A Multi-sensory Stimuli Computation Method for Complex Robot Behavior Generation

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Abstract: In this paper we present a method for obstacle avoidance which uses the neural field technique to learn the different actions of the robot. The perception is used based on monocular camera which allows us to have a 2D representation of a scene. Besides, we describe this scene using visual global descriptor called GIST. In order to enhance the quality of the perception, we use laser range data through laser range finder sensor. Having these two observations, GIST and range data, we fuse them using an addition. We show that the fusion data gives better quality when comparing the estimated position of the robot and the ground truth. Since we are using the paradigm learning-test, when the robot acquires data, it uses it as stimuli for the neural field in order to deduce the best action among the four basic ones (right, left, frontward, backward). The navigation is metric so we use Extended Kalman Filter in order to update the robot position using again the combination of GIST and range data.

1 INTRODUCTION

To avoid obstacles is considered nowadays very important behaviour in the robotic community. It is often relied to localization and mapping since the robot has to move in its environment. Therefore, the robot has to satisfy the three blocks of the reactive paradigm 1. Up to now, methods called soft computing such as fuzzy logic and reinforcement learning have been widely used in the literature. However, the neural approach inspired from the human biology is considered an alternative to the cited methods because it is simpler and more efficient. We propose in this work a novel method using the neural fields(Yan et al., 2012)for behaviour generation. The neural field method is the continuous version of the neural networks, well known in the robotic community. The neural fields have entries called *stimuli* and outputs called *actions*. Although the use of a certain single stimulus can trigger correct actions to avoid obstacles, it shows some drawbacks such as lack of information quantity. For example, if a robot moves in an outdoor environment, the use of laser signal is not efficient at all since this the distance and the orientation of the reflected signal are affected by natural noise. Consequently, we propose in this work to deal with the problem of the perception of the robot environment.

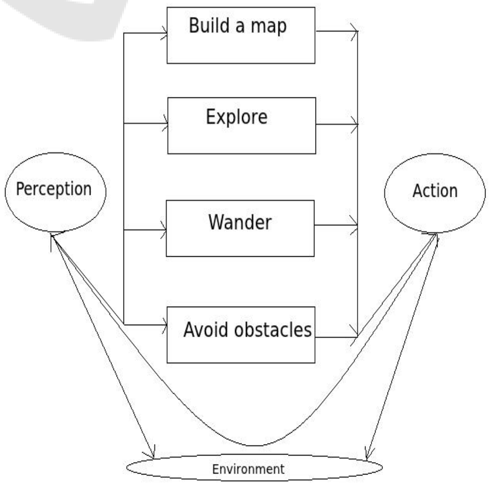

Figure 1: Reactive Paradigm.

We propose to fuse data sensors from cameras and laser range finders. We use *global features* to represent globally the contain of an image. Secondly, we will fuse these measures of luminance with the laser data observations (distance and orientation) given that we will use the range and bearing model to model the response of the laser range finders.

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2 RELATED WORKS

In (Yan et al., 2012), a neural architecture for learning new navigation strategies of a robot is proposed based of the observation of human's movements. In (Y.Sandamirskaya et al., 2011), a new architecture for behavioural organization of an agent is proposed. Since it receives data from sensors and the environment of the robot, the behaviour is determined with actions.Also a theoretical formula based on Bayes rules and neural field is given. The work of (P.Cisek, 2006) is for major importance in the robot grasping field. Indeed, it gives a theory for object grasping based on the strategies used for animals to decide which object to reach and how to do the planning of the movement. Because these processes stimulate the same brain regions, (C.Crick, 2010) developed a model which allow to fix and to plan through some parameters of the movement. In the area of navigation, (M.Milford and G.Wyeth, 2010) has given another view of SLAM by using a biological approach. This method allows the robot to localize it self in a variable large environment. (Maja, 1992) proposed a method which synthesises an artificial robot behaviour of the robot. This life like strategy should be robust, repeatable and adaptive. Concerning the global descriptor used to characterize images, many works are done. A survey is given in (Y.Raoui et al., 2010).

3 LOCALIZATION WITH EKF USING LASER RANGE FINDER

In this section, we are interested to robot localization in a structured environment using the probabilistic approach(Y.Raoui et al., 2011). This approach has induced a revolution in robotics since Thrun introduced it in 95. Indeed, it takes into account the uncertainty in the movement of the robot. This uncertainty is caused with many factors like "slippage, bumping". Through the fusion of sensor and motion model, th robot can correct its positions. In the figure "ground", we show the positions where the robot should be. These states are of crucial importance because all the steps of filtering are depending on it. The robot has to compare its noisy position with the ground truth.

