Hidden Markov Model of Spatial Localization

The internal states of the robot are represented by discrete vectors ξ which for simplicity are supposed to be nodes of a d dimensional grid Ξ. Each state carries an activation (or relevance) value which by appropriate normalization can be expressed by a probability $P(\xi)$. If no inputs are applied then the time course $P_t(\xi)$ of these activations is assumed to follow a Markovian dynamics.

$$P_{t+1}(\xi) = \sum_{\xi' \in \Xi} T(\xi, \xi') P_t(\xi'). \qquad (1)$$

$T(\xi, \xi')$ is a probability matrix ensuring $\sum_\xi P_{t+1}(\xi) = 1$ whenever $\sum_\xi P_t(\xi) = 1$. If T is symmetric and all of its elements are greater than zero then an iterated application of (1) blurs any initially peaked activity distribution and yields eventually a homogeneous activation over ξ. This diffusive effect allows to reach all states.

In order to introduce a correspondence between the internal activation and the environment the Markovian evolution is complemented by an input-dependent modulation of the activity dynamics. Inputs come, however, without an interpretation and meaning can be given to them only based on the internal activity. We have thus to apply a principle that guides the modification of the dynamics, but without involving any specific information about the present environment. A possible approach is to require the prediction of future inputs s based on the internal activity. For this purpose consider a linear predictor

$$P_{t+1}(s) = \sum_\xi P(s \mid \xi) P_t(\xi) \qquad (2)$$

with coefficients $P(s \mid \xi)$ obeying $\sum_s P(s \mid \xi) = 1$ for all $\xi \in \Xi$. The coefficients are adapted by a gradient descent rule on a suitable cost function, e.g.,

$$E = \frac{1}{2} \sum_s \left(\delta(s_t, s) - \sum_\xi P_t(s \mid \xi) P_{t-1}(\xi) \right)^2, \quad (3)$$

where $\delta(s_t, s)$ indicates whether any of the possible stimuli s is the same ($\delta(s_t, s) = 1$) as the input s_t actually received at time t or not ($\delta(s_t, s) = 0$). $P_t(s \mid \xi)$ denotes the current estimate of the prediction coefficients $P(s \mid \xi)$. From (3) we find

$$\Delta P_{t+1}(s \mid \xi)$$
$$= \eta \left(\delta(s_t, s) - \sum_\xi P_t(s \mid \xi) P_{t-1}(\xi) \right) P_{t-1}(\xi), \quad (4)$$

where η is an adaptation rate. Interpreting $P(s \mid \xi)$ as the expectance of an input s whenever state ξ is activated, we see that the occurrence of s_t increases $P_t(s_t \mid \xi)$ particularly for states which were highly activated at the previous time step. Other inputs $s_t \neq s$ will thus be expected to a lesser extend at a similar internal activation distribution in future. Equation (4) breaks the symmetry of the internal states starting from small initial fluctuations by reinforcing the predictiveness of those ξ which are coactivated with s_t.

On the other hand, the activation of those states that predict the next external input well should also increase. This can be achieved by considering $P(s \mid \xi)$ in accordance to (2) as conditional probabilities. We may, hence, determine $P(\xi \mid s)$ by Bayes' formula

$$P_t(\xi \mid s_t) = \frac{P_t(s_t \mid \xi) P_{t-1}(\xi)}{\sum_{\xi'} P_t(s_t \mid \xi') P_{t-1}(\xi')}, \qquad (5)$$

which is given here as an approximation of $P(\xi \mid s_t)$ based on the current estimates.

We are only interested in the values of the a-posteriori probabilities $P(\xi \mid s)$ for $s = s_t$ since they contain information about the current stimulus and may hence be considered as an improvement of the internal activity distribution with respect to their predictivity of external inputs. As in hidden-Markov models (Rabiner, 1989) the posterior probability is used as a new activity distribution in (1). Equations (1) and (5) are applied alternately, whereby (1) spreads the activities and (5) concentrates the distribution. Thus, the activity of units that are unlikely to correspond to the present sensation is suppressed in favor of units that predict s_t.

Before specifying the Markovian matrix (1), a few remarks are in order.

