Neural Fields for Local Path Planning

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Abstract

In this article we introduce a neural field approach for local path planning of an autonomous mobile robot. The robot's heading direction is determined by the localized peak and its velocity by the maximum activation in the field. We emphasize the neural field's ability to keep the path planning stable even in the case of noisy sensor data or varying environments.

The theoretical framework is validated by an implementation on our mobile service robot called 'ARNOLD'. Since its only sensor is an active stereo camera head, we highlight the importance of gaze control and low-level short-term memory for local path planning, particularly in cluttered indoor environments.

1 Introduction

Autonomous mobile robots move in a partially unknown and dynamically changing environment. Hence, the path planning for a given target position has to be reliable and stable even in situations where the robot has only incomplete or noisy sensor data. In addition, the robot should be able to autonomously acquire more information in ambiguous situations to make the path planning reliable.

Here, we present a model for autonomous path planning based on the neural field, introduced by Amari [1]. This model enables the robot to control the active stereo camera head to acquire more information if necessary. Thus, the robot can achieve a reliable path planning even in cluttered indoor environments.

Although Amari's original intention was to model the cortical neurophysiology, in the past years some authors have shown that the neural field can be successfully applied to the field of autonomous mobile robots [8, 11, 4]. Our work is related to that of Engles [8], who uses the neural field in the context of memory representation for making path planning more global. To decide in which direction the robot moves, he uses an approximation of the neural field. The latter one only holds under the assumption of small stimuli. Moreover, it reduces the field dynamics to a single instantiated dynamic equation. Accordingly, some of the basic properties are lost, these include clustering of obstacles and selfstabilization under sensor data noise. Since our work exploits these properties, we have to use the original field equation. In contrast to Engels [8], we do not introduce a separate memory layer but endow the stimulus field with an exponentially decaying dynamic.

Finally, we show that the neural field can not only be used for path planning, but in addition the strength of activation can be used as an important parameter for controlling the robot's overall behavior.

2 The neural field

The neural field used here was introduced by Amari [1]. It can be described as a one-dimensional layer of neurons with homogeneous connections and a negligible time lag. Let $u(\phi, t)$ be the activation of the neuron located at position ϕ at time t. In our case the position encodes a direction. The output function of each neuron is defined by the sigmoid function $\sigma(u)$:

$$\sigma(u) = \frac{1}{e^{-Cu} + 1} \tag{1}$$

In equation (1) C fixes the slope of the transfer function. The maximum activation of the neural field, determining the movement direction of the robot, has to be unimodal. Hence, the neural field is of global inhibition type. The excitatory connections dominate for proximate neurons and the inhibitory connections dominate at greater distance. Thus, we choose an interaction function $w(\varphi, \varphi')$ with a short-range excitatory term and a global inhibition constant H_0:

$$w(\varphi, \varphi') = k \cdot e^{-C'(\varphi - \varphi')^2} - H_0 \tag{2}$$

Now, the activation of the neurons can be written as an integro-differential equation:

$$\tau \dot{u}(\varphi, t) = -u(\varphi, t) + \int_0^{2\pi} w(\varphi, \varphi')\sigma(u(\varphi'))d\varphi' + h + s(\varphi, t) \quad (3)$$

Here, h is a global constant fixing the threshold for the localization interaction defined by $\sigma(u)$, $s(\varphi)$ represents the input with respect to $u(\varphi)$, and τ determines the time scale of the dynamics.

It can be shown analytically that eq.(3) has three basic types of solutions: (a) the homogeneous solution $u = h$ (ϕ-solution), (b) an unstable localized solution (a_1-solution) and (c) a stable localized solution (a_2-solution). Further details can be found in [9].

The neural field is particularly appropriate for local path planning, even in cluttered environments. The localized peak can be interpreted as the desired movement direction, the uniqueness of the activation peak can be realized by choosing the global inhibiting interaction function $w(\varphi, \varphi')$ and, if the peak is of an a_2-type, the peak is self-stabilizing.

We are able to measure the quality of the desired movement direction which is proportional to the strength of the corresponding peak. This will be important in ambiguous situations where the stimulus field is multi-modal. Thus, we can control the translatory velocity of the robot depending on the quality of the activation. If the quality is high, i.e., the strength of the peak is high, the robot moves fast, otherwise it slows down.

3 Autonomous mobile Robot ARNOLD

Within the framework of NEUROS[1] (Neural robot skills) we have developed an anthropomorphic mobile robot called 'ARNOLD'.