3.1 Prediction of the Position

The most important thing to consider in the prediction phase is the motion model or the model of displacement of the robot. It should be in fact determined with a probabilistic way, in order to move the mobile robot. Let's have the following probability with rely the robot position from x_t tox_{t+1} with an action u.

$$p(x_{t+1}/x_t, u)$$

In order to implement this equation, we use the prediction step of the Kalman filter:

$$X_{t+1} = A.X_t + B * u$$

In this implementation, we consider the robot state as a couple of the robot mean position and the covariance. This distribution will evolute until the robot ends its path.

The figure 1 shows the movement of the robot in a structured environment. We consider the state of the robot represented with (x, y, θ) which simplifies its estimation. For more complete formulation, we should integer Euler angles. As shown in the figure, the robot positions are affected with error which disable the robot to close the loop. This ability is important for both indoor and outdoor environments. At the same time, the ellipse of uncertainty grows also because the predicted covariance is growing. Thus, a step of correction must be included so as we can reduce this ellipse of uncertainty, in other words decrease the values of the diagonal of the covariance matrix.

3.2 Correction of the Position

To update the position of the robot we use the observation computed from Laser range data and GIST descriptor both as done for the stimuli. Let us have the function $z(x)$ where x is the robot position and z is the observation.

We have $H = \frac{dz}{dx}$ is the Jacobian which will allow us to update the robot metrical position using the following equations:

$$Q_t = \begin{pmatrix} \sigma_r^2 & 0 \\ 0 & \sigma_r^2 \end{pmatrix}$$

Where σ_r is the standard deviation of the robot motion.

$$S_t = H_t \sum_t * H_t^T + Q_t$$

S_t is the covariance on the predicted measure, which the noise could be from the monocular camera or the Laser range finder.

$$K_t = \overline{\sum_t} * H_t^T * S_t^{-1}$$

K_t is the Kalman gain. Q is the error on the robot position.
The equation of the update of the robot position is:

$$X_{t+1} = X_t + K_t * (z_t - \hat{z}_t)$$

The covariance of the update is:

$$\sum_t = (I - K_t * H_t)\overline{\sum_t}$$

and $(z_t - \hat{z}_t)$ expresses the data association for localization, in other words the difference between the observation and the prediction of the measure.

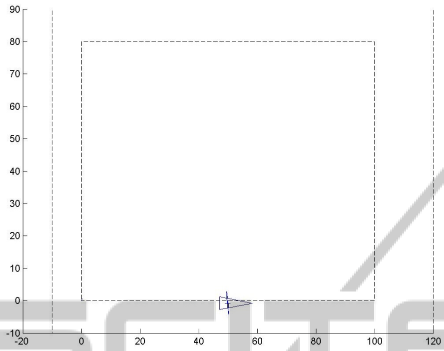

Figure 2.

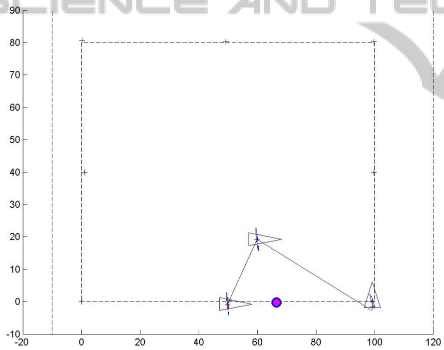

Figure 3.

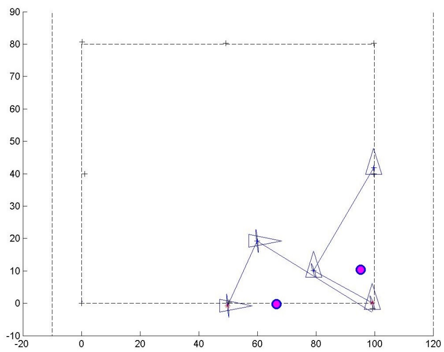

Figure 4.

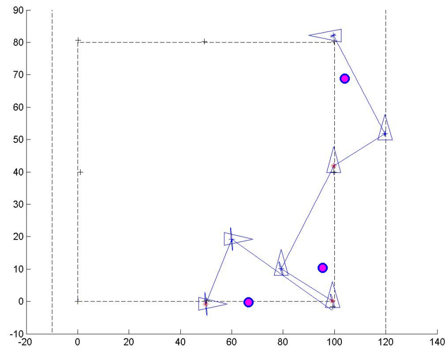

Figure 5: Figures 2,3,4 and 5 represent ground truth with red points, predicted positions with blue points and estimated positions with triangle.

