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Simple Agents Benefit Only From Simple Brains

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Abstract**—** In order to answer the general question: "What does a simple agent with a limited life-time require for constructing a useful representation of the environment?" we propose a robot platform including the simplest probabilistic sensory and motor layers. Then we use the platform as a test-bed for evaluation of the navigational capabilities of the robot with different "brains". We claim that a protocognitive behavior is not a consequence of highly sophisticated sensory–motor organs but instead emerges through an increment of the internal complexity and reutilization of the minimal sensory information. We show that the most fundamental robot element, the short-time memory, is essential in obstacle avoidance. However, in the simplest conditions of no obstacles the straightforward memory-less robot is usually superior. We also demonstrate how a low level action planning, involving essentially *nonlinear* dynamics, provides a considerable gain to the robot performance dynamically changing the robot strategy. Still, however, for very short life time the brain-less robot is superior. Accordingly we suggest that small organisms (or agents) with short life-time does not require complex brains and even can benefit from simple brain-like (reflex) structures. To some extend this may mean that controlling blocks of modern robots are too complicated comparative to their life-time and mechanical abilities.

Keywords**—** Neural network, probabilistic control, robot navigation.

I. INTRODUCTION

Cognition is one of the core concepts of artificial intelligence, involving processes such as perception, memory, and thinking usually related to humans. Recent advances in behavioral studies and robot design have led to formulation of the concept of *minimal* cognition (see e.g. [1], [2]) that in particular states: a model agent must be simple enough to be computationally and analytically tractable, otherwise there is no chance to deeply understand its behaviour. In this article we address the navigation problem in mobile robotics exemplifying the principle of minimal cognition by drawing relation between the agent sensory-motor complexity, life-time and the complexity of its brain.

In the 1980s and the first half of 1990s deterministic approach to guide a robot towards a goal was in high prominence (see e.g. [3]-[5]). This approach assumes implicitly that the robot has infinite computational capacity, the complete information on the external world, and the measurement, e.g. of the distance or position, has no error. Although this concept may work in some ideal (toy-like) conditions, frequently such robots fail to perform properly.

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Numerous studies show that living organisms (especially the simplest) have no huge computational capacity, neither they rely on the precise measures nor reconstruct an exact physical model of the environment, but they do perform very successfully in a complex, dynamically changing world. So a different logic should be behind of this success. Then a new methodology, opposite to the deterministic approach, gained interest.

Robots are inherently uncertain about their state and the state of the environment. Accordingly the new approach was based on probabilistic principles that scale better with the complexity of real-world applications [6], [7]. The core of the probabilistic approach is built upon the two items: probabilistic perception and control. When, for example, guessing a quantity from sensor data, the probabilistic approach computes the whole probability distribution, instead of generating a single best guess only. Moreover, a probabilistic robot knows about its own ignorance, a key prerequisite of truly autonomous robots. As a result, such a probabilistic robot can gracefully recover from errors, for instance in the kidnapped robot problem [8]. A recent example of the probabilistic approach is MEDUSA algorithm [9]. Offering many advantages over the deterministic approach the probabilistic robots usually require a very high computational capacity to the robot and a need of approximation.

In the following sections we make use of the concept of minimally cognitive artifacts to answer the question: What does a simple agent with a limited life-time really require for constructing a useful representation of the environment? A widely accepted idea is that the system should exploit statistical dependences contained in the sensory signals and reduce redundancy [10]-[15]. However, the limited life-time implies that sometimes an agent has no time or capability to generate objective and action-independent response. The system should make use of a personalized representation of the world that depends on its own physical properties, which, as we shall see further, in certain circumstances can lead to the surprising conclusion that a complex brain is useless for a simple organism.

II. THE ROBOT PROBABILISTIC SENSORY - MOTOR LAYERS

In this section we adopt the concept of probabilistic perception and motor control, and propose a robot platform, i.e. the sensory and motor layers. To reduce the problem dimension, staying in the minimal cognition principle, we consider very simple sensor and motor layers. This will later allow us to study how the navigational capabilities of the robot change when its brain evolves.

Figure 1A sketches the general robot architecture including the sensory, neural network (the "brain"), and motor layers.

We shall deal with a robot having a limited life time, able to move in a limited space (a room) with a goal to reach a target. The robot moves one step at a time (Fig. 1B) in either of four directions (left, right, up, down). The limited life-time implicitly forces the robot to go to the target in the minimal number of steps.

