Biologically Inspired Visual Odometry Based on the Computational Model of Grid Cells for Mobile Robots

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Abstract— **Visual odometry is a core component of many visual navigation systems like visual simultaneous localization and mapping (SLAM). Grid cells have been found as part of the path integration system in the rat's entorhinal cortex, and they provide inputs for place cells in the rat's hippocampus. Together with other cells, they constitute a positioning system in the brain. Some computational models of grid cells based on continuous attractor networks have also been proposed in the computational biology community, and using these models, self-motion information can be integrated to realize dead-reckoning. However, so far few researchers have tried to use these computational models of grid cells directly in robot visual navigation in the robotics community. In this paper, we propose to apply continuous attractor network model of grid cells to integrate the robot's motion information estimated from the vision system, so a biologically inspired visual odometry can be realized. The experimental results show that good dead-reckoning can be achieved for different mobile robots with very different motion velocities using our algorithm. We also implement a full visual SLAM system by simply combining the proposed visual odometry with a quite direct loop closure detection derived from the well-known RatSLAM, and comparable results can be achieved in comparison with RatSLAM.**

I. INTRODUCTION

In robotics and computer vision, visual odometry is the process of determining the pose of a robot using only the sequential images acquired by its vision system. It has been used in a lot of robotic applications, such as on the Mars exploration rovers [1]. Visual odometry is a core component of many visual navigation systems for mobile robots. For example, it can be used as a building block for a visual simultaneous localization and mapping (SLAM) system. Most of the existing visual odometry algorithms can be divided into the following stages: image acquisition, feature detection, feature matching or tracking across frames, ego-motion estimation, and local optimization. More introductions about visual odometry including the history, fundamentals, important algorithms related to different stages and applications, can be found on the two-part tutorial [2] [3]. The evaluation results of lots of visual odometry algorithms and the related dataset can be found on the website of the KITTI vision benchmark suite [4][1].

In the past decades, several cells have been discovered in the brain of many mammals, such as place cells, grid cells, head-direction cells, border cells, etc., which constitute a positioning system in the brain. These discoveries in the physiology/biology community are very important to understand how navigation processes are computed, which can also inspire new routes for the research of autonomous robot navigation in robotics [5]. Place cells, found in the hippocampus by O'Keefe [6], are only active when the animal reaches a particular place in the environment, namely their place field. Different place cells in the hippocampus fire at different places. Head-direction cells act like a compass and are active when the head of the animal points in a certain direction [7]. Grid cells were found by the Mosers in the entorhinal cortex which provides the input for the hippocampus [8]. A single grid cell fires when the animal reaches particular locations arranged in a hexagonal pattern in the environment. Grid cells are part of a navigation or path integration system, and provide a solution to measure movement distances and add a metric to the spatial map in the hippocampus.

According to these discoveries, animals like rodents can update their representation of pose based on the estimates of self-motion, and update and even "re-localize" their neural estimates of pose using external sensing like vision, which is similar as the process of robot visual SLAM based on odometry and camera/laser sensors. Rodents' pose estimates degrade with time in the absence of external cues, which is similar to the visual odometry drift with time. Rodents' pose estimates can be corrected using visual sighting of familiar landmarks, which is similar as loop closure in visual SLAM. So biologically inspired visual navigation methods can be developed according to these mechanisms [9]–[13]. A most famous work is RatSLAM [9], in which the robot's pose is represented using a three dimensional continuous attractor network (CAN) with wraparound excitatory connections. The network activations are updated by attractor dynamics, displaced by visual odometry, and calibrated by local views. The calculation of visual odometry and local views are performed by matching a quite simple feature, scanline intensity profile, extracted from respective subimages. A fine-grained topological map, namely an experience map, is created and corrected by loop closure detection. Using RatSLAM, the robot can generate a coherent map of the large

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[1]www.cvlibs.net/datasets/kitti/eval_odometry.php

scale and visually ambiguous environment efficiently using only one monocular camera as its sensor. In comparison with the classic visual SLAM approaches, RatSLAM does not detect and track those local visual features, which reduces the computation cost and allows the system to operate at relatively low frame rates and high movement speeds. It can deal with large scale environments which are difficult for probabilistic SLAM methods. In [12], the same three dimensional CAN was used to model conjunctive grid-cell-like cells, and experimental results show that multiple estimates of pose can be maintained, and RatSLAM can deal with the navigation problem in perceptually ambiguous environments.