4 NEURAL FIELDS

4.1 Behavior Control with Neural Fields based on Laser Range Finders

The main actions of the mobile robot are moving forward, backward, left or right. Indeed, the neural fields are used to encode the direction of the robot by mean of their peaks. The stimulus are supposed to be the sensory data which are provided by the robot sensors. This method implies the use of the sensing-action paradigm without using any planning task. Therefore, the neural field is expressed by the one-dimensional equation:

$$\tau . u(\varphi, t) = -u(\varphi, t) + s(\varphi, t) + h +$$

$$\int w(\varphi, \varphi^{'}).f(u(\varphi^{'}, t))d\varphi^{'}$$

where T ¿ 0 defines the time-scale of the field, u is the field excitation at the position neuron. The temporal derivative of the excitation is defined by:

$$u^{\cdot}(\varphi, t) = \frac{u(\varphi, t)}{dt}$$

The stimuli represents the input of the field at a certain position and at time t. Depending on the stimuli, the equation can have different solutions:

- 0-solution, if $u(\varphi) < 0$
- infinite solution, if $u(\varphi) > 0$
- a-solution, if there is localized excitation from a position a_1 to a position a_2. This solution is also called a single-peak or mono-modal solution.

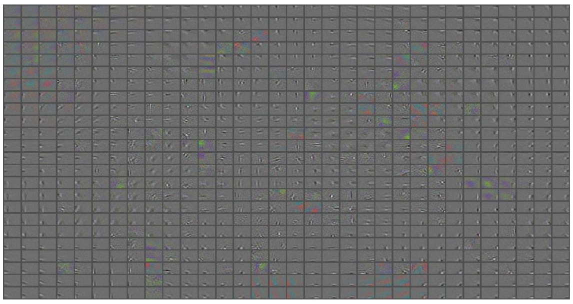

Figure 6: Receptive neural field.

The neural fields can control the robot's planar movements with:

- Target-Acquisition: moving towards a given target point.
- Obstacle Avoidance: moving while avoiding obstacles.
- Corridor Following: moving along corridors in the absence of obstacles.
- Door Passing: passing a door to traverse between two rooms, from a corridor to a room, or vice versa.

4.1.1 Control Design

The behavioural variable is taken as the robot's heading φ relative to a world fixed reference. Then, the neural field has to encode angles from $-pi$ to $+\pi$. The global inhibition allows only one localized peak on the field. After the stabilization of the field, the most activated neuron decodes the direction to be executed by a robot.

Field of Stimuli
The neural field needs some necessary informations (stimuli). The stimulus is determined according to some stimulus functions. These functions describe the target direction, the direction to obstacles. A novel feature of our approach is the use of vision and laser range informations as stimuli. We will propose a model of sensor with noise which will correct the position of the robot.

Dynamics of Speed
In a free obstacle situation, the robot moves with its maximum speed Vmax, and slows down when it approaches a target. This velocity dynamics can be chosen as:

$$V_T(t) = V_{max}(1 - \exp^{\sigma_v . d_T})$$

where σ_v is a positive constant tuned in a relation with the acceleration capability of the robot. dT represents the distance between the robot and the target at time t.

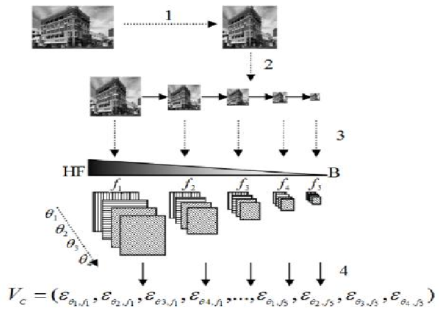

Figure 7: An explivative scheme of the GIST descriptor.

5 METHODS

We present a novel method, based on Dynamic Neural Fields, for multi-sensory fusion of visual and laser data. Wo compute the GIST global visual features (Oliva and A.Torralba, 2001) for images which we fuse with range and bearing data measured with laser range finders.

5.1 GIST Descriptor

Visual global features are 1D vectors that allows to describe and index images. GIST reduces the dimension of such features. First the images are decomposed into small images which size are 32*32 and 128*128. Second, they are smoothed with Gabor filters having n_θ and n_σ scales. Third, the obtained filtered images are divided on M*N regions and transformed on a vector.

5.2 Stimuli Computation

We compute our stimuli using monocular camera and laser range sensors as showing in the figure 6 . The neural fields are machine learning methods which are better that the other non-linear methods such as SVM and Mixture of Gaussians.