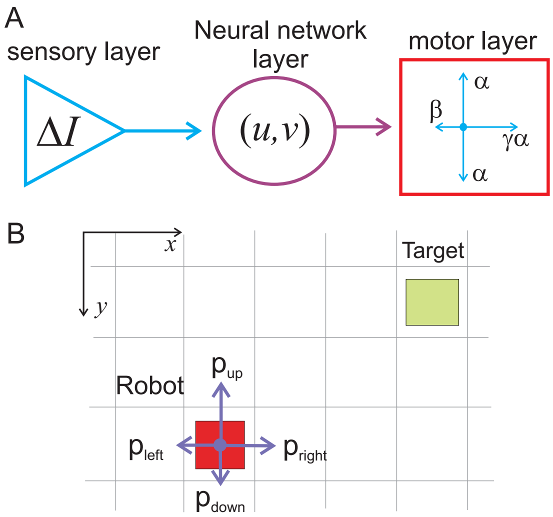

Fig. 1. A) General scheme of a robot consists of three main blocks: sensory system, neural network (brain), and motor control. B) The robot moves one step at a time in either of four directions with probabilities depending on the input received by the motor layer.

A. Sensory Layer

The robot sensory system perceives stimulus emitted by the target (e.g. sound or smell), whose intensity decreases with the distance. For illustrations we assume that the stimulus intensity decays as:

$$I(r) = \frac{hI_0}{r+h}, \tag{1}$$

where r is the distance from the current robot position to the target, I_0 is the intensity at the target, and h is the cut-off constant. According to the limited resources concept, the exact world model (1) is not available to the robot. Instead the robot can compare *but not measure* the stimulus intensity between the two consecutive steps getting the differential characteristic:

$$\Delta I_i = I_i - I_{i-1} + \delta_i, \tag{2}$$

where δ_i is the sensor noise describing the measurement uncertainty and uniformly distributed in $[-\delta, \delta]$. When the stimulus difference is much higher than the uncertainty $|\Delta I_i| \gg \delta$ the sensory system provides a reliable output. The radius at which the robot "correctly hears" the target is:

$$r \approx \sqrt{\frac{hI_0}{\delta}}. \tag{3}$$

The robot performs a step at a time consequently the sensory output occurs at integer multipliers of the step time interval Δ. Without loss of generality we set $\Delta = 1$. When the robot does a step towards the target its sensory system produces a spike. Then the output can be presented as a sequence of δ-functions or spikes:

$$S(t) = \sum_k \delta(t - m_k), \tag{4}$$

where $\{m\}$ is the set of steps with positive ΔI.

Here we note that the stimulus measurement, i.e. inferring on the absolute value of $I(r)$ is much stronger, unnecessary requirement to the robot skill. The possibility of testing the gradient of the stimulus intensity means that the robot has got a simple one-step-memory capacity in the sensor. This allows us to draw the first important conclusion: minimal (proto) intelligence requires the memory capacity in the sensors. We also add that the hardware implementation of such a sensor can be achieved with few capacitors and switches.

B. Motor Layer

The robot motor layer is defined by two parameters: α and γ (Fig. 1A). These parameters, either fixed in time or changing from step to step, determine the robot navigational behaviour.

1) Directionality parameter α: Let us for simplicity fix $\gamma = 1$, and assume that the sensory output is fed directly to the motor layer (i.e. there is no intermediate neural network between the sensory and motor layers). Then the robot next step is defined by the successfulness of the previous action, i.e. by the presence or absence of sensory spike. From Fig. 2 (left inset) it follows that the probabilities (Fig. 1B) are given by:

$$\begin{aligned} p_{\text{left}} &= p_{\text{right}} = \alpha, \\ (p_{\text{ahead}},\ p_{\text{back}}) &= \begin{cases} (\alpha,\ 1-3\alpha), \text{a spike received} \\ (1-3\alpha,\ \alpha), \text{otherwise}. \end{cases} \end{aligned} \tag{5}$$

An increase of α diminishes the probability of going back and increases the probability to follow the successful direction. Thus the constant α controls the robot directionality. In the appropriate limits we get "Brownian" robot ($\alpha = 1/4$, absolutely stochastic), and "Purposeful" robot ($\alpha = 1/3$) that always does a step in the direction of the possible target location. However, even in the later case the robot remains probabilistic.