In the computational biology community, many computational models based on continuous attractor networks have been built to mimic the rat's path integration using the rat's velocity and heading direction as inputs [14]. The simulation results show that grid-cell-like responses can be produced, and accurate dead-reckoning can be realized. Grid cells are a core part of a navigation system for mammals. But so far, few researchers have tried to use these computational models of grid cells directly in robot visual navigation in the robotics community. In this paper, we try to verify whether these computational models of grid cells can also be used on mobile robots, and propose a biologically inspired visual odometry algorithm. Then we combine it simply with loop closure detection to implement a full visual SLAM system.

The next sections are organized as follows: the computational model of grid cells and the proposed biologically inspired visual odometry algorithm are presented in section II; a full visual SLAM based on biologically inspired visual odometry and loop closure detection is proposed in section III; in section IV, simulation results are presented firstly, and then experimental results on different datasets are presented, where different robot platforms are moving with very different velocities; section V concludes this paper.

II. BIOLOGICALLY INSPIRED VISUAL ODOMETRY

A. The computational model of grid cells

In [14], Burak and Fiete proposed periodic and aperiodic continuous attractor networks to mimic the path integration of the rat's grid cells based on the rat's velocity and heading direction. The simulation results show that both networks work, but higher accuracy can be achieved using the periodic network. Furthermore, the integration performance of the periodic network is much less dependent on parameter tuning. So in this paper, we just consider periodic continuous attractor network.

In the periodic network, there are $N = n * n$ neurons arranged in a two dimensional square sheet where neuron i is located at $\boldsymbol{x}_i$, and the vector $\boldsymbol{x}_i$ ranges from $(-n/2, -n/2)$ to $(n/2, n/2)$. Neurons on each edge of the sheet form connections with neurons on the opposite edge, so the topology of the network is that of a torus. The synaptic activation of neuron i is s_i. The dynamics of the neuron is specified as follows:

$$\tau \frac{ds_i}{dt} + s_i = f_i = f(\sum_j W_{ij} s_j + B_i) \tag{1}$$

where τ is the time constant, and $f(\cdot)$ is the neural transfer function: $f(x) = x$ for $x > 0$, and is 0 otherwise. The neuron i is active for $f_i > 0$, and is inactive otherwise. W_{ij} is the synaptic weight from neuron j to neuron i, and it is defined as follows:

$$W_{ij} = W_0(\boldsymbol{x}_i - \boldsymbol{x}_j - l\hat{\boldsymbol{e}}_{\theta_j}) \tag{2}$$

with

$$W_0(x) = \alpha e^{-\gamma|x|^2} - e^{-\beta|x|^2} \tag{3}$$

where α, β, γ are parameters needed to be set. According to Eq. (2) and (3), the weight matrix has a center-surround shape, and is centered at the shifted location $\boldsymbol{x}_i - l\hat{\boldsymbol{e}}_{\theta_j}$.

B_i is the input to neuron i provided by the rat's motion information including velocity and heading direction:

$$B_i = A(\boldsymbol{x}_i)(1 + \eta\hat{\boldsymbol{e}}_{\theta_i} \cdot \boldsymbol{v}) \tag{4}$$

where $\hat{\boldsymbol{e}}_{\theta_i}$ is the unit vector pointing along the rat's heading direction θ_i, and $\boldsymbol{v}$ is the rat's velocity vector. The envelope function $A(\cdot)$ is 1 everywhere for the periodic network.

Here, if the parameter $l = 0$ and $\eta = 0$, neural activations of the network will form a static triangular lattice pattern, which is determined by α, β, and γ, as shown in Fig. 1. If l and η are non-zero, the lattice pattern or the neural activations will be driven to flow by velocity inputs, which is determined by the magnitudes of both l and η multiplicatively. More details about the periodic continuous attractor network, including how to initialize the network activations, can be found in [14].

