# Cognitive navigation modeling in robots

**Student**
R.S.N. Fehrmann 0997196

**Thesis Advisor**
Prof. Dr. L.R.B. Schomaker
Lambert@ai.rug.nl
Artificial Intelligence
RijksUniversiteit Groningen

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Artificial Intelligence
RijksUniversiteit Groningen

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# 1 Introduction

Navigation methods in mobile robots are usually based on an absolute coordinate system. The position of the robot is expressed in $x, y$ coordinates which are obtained by means of an external technical resource such as a GPS system or laser-range finders. The position of an object in the robots environment is carefully mapped into a geometrical model. This model is then incorporated as *a-priori* information concerning the environment within the navigational subsystem of the robot. The robot 'knows' at any moment in time its current position in the environment and can accurately plan a theoretical navigational path to a certain goal, without colliding into obstacles.

Robot navigation based on an absolute coordinate system and a geometrical model perform well in known an environment where objects are of a static nature. These static objects have a fixed position in the environment and can easily be mapped into a geometrical model.

The first problem arises when the robot is situated in a unknown environment. A geometrical model is not at hand and the robot can not plan a theoretical path in the environment. Subsequently, a complete new geometrical model of this environment must be constructed and incorporated into the navigational subsystem of the robot. This modeling is a time and money consuming human effort. Consequently, the robot will be much less autonomous than one would like to see: Human intervention is needed every time the robot is situated in an unknown environment.

Objects of a dynamic nature, such as people or other mobile robots, form the second problem. The position of a dynamic object in the environment is constantly changing. Consequently, the object can not be mapped into a geometrical model of the environment. Such a model only captures the positions of objects with a fixed position in the environment. In order to proper react to such dynamic objects, robot-environment interaction is needed. Ultrasonic sonar or laser-range finders will in most cases not be sufficient. A more sophisticated perceptual sensor such as a camera is needed to be able to correctly identify these dynamic objects and determine their behavior in the environment.

How does nature solve the problem of robust navigation in highly dynamical and unknown environments? Humans and animals make no use of an absolute coordinate system and cannot determine there relative distance to nearby obstacles with great accuracy or pin point their exact position on the globe in $x, y$ coordinates. A global navigational plan is not being constructed in every detail in advance.

Humans and animals primarily make use of visual perception and memory in combination with cognition for navigation in an environment. This use of visual perception enables humans and animals to navigate in highly dynamical or unknown environments without the need of exact *a priori* geometrical knowledge. The robust solution for navigation suggest that artificial autonomous systems may benefit from a cognitively inspired implementation of a navigational subsystem. A generic navigation system based on navigational aspects found in humans and animals will enable the robot to explore and navigate in highly dynamical and unknown environments. The need for an artificial infrastructure or an *a priori* geometrical model becomes obsolete.

The purpose of this research study is to explore the concept of cognitive robot navigation based on navigational principles found in relative simple organisms, such as insects. Many insects have a navigational system based on 'visual' landmarks in the environment that are being used as reference points for navigational purpose.

The ultimate end result in our approach will yield a robot that is capable of navigation on basis of a landmark-based map of the environment that is being constructed incrementally while the robot is exploring the environment. This is addressed in the literature as the SLAM problem, which stands for Simultaneous Localization and Map-building[2]. System capable of such a task would be considered as autonomous.

**Concrete research question of this paper**
Will a cognitive inspired navigational subsystem yield a robot that is capable of performing robust navigation in dynamical and unknown environments?

# 2 Theoretical Background

As put forward in the introduction the robust solution for navigation suggest that an artificial autonomous system may benefit from a cognitive inspired navigational subsystem. Animals show an remarkable ability to navigate through their environment. Birds for example who fly from their nest to search for food occasionally enter a new location which they have not visited before. Time over time they seem to be able to calculate a direct path form this unknown location back to their nest. Section 2.1 will review research done on animal navigation done with rats,ants and bees. The components found to be involved in the navigational task of these animals will serve as inspiration for our design of a navigational subsystem for artificial autonomous systems which is described in section 2.2.

## 2.1 Animal navigation

In the following subsections the basic components of navigation in relative simple organisms such as bees, ants and rats will be discussed. Results from research done on the navigational task of these organisms on the neural and behavioral level will show the involvement of the components.

### 2.1.1 Gradient-based navigation

The first component that seems to be involved in animal navigation is that they rely on so called *gradient-based* navigation: Using the gradient of sensory information in the environment for navigational purpose. Sensory information that can be used by animals when they navigate on basis of gradients are for example polarization of the sky and the magnetic field of the earth. This sensory information is emitted from objects or points in space that do not change their relative position due to animal motion, such as the sun or the magnetic north pole *etc.* The intensity or gradient of sensory information emitted from such objects on a navigational path will help animals to return to a certain location in the environment. Nehmzow[11] refers to reports of Waterman[18] that suggest that bees orientate their flight paths in relation to a hive with help of the sun and the polarization of the sky. When the hive is moved over night several kilometers, the bees will leave the hive in the morning in the same direction as they did the previous day. Moving the hive while the bees were away feeding resulted that the bees returned to the original location. Consequently, they discovered the hive was not in its original location and flew to the new location of the hive. In the third case the hive was moved to a different continent. Consequently, the movement of the sun diverges from the movement at the original location. The bees flew out of the hive in the same direction as the original situation, but got confused of their location during the day.

### 2.1.2 Dead Reckoning

The second component which seems to be involved in animal navigation is called *dead reckoning*: The continual updating of position and heading by summing successive small displacements in the environment. This process is also called *path integration* when the differences between successive positions are made arbitrarily small: Integrating the velocity vector with respect to time gives us the position vector. With this method the animal is capable to keep track of its current position and directional heading in the environment when there is no perceptual input available to serve as an orientation cue on which it can determine its current position and directional heading otherwise.

On the neural level of animal navigation two types of neurons in the rats brain have been implicated in spatial learning and navigational processes: the so called *place cells*[6] of the hippocampus and *head direction cells*[7] of the thalamus and postsubiculum. Research done on rats suggests that these two type of cells form the basis for dead reckoning and that the firing pattern of these cells form a neural representation of the current position and directional heading in the environment.

Results from studies[9] done on spatial firing patterns of place cells in the hippocampus of rats suggest that these cells are responsible for keeping track of the current position of the rat in the environment. Muller conducted experiments on rats that were situated in a large cylindrical apparatus with uniformly gray walls. In this artificial created environment no visual cues were available that could serve as orientation landmarks. As the animal made a continuous repeating winding in this artificial created environment, individual place cells in the hippo campus kept their firing pattern when the rat was situated again in the same position. The ability of a specific located place cell in the hippocampus to keep its firing pattern when the animal returned at the same location in this artificial created environment was reasoned to be based on the dead-reckoning method. The absence of orientational, visual cues or landmarks resulted that position information in the environment could only be obtained by the animal by keeping track of its own displacements.

Research on head direction cells[8][10] suggest that these cells are also involved in the dead reckoning method. The head direction cells complement the place cells in the hippocampus by signaling the animals directional heading it is facing in the environment over a range of approximately 90 degrees, regardless of its current position. Each individual head direction cell has its own unique directional preference. Directional headings in the environment are represented by particularly activity in subsets of head direction cells. Analogue to research done on place cells, Blair and Sharp[10] did research on the head direction cells. Their result also suggest that when there are no visual orientation cues in the environment, the directional heading in the environment is retained on basis of summing successive displacements.

### 2.1.3 Landmarks

The third component involved in animal navigation is called *landmark orientation*. An animal uses the perceptual pattern of familiar, distinctive and easily perceptible points in the environment to determine its current directional heading and position in the environment. The animal is constantly trying to match its current perceptual input with the learned perceptual patterns of landmarks in a map, which forms a representational layout of the environment. In this map the relative positions of landmarks to each other are represented and so forms a general layout of the environment. We will further discuss the use of this so called cognitive map in section 2.1.5.

Why do animals make use of landmarks to establish a fix on the current position and directional heading when the have the dead reckoning method at hand? It is reasoned that occasionally it is necessary to establish a fix on the position and directional heading in the environment on basis of landmarks in a cognitive map to correct the inevitable cumulative error in position and directional heading when the dead reckoning method is used.

Wehner and Raber[12] conducted experiments done on desert ants *Cataglyphis bicolor* that suggest that in order to move to a particular location ants try to match their current perceptual input in the form of a visual percept, with stored visual inputs of landmarks. In a artificial created environment two identical visual cues were placed that served as landmarks. The homing positions of ants in this artificial created environment were recorded. Moving the landmarks to different positions in the environment also resulted in different homing positions of the ants. When the landmarks were placed back in their original location, the homing positions of the ants also returned to their original position. The ants seemed to use the angular extent of the two landmarks for navigational purpose and enables them to return to their homing position.

Cartwright and Collet[13] conducted similar experiments on bees. As it is in the case of ants, bees also seem to use the angular extent of landmarks for navigational purpose. Displacement of artificial landmarks lead to a corresponding displacement in the returning positions of the bees in the environment.

On the neurological level of navigation Muller and Kubie[9] conducted an experiment with rats that provided evidence that place cells are capable of also making use of landmarks in the environment to establish the place specific firing pattern, which represents the current position in the environment. Rats were situated in a artificial created environment that consisted out of a large, cylindrical apparatus, equipped with a single, white cue card on its otherwise uniform gray wall. Displacement of this white cue card resulted in corresponding rotation of the place cell firing fields.

Similar experiments done on head direction cells by Taube, Muller and Ranck[8] also suggest the use of landmarks to retain the animals current directional heading in the environment. Research done by Blair and Sharp[10] supports this conclusion.

From this section and the previous section on dead reckoning we can conclude that both place cells and head direction cells use both vestibular and optic flow information to update their firing pattern that represents the current directional heading and position in the environment.

### 2.1.4 Beacon navigation

Minor reliance is placed on *beacon navigation*. Sensory cues from a goal or its immediate surrounding is used to determine its locations. A beacon can be seen as a landmark in sight. Experiments done on chimpanzees[16] suggest however that in locating a certain goal, the correct position of the goal in the wider context has a greater influence than the sensory characteristics. A chimpanzee saw food being hidden in one of two differently colored boxes after which the positions of the boxes were interchanged. Subsequently, the chimpanzee started looking for the food in the box at the correct location, rather than in the one with the correct color. The sensory cues from a certain goal appear to control navigation only when the animal has the goal in sight at the final approach. Even then the goal has to occupy approximately the correct location in the wider context the animal is familiar with.

### 2.1.5 Cognitive maps

Tolman[5] describes a number of experiments conducted on rats, who were trained to follow a complex indirect path to a food box. This path contained numerous turns and changes of direction. In the test situation the learned path was blocked and alternative routes to the food box were offered. The large majority of the rats chose a route that was heading to the direction of the food-box and not in the direction of the original learned indirect path. These experiments show that rats do not navigate on basis of maps which describe the accurate path to an object in an environment. The heading of the rats to the direction of the food-box suggest that a topological representation of the environment in rats brain is used for navigation. Tolman therefore introduced the notion of *'Cognitive map'*.

A cognitive map of the environment is a crucial component in animal navigation. As was shortly mentioned in the section on landmarks 2.1.3, a cognitive map represents the environmental layout. It encodes the metrics(angle, distance) and sense relation(left versus right) between landmarks in the environment. Research done on rats by Cheng[17] supports this. A rat is shown the location of a hidden goal in a featureless rectangular environment. Before allowing the rat to search for the goal, it is diss-orientated by slow rotation in the dark. When the rat was allow to search it did so at the correct location and the rotational equivalent.

Research at the neural level of navigation suggest that the dead reckoning process is the key to construction of this cognitive topological map in the brain[14]. Place cells and head direction cells appear to be part of a predefined network which serves as a path intergrator. This path intergrator generates an abstract internal two-dimensional spatial representation of the environment where visual sensory information from the environment becomes secondarily bound to this representation by associative learning. The association between landmarks and the two-dimensional spatial representation serve to correct the cumulative error from the path intergrator.

### 2.1.6 Fusion of multi-sensory modalities

In the above section on cognitive maps it is suggested that combining visual sensory information from the environment with vestibular sensory information leads to a cognitive map of the environment. Duhamel, Colby and Goldberg[3] refer to research that describes neural maps in many brain areas such as the superior colliculus[4], that converge input from different sensory modalities, such as vision and somatic sensation. These neural maps are believed to contribute to the spatial representation of the environment that surrounds the body and to generate a representation of external events where all the sensory modalities are integrated. What perceptual patterns are the basis for the autonomous development of cognitive maps? What constitutes a landmark? We assume here, that landmarks are represents of sensory input referring to location in the environment where 'egocentric space' is invaded by physical objects. In other words a (near) collision constitutes a singularity or meaningful event. Colby and Goldberg[21] describe neurons in the medial intraparietal(MIP) area specialized for responding to stimuli(landmarks) that invades this 'egocentric space'.