2) Modulation parameter γ (stochastisity level): A successful previous step, defines the target location in the right half space (Fig. 2 left inset). Consequently, the robot next move should be either to go ahead or turn to the left or right. As above mentioned the directionality parameter α is responsible for that. Parameter γ scales the probability of going ahead, so generalizing the motor layer.

The next robot step further divides the half-space into two unequal parts. Since we assumed no a priory knowledge on the target position, the probability to find the target in the corresponding part is proportional to its area:

$$\frac{P_{\text{successful}}}{P_{\text{unsuccessful}}} = \frac{S_2}{S_1} \quad \Rightarrow \quad P_{\text{successful}} = \frac{S_2}{S_1+S_2}, \tag{6}$$

where S_1 and S_2 are the areas behind and in front of the robot, respectively (Fig. 2 middle and right insets). According to (6) the best strategy for the next step depends on the area

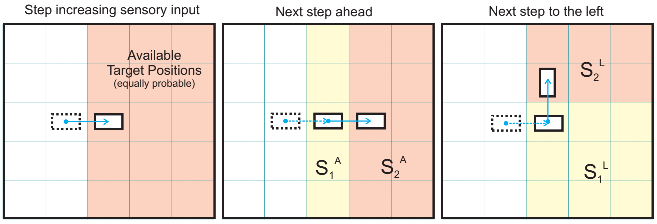

Fig. 2. Sketch diagram illustrating the relation of the areas with possible location of the target. The ratio of different areas gives the probability of the next step to be successful or not.

ratio, i.e. on the current robot position in the room. Since the robot has no information on its position in the room, a good approximation is an open space, i.e. room boundaries are far enough from the robot position. In this case the probabilities are:

$$P_{\text{ahead}} = 1 - \frac{2}{L}, \quad P_{\text{turn}} = \frac{1}{2} - \frac{2}{L}, \tag{7}$$

where L is the room size. For $L \gg 1$ $P_{\text{ahead}} = 2P_{\text{turn}}$, thus suggesting the optimal parameter value to be $\gamma \geq 2$.

The motor layer parameters satisfy to the condition: $\beta + (2 + \gamma)\alpha = 1$. From this condition γ is limited by $\gamma \leq \gamma_{\max} = (1 - 2\alpha)/\alpha$. We can equal the probability of going ahead and back by setting the modulation parameter: $\gamma_{\text{eq}} = \frac{1}{2\alpha} - 1$. $\gamma < \gamma_{\text{eq}}$ corresponds to a robot that tends to escape (go away) from the target. The robot with $\gamma_{\text{eq}} < \gamma \leq \gamma_{\max}$ will move to the target.

Let us make an important note here. The case

$$\gamma \to \infty, \quad \alpha\gamma \to 1$$

corresponds to a *deterministic* robot. Indeed, such a robot always (with probability 1) follows the previous step in the direction of increasing of the stimulus intensity. Hence in one limit our concept of the probabilistic motor layer also includes the deterministic case. Thus the modulation parameter γ biases the robot behaviour from stochastic to deterministic.

III. Obstacles, Path Complexity and the Robot IQ Test

We assume that the obstacles do not change the sensory information available to the robot, but the robot never crosses an obstacle. We recall that the robot has no information on the presence and positions of the obstacles. In general, obstacles on the pathway make harder the robot task of reaching the target. Path complexity quantifies how complex the way from the start to the end is. We define it as the mean number of steps needed by Brownian particles (i.e. Brownian robots without step limit) to reach the target:

$$\text{Pc} = \langle N_{\text{Brownian}} \rangle . \tag{8}$$

Note that the definition (8) is universal. It is expressed in a natural robot measure – the number of steps, and it is a function of the obstacle geometry and the distance to the target, but not of the capabilities of a particular robot. Besides its use does not require precise and complete information on the external world (room) configuration. The Pc is limited from below by the minimal initial distance to the target and can

	Room configuration		
	Empty	Small obstacle	Complex obstacle
Path complexity ($\times 10^5$)	6.44	6.59	6.81

be infinite when the target is unreachable, i.e. when no path connecting the starting robot position and the target exists. We quantified the path complexity for three room configurations (see table): empty, with small obstacle and with complex obstacle. As expected the empty room has the minimal Pc and the room with the complex obstacle exhibits the highest path complexity.