B. Biologically inspired visual odometry algorithm

According to the description, the lattice pattern will be driven to flow by velocity inputs, and the rat's displacement can be represented by the flow, which means that dead-reckoning can be realized based on the motion information. For mobile robots, if the robot's motion information like translational and angular velocities, or the translation and rotation, are estimated from the vision system, we can calculate the robot's velocity vector $\boldsymbol{v}$ and heading direction θ_i, and then use them to drive the periodic network to generate a flow of the lattice pattern. This is reasonable from the bionic perspective of grid cells, because according to the latest finding [15], speed cells are identified to have a linear response to the running speed in the medial entorhinal cortex, and they will provide the motion information to grid cells. After estimating the robot's placement based on the flow, a biologically inspired visual odometry is realized. Two typical subsequent lattice patterns are shown in Fig. 1, and two typical groups of active neurons are marked by the blue and green circle, from which we can find that the lattice pattern flows towards upper right, and those neurons on each edge of the sheet connect with neurons on the opposite edge.

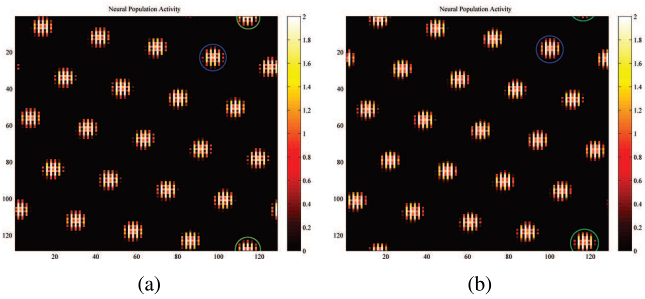


Fig. 1. Two typical subsequent lattice patterns of the periodic network driven by the robot's motion information. The color represents the neural activation, and the black corresponds to inactive neurons. Two typical groups of active neurons are marked by the blue and green circle, which shows that the lattice pattern formed by neural activations flows towards upper right, and those neurons on each edge of the sheet form connections with neurons on the opposite edge.

TABLE I

THE ALGORITHM TO CALCULATE THE 2-D DISPLACEMENTS.

Inputs: two subsequent frames of neural activations: $F^t = [f_{ij}^t]_{n*n}$ and $F^{t+1} = [f_{ij}^{t+1}]_{n*n}$, searching space: $[-\Delta\ \Delta]$
Outputs: two dimensional displacement (dx, dy)
Method:
Initializing $d_{min} = +Inf$
for $d_i = -\Delta : 1 : \Delta$
  for $d_j = -\Delta : 1 : \Delta$
    Acquiring a new matrix $F^{t'}$ by shifting F^t with (d_i, d_j);
    Calculating the distance d between $F^{t'}$ and F^{t+1};
    if $d < d_{min}$
      $dx = d_i$;$dy = d_j$;$d_{min} = d$;
    end
  end
end

Assuming that we have acquired two subsequent frames of neural activations f_i^t and f_i^{t+1}, $i = 1 : N$, and t is the time stamp, because neurons are located in a two dimensional square sheet, these neural activations can be rewritten as two matrices: $F^t = [f_{ij}^t]_{n*n}$ and $F^{t+1} = [f_{ij}^{t+1}]_{n*n}$. We can define a searching space $[-\Delta\ \Delta]$, where Δ is a half of the periodicity of the lattice in the neural sheet, and then calculate the two dimensional displacement (dx, dy) using the algorithm described in Table I. In Fig. 1, Δ is 9, so the estimated two dimensional displacement (dx, dy) is (4, -4). Finally, the robot's real displacement (rx, ry) can be acquired by scaling (dx, dy) according to the magnitude of the robot's velocity vector $\boldsymbol{v}$, as shown in (5). Here, the unit of $\boldsymbol{v}$ is not m/s, but meter per frame.

$$\begin{aligned} rx &= +dx * ||\boldsymbol{v}|| / \sqrt{dx^2 + dy^2} \\ ry &= -dy * ||\boldsymbol{v}|| / \sqrt{dx^2 + dy^2} \end{aligned} \tag{5}$$

In the proposed biologically inspired visual odometry, only the robot's positions are integrated using the computational model of grid cells. The robot's directions are acquired by accumulating the robot's rotations, or integrating the robot's angular velocities directly. This kind of solution is reasonable from the bionic perspective, because there are head-direction cells existing in the brain to provide direction information for mammals. Furthermore, besides visual odometry, general