The equation of Amari (Amari, 1977) has as unknown variable $u(\phi,t)$ which solution is given in the following equation(see 8):

$$u(\phi,t) = a\exp(-(1-\alpha.K)\frac{t}{\tau} + \frac{1-\alpha}{1-\alpha.K}.S$$

where $\alpha = \frac{1}{2}$ et $\tau = 10$.
and

$$K = \sum_{\phi=1}^{N} \omega(|\phi - \phi'|) * H(\phi) \qquad (1)$$

$H(\phi)$ is the heaveside function.

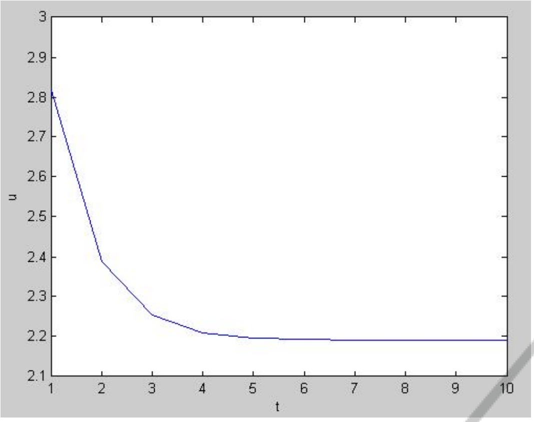

Figure 8: Activity of the neural field $u(\phi,t)$.

The state $u(\phi,t)$ depends on the stimuli S which we will compute using a fusion scheme of GIST visual descriptor and Laser data. The computed signal will allow us to determine the best action.

5.2.1 Laser Range Stimulus

We extract range and bearing information from the Laser range sensors which are stimuli for the dynamic neural field. These sensors give perceptions when the robot is facing an obstacle, for example a human that moves randomly in an indoor environment. Let's consider the observation function $h(X)$, where $X = (x,y,\theta)$:

$$Z_t = [r_t^k, phi_t^k]^T$$

The model of observation is given with:

$$Z_t = h^t(X_t) = \begin{bmatrix} ((delta)) \\ \arctan(\frac{delta(2)}{delta(1)}) - \theta_t \end{bmatrix}$$

$$S = C_0 * (\frac{1}{1*\pi^2*\sigma^2}\exp(\frac{-r^2}{2*\sigma^2}) * \exp(\frac{-phi^2}{2*\sigma^2})$$

Where C_0 is the amplitude of the stimulus and σ is the range of inhibition of the stimuli

5.2.2 Visual Stimulus

We consider the GIST vector as visual stimulus. It quantifies the visual cue of an image which is very important when the robot navigates in an indoor environment because the objects may have different appearances. Besides of that, the obstacles may be whatever which sustain the choice of global features as stimuli. We note that don't use local features in spite of their high distinctiveness because their calculation is time consuming.

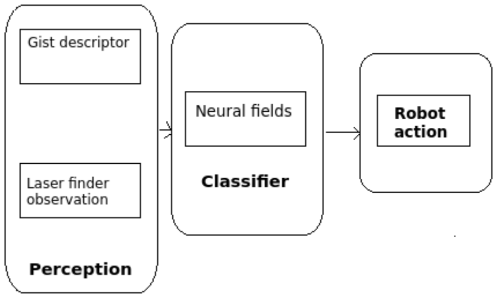

Figure 9: The scheme of our method of obstacle avoidance.

Lets have the GIST descriptor:

$$D = gist_i / i = 1..N$$

$gist_i$ represents the i_{th} component of the GIST descriptor for an acuired image.

$$S_i^v = \exp(\frac{g_i^2}{2*sigma^2})$$

Thus the equation of the GIST visual stimuli is given with:

$$S^v = (S_1, S_2, S_3, ..., S_N)$$

N represents the dimension of the GIST descriptor.

6 OBSTACLE AVOIDANCE WITH NEURAL FIELDS

The robot moves in a square environment using the motion model $p(x_{t+1}/x_t, u)$ affected with Gaussian white noise (x_{t+1} and x_t are the robots positions at time t+1 and t respectively, u is the odometry displacement. When the robot is moving between two estimated positions, we put an obstacle in the surrounding of the robot. We change the action on the robot if the distance separating the robot from the obstacle is less that 0.7 meters.