## 2.2 Design issues

The navigational subsystem for an artificial autonomous system described in this section is inspired on the navigational components found in animal navigation based on research reviewed in the above sections. As it was reasoned in the introduction(Section 1), the hypothesis is that a cognitive inspired navigational subsystem will lead to robust robot navigation in a dynamic and unknown environment.

The navigational subsystem will be based on landmark navigation in combination with a topological representation of the environment. Landmarks in the environment will be learned on basis of a self-organization of the robot's sensory data. This learning of landmarks based on a self organizing principles has two advantages.

First, interpreting the world using the robot's impoverished sensors is difficult for a human designer. As a result human tend to model landmarks in the environment to simplistic.

Secondly, the clustering technique used in self-organization results in generalization of sensory information. As a result the average perceptual impression of a landmark in the environment is constructed. This generalization over perception gives us a robust, noise tolerant, method of landmark detection.

The self organizing principle used for generalization of landmarks will be a Kohonen Self Organizing Map. The theory on this Kohonen map will be discussed in Section 2.2.1.

The perceptual pattern of a landmark in the environment will be constructed by combining sensory information from multi-sensory modalities on the robot: vision, sonar and odometry. Combining the information from these modalities will lead to a perceptual pattern of a landmark that consist out of a visual pattern, sonar reflective field and $\Delta x, \Delta y$. The $\Delta x, \Delta y$ gives us the information of where the previous observed landmark was situated relative to the landmark that is observed at the moment. The visual pattern of a landmark will be transferred to HS,$V_{max}$ color space. This transformation will be explained in Section 2.2.2. The reason for transforming the perceptual pattern to HS,$V_{max}$ color space is to make the representation of a landmark less sensitive for variation in lighting conditions.

As mentioned earlier, the generalization and classification of perceptual patterns of landmarks in the environment will be based on a Kohonen Map. Classification in this Kohonen map will primarily be based on the visual pattern of a landmark. When two landmarks in the environment located at different points have the same visual pattern, the sonar reflective field configuration will set the two landmarks apart from each other in classification. When the sonar reflective field of the two landmark also resemble each other, the $\Delta x, \Delta y$ will be the decisive factor. Two landmarks located in distinct points in the environment will be ambiguous when the perceptual patterns of these landmarks resemble each other on every sensory component: visual pattern, sonar-reflective field and $\Delta x, \Delta y$. In short, with landmark detection the sonar reflective field configuration and $\Delta x, \Delta y$ will determine the subclass of visual patterns and the corresponding potential landmark the robot is observing.

In this study it is the assumption that perceptual patterns of potential landmarks can be collected on the basis of collisions or near-proximity events. Rather than expecting landmark singularities to emerge solely from the training of all visual patterns[1] which are present during all of the ego-movement, the subset of visual patterns at and around a physical collision or near proximity point are deemed essential for the development of a landmark map. As is described in Section 2.1.6 neurons are found in the medial intraparietal area that are sensitive for stimuli that invades the proximal 'ego-centric' space. In our design the sonar reflective field will be used to observe if an object invades the proximal 'ego-centric' space of the robot and a proximity events occurres. Combining the visual pattern and the sonar reflection field of a potential landmark at a collision or near proximity event will result in a strong correlation between perceptual representations of landmarks and the physical world: A visual edge becomes a real edge after tactile sensing.

With the extracted perceptual representation of landmarks a cognitive or topological map of the environment will be constructed. As it is the case in animals this cognitive map will represent the relative positions of landmarks in the environment to each other. The angles and distance between landmarks will be collected with a mechanism based on the dead-reckoning method found in animals. The robot keeps track of changes in the directional heading and position between successive observed landmarks by summing successive displacements.

With the cognitive or topological map of the environment the robot can determine its current location and directional heading by means of comparing its current observed perceptual pattern of the environment with learned perceptual landmark representations on the topological map. When a landmark is observed on the topological map, the robots knows that it is located at the corresponding location in the representational map of the environment.

The design of a navigational robotic subsystem with the cognitive inspired aspect describe above, will yield an autonomous mobile robot capable to adapt to the surroundings without the need to define and model the relevant aspects of the environment *a priori*.

### 2.2.1 Kohonen Self Organizing Map

As mentioned in the design issues above(Section 2.2), landmarks in the environment will be learned on basis of a self organization of the robot's sensory data. The perceptual patterns of potential landmarks are collected on basis of proximity events. From these perceptual patterns of potential landmarks, generalized landmarks are constructed. In our design this is done on basis of a *Kohonen Self Organizing Map.* This section will review the theory behind a KSOM.

**Introduction** A self-organizing map is a special class of artificial neural networks based on competitive learning. The output neurons of the network compete among them self to be activated. The results is that only one output neuron wins the competition and is activated, the so called winner-takes-all neuron.

The output neurons of a self-organizing map are usually order in a one- or two dimensional area. During the course of the competitive learning process, the output neurons become selectively tuned to specific variations of input patterns. The location of tuned output neurons in the one- or two dimensional array become order with respect to each other in such a way that a meaningful coordinate system is created over the output neurons for different input patterns.

Training a self-organizing map can be done for two reasons. First, reducing a arbitrary multi-dimensional input space, where the output neurons preserve a topological representation of the input data. Second, to obtain a finite table of prototypical input patterns.

**Self-organizing landmark map** In this research project the Kohonen self-organizing map will be used to created a finite table of prototypical landmarks. These prototypes form generalized perceptual representations of landmarks in the environment. Perceptual patterns of potential landmarks in the environment will be linked with the input neurons of the self-organizing map. The learning procedure will try to fit patterns from a large or huge ensemble of patterns within a small map of $n^{dim}$ prototypes(e.g. a 2d map of $4^2$ or $5^2$ nodes).

**SOM algorithm** The SOM algorithm described below is taken from Haykin[19] and adapted to our actual algorithm.

- *Initialization* : Choose random values for the initial weight vectors $\mathbf{w}_j(0)$. The only restriction here is that the $\mathbf{w}_j(0)$ be different for $j = 1, 2, ..., l$, where $l$ is the number of output neurons. The synaptic weight vector of each neuron in the network has the same dimension as the input space. In Kohonen networks the weights correspond to pattern values, not connection strength. The synaptic weight vector of neuron $j$ is denoted by.

$$\mathbf{w}_j = [w_{j1}, w_{j2}, ..., w_{jm}]^T, j = 1, 2, ..., l \tag{1}$$

- *Sampling* : Draw a sample vector $\mathbf{x}$ from the input space with a certain probability; the vector $\mathbf{x}$ represents the activation pattern that is applied to the input neurons. In this study, $\mathbf{x}$ corresponds to a 'frame' of the perceptual input. The dimension of vector $\mathbf{x}$ is equal to $m$.

$$\mathbf{x} = [x_1, x_2, ..., x_m]^T \tag{2}$$

- *Similarity Matching* : Find the best-matching winning neuron i($\mathbf{x}$) at time step $n$ by using the minimum-distance Euclidean criterion:

$$i(\mathbf{x}) = \arg\min_j \|\mathbf{x}(n) - \mathbf{w}_j\|,\ j = 1, 2, ..., l \tag{3}$$

$$\|\mathbf{x}(n) - \mathbf{w}_j\| = \sqrt{\sum_{i=1}^{m} (x_{ij} - w_{ij})^2} \tag{4}$$

- *Updating* : Adjust the synaptic weight vectors of all neurons by using the update formula

$$\mathbf{w}_j(n+1) = \mathbf{w}_j(n) + \eta(n) h_{j,i(\mathbf{x})}(n) \left(\mathbf{x}(n) - \mathbf{w}_j(n)\right) \tag{5}$$

  where $\eta(n)$ is the learning-rate parameter, and $h_{j,i(\mathbf{x})}(n)$ is the neighborhood function centered around the winning neuron i($\mathbf{x}$); both $\eta(n)$ and $h_{j,i(\mathbf{x})}(n)$ are varied dynamically during learning for best result. $\eta(n)$ and $h_{j,i(\mathbf{x})}(n)$ are determined by a function taken from Schomaker[20] .

$$x_k = \left( (\sqrt[s]{\alpha_1} - \sqrt[s]{\alpha_N}) \frac{(k-1)}{(N-1)} + \sqrt[s]{\alpha_N} \right)^s \tag{6}$$

  where $s(>0)$ is the steepness factor, $x$ is a decreasing training parameter (here learning rate or Kohonen bubble radius), $k = [1, N]$ is the epoch number and $N$ is the total number of epochs. If $s = 1$, $x_k$ is a linear function. Network bubble radius similarly decreased from full network size to 0 with a steepness factor $s$.

- *Continuation* : Continue with step 2(sampling) until no noticeable changes in the feature map are observed or a predetermined number of epochs.

#### 2.2.2 Hue Saturation Value

In this section the HSV representation of color will be discussed and the theory behind the HS,$V_{max}$ transformation of the visual pattern of a landmark in the environment is given.

The HSV(Hue, Saturation, and Value) representation is more intuitive representation of colors than the RGB(Red, Green, Blue) representation. There are 3 color parameters: Hue, Saturation, and Value. Changing the saturation parameter corresponds to adding or subtracting white and changing the Value parameter corresponds to adding or subtracting black: Value corresponds with luminance.

The 3D representation of the HSV model is derived from the RGB mode cube. If we look at the RGB cube(left model in Figure 1) along the gray diagonal from the points representing white and black we can see a hexagon that is the HSV hex cone(right model in Figure 1). The Hue is given by the angle about the vertical axis with red at 0° , yellow at 60°, green at 120°, cyan at 180°, blue at 240°, and magenta at 300°. As you can see in the model the complementary colors are 180° degrees apart. The Value is given by the position on the vertical axis of the hex cone, where the top of the cone correspond to a value of zero.

With the HS,$V_{max}$ transformation of the visual pattern of a landmark, the original visual pattern in RGB is transformed to HSV with V set to maximum luminance(100%) to discard of the luminance(brightness) variation but keep the white. This will make the representation of a landmark on the visual pattern less sensitive for variations in luminance. The image in HS,$V_{max}$ space is then transform back to R'G'B' space.

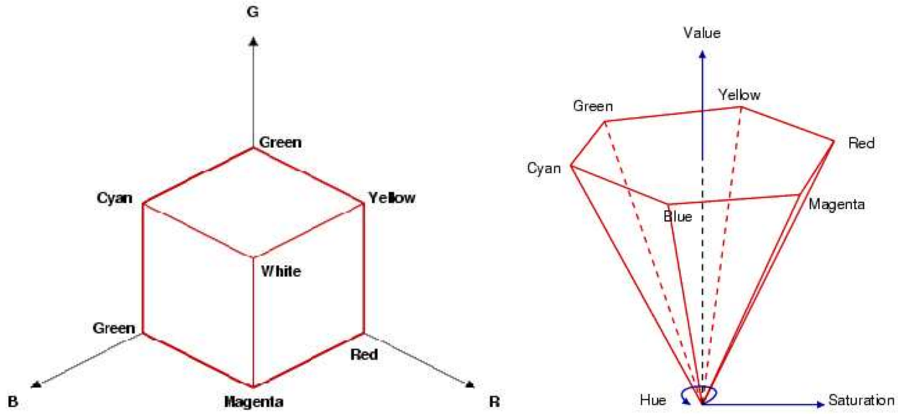


Figure 1: Left : RGB cube ; Right : HSV hex cone, Here only values with the top hexagonal plain will be used and transformed back to R'G'B'.

# 3 Scientific Goals

In this section the general research question put forward in the introduction will be crystallized and made operational. This will be done by subdividing the general research question in a set of smaller research questions.

## 3.1 Research Questions

The general research question put forward in the introduction was: Will a cognitive inspired navigational subsystem yield a robot that is capable of performing robust navigation in dynamical and unknown environments? The answer to this research question will be found by conducting experiments(described in Section 4) that will answer the subquestions summarized below. Subsequently, the answers to these subquestions will be put together to form an answer on the general research question.

*Sub-research questions:*

- Can a robot learn important landmarks in its environment on basis of self-organizing combined sensory information from multiple modalities?
- Can the robot use the learned perceptual landmark map, live, while moving around? Is the map stable (regardless of weather and lighting conditions)?
- Can the robot know what landmarks are directly reachable from a given landmark observation?
- Can the robot generate a global view (map) of its environment?

## 3.2 Scientific relevance for AI

One of the main principles of Artificial Intelligence is to design artificial systems that can perform a certain task autonomous and robust: No human intervention or the use of external technical resources is needed in performing the task. The design philosophy of AI is that an artificial system capable of robust and autonomous task performance can benefit from a system design inspired on biological systems capable of performing the desired task.

In this research project a cognitive inspired system design is given for the task of robust robot navigation in unknown environments. As put forward in the introduction most of the navigational systems nowadays incorporated in robots are not inspired on navigational system found in biology. Components that are being used, are for example an absolute coordinate system and *a priory* information concerning the environment in the form a geometrical models. Robot navigational systems based on such components rely on human intervention when they are situated in unknown environments. Humans have to map the environment into geometrical models or have to provide an artificial infrastructure in a unknown environment, before the robot is capable to navigate in this environment.