- In order to decide whether s and s_t are identical (cf. (3)) both are considered to refer to input categories. In a more general setting, it is possible to consider $s = 1, \dots, S$ as labels of input connections carrying continuous activities $P(s_t, s)$ when an S dimensional stimulus vector s_t is applied. In this case (2) is required to match $P(s_t, s)$. The left hand side of Eq. (5) would becomes a weighted sum over s with weights $P(s_t, s)$ and individual normalization for each s. Our assumption, $P(s_t, s) = \delta(s_t, s)$, is appropriate for binary inputs as occurring in the experiments below.
- In particular for continuous inputs other cost functions can be used instead of (3) such as the Kullback-Leibler divergence between $P(s)$ and the predictions of this distribution. The resulting learning rule is similar to Eq. (4) in that the increment is proportional to $P_{t-1}(\xi)$. Note, that in Eq. (4) $P_t(\xi)$ can be considered also as a learning rate which automatically increases with the degree of sureness about the internal state.
- Apart from computational tractability of the problem we have so far not made any assumptions on s or ξ. In particular, the input distribution $P(s)$ does not occur explicitly in (1) and (5). The implicit occurrence in the denominator of (5) can be replaced by an explicit normalization of $P(\xi \mid s_t)$ over ξ.

- The update rule for the expectancies $P(s \mid \xi)$ should allow for a quick adaptation since the impact of the modulation of the internal activities via (5) has to become effective before $P(\xi)$ get close to a homogeneous distribution. It is possible to set η equal to unity or even to use an enhancing function such as $f(x) = \sqrt{x}$, i.e., $\Delta P_{t+1}(s \mid \xi) = (\delta(s_t, s) - \sum_{\xi} P_t(s \mid \xi) P_{t-1}(\xi)) f(P_{t-1}(\xi))$.

  We have alternatively chosen to introduce a nonlinear version of the Markovian dynamics, namely to cut small values of $P_t(\xi \mid s_t) \equiv P_t(\xi)$ and to normalize $P_{t+1}(\xi)$ explicitly. This corresponds to a threshold in real neurons and introduces a competition among activated states which is advantageous in ambiguous environments. Since those ξ' with $P_t(\xi') = 0$ can be omitted in Eqs. (1) and (4) the thresholding is also beneficial in the numerical implementation.

Although it is in principle possible to determine the transition matrix from the sequence of external inputs (Rabiner, 1989), this is infeasible already for moderate numbers of internal states. We instead assume that the structure of internal connectivity allows to perform path-integration as hypothesized for the hippocampus in rats (Samsonovich et al., 1997). This requires that activity is propagated preferentially among units ξ that correspond to nearby positions. In rats these units do not need to be located close to each other, but are connected by a specific synaptic matrix (Samsonovich et al., 1997). In addition, activation correlated to the direction of motion is to be suitably affected by turns of the robot. We model path integration and effects of motor actions, resp., by two different factors in the transition matrix in (1), i.e.,

$$T(\xi, \xi') = T_{\mathbf{k}_t}^{(d)}(\xi, \xi') \, T_{\mathbf{k}}^{(p)}(\xi, \xi'). \qquad (6)$$

$T_{\mathbf{k}}^{(p)}$ denotes a positional part including a drift in direction of the internal direction estimate $\mathbf{k}$ and $T_{\mathbf{k}_t}^{(d)}$ is a directional part which includes information about the current motor action $\mathbf{k}_t$. The separation allows (cf. below) to process directional and positional information in two interacting subsystems. Correspondingly, we assume the internal state to be decomposed into two components that potentially represent, resp., position and direction estimations: $\xi = (\mathbf{i}, \mathbf{k})$, where $\mathbf{i} = (i_1, i_2)$, $i_1, i_2 \in \{1, \ldots, N\}$ is a two dimensional integer vector and $\mathbf{k}$ is a two dimensional vector of unit length (internal and external scales can be different), representing a direction $\phi = 2\pi n / K$ with