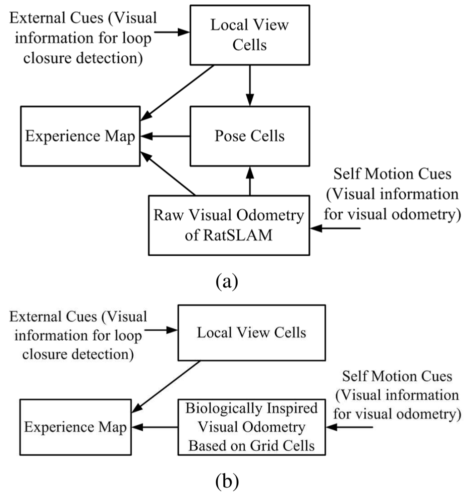


Fig. 2. The main difference between RatSLAM (a) and our SLAM system based on biologically inspired visual odometry and loop closure detection (b).

biologically inspired odometry can also be realized based on the proposed algorithm, when the motion information acquired from other sensors like motor encoders and laser range finders are used as inputs to the computational model of grid cells.

III. VISUAL SLAM BASED ON BIOLOGICALLY INSPIRED VISUAL ODOMETRY AND LOOP CLOSURE DETECTION

Visual odometry is a core component of a visual SLAM system. In this section, we combine our biologically inspired visual odometry with loop closure detection to implement a full SLAM system. Our work is based on RatSLAM. In biologically inspired visual odometry, we also use the rotation and speed estimates based on the matching of scanline intensity profiles as motion inputs to the periodic network. Based on visual odometry results, an experience map is created incrementally, which is the same as in RatSLAM. Unlike RatSLAM, we realize explicit loop closure detection by matching the visual templates which are proposed in RatSLAM. If the current scanline intensity profile is sufficiently similar to a previously stored template, a possible loop closure is detected. If more than six possible loop closures are detected in ten consecutive frames, and these loop closures are consistent, a loop closure is confirmed. This loop closure detection method is simple, but quite effective, which will be validated by experimental results. Once loop closure is detected, the experience map will be corrected, which is the same as RatSLAM again.

As shown in Fig. 2, the main difference between our SLAM system and RatSLAM is as follows: pose cells, which are the core component of RatSLAM, and the original raw visual odometry are replaced by our biologically inspired visual odometry, or we can say pose cells are replaced by the computational model of grid cells. The success of this SLAM system will also validate the effectiveness of the proposed biologically inspired visual odometry.

TABLE II

THE ALGORITHM PARAMETERS USED IN THE BIOLOGICALLY INSPIRED VISUAL ODOMETRY.

Parameter	Value	Parameter	Value
n	128	l	2
τ	5	dt	0.5
α	1	β	$3/18^2$
γ	1.05*β	η	2

IV. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, we will first perform simulation experiments to test the proposed biologically inspired visual odometry algorithm, and validate whether the property of grid cells will appear. Then we will perform real experiments using three different datasets acquired by different mobile robots. Finally, we will test the full visual SLAM based on biologically inspired visual odometry and loop closure detection, and compare it with RatSLAM.

A. Simulation results

We perform simulation experiments based on the source code for continuous attractor network model of grid cells released by Y. Burak and I. R. Fiete[2]. During the experiments, the agent (the robot or the rat) is moving randomly with the maximal speed of 2.5 m/s within a fixed area, the radius of which is two meters. The algorithm parameters introduced in Section II are listed in Table II, and almost all of them will be used in all the experiments of this paper. The only exception is that η will be set as 0.2 when performing experiments using the dataset "stlucia_0to21000"[3], because the images were acquired when the camera was moving at very high speeds.

We run our algorithm using 3500 frames of simulated motion data. The real trajectory and the estimated trajectory of the agent are shown in Fig. 3(a), and the drift of the odometry is shown in Fig. 3(b). From the results, we can conclude that the integration of motion information is quite accurate using the proposed algorithm. After increasing the duration of the experiment greatly, we track the activations of a single neuron located on $(0, 0)$, as shown in Fig. 4, where red color represents that this neuron is active when the agent moves to the corresponding positions. From Fig. 4, we can find that the property of grid cells appears that a single grid cell fires when the animal reaches particular locations arranged in a hexagonal pattern.