Then we compute the stimuli used in the neural field by computing the sum of the laser range finder observation and the extracted visual GIST feature. This computed observation is based on the calculus of the distance and the directions of the laser sensor and the global visual descriptor. This observation is novel because it fuses two sensors: Laser range finder and the camera. Therefore we compute the solution of the Dynamic Neural Field given by the equa. 1. We mentionne that this method is based on the learning decision paradigm. That's why we start with the contruction of 4 classes of the stimuli where each one is associated to one of these actions (move right, left, forward, backward). The fusion of the camera and the

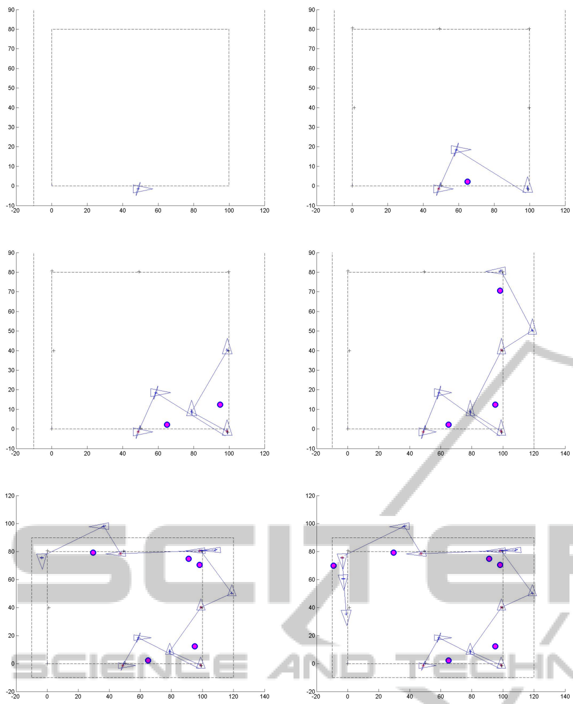

Figure 10: The robot motion with obstacle avoidance and EKF, elementary behaviour of the robot is given with outputs of neural fields stimulated with laser range data.

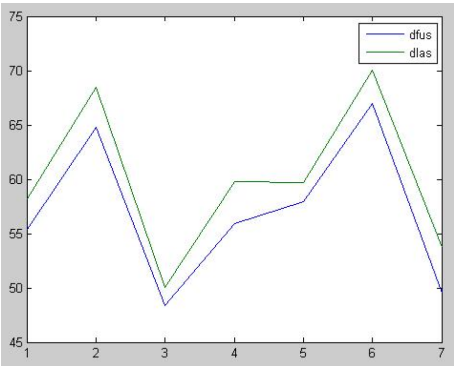

Figure 11: Standard deviation of the error between the positions generated with neural field and the ground truth (blue for the fusion of multi sensory data and green for the laser only data).

laser sensor data improve the accuracy of the robot localization. We show from the figures 11 12 13 that the curve related to fusion is always lower that the one of laser only.

7 CONCLUSION

We enhanced the accuracy of the robot navigation by

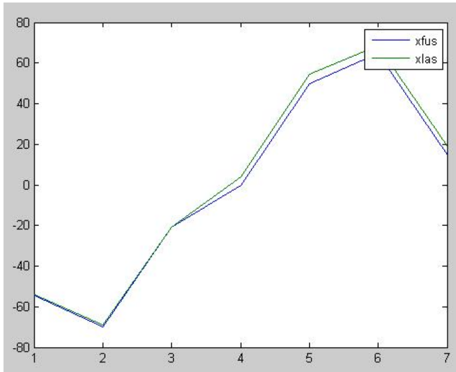

Figure 12: Standard deviation of the error on x coordinates between the positions generated with neural field and the ground truth (blue for the fusion of multi sensory data and green for the laser only data).

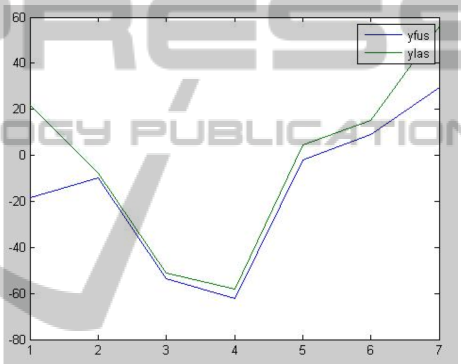

Figure 13: Standard deviation of the error on y coordinates between the positions generated with neural field and the ground truth (blue for the fusion of multi sensory data and green for the laser only data).

using two types of sensors, Camera and Laser range finder, instead of only one. The neural field is good because it is inspired from biological processes, so the algorithm are better. We use GIST descriptor instead of local feature points to increase the run time of our program. Our method could be implemented on mobile robots in dynamic environments to avoid obstacles. The metrical navigation is more accurate than the topological navigation, that is why we have used it, through the application of the Extended Kalman Filter to update the position when the robot avoids the obstacle. We aim at the future to use neural field in robot localization and mapping with the application of topological mapping. We will focus on the improvement of the attractors dynamic that use neural fields to move the robot with less error on the odometry displacements.

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