Behavior-Based Map Representation for a Sonar-based Mobile Robot by Statistical Methods

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Abstract

Many conventional methods for map generation by mobile robots have tried to reconstruct 3-D geometric representation of the environment, which are time-consuming, error-prone, and necessary to transform the map into the information available for the given task. This paper proposes a method to acquire a statistical map representation robust to sensor noise and directly usable for navigation task. The robot is equipped with a ring of ultrasonic ranging sensors and a collision avoidance behavior is embedded in it. First, the mobile robot explores in the environment in order to store a set of sequences of sonar data, and the principle component analysis is applied to reduce the dimensionality of the sonar data. As a result, each sequence of sonar data can be described as a score pattern of principal components. Next, these patterns are classified into typical local structures of the environment in order for the robot to discriminate them. Finally, a graph representation of the environment is constructed in which nodes and arcs correspond to these local structures and the transition probabilities between them, respectively. The validity of the method is shown by computer simulations and real robot experiments.

1 Introduction

A mobile robot has to acquire a map of its environment so as to explore and perform path planning in an unknown environment. The traditional approach to path planning involves some types of reasoning mechanisms that generate a plan by manipulating a geometric map usually stored in a centralized data structure. The success of the plan depends on the accuracy of the geometric information in the map. Many conventional methods for map generation analyze internal or external sensor inputs to build a two or three dimensional geometric map of the environment represented in global coordinates (for example, [1, 2, 3, 4]) which are time-consuming to construct, error-prone by sensor noise, including unnecessary information, and necessary to transform the map into the information available for the given task.

As a work for navigation task without geometric representation of the environment, Nakamura and Asada [5] proposed a method called *motion sketch* in which reaching and obstacle avoidance behaviors are obtained by analyzing the relationship between optical flow patterns and motor commands. Dubrawski and Crowley [6] has experimented with learning navigation reflexes from ultrasound using the ART(Adaptive Resonance Theory) technique. Since they intend to determine motor commands facing with the local structures, this methods cannot be directly applicable for global navigation task.

Reignier, Hansen, and Crowly [7] investigated the use of a neural network method named GAL(Grow and learn), in which a sequence of sonar patterns is described by an incremental adapted network which reconstructs the input data. They compared the use of GAL with use of principal components analysis to describe sensor data. In a preliminary experiment they observed that the first three principal components form data taken in a hallway corresponded to the distance to a wall,the angle of the wall,and a corner. These experiments were not performed in a systematic way and the results were inconclusive.

Kuipers [8], Mataric [9] and others have developed an alternative approach based on a topological network description. In such an approach, the graph representation in which each node corresponds to a unique landmark in the world is acquired as a map of the environment. Although this approach enables the robot to reduce the uncertainty of robot localization by its topological representation, its performance severely depends on the accuracy of landmark detection, which seems to have the same drawback as the conventional methods do.

Tani [10] proposed a dynamical system's approach to the robot navigation problem. His method utilizes no explicit representations such as a geometric map or symbolic landmark graph, and is expected to produce a certain global structure in the phase space, which is self-organized through local interactions. However, his method implicitly utilized the knowledge that focusing on the branching points play an important role of representing the environment although it is generally difficult to discover such a distinctive structure of the local environment.

In this paper, we propose a method for autonomous acquisition of a statistical map representation based on robot behaviors (forward motion, random turn, and collision avoidance), which is robust to sensor noise and directly usable for navigation task. The robot is equipped with a ring of ultrasonic ranging sensors and a sequence of sonar data taken during forward motion are gathered and analyzed by statistical methods in order to detect local structures to be discriminated by the robot. A graph representation of the environment is constructed in which nodes and arcs correspond to these local structures and the transition probabilities between them, respectively.

The remainder of this article is structured as follows: In the next section, we give a brief overview of our method of map generation. Then, we describe the method for processing the sequence of sonar data, the procedure of discovering the local structure in the environment, and the method of constructing a probabilistic network description as a map with computer simulation results. Finally, we give real robot implementation results and concluding remarks.