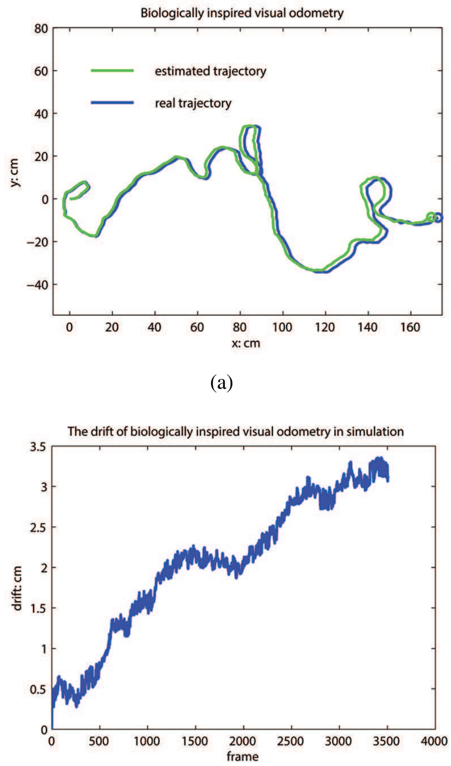
B. The experimental results of biologically inspired visual odometry on different datasets

We use three different datasets to test the biologically inspired visual odometry algorithm. The first one was acquired in the NUDT campus by the NuBot rescue robot developed by the first author's research group on NUDT[4], as

[2]http://clm.utexas.edu/fietelab/code.htm

[3]https://wiki.qut.edu.au/display/cyphy/RatSLAM+MATLAB

[4]https://github.com/nubot-nudt/Biologically-Inspired-Visual-Odometry-data



(a)

(b)

Fig. 3. (a) The real trajectory and the estimated trajectory using the proposed algorithm in the simulation experiment. (b) The odometry drift of the proposed algorithm.

shown in Fig. 5. The robot is equipped with a Bumblebee2 stereo vision system. During the experiment, the robot was moving along a square-like trajectory. The typical left image is shown in Fig. 6(a). We adopt the feature matching and ego-motion estimation algorithm from the famous LIBVISO2 developed by Andreas Geiger, et al. [16] to acquire the robot's ego-motion information from stereo images, and use this information to drive the periodic network. The results of the biologically inspired visual odometry and LIBVISO2 are shown in Fig. 6(b) and (c). In comparison with LIBVISO2, comparable results can be achieved using the biologically inspired visual odometry. The running process of biologically inspired visual odometry especially how the lattice pattern of neural activations is driven by motion inputs, can be found on our submitted accompanying video.

Then we test our algorithm using the Karlsruhe dataset, which was acquired in a city by a stereo camera rig mounted on a driving car. Because ground truth data acquired by a GPS/IMU system are also provided in the dataset, we can estimate the drift of visual odometry, and compare our algorithm with LIBVISO2 quantitatively. We run biologically inspired visual odometry and LIBVISO2 on the three image sequences[5]. The results are shown in Fig. 7 and Fig. 8. The results show that the drifts of biologically inspired visual odometry are just a little bit larger than LIBVISO2. Although