As a measure of the robot quality we introduce its intelligence coefficient:

$$\text{IQ} = k \log \left(\frac{\text{Pc}}{\langle N_{\text{steps}} \rangle}, \right) \tag{9}$$

where $\langle N_{\text{steps}} \rangle$ is the mean number of steps required by the robot to reach the target, and $k = N_{\text{sc}}/N_{\text{tr}} \leq 1$ is the robot successfulness, i.e. the ratio of the number of successful target reaching to the number of statistical experiments or trials. Thus the robot that frequently fails to reach the target is penalized.

We performed exhaustive statistical experiments using as a test bed the three different room configurations: empty, with small obstacle, and with complex obstacle. In the empty room the robot IQ (Fig. 3A) is a growing function of both parameters α and γ. The maximum "intelligence" the robot shows at $\gamma = 10$ and $\alpha = 0.083$. However, when even a small obstacle appears on the path, this robot strongly loses in performance (Fig. 3B). The better strategy would be to reduce the modulation parameter γ to 2 but still keeping α maximal. Thus *for simple obstacles we need to decrease the robot determinism without changing the strategy*.

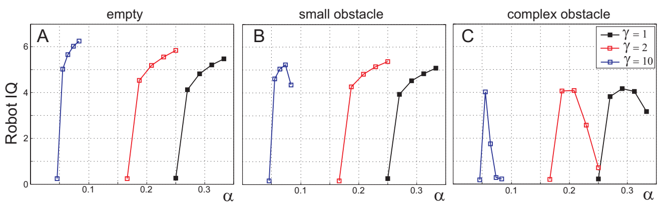

Fig. 3. Robot IQ for different values of the motor layer constants and different configurations of the environment (room): A) in an empty room, B) in a room with small obstacle, and C) in a room with complex obstacle.

In the presence of the complex obstacle (Fig. 3C) all curves for different modulation parameter γ have a maximum at intermediate values of α. Surprisingly all maxima have similar robot IQ. This means that *in the presence of complex obstacles the robot determinism is less important but the strategy should be changed*, by decreasing of the directionality coefficient α to an intermediate value. Indeed to avoid a complex obstacle the robot should make a random walk backwards from the target and then to one of the side. Just decreasing γ we cannot achieve this behavior, since the robot most likely will return back to the trap.

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IV. First neuron: Memory skill

In the previous section we considered robot models having no "brain", but only direct sensory – motor connection. Experiments with such a robot showed that in different environmental conditions different choice of the motor layer parameters is required. The next step introduces a simple brain (a network of artificial deterministic neurons) to the simple agent. This network can have an internal dynamics and is activated by the robot sensory system.

The sensory spike train (4) innervates the neuron according to:

$$\frac{du}{dt} = -\frac{u}{\lambda} + J + wS(t), \tag{10}$$

where u is the "membrane" potential, J is the constant membrane current, w accounts for the synaptic strength, and λ is the membrane time constant. As we shall show below this neuron adds a short-time memory skill to the robot with λ defining the "forgetting" time scale.

To finish the robot design we couple the internal brain state to the motor parameters:

$$\alpha = \alpha(u, j), \quad \gamma = \gamma(u, j). \tag{11}$$

A. Memory Updating Rule

The dynamics of the membrane potential u at the j-th step is given by:

$$u(j+\varepsilon) = u(j-1+\varepsilon)e^{-\frac{1-\varepsilon}{\lambda}} + (1-e^{-\frac{1-\varepsilon}{\lambda}})\lambda J + w\delta_{j,m}, \tag{12}$$

where ε is an infinitesimal constant, δ_{jm} is the Kronecker symbol defining whether a sensory spike at j-th step occurs or not. Without loss of generality, rescaling and shifting the membrane voltage $u \mapsto wu + \lambda J$, we get from Eq. (12) the following 1D map:

$$u_j = Bu_{j-1} + \delta(j, m), \tag{13}$$

where $B = e^{-1/\lambda}$ defines how strongly the next brain state keeps track of the previous one. Thus map (13) describes short time memory. The bigger the λ the slower the system forgets its past. Our previous robot design corresponds to $\lambda = 0$, i.e. to a robot with no memory.