2 Our Robot and Map Generation

Fig.1 shows a picture of our robot which has a Power Wheeled Steering (hereafter PWS) system driven by two motors into each of which we can send a motor command, independently. The robot is equipped with a ring of ultrasonic ranging sensors (ranging from 0.0 to 250 cm) which has high accuracy for incident angle less than 20° from the surface normal.

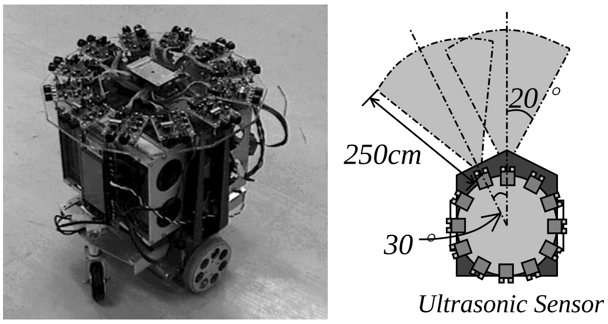


Figure 1: Our robot

In the map generation process, we use a sequence of sonar data instead of a discrete snapshot. Because, if the robot utilizes a discrete snapshot of the environment based on a single set of sonar data, the robot can only discriminate where walls or obstacles are. The accuracy of any one data point is low, and the different sonar data are generated in different trials at the same place due to sensor error and noise. While, if the robot utilizes a sequence of sonar data acquired from the previous time to the current one, the robot can take account of the changes of sonar data and reduce the uncertainties in discriminating the local structures.

In order to realize the above process, the robot behavior is controlled such that the robot takes actions of forward motion while a sequence of sonar data is taken, random turns when other sequences are taken, and collision avoidance to avoid collision with walls or corners. In the experiments, one step corresponds to about 20cm, and one sequence of sonar data includes four snapshots of 12 sonar readings at four locations along a line. We construct the action space consisting of ±30°, ±60°, and ±90° turns, and totally we have 7 actions including no turns (see Fig.2). Note that the robot is given no knowledge of the structure of its sensory system nor of any physical meanings of these actions.

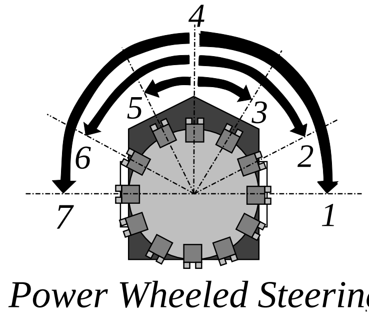


Figure 2: Action Selection

Map generation process is summarized as follows (see Fig.3):

1. Explore in the environment in order to store a set of sequences of sonar data.
2. Apply the principle component analysis to reduce the dimensionality of the sonar data. As a result, each sequence of sonar data can be described as a score pattern of principal components.
3. Classify these patterns into typical local structures (we call them “states”) of the environment in order to discriminate them.
4. Construct a graph representation of the environment in which nodes and arcs correspond to the states and the state-transition probabilities in terms of action (turn) that are obtained by MLE (the maximum likelihood estimation) method.

In the following, we explain each procedures with computer simulation results using the environment shown in Fig.4.

3 Principal Component Analysis for Sequences of Sonar Data

3.1 Principal component analysis

Principal component analysis is the method for finding new explanatory variables by which the internal structure in multivariate data can be described more appropriately in terms of the smaller number of variables. Therefore, this method can reduce the amount of information embedded in the multivariate data. We apply the principle component analysis to a set of sequences of sonar data in order to reduce the high dimensionality of the data.

A set of sequences of sonar data generated in nth trials is described by $n \times p$ matrix $\boldsymbol{X}$, where p indicates