[5]http://www.cvlibs.net/software/libviso/

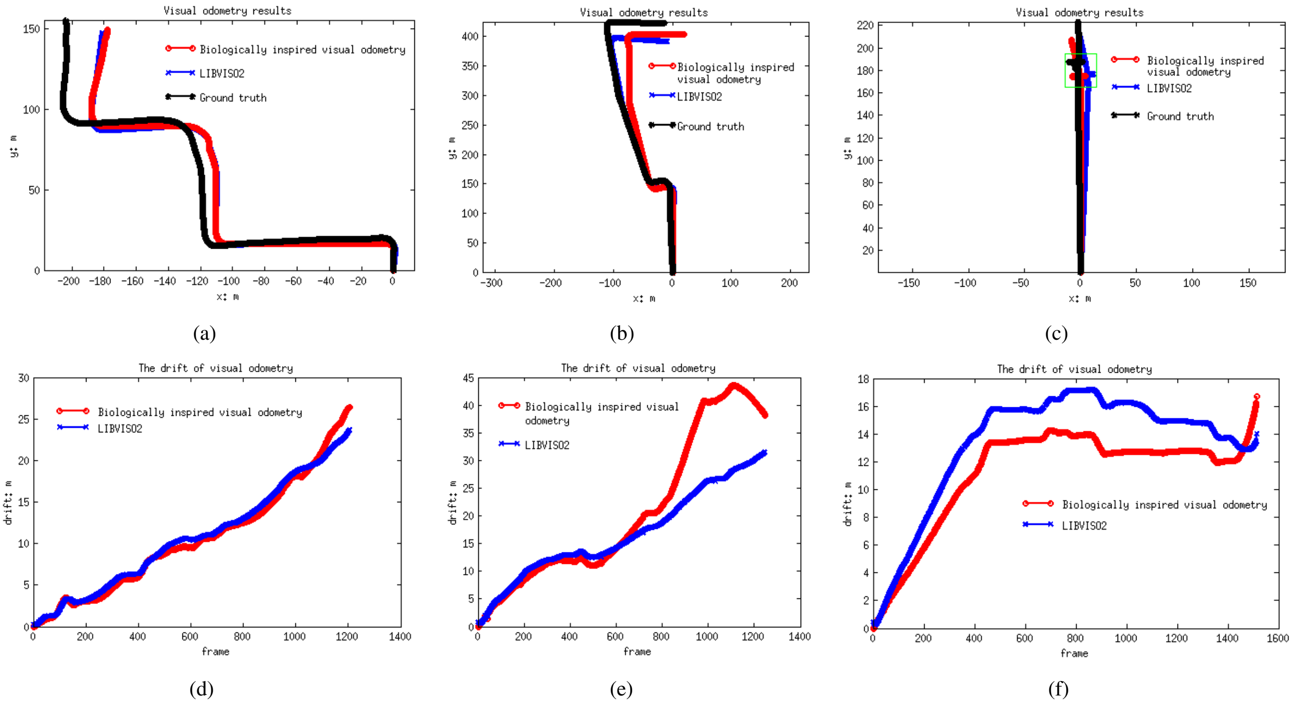


Fig. 7. The visual odometry results and the drifts of our algorithm (red) and LIBVISO2 (blue) when using the image sequence "2009_09_08_drive_0016" (a)(d), "2009_09_08_drive_0019" (b)(e) and "2009_09_08_drive_0021" (c)(f). The region within the green rectangle in (c) is enlarged in Fig. 8. The ground truth data are represented in black.

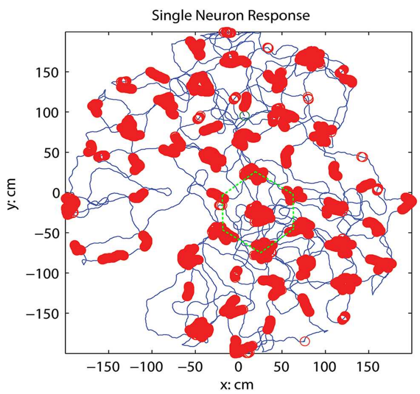


Fig. 4. The activations of a single neuron during the simulation experiment. Red color represents that the neuron located on (0, 0) is active when the agent moves to the corresponding positions. The green hexagon was painted manually to show the property of grid cells.

Fig. 5. The NuBot rescue robot equipped with a Bumblebee2 stereo vision system.

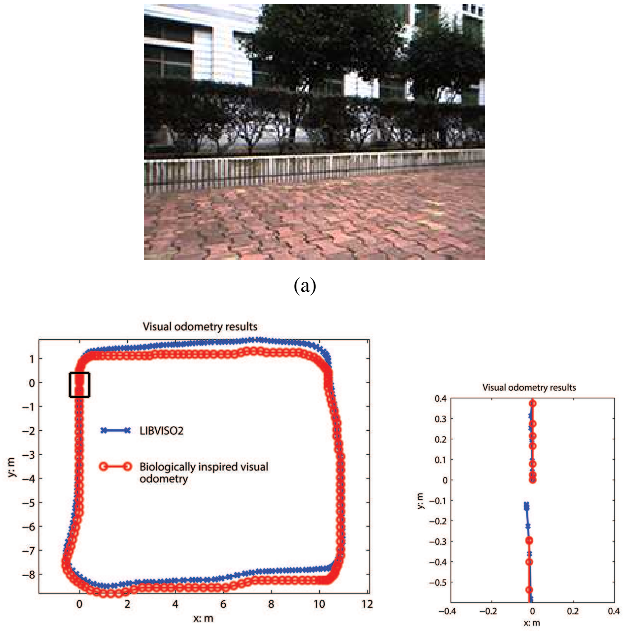
the accuracy of biologically inspired visual odometry is lower than classic non-bionic algorithms like LIBVISO2, the path integration results maintain the important structures of the robot's trajectory, which is consistent with human navigation.