$n \in \{0, \ldots, K - 1\}$. More specifically, the transition matrix $T(\xi, \xi') \equiv T(\mathbf{i}, \mathbf{k}; \mathbf{i}', \mathbf{k}')$ is defined as

$$T(\mathbf{i}, \mathbf{k}; \mathbf{i}', \mathbf{k}')$$
$$= \exp\left(\frac{\langle \mathbf{k}, \mathbf{k}' + \mathbf{k}_t \rangle - 1}{\sigma_d}\right) \exp\left(-\frac{\|\mathbf{i} - (\mathbf{i}' + \mathbf{k}')\|^2}{2\sigma_p^2}\right), \qquad (7)$$

where $\langle \cdot, \cdot \rangle$ is the scalar product. By Eq. (7) the structure of internal states is restricted to a two dimensional positional layout, where activity propagates with speed $\|\mathbf{k}\|$. Here the robot is assumed either to turn or to move at constant speed, i.e., $\|\mathbf{k}\| = 1$, but it is possible to model different speeds or alternatively different length scales of the environment at constant speed by scaling $\|\mathbf{k}\|$. Note that for the topology induced by (7) the predictions $P(s \mid \xi)$ can be understood as evidence values assigned to the grid Ξ. It can be used for exploration analogously as in (Yamauchi et al., 1998) but arises in our model from an unsupervised learning scheme.

T is parametrized by the variances of positional and directional distributions, σ_p and σ_d, resp., which are adapted to match positional and directional errors in the path integration. The motor actions $\mathbf{k}_t$ are coded in analogy to the neurophysiological model in (Skaggs et al., 1994). In order to ensure that $\|\mathbf{k} + \mathbf{k}_t\| = \|\mathbf{k}\|$, we were led to the specific form

$$\mathbf{k}_t = \begin{pmatrix} \cos\phi - 1 & -\sin\phi \\ \sin\phi & \cos\phi - 1 \end{pmatrix} \mathbf{k}, \qquad (8)$$

when the robot turns about an angle ϕ. For the robot moving straightly we have $\mathbf{k}_t = 0$.

The sum in (1) can be decomposed in order to obtain a numerically treatable probabilistic model of the robot's behavior which is applied in the following section.

$$P_{t+1}(\mathbf{i}, \mathbf{k}) = \sum_{\mathbf{k}'} T_{\mathbf{k}_t}^{(d)}(\mathbf{k}; \mathbf{k}') \sum_{\mathbf{i}'} T_{\mathbf{k}'}^{(p)}(\mathbf{i}; \mathbf{i}') P_t(\mathbf{i}', \mathbf{k}') \qquad (9)$$

A further reduction of the computational complexity is achieved by separate representations of heading direction ($\mathbf{k}$) and position ($\mathbf{i}$). For this purpose Eq. (9) is summed up with respect to the variables $\mathbf{i}$ or $\mathbf{k}$, resp., which yields

$$P_{t+1}(\mathbf{k}) = \sum_{\mathbf{k}'} T_{\mathbf{k}_t}^{(d)}(\mathbf{k}; \mathbf{k}') \left(\sum_{\mathbf{i}'} P_t(\mathbf{k}' \mid \mathbf{i}') P_t(\mathbf{i}')\right) P_t(\mathbf{k}'), \qquad (10)$$

$$P_{t+1}(\mathbf{i}) = \sum_{\mathbf{i}'} \left(\sum_{\mathbf{k}'} T_{\mathbf{k}'}^{(p)}(\mathbf{i}; \mathbf{i}') P_t(\mathbf{i}' \mid \mathbf{k}') P_t(\mathbf{k}') \right) P_t(\mathbf{i}).$$

(11)

Position and direction are now represented in different, interconnected areas in an analogous way as in the rat's brain. Equation (10) can be considered as a dynamical representation of heading direction (O'Keefe and Dostrovsky, 1971), where the term in parenthesis is a position-modulated activity. Equation (11) represents only position, but with direction-modulated connectivity.