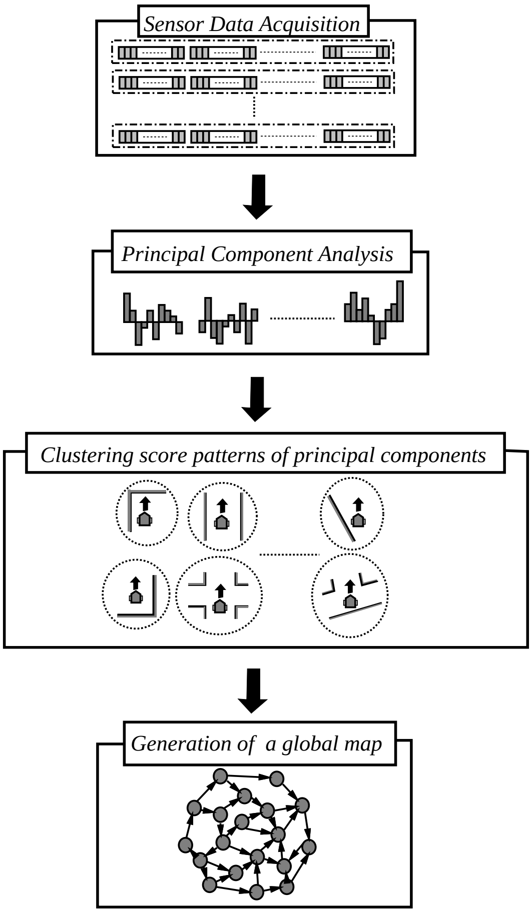


Figure 3: An overview of map generation

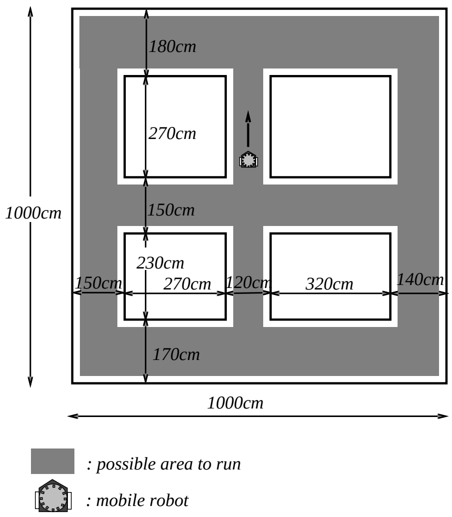


Figure 4: Simulation Environment

the number of components in one sequence data and is equivalent to the number of sonar sensors r × the number of time steps m during which the sensor information are measured in one sequence. The distribution of components for each row of $\boldsymbol{X}$ are transformed so that they may distribute normally with mean $\mu = 0$ and variance $\sigma^2 = 1$. This normalization process for all rows transform $\boldsymbol{X}$ into n×p matrix $\boldsymbol{Z}$. Let $\boldsymbol{R}$ be the correlation coefficient matrix of $\boldsymbol{Z}$. Principal component vectors $\boldsymbol{\omega}_j \quad (j = 1, \cdots, p)$ are obtained as eigenvectors that satisfied the following equation:

$$\boldsymbol{R}\boldsymbol{\omega}_j = \lambda_j \boldsymbol{\omega}_j. \tag{1}$$

The eigenvalue λ_j associated with its eigenvector gives a measure of that vector's importance in terms of explaining variation in the input information. The relative magnitudes among the eigenvalues tell how important each eigenvectors is. The eigenvector with largest eigenvalue is called the first principal component vector. The principal component vectors satisfy the following equations:

$$|\boldsymbol{\omega}_j| = 1 \quad \text{and} \quad \boldsymbol{\omega}_i \cdot \boldsymbol{\omega}_j = 0 (i \neq j).$$

The problem of deciding the number of the principal components is difficult. There is no complete method for solving this problem. It is a general method to find out the number of components so that almost part of the information in the original data can be described by the principal components. In this paper, we decided the number of principal components so that the cumulative proportion that represents the goodness of approximation becomes more than about 80%.

A sequence of sonar data is described by a p-dimensional vector $\boldsymbol{x}$. Let $\hat{\boldsymbol{x}}$ be a normalized vector by the variance that was calculated when the principal components are obtained. The principal component score f_j in terms of $\boldsymbol{x}$ for jth principal component vector $\boldsymbol{\omega}_j$ is defined as follows:

$$\begin{aligned} f_j &= \boldsymbol{\omega}_j \cdot \hat{\boldsymbol{x}}, \\ \text{where,} \quad \boldsymbol{\omega}_j &= (\omega_{j1}, \omega_{j2}, \cdots, \omega_{jp}) \quad \text{and} \\ \hat{\boldsymbol{x}} &= (\hat{x_1}, \hat{x_2}, \cdots, \hat{x_p}). \end{aligned} \tag{2}$$