The reason for building an anthropomorphic robot is that, general-purpose autonomous service robots for home or office environments have to deal with an environment intensively adapted to human anatomy, sensory and motor skills. Thus, we have designed Arnold as anthropomorphic as possible in the limits of actually available hardware. The anthropomorphic design concerns its sensor position, its arm and the shape of its body. We have chosen a pyramidal shape of the body with the active stereo camera head on top of it. Thus, Arnold can detect obstacles all around and close to its base. Furthermore, grasping of objects can be visually controlled from above like in humans. The manipulator has 7 degrees of freedom (DoF), arranged as shoulder (3 DoF), elbow (1 DoF) and wrist (3 DoF). This configuration allows Arnold to grasp objects while avoiding obstacles and the inverse kinematics of the manipulator can be computed in closed form [7]. A detailed description of Arnold can be found in [2].

Figure 1: Arnold

The control architecture of Arnold is based on the behavior robotics paradigm introduced by V. Braitenberg [5] and R. Brooks [6]. Most of Arnold's behaviors are based on nonlinear dynamical systems. A first application, the tracking of a human hand using all its degrees of freedom, is described in [3].

The sensor module for obstacle avoidance is based on the 'Inverse perspective mapping' (IPM) [10]. In IPM the image of the right camera is mapped onto the image of the left camera under the assumption that the robot moves on a horizontal plane and the parameters of the cameras are known. A difference image is calculated and the pixels exceeding a certain threshold represent an obstacle in the field of view.

Arnold was used for testing the presented method of path planning using neural fields.

4 Local path planning

As described above, the trajectory is not planned explicitly, but implicitly by controlling the rotatory and translatory velocity. The heading of the robot follows the activation peak in the neural field, representing the best movement direction to reach the target position. The neural field encodes the angular direction from 0 to 2π. Since we have chosen a periodic field, the interaction kernel (eq.2) has to be periodic, too. The robot's heading to the target position is represented by a wide ranged, bell shaped function $t(\varphi)$, which is greater than zero over the whole field (fig.2). The smallest value of $t(\varphi)$ has to be greater than $|h|$ in

[1]NEUROS is a research project supported by the German Ministry of Education and Research

the neural field (eq.3) to evoke an activation. The target stimulus $t(\varphi)$ has its maximum in target direction and its minimum in the opposite one.

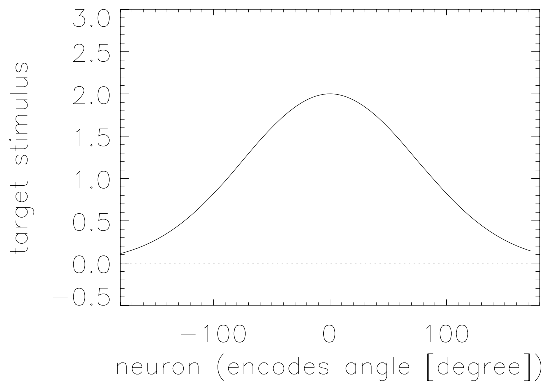


Figure 2: Target stimulus

The obstacle information is provided by the 'inverse perspective mapping' module. It is used for blocking movement directions. The corresponding stimuli $o(\varphi)$ are always negative and their absolute value reflects the distance of the robot from the corresponding obstacle:

$$o(\varphi) = -A \cdot e^{-\delta \cdot d(\varphi)^2} \tag{4}$$

The constant A denotes an amplitude and $d(\varphi)$ the distance measured by the sensor. (We set $d(\varphi)$ to infinity if the corresponding direction φ represents a free path). δ fixes the shape of the range limiting transfer function.

Since the robot has only a limited field of view and the neural field needs continuous information from the stimulus to reach a stable peak, we introduce a short-term memory with respect to $s(\varphi)$:

$$\begin{aligned} \dot{s}(\varphi) = & \frac{1-\theta\left(\beta/2-|\varphi-\alpha|\right)}{\tau_1} \cdot (t(\varphi) - s(\varphi)) \\ & + \frac{\theta\left(\beta/2-|\varphi-\alpha|\right)}{\tau_2} \cdot (t(\varphi) + o(\varphi) - s(\varphi)) \end{aligned} \tag{5}$$

where α is the current gaze direction and β the angle of view. θ is a step function:

$$\theta\left(\beta/2-|\varphi-\alpha|\right) = \begin{cases} 1 : \beta/2-|\varphi-\alpha| > 0 \\ 0 : \beta/2-|\varphi-\alpha| \leq 0 \end{cases} \tag{6}$$

and $\tau_2 \ll \tau_1$. Thus, if φ lies within the current view angle interval, $s(\varphi)$ relaxes on a fast time scale to $t(\varphi)+o(\varphi)$, i.e., to the current sensor input. Out of the view angle interval, $s(\varphi)$ relaxes on a much slower time scale to the current target stimulus $t(\varphi)$. Therefore, eq.(5) enables the robot to store information about its environment for a certain time that can be adjusted by the choice of τ_1.