3.   Robot Experiments

We tested our model by simulating a mobile robot in the Khepera simulator (Michel, 1996) and in a real Khepera robot, cf. below. The experiments are still far from a real-world application and have rather been performed to illustrate the function of the algorithm. In the simulator two stages of environment complexity were chosen: a simple square course and a maze with several obstacles, cf. Fig. 1. The challenge in the first environment
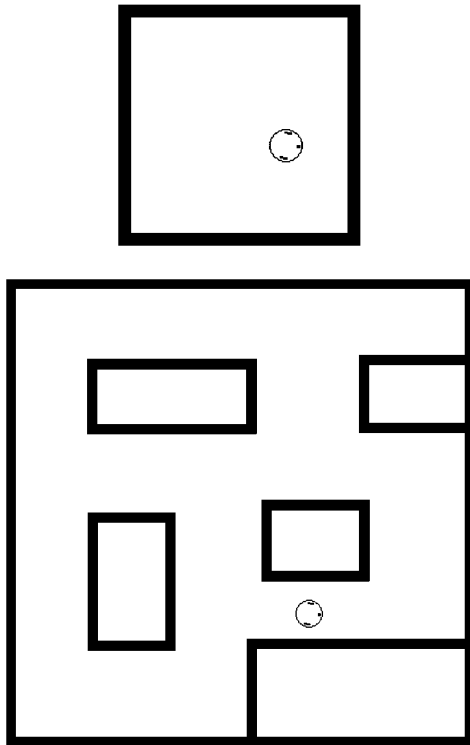

Figure 1.   Screen shots from the Khepera Simulator (Michel, 1996) displaying (top) the square and (bottom) maze environments used in the simulations.

consists in the highly ambiguous sensory input which is not specific to particular locations, whereas the second one requires larger computational resources while providing more specific information (which is still ambiguous).

The robot is controlled by a Braitenberg algorithm (cf. (Braitenberg, 1986); a version of rule "3a" is used, that is built-in in the simulator), which makes the robot turn left if an obstacle is recorded by sensors on the right and vice versa. In order to prevent the robot from getting trapped in a corner of the maze this behavior is supplemented by turns of random angle occurring on average every 100 steps. The algorithm for spatial localization turned out to be rather insensitive on the behavior of the robot provided that it guarantees a sufficient exploration of the environment. External sensations are made up from three groups of infrared sensors, i.e., $S = 8$ referring to the eight possible combinations of either one out of the two front, left or right sensors being activated. In the square (maze) problem 20×20 (32×32) spatial units have been provided though only a fraction of these becomes activated in the stationary phase. In both cases 48 directional units have been used.

For evaluating the robot's performance the mean vector $\sum_{\mathbf{k}} \mathbf{k}\ P(\mathbf{k})$ was compared to the heading direction of the simulated robot, cf. Fig. 3. The robot is able to achieve an approximately consistent orientation in the environment after 1000 to 10,000 time steps (traversing the square (maze) corresponds to about 60 (125) time steps). This base learning time depends on the accuracy of path-integration, i.e., whether after a closed-loop trajectory the predictions had a tendency to be correct. Since also the maze environment contained smaller loops the learning time is comparable in both cases. Due to a conservative choice of the learning parameters stationary values of the adaptive parameters were reached 30,000 (100,000 for the maze) time steps later. Stationarity is not required for correct prediction nor does it exclude flexibility (since learning rates were kept constant). Consistent orientation indicates that the ambiguities occurring in the square task are resolved into different internal activity patterns. For the special choice of T, cf. (7), the global spatial structure of the environment is directly represented by the network, cf. (Fig. 2). The fact that no spatial information (except that it is two dimensional) is used by the learning algorithm, has led to an arbitrary orientation and positioning of the internal map. The scale of the maps is, however, determined by the length of $\|\mathbf{k}\|$. In (Fig. 2) the representation of the global spatial structure
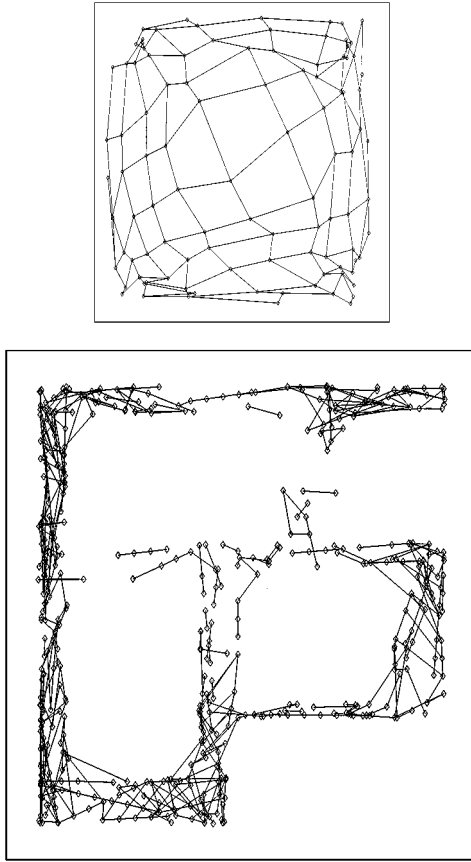
Figure 2. Reconstructed topology of the environment, cf. Fig. 1. Points correspond to the averaged location of the robot at the maximally activated internal state. Lines between points are drawn if the corresponding internal states are neighbors with respect to the internal connectivity. (top) The wide spacing in the center of the (magnified) square course reflects higher positional uncertainty due to the lack of stimuli in this region, whereas twists in the corners are caused different stimuli obtained in small nearby regions. (bottom) In the maze task the topology of the internal states is somewhat disrupted due to the complexity of the environment. This does not affect the orientation capabilities of the robot as can be seen in Fig. 3.