Finally we perform experiments using the dataset "stlucia_0to21000" for RatSLAM acquired in a suburb by one monocular camera on a driving car. In our algorithm, the rotation and speed estimates based on the matching of scanline intensity profiles in RatSLAM are used as motion inputs to the periodic network. The results of the raw visual odometry of RatSLAM and our algorithm are shown in Fig. 9(a) and (b) respectively. We find that the results of two visual odometry are also quite similar and consistent.

In these three experiments, good dead-reckoning can be achieved for different robots using the biologically inspired visual odometry algorithm, although these robots move in very different velocities from tens of centimeters per second to ten meters per second.

C. The experimental results of visual SLAM

In this section, we test the visual SLAM proposed in section III using the dataset "stlucia_0to21000", and compare it with RatSLAM. The results of biologically inspired visual odometry and the raw visual odometry of RatSLAM have been demonstrated in the last subsection. The visual template versus frame is shown in Fig. 10(a), where the same template number for two non-subsequent frames means that a possible loop closure is detected. The experience versus frame of the proposed visual SLAM and RatSLAM are shown in



(a)

(b) (c)

Fig. 6. (a) The typical left image. (b) The results of the biologically inspired visual odometry (red) and LIBVISO2 (blue). (c) The scale-up region within the black rectangle in (b).

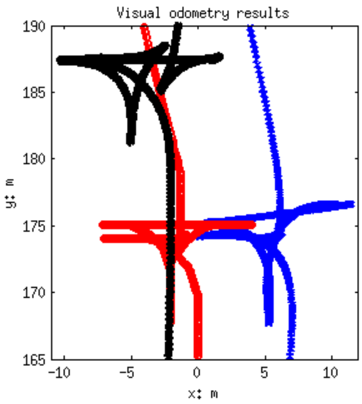
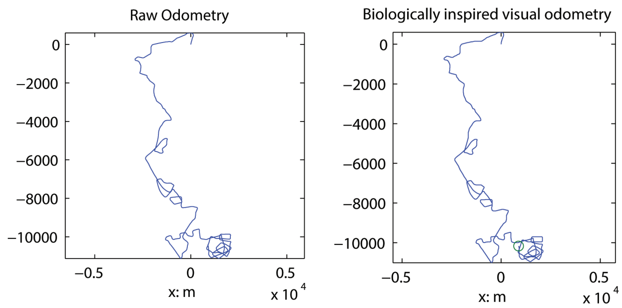


Fig. 8. The scale-up region within the green rectangle in Fig. 7(c).



(a) (b)

Fig. 9. The visual odometry results of the raw visual odometry of RatSLAM (a) and our algorithm (b). Because the environment is too large in comparison with the difference of two results, we did not demonstrate them in a single figure.

Fig. 10(b) and (c) respectively, where the same experience number for two non-subsequent frames means that a loop closure is confirmed. The final results or experience maps of the two SLAM are shown in Fig. 10(d). Although no ground truth data is provided in this dataset, we still can conclude that these two SLAM results are quite consistent. According to these results, although we use a simple and direct loop closure detection method, which causes less loop closures being detected than RatSLAM (as shown in Fig. 10(b) and (c)), comparable SLAM results can still be achieved after combining biologically inspired visual odometry and loop closure detection. It also validates the effectiveness of the proposed biologically inspired visual odometry, and the pose cells of RatSLAM can be replaced by the computational model of grid cells.