3.2 Results of the analysis

We apply the principal component analysis to 3000 sequences of sonar information. The number of sonar sensors r and the number of time steps m are 12 and 4, respectively, in the experiments. As a result, the dimension of the data is reduced from 48 to 10, and each obtained principal component corresponds to the primitive representing the local structure in the environment in terms of initial location (posture) in the environment, the configuration of the sonar sensors, and time steps. The top group of the largest components reflect the postures of the robot, and the second group of the largest components reflect the local structures of the environment such as walls in front of or back side of the robot, walls in both sides of the robot, free space around the robot, and sudden changes of sonar patterns caused by facing with corners or intersections during robot motion. The order of main components depends on the structure of the environment. If it has large free spaces, the corresponding component appears on the top position. Fig.5 shows the accumulation of contribution rate of the principle components, which indicates that the largest 10 components contribute larger than about 80%.

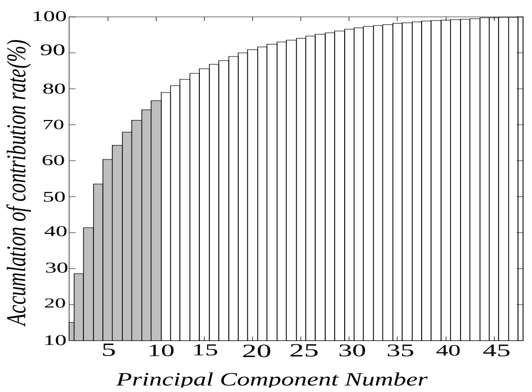


Figure 5: Accumulation of contribution rate

Fig.6 shows examples of the obtained principle components, some of which indicate the relative posture to the environment, and closeness to the wall. Note that the sonar data have been normalized so that they have a zero mean and a unit variance.

4 Discriminating Local Structures by Clustering Score Patterns of Principal Components

Any sequence of sonar data can be described with a score pattern of principle components by the above process. The next step is to classify these patterns into typical local structures to be discriminated for navigation task. We apply ISODATA clustering algorithm to classify these patterns. The ISODATA clustering is an iterative clustering algorithm which is composed of a $k-$means clustering procedure and splitting or merging procedure based on heuristics [11]. This clustering algorithm is one of unsupervised clustering method of which feature spaces is self-organized.

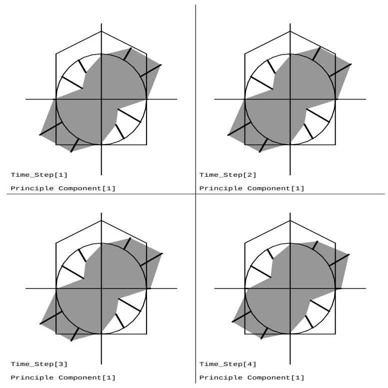
The score pattern of principle components $\boldsymbol{F}_j$ for a sequence of sonar data j is given by

$$\boldsymbol{F}_j = \{f_{j1}, f_{j2}, \cdots, f_{ji}, \cdots, f_{jk}\},$$

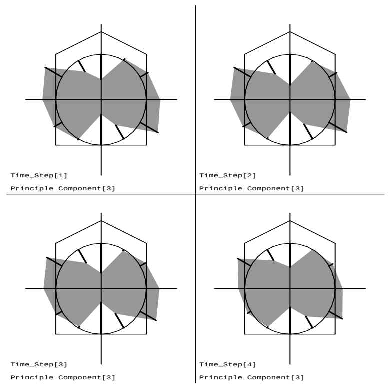
where f_{ji} denotes the score of the i-th component for j, and k denotes the number of principle components.