of the environment is plotted. For each unit the mean objective location of the robot weighted by the activity of the respective unit. The results for the maze task (Fig. 2, *bottom*) suggest that a one-to-one correspondence between unit activities and the spatial structure of the environment is not necessary for consistent orientation. Instead this is maintained by population average based on broad activity blobs.

The program developed for the Khepera simulator was also used to control a real Khepera robot. Changes had to be performed only on the thresholds for binarization of the infrared sensors, although lighting conditions were kept approximately constant. As for the simulated robot the internal representation has been
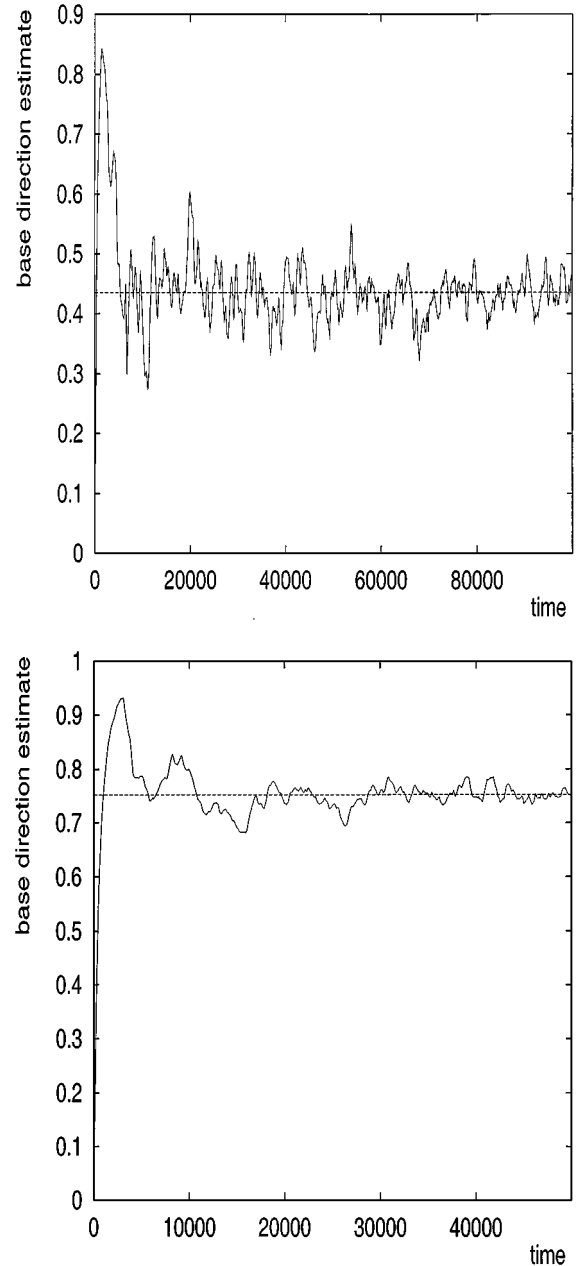