The navigational system design given in Section 2.2 is based on navigational principles found in relative simple organisms, such as insects. This will enable robots to robustly navigate in unknown environments. This solution for robust robot navigation would be of great value in a range of applications where absolute position or precise map information is unobtainable, including for example, autonomous planetary exploration, subsea autonomous vehicles.

# 4 Methods

The first experiments carried out during this research program were setup as an preliminary test of the concept that when the robot experiences a collision or is in close proximity with a new landmark it triggers an event or singularity. This event will be used to take meaningful images of the landmark the robot is perceiving. An integrated feature frame representation will be used, combining sensor information from multiple modalities. These feature frames are then run through a Kohonen Self Organizing Map which forms the basis for a perceptual landmark map.

The last experiments were conducted to see if the perceptual landmark map forms a stable representation of the environment. If it forms a stable representation, the robot should be able to recognize the environment on basis of the perceptual landmark map. Subsequently, a topological representation of the environment can be constructed by keeping track of the changes in position and directional heading between successive landmark observation.

## 4.1 Pioneer2 DX robot

The robot used for this research experiment is the Pioneer2 DX robot. It is a two-wheel based robot of modest size, which lends itself to navigation in tight quarters or cluttered spaces.

The physical characteristics of the robot are length 44 cm, width 33 cm and height of the body 22 cm. The body clearance of the robot from the ground is 5.1 cm and the total weight of the robot is 9 kg.

The Pioneer2 DX is equipped with both a front and rear sonar array, each with eight transducers that provide range information of objects in the robot its environment. The sonar positions are fixed in both arrays: one on each side, and six facing outward at 20-degree intervals. The firing rate of the sonar is 25 Hz(40 milliseconds per sonar per array) and sensitivity ranges from 10 cm to more than five meters.

On top of the Pioneer2 DX a color CCD camera is mounted with a effective resolution of approximately 440,000 pixels. The camera has a pan/tilt range of horizontal 100 and vertical 25 degrees respectively.

A high-resolution optical quadrature shaft encoder that provides 9,850 ticks per wheel revolution(19 ticks per millimeter) is responsible for position and speed sensing and dead-reckoning.

The robot can function autonomous thanks to its on-board computer and battery. It can contain up to three, hot-swappable batteries which can make the Pioneer2 DX run for more than a day. The on-board computer is based on a Pentium 266 MHz and runs the operation system Linux. Network connection is realized by a 1-3 Mb/s radio connection.

## 4.2 Agent structure

The different tasks and behaviors used on the robot in these experiments were implemented on a modular agent-based architecture XSAM. This architecture is modeled on an agent-communication framework originally used for a handwriting classification system developed at the Institute for Cognition in Nijmegen[15].

Two of the main advantages of a system based on the XSAM architecture are that functionality can be added or removed in runtime and that complex tasks can be divided into smaller more simple sub-tasks. For every sub-task an agent can be developed to execute this task. When combining the different agent for the more simple tasks into one system, the overall complex property of the global task may emerge.

In XSAM a central agent, the Task Force Manager(TFM) is responsible for maintaining a list with all of the agents that are currently active and executing a certain task on the robot. Agents have to connect to this Task Force Manager so they can interactively share information they produce or require in executing a certain task on the robot. The communication between different agents that are being executed on the same robot is based on an XML syntax. Agents can both share information with other agents or require information from others by means of these XML string. Under an example of a possible message a agent can sent to another.

```
<position X=400 Y=-230> </position>
```

Within the framework of this research three agents were developed. The first agent is the saphira agent which is responsible for obtaining all of the sensor data available on the robot and transform this information to XML strings so other agents can access this data. The second task of the saphira agent is to control the cruise speed and rotation speed of the robot. The other two agents will be described more in detail in the sections below.

### 4.2.1 Obstacle Avoidance Agent

The *Obstacle Avoidance Agent(OAA)* is a module that results in an exploration behavior of the robot in the environment. When the robot encounters an obstacle that is on its course it will change its directional heading and proceed in another direction.

The sensors that are being used by the OAA for detecting objects are the four sonars on the front side of the robot. They are positioned at $-30°$, $-10°$, $10°$ and $30°$ respectively and totally cover a range of $60°$.. The sonar-reflection readings of these four front sonars determine the state the robot currently is active in. ° The robot can be in either one of the following five states.

- When there is no object on the robots course it will maintain a cruise speed of 200 $mm/s$ and a rotation-speed of zero°.
- When the sonar at -10° detects an object within 750 $mm$ or the sonar at -30° detects an object within 700 $mm$ make the rotation speed of the robot 40 degrees/s counterclockwise.
- When the sonar at 10° detects an object within 750 $mm$ or the sonar at 30° detects an object within 700 $mm$ make the rotation speed of the robot 40 degrees/s clockwise.
- When the sonar at -10° detects an object within 600 $mm$ and the sonar at 10° detects an object within 600 $mm$ and the sonar-reading at -10° is greater than at 10° make the rotation speed of the robot 20 degrees/s clockwise.
- When the sonar at -10° detects an object within 600 $mm$ and the sonar at 10° detects an object within 600 $mm$ and the sonar-reading at 10° is greater than at -10° make the rotation speed of the robot 20 degrees/s counterclockwise.

### 4.2.2 Logging Agent

The recording of sensory data during a run in the environment on basis of the Obstacle Avoidance Agent is performed by the *Logging Agent*. The recording of the sensory data will take place at a predefined interval. The resulting samples of sensory data will be used to created a trainingset for the Kohonen Self Organizing Landmark Map. A sample recorded during this run will consist of four components of information obtained from different sensor modalities.

- *Timestamp :* When the Logging Agent is executed and a sample is being recorded it produces a timestamp in the order of millisecond.
- *Image :* At each moment the timestamp is produced, a frame grabber will grab an color image from the camera at a resolution of 160x120 pixels in 24bits RGB and write this to the hard disk as a PPM file with the timestamp as filename.
- *x and y Coordinates :* The $x, y$ coordinates are the representation of the robots current position in an environment expressed in absolute coordinates and are determined on basis of a dead-reckoning method. The origin of the coordinate system is the starting position of the robot in an environment. Due to drift in the Odometry ,caused by slipping of wheels, the data obtained from the position encoders will contain a time-variant bias error.
- *Sonar :* Reflection values of both the eight front and eight back sonar arrays are logged. The values being logged from each sonar contain information on the range of an object in $mm$.

The logging agent creates a log file where each line consists of a sample with a timestamp, $x, y$ coordinates and sixteen sonar-reflection values in the following raw form.

$$\langle timestamp\rangle\ \langle x\rangle\ \langle y\rangle\ \langle sonar1\rangle\ \langle sonar2\rangle\ ....\ \langle sonar15\rangle\langle sonar16\rangle \tag{7}$$

From raw data sets recorded during a run in the environment on basis of the Obstacle Avoidance Agent we generated subsets of samples taken at proximity events that will be used for in the experiments used of training a perceptual landmark map(KSOLM).

## 4.3 Environment setup

The environment used in this research project in conducting the experiments was the *robocup field* in the robotics lab of the Artificial Intelligence department of Rijks Universiteit Groningen.

This rectangle green field consist of white boarding with a height of approximately 40 cm on each side. The dimension of the field is approximately 4 by 4.60 meters. On each of the two short sides of the field is an colored area that represents a goal. The colors of these goals are respectively yellow and blue.

In the robotics lab the lighting is provided by fluorescent illumination and a window positioned at the side of the yellow goal. When standing in front of the blue goal there is a darker side with a wall on the right hand and a brighter side with computer terminals on the left hand.

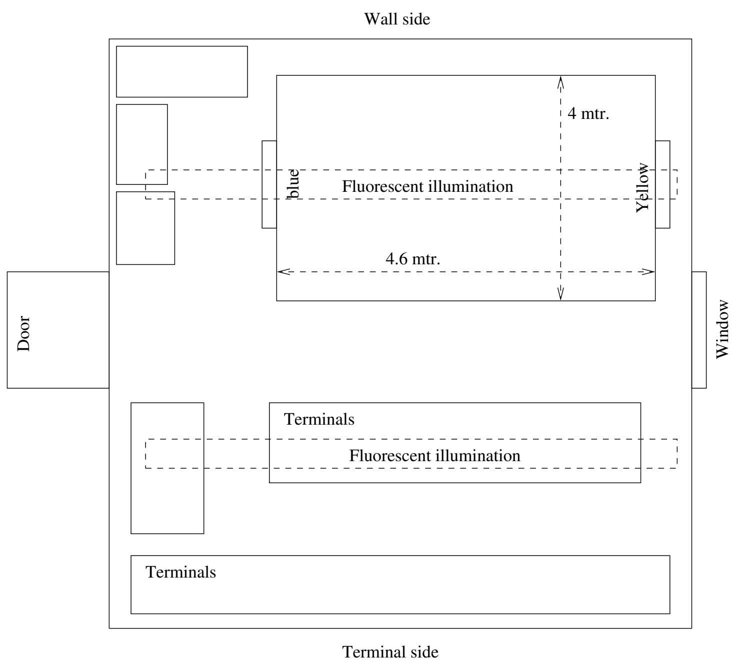


Figure 3: Robotics-lab

## 4.4 Basic preprocessing

As preparation for the experiments a basic preprocessing is done over the image in the raw dataset. The original scale of the images is 160x120 pixels, where each pixel consist of 3 bytes representing the RGB value. In the experiments we use the pixels as basis for the feature representation of an image. The total number of features of an unscaled image would be 160 x 120 x 3 = 57600. This order of features would contain a lot of redundant information and would make the training of an Kohonen network unnecessarily complex. We scaled the image back to a size of 40x30 pixels, which still contains enough information for a good visual description of the environment in front of the robot. The total number of features then became 40 x 30 x 3 = 3600. The de-scaled images are then transformed from the RGB space to HSV. Subsequently, in HSV space the V is set to 100% luminance to discard of the brightness information but keep the white. In this way the result will be effected less by variance in luminance. The image in HS,V$_{max}$ space is then transformed back to R'G'B' space.

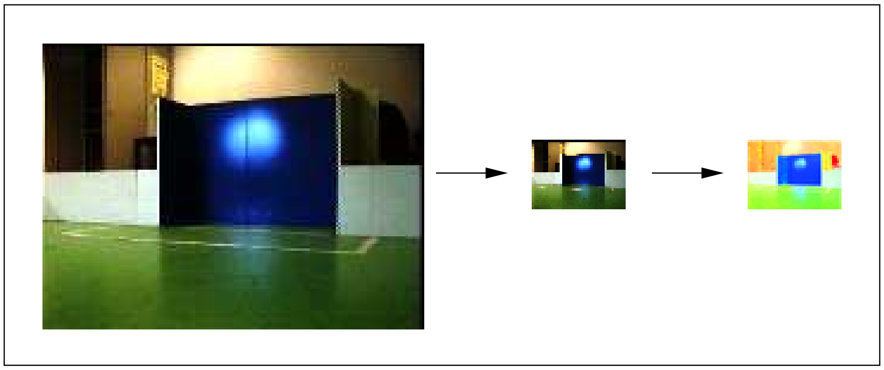

Figure 4: Basic preprocessing on the raw images: Scaling by sub sampling, RGB → HSV → V=max → R'G'B'

## 4.5 Experiments

The first experiments on training a perceptual landmark map of the environment in this research project were conducted with two constraints. The number of samples taken at proximity events, that contained the perceptual pattern of potential landmarks, used for training the Kohonen Self Organizing Landmark map had to be sufficient. Secondly, the training and testing of the KSOLM had to be done with data obtained at different moments in time.

### 4.5.1 Experiment 0 : Finding reasonable parameter settings

This experiment was conducted to examine the quality of recorded data during a run of the robot on basis of the Obstacle Avoidance Agent in the environment described in Section 4.3. The collection of data during a run was being influenced by different parameter settings. The parameter settings that could be variated were:

- Driving speed of the robot.
- Interval of logging.
- Duration of a run.
- Proximity threshold.

With the resulting raw datasets created by the Logging Agent described in Section 4.2.2 a proximity set was created that consisted out of samples taken at proximity events: An object is observed frontal within the range of 1 *mtr.*. The samples in the proximity sets were then used to create training sets of perceptual feature vectors of potential landmarks. A perceptual feature vector of a potential landmark will be called a *feature frame*. A feature frame representing the perceptual pattern of a landmark in the environment consisted out of the following components:

$$\langle 3600\, image\, features\rangle\langle 16\, sonar\, reflection\, features\rangle\langle 2\Delta x, \Delta y\, features\rangle \tag{8}$$

A training set with feature frames of potential landmark will be used to train the perceptual landmark map of the environment.

The resulting quality and quantity of frames in a trainingset created on basis of different parameter settings were compared to each other. The end result of the experiment would be values for the parameter settings that resulted in a data set, which after sample selection resulted in a proximity set with a sufficient number of samples of good quality. The proximity set is used to construct a training set with feature frames of landmarks.

**Setup** Different trials with the robot were done in the robocup field in the robotics lab. On each of these trials the values of the parameter settings were variated.