D. The computation cost of biologically inspired visual odometry

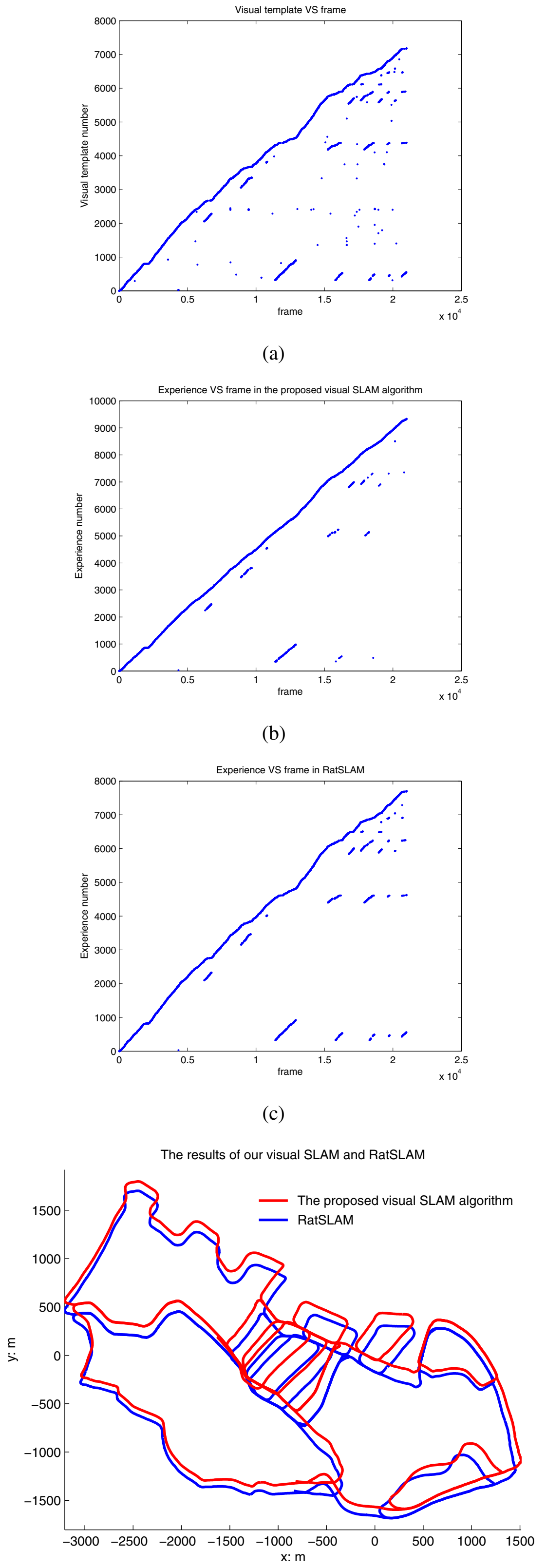
We evaluate the computation cost of biologically inspired visual odometry on a computer equipped with a 2.4GHz i7 CPU and 4GB memory. Currently, the prototype system is implemented in Matlab[6]. The time needed to perform one frame of computation is about 700 milliseconds, and about 75 percent of the time is spent on the calculation of the two dimensional displacement proposed in Table I. After optimizing the definition of the searching space according to prior information about motion inputs, implementing the algorithm in C++ and accelerating the algorithm by GPU, we expect the real-time performance to be improved greatly.

V. Conclusions

In this paper, we introduce the periodic continuous attractor network, a computational model of grid cells, into visual navigation research for mobile robots. We propose a biologically inspired visual odometry algorithm, where the robot's self-motion information is used to drive the flow of the lattice pattern of neural activations, and the robot's placement is estimated from the flow. We also implement a full visual SLAM system by simply combining the biologically inspired visual odometry with loop closure detection derived from RatSLAM. We perform thorough experiments using simulation data and three different datasets where the images were acquired by different kinds of vision systems equipped on different mobile robots with very varying motion velocities. In comparison with LIBVISO2 and RatSLAM, comparable results can be achieved using the proposed visual odometry and visual SLAM algorithm. The experimental results validate that the computational model of grid cells can be used to realize path integration or dead-reckoning for mobile robots, and it can work as an important component of a fully bionic visual navigation system in the future.

In future work, we will optimize the proposed algorithm to improve the real-time performance. We are also interested in developing a fully bionic visual navigation system including visual odometry and SLAM by combining the

[6]The source code is available on: https://github.com/nubot-nudt/Biologically-Inspired-Visual-Odometry



(a)

(b)

(c)

(d)

Fig. 10. (a) The template number VS frame. (b) The experience number VS frame in the proposed visual SLAM algorithm. (c) The experience number VS frame in RatSLAM. Much less loop closures were detected by the proposed visual SLAM than RatSLAM. (d) The experience maps generated by two SLAM algorithms.

computational models of place cells, head-direction cells and speed cells [15] for mobile robots. For example, it will be a very interesting work to realize biologically inspired ego-motion estimation based on the latest finding of speed cells to provide motion inputs to our current visual odometry algorithm.

Acknowledgement

We would like to thank Y. Burak and I. R. Fiete for their release of the source code about continuous attractor network model of grid cells[7], Andreas Geiger for his release of LIBVISO2[8], and David Ball, Michael Milford and Gordon Wyeth for their release of the Matlab version of RatSLAM[9].

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