Figure 3. Time evolution of the direction estimate achieved by the robot. Displayed is the scalar product of the internally estimated heading direction and the real one. The full lines are fits to the curves. Since the baseline of the internal direction estimate is arbitrarily fixed, only the consistent relation between internal estimate and actual heading direction is of behavioral importance. Larger fluctuations in the square (top) are due to less specific information available compared to the maze (bottom).

adapted using Eqs. (10) and (11) with 20×20 positional and 48 directional units, resp. The size of the environment relative to the robots diameter was similar as in the simulated square task, here, however, a
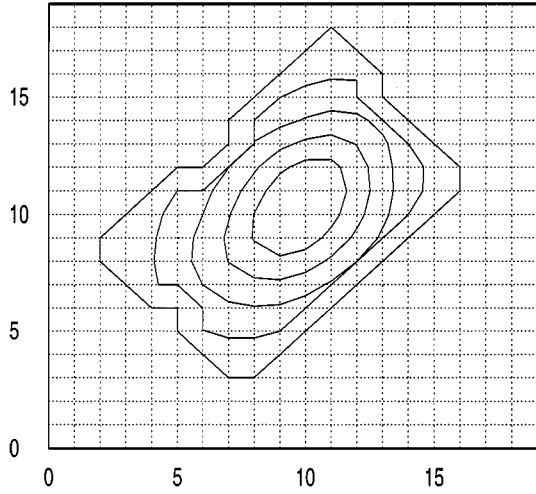
Figure 4. Internal representation of a rectangular environment. The outer line connects units which predict wall states. The inner lines are isolines of conditioned probability of the wall state with values 0.8, 0.6, 0.4, and 0.2.

rectangular region was prepared. The number of time steps required for learning was about twice as large as in the square task. Since the robot was not monitored externally an evaluation of the consistency of the heading direction could not be performed. Figure 4 represents isolines of $1 - P(s^0)$, see Eq. (2), where s^0 denotes the category of non-activated infra-red sensors. The information contained in $1 - P(s^0)$ can be used for preventive wall avoidance.

4. Discussion

4.1. Neural Implementation

Whether or not the present approach bears some explanatory power for spatial localization of animals depends on the plausibility of its neural implementation rather than merely on a successful performance in this task. Relating the internal state probabilities to the mean rates of neurons or neural assemblies, Eq. (7) can be understood as a linearized neural dynamics. Also Eq. (4) can be interpreted as a Hebbian learning rule with subtractive normalization for afferent modulatory connections projecting onto neurons in a place field. The expression $P(s \mid \mathbf{i}, \mathbf{k})$ indicates thus whether a stimulus s is in the perceptive field of a place cell at a cortical position corresponding to $\xi = (\mathbf{i}, \mathbf{k})$.

$P_t(s \mid \xi)$ is understood to project the activity $P(\xi)$ backwards onto input channel s. It may, hence, be considered as a "perceptive field" of unit ξ in contrast to

classical receptive fields which are formed by forward connections.

A challenge for present neural modeling arises from the multiplicative interaction required by Eq. (5), which is according to present experimental evidence unlikely to occur in single neurons. However, preliminary results (Salinas and Abbott, 1996) exist that demonstrate how multiplicative responses can arise through population effects. Finally, less problematic is the normalization in (5) which can be accounted for by a global inhibition that tends to stabilize the total activity.

4.2. Spatial Representations in the Hippocampus

In rat hippocampus many cells quickly become selective for a particular location of the animal (Muller, 1996; Wilson and McNaughton, 1993). Simultaneous recordings of many place cells indicated the existence of a precise population code for location (Zhang et al., 1998). In the post-subiculum and also in other brain areas so called head direction cells have been found whose activity mainly depends on the allocentric orientation of the animal (Taube et al., 1990a). These responses depend only weakly on particular visual cues and also persist in the dark (Taube et al., 1990b). Previously place fields and direction selectivity have been modeled at different levels of abstraction and biological plausibility (Skaggs et al., 1994; Touretzky et al., 1994).