**Result** The parameter values in Table 1 resulted in a data set, consisting of sequences of image frames and corresponding sonar reflection distances and odometry. Sample selection consisted of using samples where an object is frontal observed within the range of 1 *mtr.* and resulted in a proximity set containing sufficient number of samples that can be used to construct a training set.

| **Parameter** | **Setting** |
|---|---|
| Driving Speed | 200 $mm/s$ |
| Interval of logging | 500 $ms$ |
| Duration of run | More than 20 minutes |
| proximity threshold | 1000 $mm.$ |

Table 1: Parameter values for dataset creation

**Conclusion** From the result of this experiment the parameter values in Table 1 were determined. Robot trials done with these parameter values will result in a raw dataset that meet the first general experiment constraint, that sufficient feature frames of potential landmarks can be constructed to training a perceptual landmark map of the environment(KSOLM).

The quantity of samples in a proximity set is determined by the values of the parameter settings described in the setup of this experiment. Each of these parameter setting have a different influence on the total number of samples in a proximity set.

- Increasing the speed of the robot will lead to a greater amount of samples in the proximity set. The total distance traveled by the robot will increase. Consequently, the robot will visit points in the environment more often that are being classified as a point at a proximity event.
- Decreasing the time interval between logging event will increase the number of samples taken at a run. Consequently, the total number of proximity events after sample selection will increase.
- Longer duration of the run of the robot in the environment will result in a larger amount of data collected. More data will result in more proximity samples.

- Increasing the proximity threshold will also result in increased number of samples in a proximity set. Samples taken at a point in the environment will be classified sooner as an point at a proximity event.

In order to obtain as much useful data for experiments one would like to use parameter values that result in the largest possible proximity set: Maximum driving speed, shortest possible logging interval and a run that continues for ever.

The maximum driving speed of the robot in this project is determined by the OAA and is set to 200 $mm/s$. Increasing the speed will result in less robust obstacle avoidance behavior and the image grabbed from the camera will show the effect of motion blur.

The shortest possible logging interval of 500 $ms$ is a technical constrained. Due to the amount of processor power available on the robot, the image grabber takes a certain amount of time to write the image to the hard disk. Once in every 500 $ms$ the image grabber is ready to perform another grab.

The value of the proximity threshold is determined by the quality of the samples taken at a collision event instead of the quantity. The proximity threshold of 1000 $mm$ resulted in perceptual pattern of objects in front of the robot that contained enough information to discriminate between objects. Decreasing the proximity threshold leads to images of objects that did not contain enough information to discriminate between different objects. Increasing the threshold will undermine the assumption that landmarks can be collected on the basis of collisions or near-proximity events. There will no more be a strong link between perceptual patterns of landmarks in the environment and the real physical environment.

In successive experiments conducted in this research project where data is collected during a run in the environment, the parameter values for driving speed, logging interval and proximity threshold were fixed to the values in Table 1. Subsequently, the duration of the run has the only influence on the total number of samples in a proximity set. To satisfy the first constraint that sufficient number of proximity samples are available to create feature frames of potential landmark, a minimum duration of twenty minutes for a run was needed.

### 4.5.2 Experiment 1 : Preliminary test of concept

This experiment was conducted to test the concept of a robot learning important landmarks on basis of self organization of combined sensory information observed at proximity events in the environment. Form the landmarks in the Kohonen map a good representation of unique and distinctive points in the environment. As for an example: Will the robocup goals(yellow,blue) and the corners of the field emerge in the Kohonen map?

**Setup** A raw dataset was created on basis of the Obstacle Avoidance Agent and Logging Agent with the parameter settings in Table 1 and resulted in 2712 samples. Each individual sample contained the four components described in 4.2.2: timestamp, image, sonar reflective field and odometry.

On the raw dataset a sample selection was applied that resulted in set of samples taken at a proximity event in the environment. A sample was selected when on one of the two front sonars of the robot positioned at -10° and 10° an object was detected within the range of 1 $mtr$. This sample selection resulted in a proximity set of 517 samples ordered in ascending timestamps. This set of samples will be called Prox-set-A.

From each sample in Prox-set-A a feature frame was constructed which contained the unscaled features of the image, sonar reflective field and $\Delta x, \Delta y$ with a total number of 3618 unscaled features. The $\Delta x, \Delta y$ features were calculated by taking the difference between the absolute positioning of the robot in the current sample and the previous sample in prox-set-A. The values of the individual features remained within their original ranges: image [0..255], $\Delta x$ [-3321..3380], $\Delta y$ [-2471..2666] and the sonar-array [211..8567]. This total number of 517 feature frames was used to created the training set for the Kohonen Self Organizing Map. For the training of the Kohonen map the parameters settings in Tabel 2 where used in combination with the algorithm described in Section 2.2.1. Figure 5 shows the decrease of the bubble radius and learning rate over the iterations used in the KSOLM algorithm.

| | |
|---|---|
| Network $x$-dimension | 5 |
| Network $y$-dimension | 5 |
| Learning iterations | 200 |
| Max. radius (proportion 0.-1. of 5) | 1. |
| Initial radius (in cells) | 5 |
| Steepness (1.=linear decrease of bubble radius towards 0) | 5. |
| Learning rate $\alpha$ at begin of training | 0.99 |
| Learning rate $\alpha$ at end of training | 0.01 |
| Steepness (1.=linear decrease of alpha towards $\alpha$_min) | 5. |

Table 2: Parameters for training the KSOLM

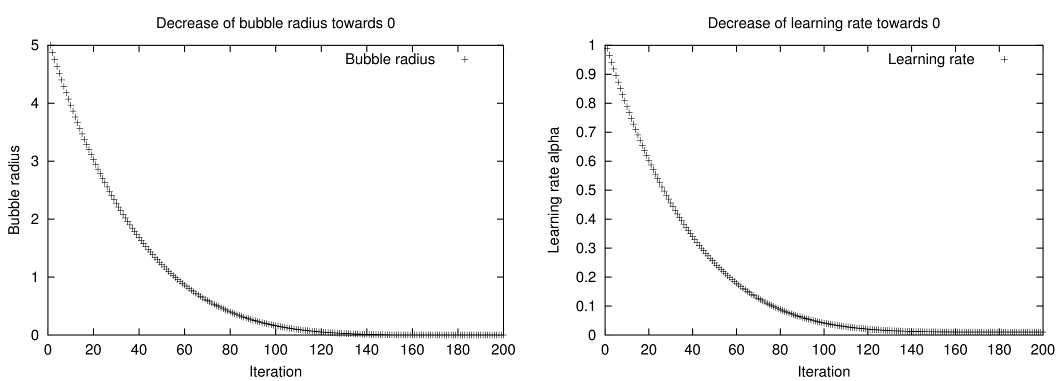


Figure 5: Decrease of bubble radius(left) and learning rate(right) using a steepness s=5.

**Result** The left image in Figure 6 is the visualization of the resulting Kohonen Self Organizing Landmark Map after training, each node forms a generalized feature frame representation of a landmark in the environment, consisting out of three parts:

- Features representing the average perceptual pattern of a landmark in the environment.

- Features representing the average sonar reflective field. This represent what a landmark 'feels' like.
- $\Delta x, \Delta y$ vector. This tells us the average position of the previous observed landmark.

The scale of the sonar and $\Delta x, \Delta y$ is inverted: The radius of the circle corresponds to a distance of 1000 $mm$. and the origin of the circle corresponds to the distances of the maximal sonar range (8567 $mm$). When a sonar vector represents a distance less than 1000 mm. it is being cutoff at the radius of the circle.

The right image in Figure 6 shows the sonar reflective fields of landmarks in the Kohonen map. In order to judge the topology detected by the Kohonen map, sonar vectors are visualized when they represent an object within the range of 1.25 $mtr$. of the robot and subjective symbolic labels are given to the sonar reflective field.

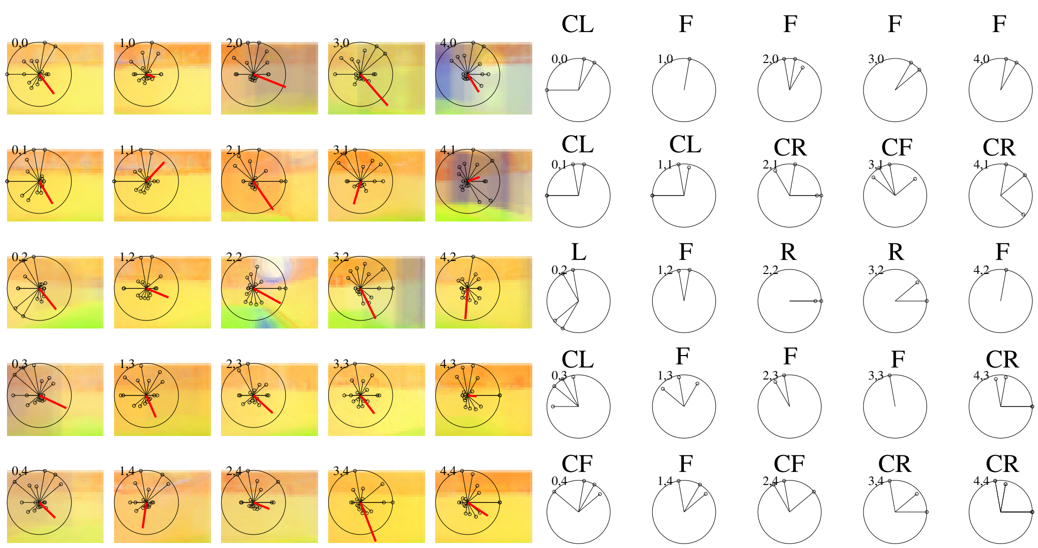


Figure 6: Left : KSOLM after training on 517 feature frames ; Right : Sonar reflective field configuration of the landmarks in the KSOLM.

| **Label** | **Description** | **N occurrences** |
|---|---|---|
| **CR** | Corner configuration right | 5 |
| **CL** | Corner configuration left | 4 |
| **CF** | Corner configuration front | 2 |
| **F** | Object in front | 10 |
| **R** | Object right | 3 |
| **L** | Object Left | 1 |

Table 3: Number of each sonar reflective field configuration.

**Conclusion** The visual pattern of a landmark forms the basis of the representation of a unique and easily perceptible point in the environment. In the resulting KSOLM one should be able to discern points in the environment such as the blue and the yellow robocup goal.

The left image in Figure 6 show that these easily perceptible points in the environment are not clearly visual represented as one would expected. Nodes (4,0) and (4,1) show a blurred pattern of the blue goal, which suggest that the set of feature frames used for training this node was heterogenous on the visual pattern. The feature frames used to train a node in the Kohonen map were not constructed on basis of samples taken at approximately the same location in the environment.

The right image in Figure 6 shows that the most important position configurations of objects relative to the robot in the environment are represented: corner configurations, objects positioned in front, left, or right. Table 3 show the total number of each sonar configuration. The corner configurations and objects in front form the majority in the KSOLM as one would suspect with the definition of proximity event and exploration behavior in this research project.

Two conclusion were drawn at this point in the research project:

- The total number of proximity feature frames used for training the Kohonen map had to be increased. Easily perceptible and unique landmarks in the environment would easilier emerge in the Kohonen map if more proximity feature frames of landmarks are used for training the KSOLM.
- The scaling of the features forms a problem in classifying the landmarks in the KSOLM. It seemed that the sonar features override the visual features. Landmarks with different visual patterns, but similar sonar configuration will be classified on the same node in the KSOLM. Subsequently, the visual patterns of landmarks in the KSOLM become blurred.

#### 4.5.3 Experiment 2 : Training with more samples and test if the landmarks in the *KSOLM* represent unique points in the environment

This experiment was run to see if training the KSOLM with more proximity samples would result in more landmarks representations in the map where the visual patterns of easily perceptible and unique points in the environment, such as the blue and yellow robocup goal, emerge.

The second goal of this experiment is to see if the landmark in the KSOLM do form representations of unique points in the environment. An landmark representation in the KSOLM could be the average of two or more landmarks that are located at different positions in the environment. Such a landmark representation can not be easily used for navigational purpose.

**Setup** On the raw dataset a different sample selection than the one used in experiment 1 was applied that resulted in an second proximity set. The criteria for these samples were that on one of the four front sonars of the robot positioned at -30°, -10°, 10° and 30° respectively, an obstacles was detected within the range of 1 $mtr$. The effective perception range is broaden from 20° in experiment 1 to 60° in this experiment. The sample selection resulted in a subset of 711 samples order in ascending time. This set of samples will be called Prox-set-B.

With Prox-set-B of 711 samples a training set was created that consisted of unscaled feature frames in the same way as in experiment 1. This training set was used to train a KSOLM with the parameter settings in Table 2.

After training the KSOLM, each feature frame in the training set was compared with the landmark representation in the KSOLM to determine the nearest neighbor node. Feature frames in the training set with the same nearest neighbor in the KSOLM were then visualized. With this method one could determined if the Kohonen map consisted of nodes which form a good and reliable representation of unique points in the environment. The degree of homogeneity in the visual patterns of these set determines if the landmarks form good representations.