As a distance measure between two score patterns of principle components $\boldsymbol{F}_1$ and $\boldsymbol{F}_2$, the following norm is given by

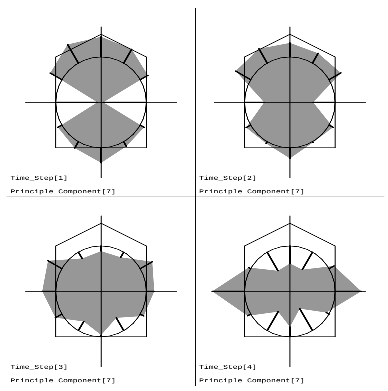
$$\|\boldsymbol{F}_1 - \boldsymbol{F}_2\| = \sqrt{\sum_{i=1}^{k} (f_{1i} - f_{2i})^2}.$$



(a) 1st Principal Component Vector



(b) 3rd Principal Component Vector



(c) 7th Principal Component Vector

Figure 6: Examples of principle components

Although the above measure is based on Euclidean distance, it can be used by ISODATA algorithm because the scores of the principle components have been already normalized with respect to the variance of the given data.

4.1 Results of clustering

We applied the ISODATA algorithm to classify 3,000 samples of the score patterns based on 10 largest principle components. As a result, we have obtained 117 local structures which are combinations of two kinds of variations: different shapes of the local structure, and the variations of the initial posture (orientation and approaching direction) of the robot in the environment. Examples for the former are "T" or "cross" intersections, corners, and corridors in the environment. The latter has a variation of relative orientation to the environment and approaching direction (ex., approaching to or leaving a local structure). The translational variation does not appear because the changes of the sonar outputs due to translation are not so large, and therefore they are absorbed in the normalization process of the sonar data. The rotational variation depends on the sensor displacement. Currently, we use 12 sonar sensors which are displaced along a circle, therefore we have 12 variations of orientations. Each cluster represents one of the combinations by these factors.

Fig.7 shows examples of local structures classified by the method. Small solid circles and line segments indicate the initial locations and trajectories of the robot.

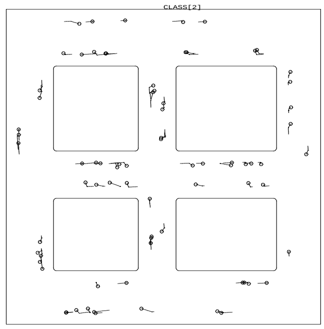
5 Global Map Generation

The classified local structure can be regarded as a state and a state transition is caused by a turning action. The final step is to construct a global map representation by a graph of which nodes and arcs correspond to states and state-transition probabilities in terms of turning actions. Once we have such a graph representation, we can easily apply the conventional path planning or reinforcement learning methods on it. From the above argument, the unit of turning angle should be 30 degrees which corresponds to the angle between two sonar sensors next to each other. Actually, we construct the action space consists of $\pm 30°$, $\pm 60°$, and $\pm 90°$ turns, and totally we have 7 actions including no turns.

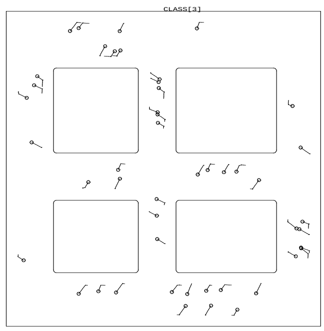
The state transition probability is obtained by the Maximum Likelihood Estimation (MLE) method. Let $Pr(s_i, a_p, s_j)$ be the state transition probability that the world will transit to the next state s_j from the current state-action pair (s_i, a_p):

$$Pr(s_i, a_k, s_j) = \frac{times(s_i, a_k, s_j)}{\sum_{t=1}^{N} times(s_i, a_k, s_t)}, \qquad (3)$$

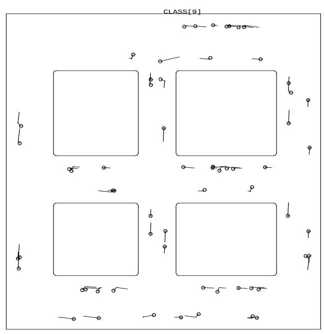
where, $times(s_i, a_k, s_j)$ denotes the number of observations of the state s_j after execution of the action a_k at the state s_i. N denotes the number of all states. After memorizing the history of these transition $times(s_i, a_k, s_j)$ to some extent during the learning process, we estimate the state transition probabilities.



(a) Cluster No.3



(b) Cluster No.4



(c) Cluster No.10

Figure 7: Examples of local structures

Fig.8 shows examples of the estimated transition probabilities. Some of them have multiple transition due to inappropriate clustering results.