Place fields depend on visual input but persist also for some time when the lights are switched off (Quirk et al., 1990). Hence, one should assume some kind of representation of the environment rather independent on direct visual input. For an autonomous robot that uses infrared or touch sensors or for a rat relying only on whisker sensations, the localization task is conceptually more difficult: Local, qualitative and highly ambiguous external inputs are to be combined with the internal motion information to form a representation of the environment.

In terms of Eqs. (10) and (11) our model (Herrmann et al., 1998) consists of two interacting networks which can be related to functional structures in the postsubiculum and the hippocampus. The activity of neurons in the post-subiculum network is projected to the hippocampus in a way that this input serves as a bias for the activity dynamics in hippocampus such that the hippocampus acts as a path integrator, cf. (Samsonovich and McNaughton, 1997). The activation dynamics in both nets is mediated by internal lateral connections which provide a prior expectation of future excitations

while sensory inputs drive the cells according to their individual input fields. These perceptive fields are learned according to a Hebbian rule which during exploration leads to a specialization of the cells of the networks for places and directions, respectively. On a slow time scale also the lateral connections are modified which further adapts the system to systematic bias and variances of motion estimates and distortions of the internal metric.

4.3. Representations by Synfire Chains

The particular parametrization of the Markovian matrix allowed for a direct interpretation of the internal states as positional estimates. In a biological architecture this assumption can presently not be ruled out, since the neurons can be connected topographically though not being physically arranged in a topographical manner in the brain. More generally, it is also possible to do without this the spatial interpretation but still to be able to predict future inputs. We have performed experiments using the Khepera simulator (Michel, 1996) with internal connections based on the notion of synfire chains (Abeles, 1991; Herrmann et al., 1995). Synfire chains are able to reliably propagate activity in a neural network and to achieve precise timing of the neural firing. In order to allow for the organization of such structures learning algorithms have been proposed (cf. e.g., Hertz and Prügel-Bennett, 1996), which however suffer from instabilities and a preference of short cycles. Within the framework of hidden Markov models more robust synfire chains can be constructed that allow for representations which do not involve the assumptions of a two dimensional environment. The resulting connectivity patterns are, however, rather complex, such that the presence of an implicit spatial representation can be guessed only from the ability to make successful predictions.

5. Conclusion

Understanding intelligent nervous systems—both natural and artificial—does not consist in merely presenting the map from sensory inputs to behavioral outputs, but should include the quest for the internal "representation" of the animal's environment and body. The present approach emphasizes the fact that such representations cannot be considered as an *image* of the environment, but are defined by their action-dependent predictive power with respect to future sensory inputs.

Only upon inspection by an external observer (such as in Fig. 2) the representations of a behaving being may be understandable in terms of a physical reality. Place fields in rats, e.g., are understandable (and have therefore been studied) in our notions of space, which, however, can readily be assumed to have evolved similar as in rats and are, hence, compatible. On the other hand the "external observer" may be another module in the same system or another agent in the same environment. In these cases representations become explicit in the communication and can act as a means for exchanging information among the agents. With respect to collective robotics it would interesting to further study the emergence of languages from representations of environmental features.

Certain aspects of the representation may be inborn and came about by evolution (such as the two dimensional structure of the states in our robot) or refer to somatic features of the animal which are acquired by life-long learning (such as the variances in Eq. (7)), whereas other expectations relate to events in the current environment.

Since in autonomous robots the situation is by definition similar to that of an animal one should refer to models of animal behavior when designing robot controllers. On the other hand, in spite of the large corpus of results obtained by experiments in primates, rodents, and ants, the theoretical understanding is mostly limited to the neural architecture of single species and to simple behaviors under restricted experimental conditions. It may be, thus, beneficial for both robotics and behavioral biology to study relations between artificial and natural agents in complex environments.

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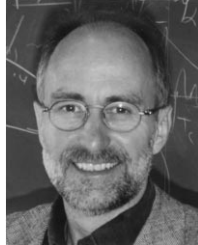
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