**Result** The left image in Figure 7 is the resulting KSOLM after training on 711 feature frames. The right image in Figure 7 is the set of feature frames with node (3,4) as the nearest neighbor in the KSOLM.

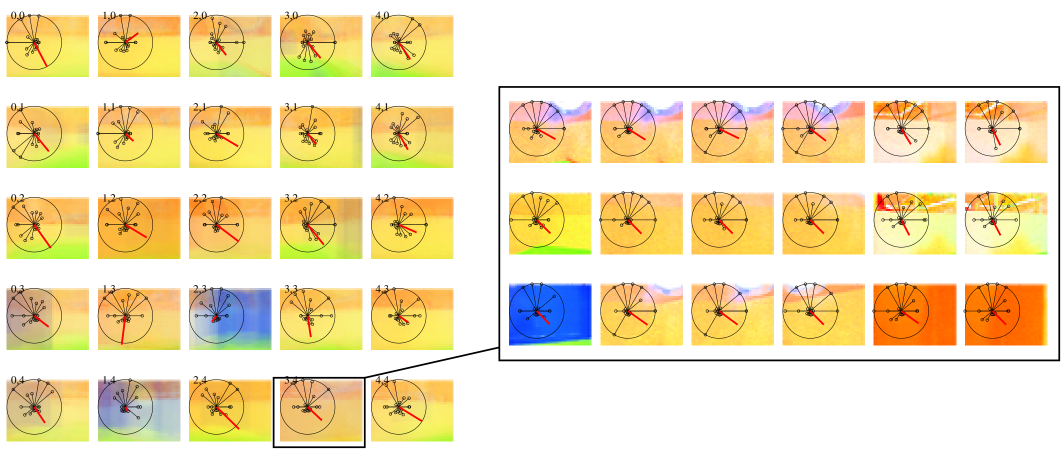

Figure 7: Left : KSOLM after training on 711 feature frames ; Right : set of feature frames with node (3,4) as the nearest neighbor in the KSOLM

**Conclusion** In contrast to the KSOLM in Figure 6 of experiment 1, the visual pattern of both the yellow and blue robocup goal emerge clearly in the KSOLM of Figure 7. Such very easily perceptible and distinctive points in the environment seem to be represented in the KSOLM when enough training samples are used. For a landmark in the environment which is not that easily perceptible or unique, the result stays more or less the same as in experiment one.

The right image in Figure 7 shows that the set with node(3,4) as the nearest neighbor in the KSOLM does not consist of proximity frames where the visual patterns are homogeneous. Frames of different points in the environment such as the blue and yellow robocup goal are part of this set. The landmarks that the KSOLM learned do not form representations of unique and easily perceptible points in space. This also supports the conclusion from experiment 1 that when using unscaled feature frames, the sonar features seem to override the visual pattern in classification of landmarks. The right image in Figure 7 shows that the sonar configurations of the landmark representations are very similar.

The conclusions drawn at this point in the research project were:

- More proximity samples used for training the KSOLM will lead to better landmark representations. All though the result from this experiment does not support this conclusion, common sense suggest that knowledge about the environment will improve when more information over the environment is presented.

- Scaling the features obtained from the multi-sensory modalities before integrating them in the feature vectors used for training will lead to better landmark representations of easily perceptible and unique points in the environment.

### 4.5.4 Experiment 3 : Training without multi-sensory fusion

In experiment 1 and 2 the features obtained from multi-sensory modalities were integrated in unscaled feature frames used for training the KSOLM. This resulted in landmark classification where the features of the sonar were of overriding importance. An interesting question arises from that result. What is the influence of each of the sensory modalities on the structure of the KSOLM? The purpose of this experiment is to determine this influence of the different sensory modalities on the structure of the KSOLM.

**Setup** Four training sets were created that consisted of feature frames constructed on basis of proximity sample from Prox-set-B.

| Training set | Content |
|---|---|
| $A_{All}$ | features of all the sensory modalities |
| $B_{Visual}$ | features of the visual pattern |
| $C_{Sonar}$ | features of the sonar reflective field |
| $D_{Delta}$ | features of $\Delta x, \Delta y$ |

Table 4: Training sets created on basis of Prox-set-B

The training sets $A_{All}$, $B_{Visual}$ and $C_{Sonar}$ were used to train three separate KSOLM's with the parameter setting from Table 2.

The same method as in experiment 2 was applied. For each feature frame from training set $A_{All}$ the nearest neighbor was determined in each of the three KSOLM's. Feature frames from training set $A_{All}$ with the same nearest neighbor where visualized. For every landmark feature representation in the KSOLM's could be determined which feature frames were captured by it.

**Result** The left images in Figure 8, 9 and 10 are the resulting KSOLM's after training on set $B_{Visual}$,$C_{Sonar}$ and $D_{Delta}$ respectively. The right images are the sets of feature frames with the same node as the nearest neighbor in the KSOLM.

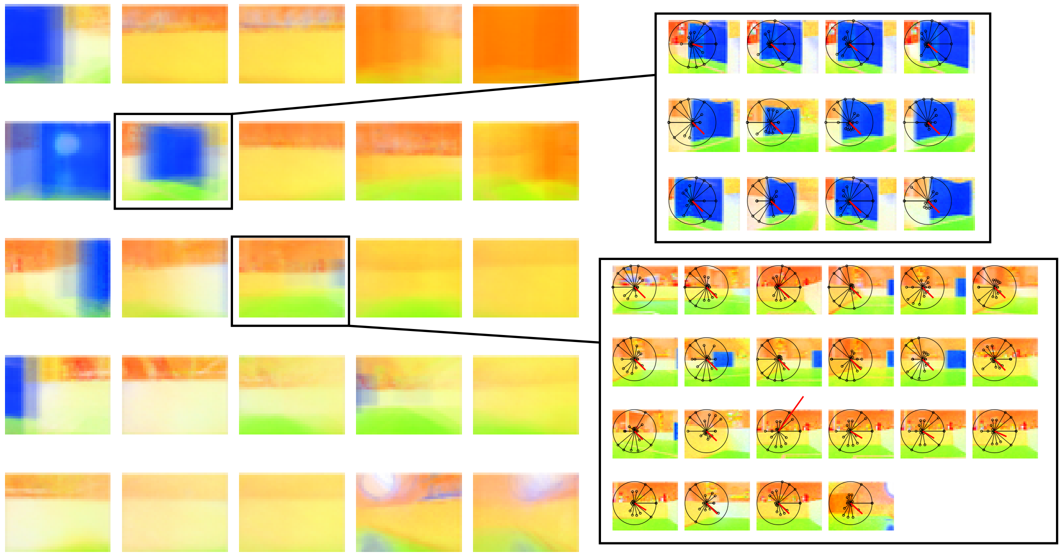

Figure 8: Left : KSOLM after training on set $B_{Visual}$; Right : sets of raw feature frames belonging to node (1,1) and node (2,2) respectively as the nearest neighbors in the KSOLM

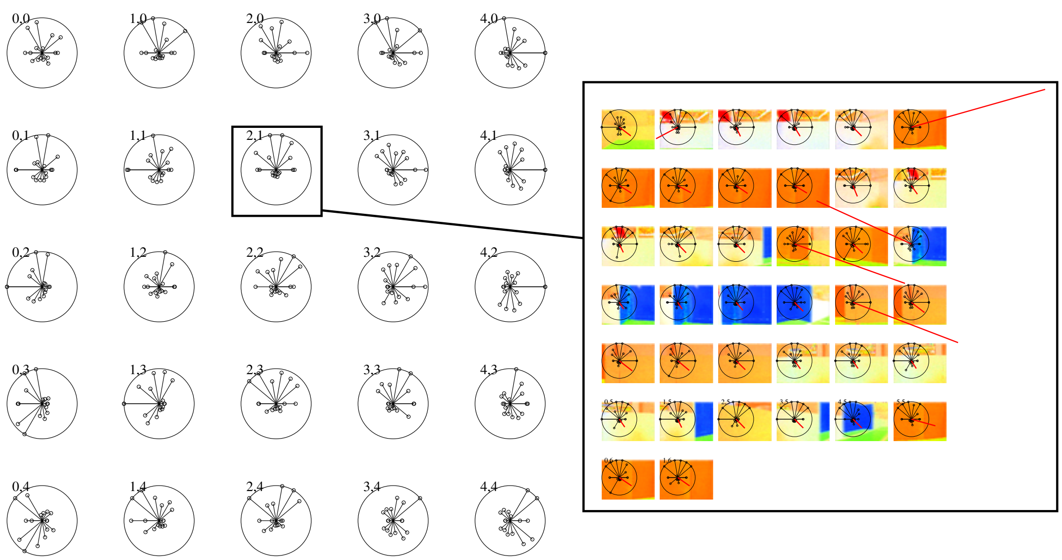


Figure 9: Left : KSOLM after training on set $C_{Sonar}$; Right : set of raw feature frames belonging to node (2,1) as the nearest neighbors in the KSOLM

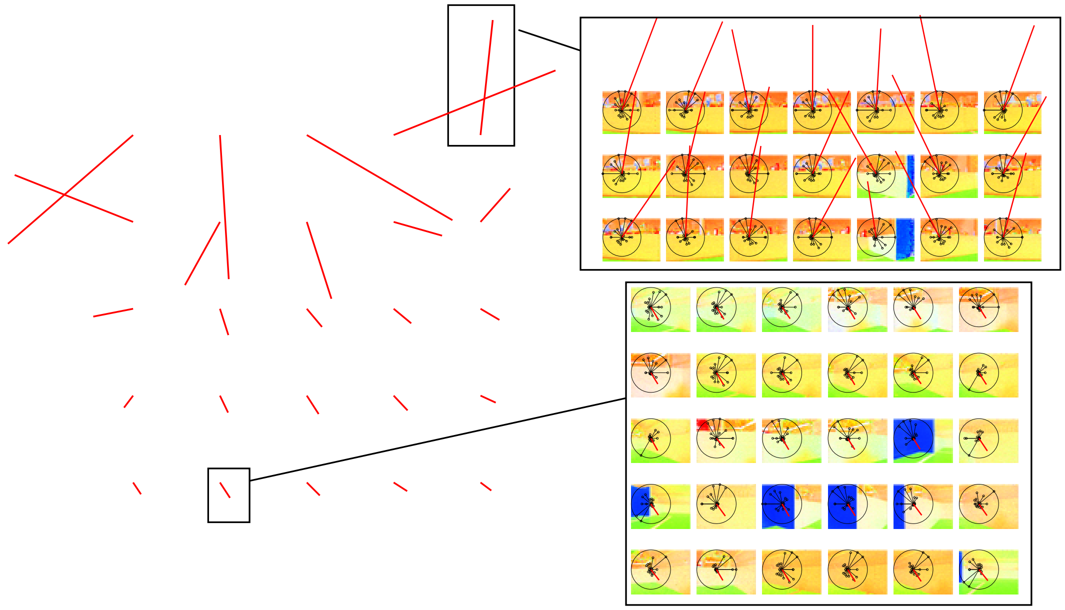

Figure 10: Left : KSOLM after training on set $D_{Delta}$; Right : sets of raw feature frames belonging to node(4,0) and node(1,4) respectively as the nearest neighbors in the KSOLM

**Conclusion** In the KSOLM of Figure 8 visual patterns of important landmarks in the environment such as the blue and yellow robocup goal, which are easily perceptible and unique, clearly emerge. The visual patterns are not as blurred and vague as with training on integrated unscaled feature frames. The feature frames which have one of these landmark representations(blue and yellow goal) as the same nearest neighbor in the KSOLM show a clear homogeneity in the visual domain. Landmarks representing points in space which are not easily perceptible or unique on the visual pattern show more heterogeneity in the set of feature frames with the same nearest neighbor. For example corners and the points on each side of the field reveal great similarity in the visual domain. Consequently, training on the visual percept alone can lead to the fact that different located points in space that look the same are fused in the landmark map, whereas other modalities could yield dis-ambiguation. This will eventually lead to incorrect position determination if the map is used as the basis for navigation .

Sonar-based training with set $C_{Sonar}$ resulted in a KSOLM where the nodes represent the *feeling* of a landmark at a collision or near proximity event in the environment. Multiple sonar reflective field configurations of objects relative to the robots body are present in the KSOLM such as for example corners. The set of feature frames with node(2,1) (see right image in Figure 9) show a very heterogeneous collection of samples. This shows that landmark representations solely based on sonar reading are inadequate for navigational purpose. The sonar representation in the Kohonen map is correct, but can not serve as basis for navigation. The environment does not show a high variation in the sonar space. As for example, landmarks in the environment such as the four corners in the robocup field have the same sonar reflective field configuration and distinction between these landmark can not be based solely on this configuration of the sonar reflective fields.