The map (13) now can be used as an updating rule for the memory state. We note that such *memory realization does not consume the memory* (computer resources) since the internal variable u is updated at each state using only the constant B, previous value of u, and last sensory output (presence or absence of spike). Nevertheless the robot past affects its current state so *the robot remembers its behavior*.

In general case the map (13) admits complex solutions. Figure 4 illustrates some important particular cases of the map dynamics under different periodic inputs from the sensory layer.

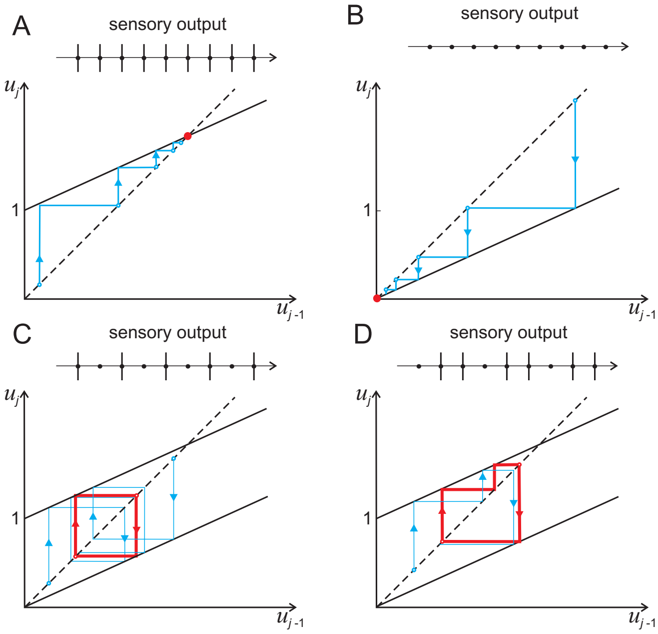

Fig. 4. Examples of periodic sensory outputs and the dynamics of the sensory neuron driven by those stimuli. A) Periodic spikes from the sensory unit lead to a successive increase of the state variable $u_j = \frac{1-B^{j-1}}{1-B} + B^{j-1}u_1$ by progressively decreasing steps towards the fixed point of the map (14) at $u^+ = (1-B)^{-1}$, i.e. the robot "learns" the good strategy; B) No spike from the sensory unit, i.e. the robot goes away from the target, leads to a successive decrease of the state variable to $u^- = 0$; C) Period two spikes, i.e. the robot does steps towards and backwards. The internal state oscillates between two different states $u_c^+ = \frac{1}{1-B^2}$, and $u_c^- = \frac{B}{1-B^2}$; D) More complicated sensory signal (two steps forward, one backward) provokes period three stable fixed point.

B. IQ of the Robot with Memory

For illustration we used the simplest form of (11):

$$\alpha_j = \alpha_0, \quad \gamma_j = \frac{\gamma_0}{1-B}u_j, \tag{14}$$

where α_0 and γ_0 are the coefficients of the motor layer of the robot with no memory. We simulated the robot motion in different room configurations evaluating the robot IQ according to (9). Figure 5 summarizes results.

Not surprisingly in an empty room the memory does not give any gain comparing to the memory-less robot. The robot IQ even reduces for longer memory scales (upper insets in Fig. 5). This is explained by the memory "inertness". Due to the inevitable presence of randomness in the sensory output, for big λ the memory state never reaches the optimal value. Instead it oscillates according to (13) around some suboptimal value similar to Fig. 4D. This is equivalent to an effective decrease of the modulation parameter γ due to (14), which biases the robot from deterministic to stochastic behavior. As we observed before (Fig. 3A) such a decrease leads to a decrease of the robot IQ leading to the conclusion that "thinking to much" is not good in a simple situation. However, the picture significantly changes in the presence of obstacles. Even small obstacle was a big problem for the memory-less robot in the case of $\gamma = 10$ (Fig. 3B). The simple memory unit with $\lambda \approx 1$ greatly improves the robot performance (middle inset in Fig. 5). In the presence of a complex obstacle the