6 Real Robot Experiments

We have shown a picture of our real robot and its architecture (see Fig.1). To show the validity of our method in a real situation, we set up a simple environment in our lab as shown in Fig.9. We took about 300 sequences of sonar data and obtained 10 principle components and 16 states. Fig.10 shows the accumulation of contribution rate of the principle components, and Fig.11 shows examples of the obtained principle components. Examples of 16 local structures are shown in Fig.12 where collision avoidance with the wall, wall following, approaching to the corner, and leaving the corner behaviors are observed as a result.

7 Discussion and Future Works

We have shown the behavior-based map generation method with computer simulation results and preliminary real experiments. In each step, we have the following issues to be attacked.

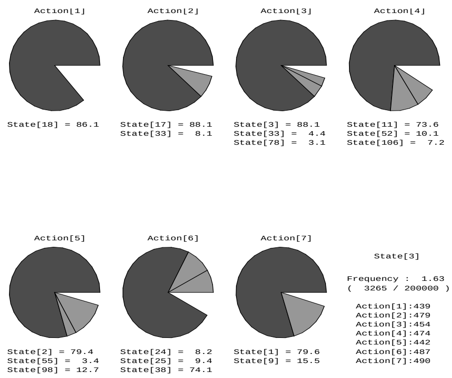
The results of the principle component analysis for the sequences of sonar data depends on the number of steps, the sensor displacement, the local structure of the environment, and others. There is a trade-off between the number of steps and the local structure. The longer steps we set up, the fewer local structures we found and small local structure might not be found. On the other hand, shorter steps found much more local structures some of which should be classified into the same one. We determined the number of steps considering the size of local structure by which the robot behavior can be controlled. The method to determine the number of steps suitable for the environment should be developed.

ISODATA clustering algorithm needs several parameters to control the clustering procedures such as initial number of clusters, average distance between two clusters next to each other, and so on. We determined these parameters experimentally. The consistent criterion to determine these parameters should be developed.

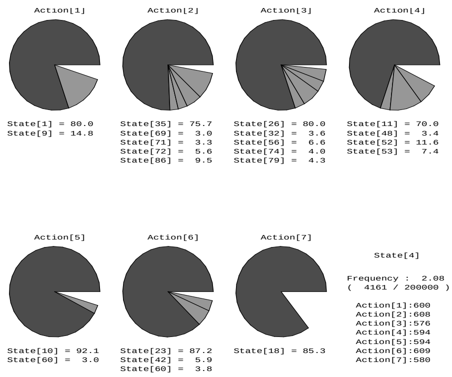
Some distributions of the state-transition probabilities in terms of action at each state did not have a single peak, but multiple transitions. This suggests:

- perceptual aliasing occurs, therefore the current sensing capability cannot cope with it,
- the principle component analysis drops the important information to discriminate the states, and/or
- the clustering did not work well due to inappropriate parameter selection.

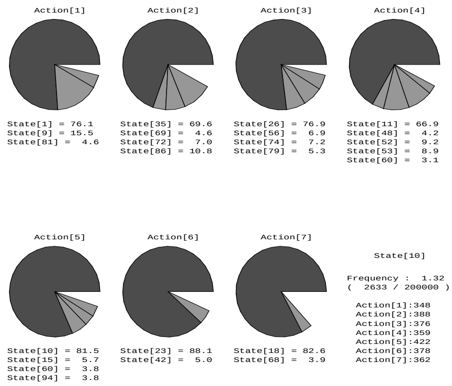
We are planning to make the above issues clear by real experiments with more complicated environment.