With respect to translatory movements the information stored in the short-term memory is not updated correctly. Here are several reasons why this is not necessary: (a) the information is only used as a coarse and temporarily limited description of the environment and (b) the gaze direction of the active stereo camera head is controlled by the maximum activation of the neural field, too. Therefore, the most relevant information, namely that corresponding to the current movement direction, is updated almost immediately.

In order to keep the information stored in the stimulus field and the activation in the neural field as continuous as possible, we apply a coordinate system which is robot centered, but globally fixed with respect to its orientation.

As described above controlling the gaze direction plays an important role in local path planning for Arnold. The corresponding degree of freedom, the gaze direction of the stereo camera head, follows the field's maximum activation on a fast time scale. This way the current obstacle situation can be evaluated. The strength of the peak is a measure for the quality of the current path planning. In contrast to the gaze direction, the rotatory and translatory velocity of the robot has to be slowed down if the quality is not high enough.

This can easily be achieved by setting the corresponding velocity components proportional to the thresholded maximum activation of the field:

$$\begin{aligned} v'_R &= v_R \cdot \sigma(u_{max}, t_R) \\ v'_T &= v_T \cdot \sigma(u_{max}, t_T), \end{aligned} \tag{7}$$

with

$$\sigma(u_{max}, t_{R/T}) = \frac{1}{e^{-\gamma(u_{max}-t_{R/T})}+1} \tag{8}$$

$v_{R/T}$ denotes the original velocity and γ the slope of the sigmoidal function $\sigma(u_{max})$. t_R and t_T are the thresholds of activation necessary to evoke a rotatory or translatory movement.

5 Experiments

The neural field for path planning has been applied successfully in several experiments. In the following we will describe only one example in more detail.

In this experiment Arnold has to reach a target positioned 6 meters straight ahead. It has to pass a gap, which is only slightly wider than the robot itself. Figure 3 shows the experimental setup.

Figure 3: Experimental setup

While Arnold is approaching the gap (fig. 3) a persons is blocking the way (fig. 4).

Figure 4: A person blocks Arnold's way

Arnold performs the experiment in real time, it moves at a maximum speed of $250\frac{mm}{s}$. Here the limiting factor is the inverse perspective module which calculates the obstacles. It needs about $300ms$ to evaluate one image pair. In order to perform the given task the robot needs about one and a half minute and the data has been sampled every second.

The trajectory of the robot in measured odometry coordinates is shown in figure 5. Arnold shows an appropriate path planning during the experiment. It chooses a straight path to the target position as long as there are no obstacles. When the person blocks the way, the robot stops, gathers new information and the new path is planned to pass the person and the obstacle on its left side. After the obstacle is passed, Arnold changes to target direction and reaches the required target position.

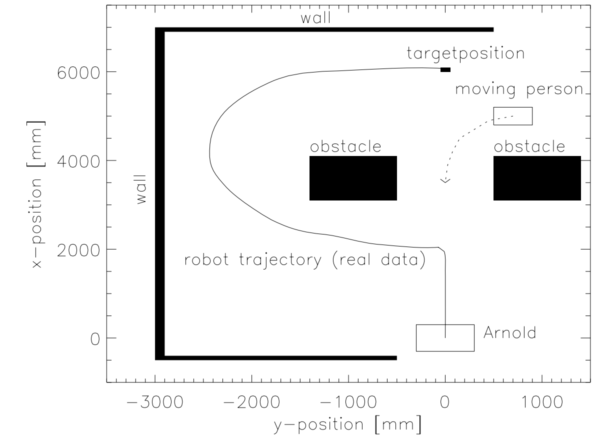


Figure 5: Robot trajectory

Figure 6 shows the orientation of the robot and the camera head, as well as the peak's strength in the neural field representing the quality of the path planning.