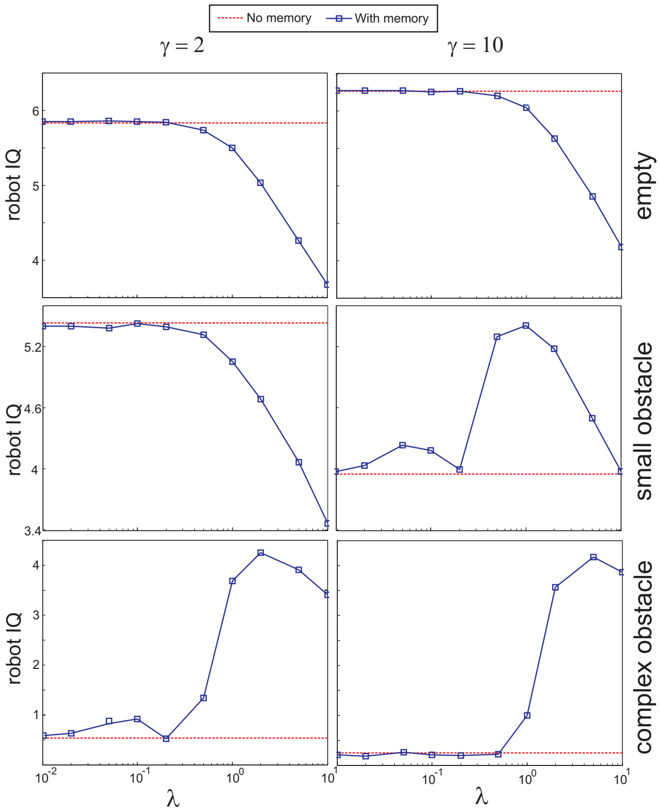

Fig. 5. Comparative performance (IQ test) of robots with (blue curves) and without (red dashed lines) memory skill in different environments. λ defines the memory time scale with $\lambda = 0$ corresponding to the memory-less robot.

robot with the simplest brain does not leave any chance to its memory-less counterpart. For $\lambda \approx 2$ it wins both for $\gamma = 2$ and $\gamma = 10$ (Fig. 5 lower inset). Noticeably that the robot IQ raises up to the values relatively closed to the IQ of the simple memory-less robot in the empty room (IQ $= 4$ vs 6), i.e. such a robot copes very successfully with the complex obstacle and performs practically equally in the empty room. We also note that IQ of the robot with memory is practically the same (about 4) for essentially different values of the modulation parameter γ, i.e. the robot behavior is more robust.

V. Second neuron: Action planning

To make the robot more flexible, capable to change the strategy "on the fly", let us now further improve the robot brain model by introducing one more neuron that we shall refer to as motor neuron.

First, we note that a change of strategy is not possible without having memory, i.e. planning is a superior brain function. Second, it involves essentially *nonlinear dynamics*, i.e. any linear extension can be viewed as a memory modification that may lead to quantitative but not qualitative improvements.

The membrane dynamics of the moto-neuron reads:

$$\dot{v} = f(v) + u, \tag{15}$$

where $f(v)$ is a nonlinear function that for reasons of hardware implementation we choose in a piece-wise linear form:

$$f = \begin{cases} -\frac{v}{k}, & \text{if } v < bk \\ \frac{(b-a)v - b(1-k)}{1-(1+b-a)k} & \text{if } bk \le v \le 1-(1-a)k \\ -1 + (1-v)/k & \text{if } v > 1-(1-a)k \end{cases} \tag{16}$$

with a, b, and k being constants. Equations (15) and (16) define a piece-wise linear map, which then is used as an updating rule for the new brain variable $v_j = g(v_{j-1}, u_{j-1})$ similar to (13).

The motor neuron allows better tuning the motor layer parameters according to the task performing by the robot at a given time instance. To test the robot performance we built a room model with different obstacles of different shape (Fig. 6A) and ascribed to three different robots, called according their brain structures as: "brain-less", "sensory neuron", and "sensory+motor neurons", a task to search for objects appearing at random positions in the room. The robots have limited operational time interval (life-time) to perform each task. If in the given time interval the robot finds an object we assume that the task has been accomplished.