Landmarks representation solely based on their travel distance $\Delta x, \Delta y$ are not suited for the task of navigation, as one would expect. No landmark representation in the KSOLM can be mapped on a unique point in the environment. A great drawback of using $\Delta x, \Delta y$ information for landmark extraction is the error in the Odometry caused by drift of the robot due to slipping wheels, which can result in erroneous landmark representation: bias and whole-field rotations.

The results from this experiment suggest that in order to obtain representations of unique and easily perceptible landmarks in the environment, the visual pattern must be the decisive factor in classification. When landmarks can not be distinguish from each other on basis of the visual pattern, the sonar configuration followed by the $\Delta x, \Delta y$ must be the decisive factor in classification of landmarks.

The conclusions drawn at this point in the research project were:

- The visual pattern must be the decisive factor in classification of landmarks in the environment.
- The features obtained from multi-sensory modalities have to be scaled within the same range.
- Different biases have to be put on the features obtained from different sensory modalities to determine how much influence a feature obtained from a certain sensor modality has on classifying landmarks.

### 4.5.5 Experiment 4 : Training with scaled integrated feature frames

In experiment 2 and 3 unscaled feature frames were used for training the KSOLM. This resulted in representations were the features taken from sonar reflective field configurations formed the decisive factor in classification. The conclusions in experiment 3 were that the features from the multi-sensory modalities had to be scaled and a bias had to be attached to set the influence of the features on classification of landmarks. This experiment was conducted to analyze the structure of the KSOLM after learning with scaled integrated feature frames, where the features from the multi-sensory modalities have the same weight. The influence of the different sensory information is than determined by the number of features extracted from the modality. Features extracted from the visual pattern are in the majority and will have the most influence on classification, followed by features from the sonar configuration and $\Delta x, \Delta y$.

**Setup** The design of this experiment is the same as experiment 2, with the difference that the features obtained from the sonar configuration and $\Delta x, \Delta y$ are scaled within the range of [0..255] and [-255..255] respectively, before they are integrated in feature frames used for training. The values of features obtained from the visual pattern remain within their original range [0..255].

**Result** The left image in Figure 11 is the resulting KSOLM after training on 711 scaled integrated feature frames. The right images in Figure 11 are the sets of raw feature frames in the trainingset with node (2,2) and node (3,4) respectively as the nearest neighbor in the KSOLM. Figure 12 shows the sonar reflective field of the landmarks in the KSOLM. In order to judge the topology detected by the Kohonen map, sonar vectors are visualized when they represent and object within the range of 2 *mtr.* of the robot and subjective symbolic labels are given to the sonar reflective field.

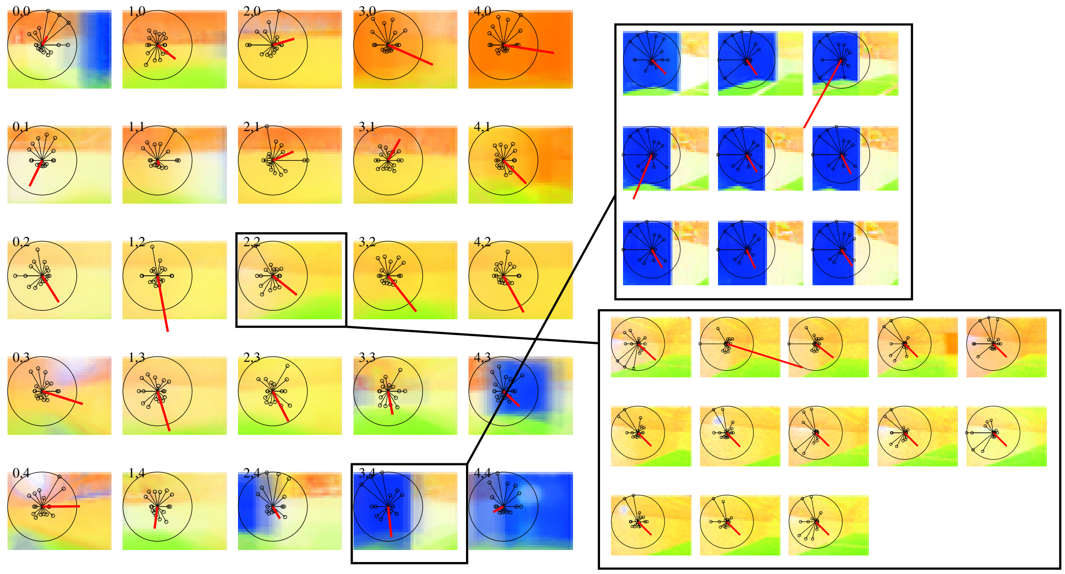

Figure 11: Left : Kohonen SOM after training on 711 sonar scaled integrated feature frames ; Right : sets of raw feature frames in the trainingset belonging to the same nearest neighbor in the KSOLM

**Conclusion** When the integrated feature frames used for training the Kohonen Self Organizing Map are scaled within the same range and the bias on each feature is equal, the end result show great resemblance with training solely based on features obtained from the visual pattern of a landmark (see Figure 8).The total number of features of each perceptual channel determines the decisiveness of the sensor modality in classifying landmarks, with scaled, equally biased features. The ratio of total number of features obtained from the visual pattern, sonar configuration and $\Delta x, \Delta y$ in the integrated feature frames used for training is 3600:18:2 respectively. Thus training will result in classification of landmarks, where the visual pattern of the landmark is of overriding importance.

The sets of integrated feature frames in the training set with a nearest neighbor node that represents a landmark which is easily perceptible(blue or yellow robocup goal), show great extent in the homogeneity. When the nearest neighbor does not represent such a landmark with a distinct visual pattern, the set show less homogeneity.

Figure 12 and Table 5 shows that every important sonar reflective field configuration is captured by the Kohonen map. The sonar reflective field configurations are not so clear as in experiment one where the sonar-reflective field was the decisive factor in classifying feature frames of potential landmarks. The reason for this is that in this experiment the visual pattern forms the decisive factor in classifying. Feature frames with similar visual patterns will have the same nearest neighbor in the Kohonen map, but the sonar reflective field of these feature frames can be quit different, resulting in not so clear, fused sonar reflective field configurations in the Kohonen map.

From the resulting Kohonen map in Figure 12 can be concluded that the behavior of the robot in the environment determines the structure of the perceptual landmark map. The

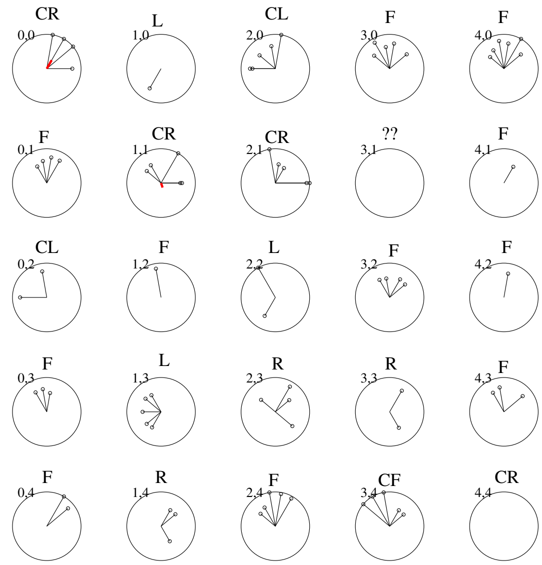


Figure 12: Sonar reflective field of the landmarks in the KSOLM

| **Label** | **Description** | **N in map** | **N in world** |
|---|---|---|---|
| **CR** | Corner configuration right | 4 | 82 |
| **CL** | Corner configuration left | 2 | 102 |
| **CF** | Corner configuration front | 1 | 12 |
| **F** | Object in front | 11 | 335 |
| **R** | Object right | 3 | 67 |
| **L** | Object Left | 3 | 95 |
| **??** | Not very clear | 1 | 18 |

Table 5: Number of each sonar reflective field configuration.

exploration behavior used in this research project was based on the Obstacle Avoidance Agent described in Section 4.2.1. This agent resulted in stereotypical exploration behavior which was not very random. Most of the time the robot traveled the same pattern in the environment. Potential landmarks in the environment are usually being observed from the same approach in the environment and some are never or rarely observed. Potential landmarks that are not being observed during a run in the robot will not be represented in the perceptual landmark map. In order to obtain a good perceptual representation of the environment a exploration behavior has to be incorporated in the robot that travels with a random pattern in the environment.

The conclusion drawn at this point in the research project was:

- Biases have to be found to set the degree of influence the features from a sensor modality have in classification of landmarks from the environment. This has to been done in such a way that the visual pattern of the landmark has the greatest influence, followed by sonar and $\Delta x, \Delta y$. Two different locate landmarks in the environment with the same visual pattern can be correctly classified on basis of the features obtained from the sonar reflective field configuration of the landmarks.

- Perceptual landmarks map(KSOLM) can be learned on basis of a self learning principle when using perceptual patterns of potential landmarks at proximity event. The most important landmark do emerge in the perceptual landmark map.

- There is a strong link between action and perception. The exploration behavior of the robot in the environment has great influence on the perceptual landmark map of the environment that is being constructed.

### 4.5.6 Experiment 5 : Time variant testing of the KSOLM under different environmental conditions

For robust navigation on basis of landmarks in the environment, the Kohonen Self Organizing Landmark Map must form a stable time invariant representation of the environment. Different weather and lighting conditions at daytime must have no effect on the recognition of landmarks. In this research project the visual pattern is transferred from RGB space to HS,$V_{max}$ and back to R'G'B. The assumption was that this transformation makes the recognition of visual patterns of landmarks invariant for different lighting conditions. This assumption will be tested in this experiment with the two following questions in mind:

- Forms the KSOLM a robust time invariant representation of landmarks in the environment?
- Results the HS,$V_{max}$ transformation of the visual pattern of a landmark in the environment in better classification and recognition?

**Setup**

- On four different moments in time, data was collected during a run in the environment(see Table 6).

| Raw dataset | Time | Samples | Lighting conditions |
|---|---|---|---|
| run 1 | 30 May 12:00 pm | 3096 | lightly clouded with some sun |
| run 2 | 30 May 03:30 pm | 3201 | raining, clouded |
| run 3 | 31 May 10:00 am | 3097 | lightly clouded |
| run 4 | 31 May 02:45 pm | 3099 | lightly clouded |

Table 6: Raw datasets

- From each of these raw datasets, two proximity sets were created (see Figure 13) on basis of sample selection described in experiment 2(see Section 4.5.3). Each proximity set contained 800 samples where the features of the visual pattern of a proximity event was in RAW-rgb or HS,$V_{max}$-rgb.
- The proximity sets were subsequently split up to a training and a test set(see Figure 13). This resulted in:
  - 4 training sets and 4 test sets based on RGB (train-rgb1 .. train-rgb4 ; test-rgb1 .. test-rgb4).
  - 4 training sets and 4 test sets based on HS (train-hs1 .. train-hs4 ; test-hs1 .. test-hs4).

- Two training sets and two test sets were additionally made.
  - The 4 training sets based on RGB were merged in a training set that consisted out of 1600 frames (train-rgb1600).
  - The 4 training sets based on HS were merged in a training set that consisted out of 1600 frames (train-hs1600).
  - The 4 test sets based on RGB were merged in a test set that consisted out of 1600 frames (test-rgb1600).
  - The 4 test sets based on HS were merged in a test set that consisted out of 1600 frames (test-hs1600).
- With the training sets ten different KSOLM's were trained with the parameter values from Table 2: 5 HS,$V_{max}$-rgb based and 5 RAW-rgb based.
- The average Root Mean Square Error(RMSE) per feature between frames in a tests and their accompanying nearest neighbor frame in a KSOLM were calculated(see Equation 9).
  - $x$ is a feature from a frame in the test set.
  - $w$ is a feature from the nearest neighbor frame in the KSOLM.
  - $m$ is the number of features in a frame.

$$RMSE_{per\ feature} = \sqrt{\frac{\sum_{i=1}^{m}(x_i - w_i)^2}{m}} \tag{9}$$

  The average RMSE of every feature frame in a test set was added up and divided by the total number of feature frames in a test set. The average RMSE per feature of a test set was the result.

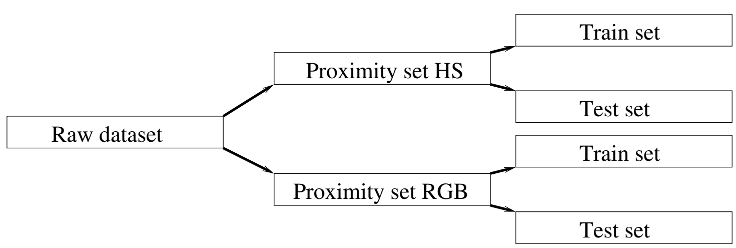


Figure 13: Preparation of training and test sets

**Result** Tables 7 and 8 show the average RMSE per feature with different combinations of test and training set in both HS,$V_{max}$-rgb and RAW-rgb color space. The columns represent the set used for training and the rows represent the sets used for testing. The last row in each table(self) is the average RMSE per feature when the set used for training and testing is the same. The Kohonen map tries to classify feature frames in the test set, that are exactly the same that were use to train the Kohonen map. This test set can be considered as an ideal set of feature frames for classifying, because the Kohonen map is precisely tuned on this set of feature frames. The result from the self test gives us a measurement of the best possible representation of the environment. The average RMSE value of the self test is the absolute minimum.