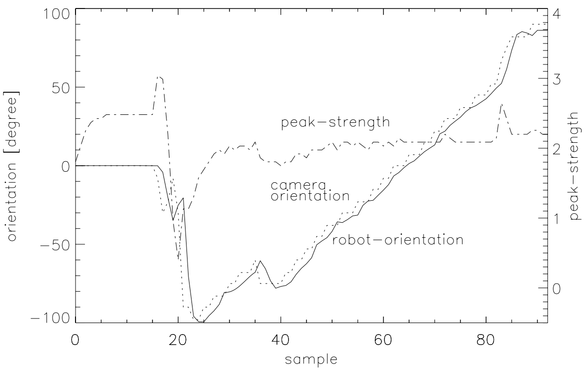


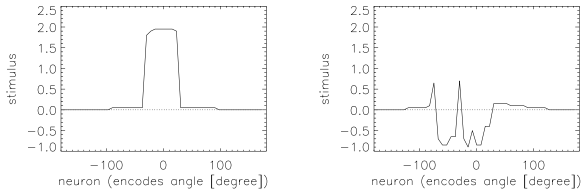
Figure 6: Orientation and peak strength

The short increase of strength at about sample 18 is caused by the fact that the peak is self-stabilizing, i.e., of a_2-type. Hence, being surrounded by obstacles the peak's height initially increases compensating its decreasing width. However, due to the competition the 'weakened' peak breakes down, and a new peak arises voting for another direction of movement.

Figures 7 and 9 show four steps of the short-term memory (stimulus), figures 8 and 10 show the same steps of the neural field.

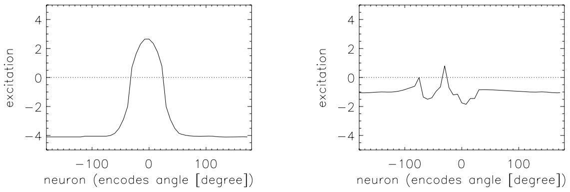
As an example we have picked four situations of the stimulus and the neural field to discuss the path planning in different situations.

Figure 7 (a) shows the stimulus while the robot is moving in target direction. In the field of view the short-term memory is updated on a fast time scale, outside the field of view it is updated on a slow time scale. The peak in the neural field (fig. 8 (a)) relaxes to target direction with large strength, so that the robot moves at its fastest velocity. The path is planned straight to the given target position.



(a) Step 10 (b) Step 20

Figure 7: Short-term memory (stimulus) (1)



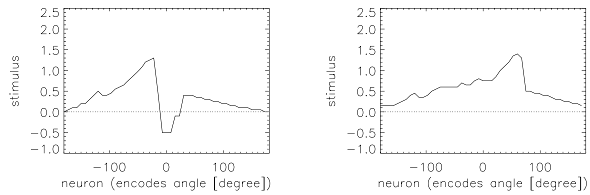
(a) Step 10 (b) Step 20

Figure 8: Neural field (1)

Figure 7 (b) shows the stimulus when a person is blocking the robot's way. In the field of view it is updated on a fast time scale to negative values. Therefore, the peak in the neural field collapses (fig. 8 (b)). Due to the decreased maximum activation the robot stops.

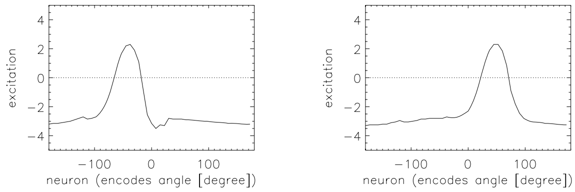
After Arnold has estimated the obstacle's position on its right, a new peak arises in the neural field at about $-90°$ in our coordinate system. Therefore, it changes its path and begins to move to its left along the obstacle. At about step 35, Arnold's short-term memory has 'forgotten' the obstacle and it begins to move in target direction. Since the obstacle has not been passed, the short-term memory is updated and Arnold continues to move alongside the obstacle.

Figure 9 (a) shows the stimulus when the robot is close to the end of the obstacle. The short-term memory shows the memorized obstacle on its right and the peak represents the current movement direction (fig. 10 (a)) of the robot.



(a) Step 50 (b) Step 80

Figure 9: Short-term memory (stimulus) (2)



(a) Step 50 (b) Step 80

Figure 10: Neural field (2)

Finally, the figures 9 (b) and 10 (b) show the stimulus and the neural field, when Arnold has passed the obstacle and is moving directly to the given target position.

6 Conclusion and future work

We presented a model for autonomous path planning which is exclusively based on a nonlinear competitive dynamic system, the so-called neural field. As an example we applied the path planning to the problem of local navigation in an unknown and dynamical varying environment. We were able to show that the neural field can be employed to plan a reasonable path and acquire more information in ambiguous situations. Furthermore the quality of the current movement plan was successfully used to control the robot's velocity.

We believe that our results can be transfered to general effector control. Hence, our recent work is dedicated to the field of manipulators, where we are faced with a higher dimensional task space. However, this only makes the underlying mathematics regarding the neural field more sophisticated, it does not change the overall concept. Moreover, the uniform language has the advantage of coordinating mobility and manipulation in an easy fashion.

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