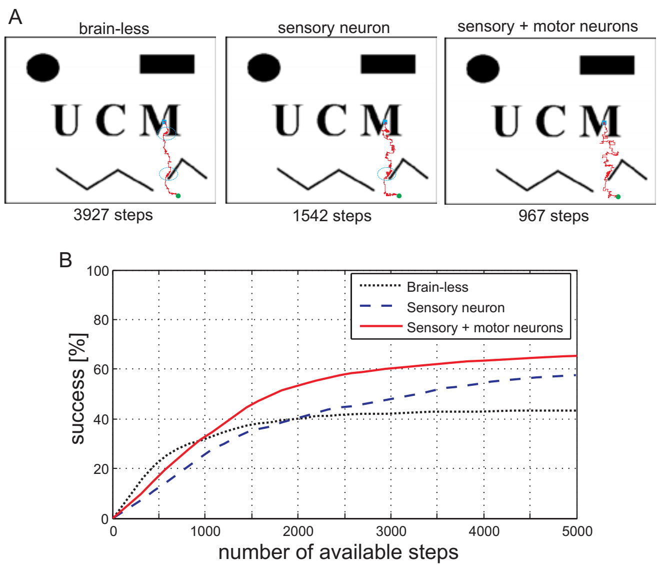

Fig. 6. Comparative performance in target searching for three different robot designs. The robots are instructed to search for the targets that appear at random positions in the untidy room of (353×448) size. A) Examples of the robot trajectories from the initial position marked by blue square to the target marked by green circle. Obstacles are shown in black. Blue dashed circles highlight the points where robots got stacked and spent a lot of steps before finding a way out. B) Mean success rate to find an object by different robots for a given number of steps.

Figure 6A shows examples of robot trajectories. All the three robots find the object. However they spend considerably different amount of steps: 3927, 1542 and 967. In general trajectories of the brain-less robot are quite straightforward, so it usually wins when the target is nearby. However it also frequently stacks even in simple obstacles (Fig. 6A). The internal neural dynamics makes the robot trajectory less direct but also helps to get out from obstacles.

Figure 6B shows the mean success rate. For a given acceptable percentage of success the robots require different time intervals. For small rates, less than 30% (i.e. only about 1 of 3 objects is found by the robots), the brain-less robot wins the competition. It occurs due to frequent appearance of objects just in front of the robot initial position. However, such a robot cannot reach even 45% of success for any time interval, i.e this robot finds less than 45% of the target whatever time it has. The presence of the memory neuron provides a gain for the number of steps bigger than 2000. Then the robot possessing the short time memory significantly improves the success rate, finding those targets that are unreachable for the "brain-less" robot. This result is in accordance with Fig. 5, where the memory function led to a gain only in environments with obstacles on the robot path. Finally the second "action planning" neuron improves even more the robot skill. As we expected, for the small number of steps it provides much better performance over the robot with single memory neuron, achieving the same as the brain-less robot performance at 1000 steps. For bigger step number, the robot with action planning is superior. Thus the motor neuron profitably changes the robot strategy according to the task complexity.

VI. Conclusions

We have proposed a probabilistic model of a robot platform including sensory and motor layers. We have implemented a limited life time, which may be given e.g. by the battery charge or a limited operational time interval, and ascribed to the robot a goal of searching for a target. The robot sensory skill includes the simplest differential sensor that does not explicitly measure the sensory intensity neither its absolute position. The motor layer is described by two parameters controlling the strategy and stochasticity. With no doubts the robot performance could be easily increased by improving the robot sensory or/and motor layers. However we claim that a protocognitive behavior is not a consequence of highly sophisticated sensory–motor organs but emerges through an increment of the internal complexity and reutilization of the minimal sensory information.

Using the platform as a test-bed we have shown that in the presence of obstacles the robot strategy and the level of determinism on the motor layer should be flexible. Simple obstacles can be overcome by reducing the robot determinism and keeping the strategy, whereas for avoiding complex obstacles a strategy change is required.

Starting from the simplest robot we have introduced a "brain" based on a simple neural network using deterministic dynamical systems. This helped to solve the problem of extensive computation and also provided robustness against perturbations. We have shown that the most fundamental robot element, the short-time memory, is essential in obstacle avoidance. However, in the simplest conditions of no obstacles the straightforward memory-less robot is usually superior. Thus the memory is only good in complex environments and a superior brain function is necessary to improve the robot performance. Then we have shown that low level action planning involves essentially *nonlinear* dynamics and provides a considerable gain to the robot performance dynamically changing the robot strategy. Still, however, for very short life time the brain-less robot was superior. Accordingly, we suggest that small organisms (or agents) with short life-time do not require complex brains and even can benefit from simple brain-like (reflex) structures. To some extend this may mean that controlling blocks of modern robots are too complicated comparative to their life-time and mechanical abilities.

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