Figure 14 contains 3d plots of the RMSE's for both the Tables 7 and 8. The numbers on the axis "Test sets" and "KSOLM" correspond to the numbers in both the Tables 7 and 8. Only the values of the first four rows in the tables are plotted.

In Figure 15 the values of the self test and average RMSE of a KSOLM are plotted(last two rows in the tables). The average RMSE's results from using test set test-hs1600 and test-rgb1600 on each KSOLM.

Figure 16 show the average feature distance of frames in test-rgb1600 versus frames in test-hs1600, when compared with their accompanying nearest neighbor node in the KSOLM trained with train-rgb1600 and train-hs1600 respectively. The samples are smoothed over 31 samples.

| *HS-rgb* | **train-hs1**(1) | **train-hs2**(2) | **train-hs3**(3) | **train-hs4**(4) | **train-hs1600**(5) |
|---|---|---|---|---|---|
| **test-hs1**(1) | 32.3 | 41.0 | 34.9 | 33.0 | 31.3 |
| **test-hs2**(2) | 29.2 | 24.9 | 27.4 | 31.2 | 25.1 |
| **test-hs3**(3) | 30.0 | 34.7 | 30.7 | 32.3 | 29.0 |
| **test-hs4**(4) | 32.3 | 38.5 | 33.4 | 33.0 | 30.9 |
| **test-hs1600** | 31.0 | 34.8 | 31.6 | 32.4 | 28.6 |
| **self** | 26.6 | 21.4 | 25.6 | 27.8 | 29.1 |

Table 7: Test result in HS-rgb color space: The numbers 1-4 represent individual measurement days(light conditions)

| *RAW-rgb* | **train-rgb1**(1) | **train-rgb2**(2) | **train-rgb3**(3) | **train-rgb4**(4) | **train-rgb1600**(5) |
|---|---|---|---|---|---|
| **test-rgb1**(1) | 34.6 | 38.9 | 36.2 | 36.5 | 34.5 |
| **test-rgb2**(2) | 32.0 | 30.1 | 31.1 | 33.0 | 29.4 |
| **test-rgb3**(3) | 34.2 | 36.1 | 34.2 | 35.6 | 32.9 |
| **test-rgb4**(4) | 34.6 | 37.9 | 35.8 | 35.3 | 34.2 |
| **test-rgb1600** | 33.9 | 35.8 | 34.3 | 35.1 | 32.7 |
| **self** | 29.6 | 26.0 | 29.4 | 30.7 | 32.2 |

Table 8: Test result in RAW-rgb color space: The numbers 1-4 represent individual measurement days(light conditions

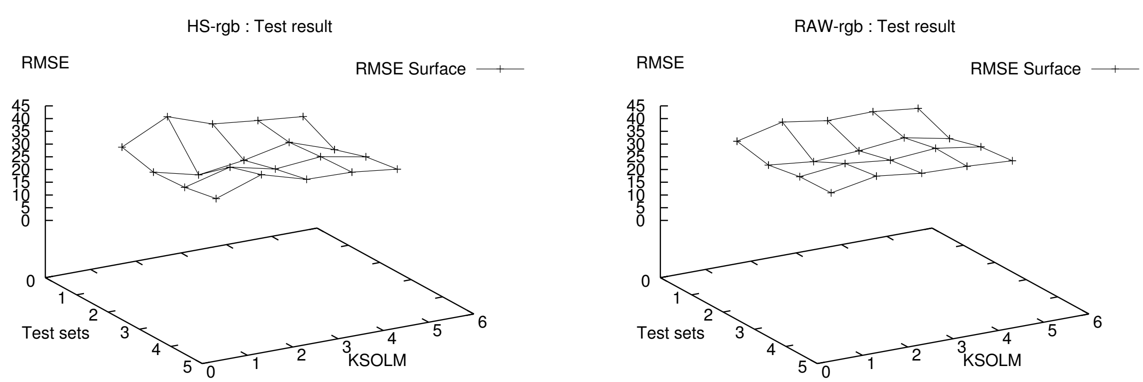


Figure 14: Test results in the HS,V$_{max}$-rgb and RAW-rgb color space

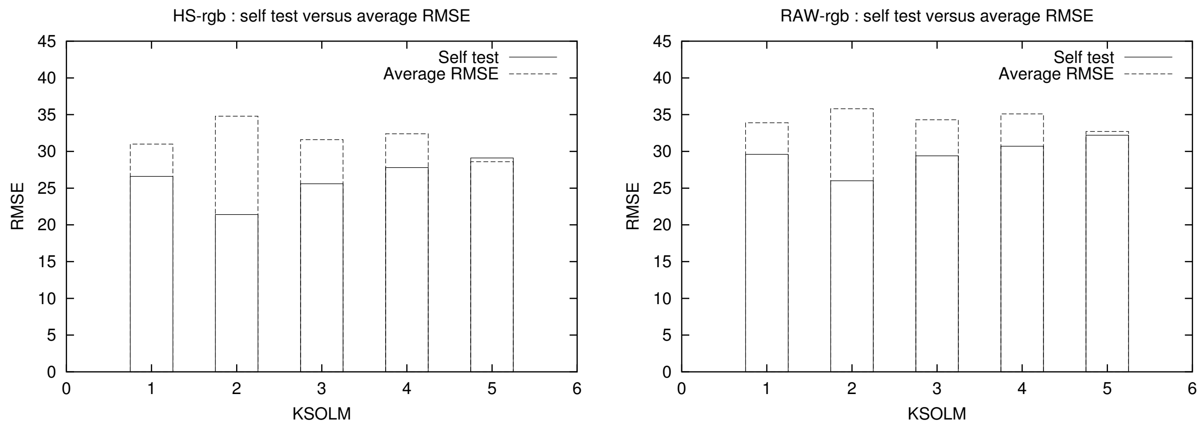


Figure 15: Self test versus average RMSE in HS,$V_{max}$-rgb and RAW-rgb color space

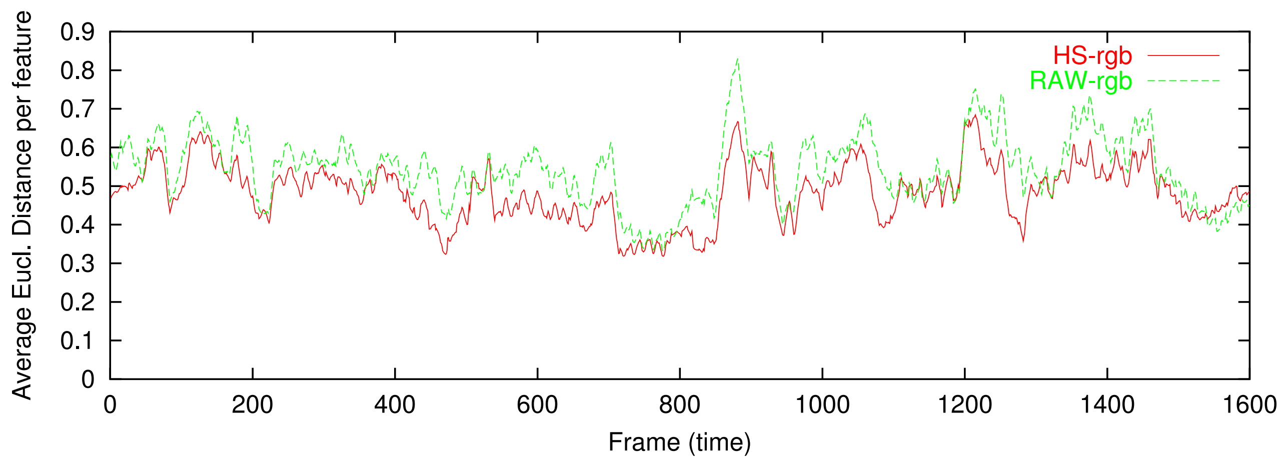


Figure 16: Average feature distance of HS,$V_{max}$ versus RGB, smoothed over 31 samples

**Conclusion** In this experiment the self test gives us a performance measurement of the robot in classifying landmarks in the environment when the conditions, such as lighting and weather during learning and testing are identical. Figure 15 shows us that KSOLM's trained under static conditions perform better in the self test than KSOLM's trained under variable conditions. KSOLM 2 was trained with data obtained during a run in the environment with relative static conditions: Clouded and slightly raining. The lighting conditions during this run where relative dark and stable. KSOLM 2 is tuned for classifying landmarks under these specific rainy, dark conditions. The high average RMSE of KSOLM 2 relative to the self test tells us that the performance of classifying landmarks in the environment under different conditions than during training deteriorates when a KSOLM is tuned for a particularly stable condition.

KSOLM 5 is trained with a dataset constructed by merging the different runs, frames of the environment under different conditions were used to train the KSOLM. A landmark representation in KSOLM 5 is the average feature pattern of a landmark in the environment under different conditions. As a result the performance of KSOLM 5 will decrease in the self test relative to KSOLM 2, but the average performance of classifying landmarks under different conditions increases. The distance between the average RMSE and self test decreases when the conditions in environment during training were variable. This leads to KSOLM's that on the average perform better on landmark classification under different conditions in the environment.

When our concept of constructing a KSOLM is time invariant, the values of the RMSE with different combinations of test sets and training sets will approximately be the same. All though the results show some difference in performance of the KSOLM's, these differences are relative small. Both the plots in Figure 14 show a relative smooth surface which suggest that the performance of KSOLM constructed under different conditions are approximately the same. An absolute smooth surface will mean that there will be no difference in performance of KSOLM's trained under different conditions.

The results of this experiment also show that the performance of KSOLM's are better when the visual patterns of landmarks in the environment are transferred to HS,$V_{max}$ space. The surface of the RAW-rgb plot in Figure 14 is smoother than the HS,$V_{max}$-rgb plot, but is positioned higher on the RMSE axis. This means that the overall performance of landmark classification in HS,$V_{max}$-rgb color space is better than in RAW-rgb space. This can also be seen in Figure 16 where the average distances of HS,$V_{max}$ feature frames are lower than the feature distance of RGB feature frames during a sequence of 1600 frames.

The conclusions drawn at this point in the research project were:

- The KSOLM forms a time invariant and robust representation of landmarks in the environment.
- HS,$V_{max}$-rgb transformation of the visual patterns of landmarks in the environment lead to better recognition and classification.
- Recognition of the environment under variable conditions is best done with a perceptual landmark map which is trained in the environment with feature frames taken under variable conditions

### 4.5.7 Experiment 6 :

In this stage of the research project the robot is capable of learning perceptual representations of the 25 most important landmarks in the environment that were observed during exploration. The most important landmarks in the robocup field are clearly represented in the visualized Kohonen map. Experiment 5 (see Section 4.5.6) showed us that the generalized landmarks in the Kohonen Self Organizing Landmark Map formed stable representations of landmarks in the environment under variable conditions(lighting). The next step in the research project is to let the robot perform a live run in the environment. The robot will explore the robocup environment on basis of the Obstacle Avoidance Agent which is also used during the training of the perceptual landmark map. During this exploration of the environment it is tested if the robot can recognize points in the environment on basis of the perceptual landmark map. Once the robot is capable of recognizing its environment it can construct a topological representation of the environment by keeping track of changes in directional heading and position between two landmark observations. By also keeping track of the sequence of observed landmark, the robot is capable of constructing a transition network of landmarks in the environment where the probability of a transition between two landmarks is calculated. This network in combination with the topological representation of the environment can be used to determine the next action for the robot: Which action has the robot to perform to reach a certain goal in the environment, when landmark $x$ is observed.

**Setup** A perceptual landmark representation based on the training set with 1600 feature frames from experiment 5(see Section 4.5.6), with the visual pattern of a potential landmark in HS,V$_{max}$-rgb representation is incorporated in the robot(see Figure 17).

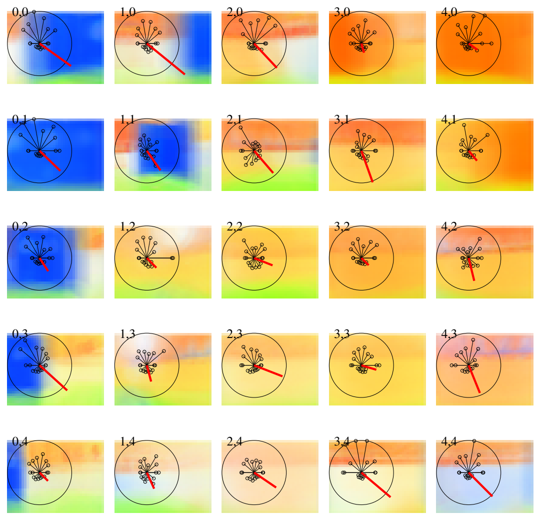

Figure 17: Incorporated perceptual landmark map

During a live exploration run of the robot on basis of the Obstacle Avoidance Agent(see Section 4.2.1) an agent is executed with a interval of 500 $ms$ During this execution the following tasks are performed:

- A feature frame is constructed from the perceptual pattern the robot is perceiving at the current moment in the environment.
- The nearest neighbor in the incorporated perceptual landmark map is determined for the feature frame.
- Visualize the constructed feature frame and the corresponding nearest neighbor frame next to each other on the screen.
- Determine if the robot is at a proximity event. When the robot perceives a object within the range of 1000 $mm$ of the front four sonars a proximity events occurs, otherwise the robot is in a so called mid field situation: No objects are frontal observed.
- Calculate the $\Delta x, \Delta y$ of the last observed landmark at a proximity event.