(a) Cluster No.3



(b) Cluster No.4



(c) Cluster No.10

Figure 8: State transition probabilities

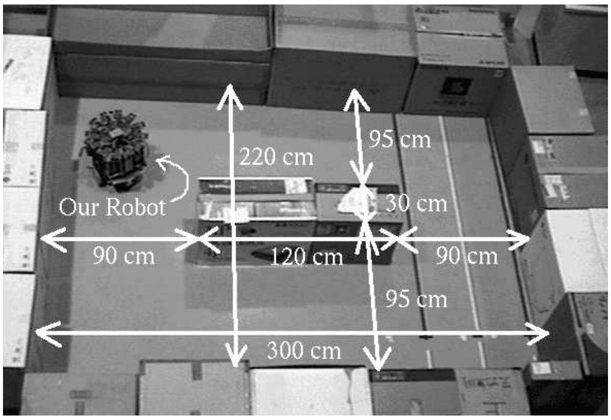


Figure 9: An environment for real robot experiments

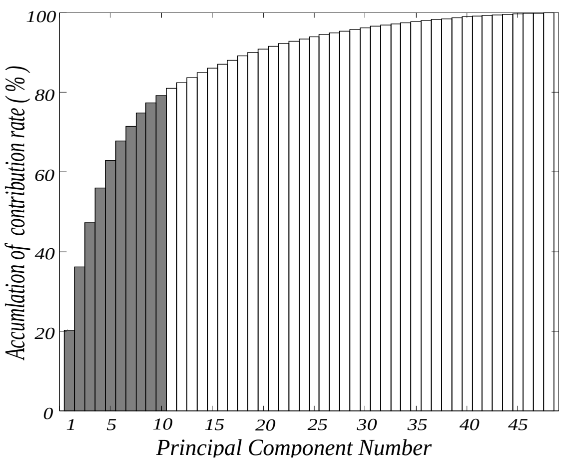
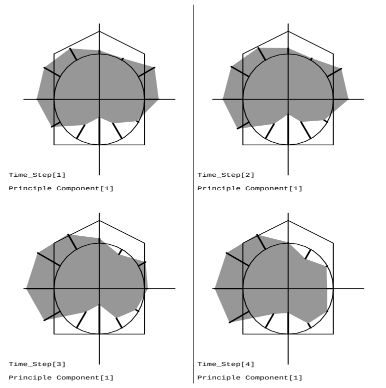
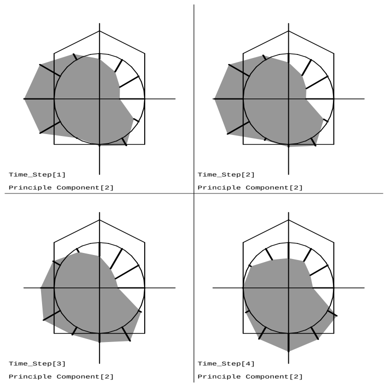


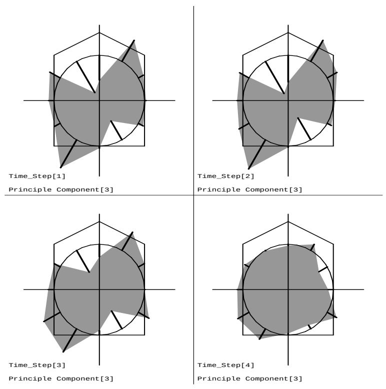
Figure 10: Accumulation of contribution rate



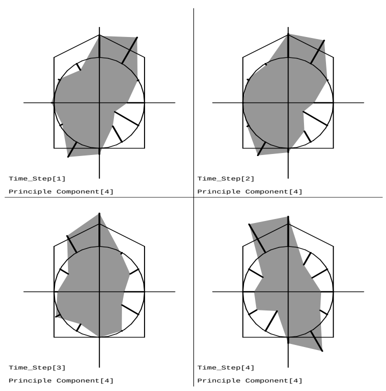
(a) 1st Principal Component Vector



(b) 2nd Principal Component Vector



(c) 3rd Principal Component Vector



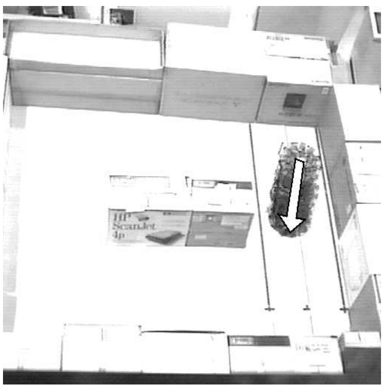
(d) 4th Principal Component Vector

Figure 11: Examples of principle components

(a) Collision avoidance

(b) Wall following

(c) Approaching the corner



(d) Leaving the corner

Figure 12: Examples of local structures

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