The obtained data is added to a log file that consists of a sequence of landmark observations. Each line of this log file is constructed as followed:

$$< proximity\, bit >< landmark\, ID >< \Delta x, \Delta y > \quad (10)$$

The proximity bit tells us if a landmark is observed at a proximity event or in mid field, landmark ID tells us which landmark in the perceptual landmark map the robot is currently observing and $\Delta x, \Delta y$ tells us the position of the previously observed landmark at a proximity event.

Plotting the current feature frame the robot is observing and the corresponding nearest neighbor in the perceptual landmark map on the screen enables us to give a subjective judgment on the correctness of recognizing landmarks in the environment.

The robot traveled in the environment for 6368 seconds. During this run a log file was created which consisted out of 12736 samples of landmark observations ordered in ascending time. From this log file it was determined for every possible landmark transition how often it occurred during the run. This data will be used to create a transition network.

Preliminary test on the construction of a topological representation of the environment on basis of the $\Delta x, \Delta y$ between two observed landmarks showed us that this information could not be used to create such a map. Due to drift in the odometry of the robot, the $\Delta x, \Delta y$ provided us with highly inaccurate information. A topological map based on this information resulted in a map which did not contain a sensible representation of the environment. Differential drift on $x$ and $y$ lead to translation and rotation of the 2D space. When the robot is equipped with a more accurate odometry in the future, a map can possible be realized on basis of the $\Delta x, \Delta y$. In short, the result of this preliminary test showed us that one of the original goals of this experiment, to construct a topological map of the environment on basis of $\Delta x, \Delta y$ between two observed landmarks could not be done.

What information do we have that can be used to generate a topological map of the environment. The answer to this question was : estimated distance traveled between two landmark observations. On the log file a sample selection was applied that resulted in a sequence of landmark observations that took place when the robot entered a proximity event from a mid field observation. The time span between these landmark observation and the average driving speed of the robot formed the basis for estimating the distance traveled. From this data a 25 by 25 distance matrix was constructed that holds the distance information between the 25 landmarks in the perceptual landmark map. A Location in the distance matrix that contained the distance of a landmark transition that did not occurred during the run was set by random noise.

The distance matrix can be seen as an 25-dimensional space where each landmark has its unique location. A Principle Component Analyses will be applied on the distance matrix in order to bring the 25 dimensions back to 2 dimensions. After PCA, each landmark will have its unique location in this 2 dimensional space, which can be seen as a $x, y$ coordinate map of the environment.

Figure 18 shows that the PCA method for creating a topological representation of the environment on basis of a distance matrix works. An artificial distance matrix was constructed that represented the distances between 25 points uniform distributed in a 5 by 5 square(left plot in Figure 18) . On this 25 by 25 artificial created distance matrix a PCA was applied that resulted in the middle plot of 25 points in Figure 18. The middle plot represents the best possible reconstruction of the original plot(left) on basis of a distance matrix. A linear transformation has to be applied on the resulting PCA map(middle) to obtain a map(right plot in Figure 18) that is in on the same scale as the original map. When comparing the left and right plot with each other the conclusion can be drawn that the reconstruction is not without error, but the general layout is reconstructed. Noise on the distances in the matrix will increase the error in a reconstruction of the map somewhat. Missing distances have a stronger bias effect.

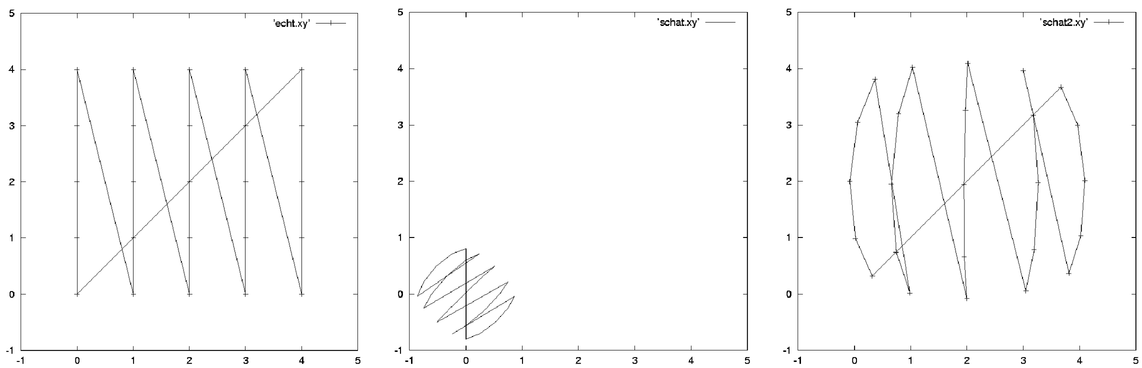


Figure 18: PCA on artificial created distance matrix with no missing links and no white noise on the distances.

**Result** After performing a live run with the robot in the environment a sequence of observed landmarks was the result. Our subjective judgment on the correctness of recognition of landmarks is that the robot is most of the time capable of recognizing the environment. Easily perceptible and distinct landmarks such as the blue and yellow robocup field are identified correctly all of the time. The recognition of landmarks in the environment that are not that easily perceptible or distinctive shows more error, but is acceptable.

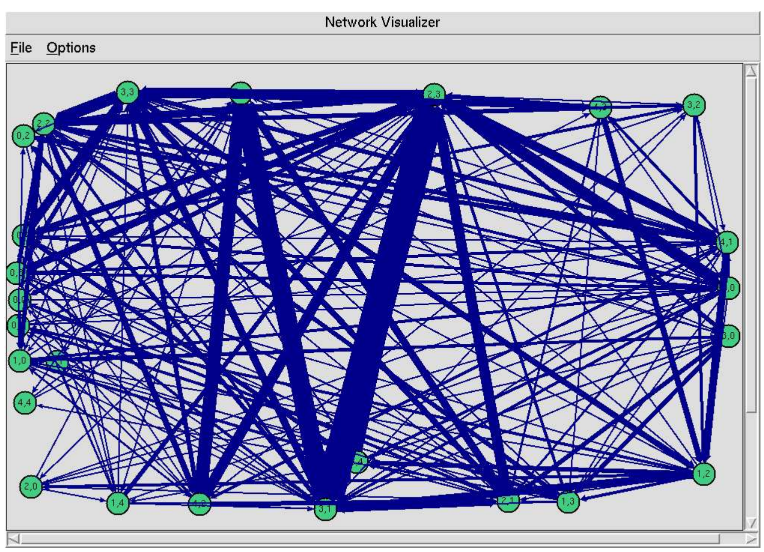


Figure 19: Transition network based on the live run. The nodes were manually placed on approximate position in the plane:blue goal is on the left, yellow goal is on the right.

Figure 19 show the visualization of the transition network constructed on basis of the live run. The green dots represent the landmarks in the incorporated perceptual landmark map. The purple arrows represent a transition between landmarks that occurred during the live run. The thickness of the arrows corresponds to the probability of a transition between landmarks in the environment: a thick arrow corresponds to a high probability.

Figure 20 show the topological landmark representation of the environment which resulted after a PCA on the distance matrix. The labels in the topological map correspond to the labels in the perceptual landmark map in Figure 17.

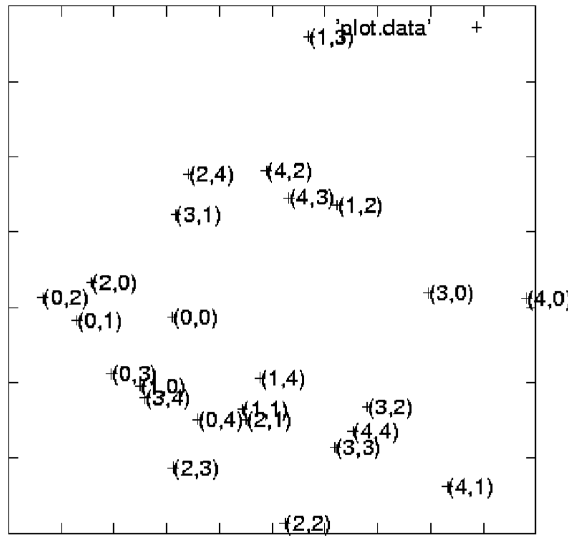


Figure 20: Topological landmark representation based on PCA of the distance matrix. Without human intervention, the system has correctly place the blue(0,1) and yellow(4,0) goals in opposing positions. The window in the room[(1,2),(1,3)] at the top, indicates that the y-axis should be flipped.

**Conclusion** The robot is capable of recognizing the environment during a live run. The result is a sequence of abstract representations of landmarks. In this experiment the index in the perceptual landmark map is used as reference to a observed landmark. With this sequence of observed landmarks a transition network can be created. The transition network has a clear probability distribution for the next expected landmark.

The topological landmark representation of the environment shows that the general layout of the robocup field can be represented by applying a PCA on a distance matrix of the landmarks. The map represents the two main axis of the robocup field: Blue opposite to the yellow goal and terminal side opposite to the dark wall side.

# 5 Conclusion

This thesis started with the general research question if a cognitive inspired navigational subsystem would yield a robot that is capable of performing robust navigation in dynamical and unknown environments. This general question was divided into a subset of smaller research questions. This section will give a summary of the conclusion drawn after each experiment conducted in this experiment in the form of answers on this subset of research questions.(Section 3.1).

- *Can a robot learn important landmarks in its environment on basis of self-organizing combined sensory information from multiple modalities?* In experiments 1 to 4 we showed that a Kohonen Self Organizing map is capable of learning important landmarks in the robocup environment such as the blue and yellow robocup goals. A proximity event was used to collect perceptual pattern of potential landmarks to create feature frames that were use to train the Kohonen map. This perceptual pattern of a potential landmark is constructed by combining sensory information from multiple modalities: vision, sonar, odometry. The visual pattern of a potential landmark is transformed to a HS,$V_{max}$ representation, which makes it less sensitive to variation of lighting condition. The features of a landmark frame were all scaled within the same range so that the visual pattern of a potential landmark would be the decisive factor in classification, followed by sonar reflective field and $\Delta x, \Delta y$. Further research can be done on the influence of the features of the multiple-sensory modalities on the structure of the perceptual landmark map. Different ratios of weights can be put on the features of the different sensory modalities to set their influence on the classification of landmarks. In this way it can be determined which ratio of weights results in the best landmark representations in the environment.

The results of experiments 1 to 4 also showed that there was a strong link between action and perception. The behavior of the Obstacle Avoidance Agent used to let the robot explore the environment has great influence on the structure of the learned perceptual landmark map of the environment.

- *Can the robot use the learned perceptual landmark map, live, while moving around? Is the map stable regardless of weather and lighting conditions)?* Experiment 5 shows that the learned perceptual landmark map of the environment forms a stable representation of the environment under different lighting conditions. Experiment 6 showed that the robot is capable to recognize its environment on based of the perceptual landmark map during a live run. A sequence of abstract representation of landmark was the result. Such a abstract representation formed a reference to an index in the perceptual landmark map. We as outsiders could give symbolic names to these abstract references and robots could determine if they observe the same landmark in the environment on basis of Euclidean distance between two observed Kohonen nodes. RobotA observes node(1,3) in his Kohonen map en robotB observes node(2,1), Euclidean distance will be used than to determine if the two observation are the same.

- *Can the robot know what landmarks are directly reachable from a given landmark observation?* From the resulting sequence of observation of landmarks in experiment 6 a transition network could be created. This network showed a clear probability distribution of possible landmark transition. Some landmark transition have a higher possibility to occur during a run in the environment. This transition network gives us information on the structure of the environment. Transitions with probability of almost zero will usually not occur in the environment, this could mean that landmark A can not be reached from landmark B. Take for example a room, when you want to leaf the room, the door will almost always be used(transition probability 1). To leaf the room through a window, when it is situated on the fifth floor is probably not a good idea, survival rate would be low, so this 'transition' in the room would probably be zero.

- *Can the robot generate a global view(map) of its environment?* Experiment 6 showed us that a topological map of the environment could be theoretically constructed on basis of a distance table and Principle Component Analysis. On the resulting 2D representation of the environment a linear transformation has to be applied to obtain a 'real' map of the environment.

For behavior-based robotics we have made a great step in the right direction: robots that are capable of constructing a local topological-landmark map of the environment. In the future robots should be able to determine their next action when a certain landmark in the environment is observed to reach a specific goal. More research can be done on this area based on the findings of this research project.

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