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Sensory and Memory-Based Path-Planning in the Egocentric Reference frame of an Autonomous Mobile Robot

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Abstract
This paper describes a path planning system using combined information from memory and sensors in a egocentric map. This technique enables autonomous mobile robots to use optimal path planning techniques such as the resistive grid. Using an egocentric map solves the self-localisation problem for mobiles robots and facilitates the reading of potential gradients in the resistive grid because the central node corresponds always to the position of the robot. In the described system, obstacles found with distance sensors are placed on the portion of an egocentric sensory map corresponding to the "visible space", with angles and distances determined by the current orientation and position of the robot. This current sensory knowledge is used to retrieve the positions of other, currently invisible, obstacles from an invariant spatial memory. The knowledge from the memory is then added to the sensory knowledge on the sensory map which has short-term memory nodes connected one-to-one to those of the resistive grid. The activities of nodes in the sensory map constrain the activities of the nodes in the resistive grid corresponding to target and obstacles positions, thereby providing the necessary information for path planning. After each movement of the robot, the content of the sensory map is reconstructed. We have developed a form of invariant spatial memory based on the recognition and storage of views of the obstacles configuration observed from a set of focus points. These are objects chosen for their special appearance, for instance corners. Such views are stored in a polar representation. For their recognition by "view-neurons", a polar shifting map has been developed. The behaviour of the view-neurons connected to the shifting map is reminiscent of that of place cells in the hippocampus. This form of invariant spatial memory allows to learn a number of different new environments of any size and to retrieve relevant information when required. The proposed system is demonstrated by simulations. Possible and necessary improvements are discussed. The system can be extended to path planning in states spaces of any dimensionality and offers the potential for mental exploration based only on information from memory placed in the sensory map.

1) Introduction.

Path planning problems for mobile robots are usually presented in a room based reference frame: Knowing the dimensions of a room, the positions of a target, of a set of obstacles and the initial position of the robot, what path should the robot take to reach the target ? Optimal solutions can be found using dynamic programming techniques [Barto et al., 1993]. Similar solutions are also found using the resistive-grid technique. We present a variant of this later technique in more detail in section 2. However, when these path planning techniques are to be used on-board mobile robots a number of difficulties arise: The dimensions of a room are not always known in advance and it is difficult to determine the size and resolution of the internal map and where the first found obstacle should be placed. The sensors of the robot have a limited range and cannot see obstacles hidden behind other obstacles. Thus the knowledge of the obstacle configuration is incomplete and the optimal path cannot be found. Even when the robot is in a known environment, in which case the above mentioned difficulties do not arise, the on-board motion tracking system is subject to drifts and after a few displacements, the robot has no longer a reliable information on its position in the room. In view of these difficulties, a number of approaches have been developed which do not rely on spatial maps but on associations between a set of scenes as seen by the robot at different positions and a set of control actions [see for instance: Verschure et al., 1992]. A path is obtained from a sequence of actions called by a succession of views in successive positions. These techniques involve lengthy learning procedures via trial and error and require that the robot has reached the target at least once by chance in order for it to learn which scenes lead to the target. Spatial map based techniques allow faster adaptation to new environments and offer the advantages of optimal path planning techniques in complex environments. Therefore, we have developed a system enabling a mobile robot to use the resistive-grid based path planning technique. Although we have not attempted to model biological systems, we have used knowledge on computational capabilities and strategies in biological systems to solve essentially an engineering problem. The resulting system is biologically "plausible", because it can be realised with biological hardware modulo small changes. Therefore, our system may constitute a basis for discussing path planning strategies used by animals.

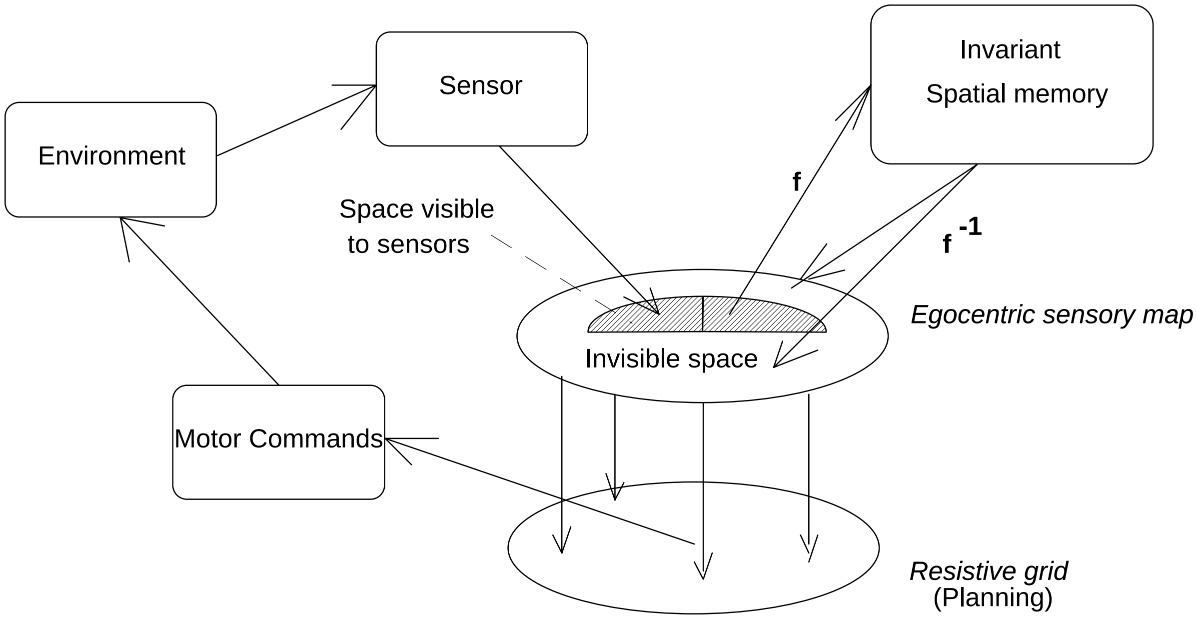
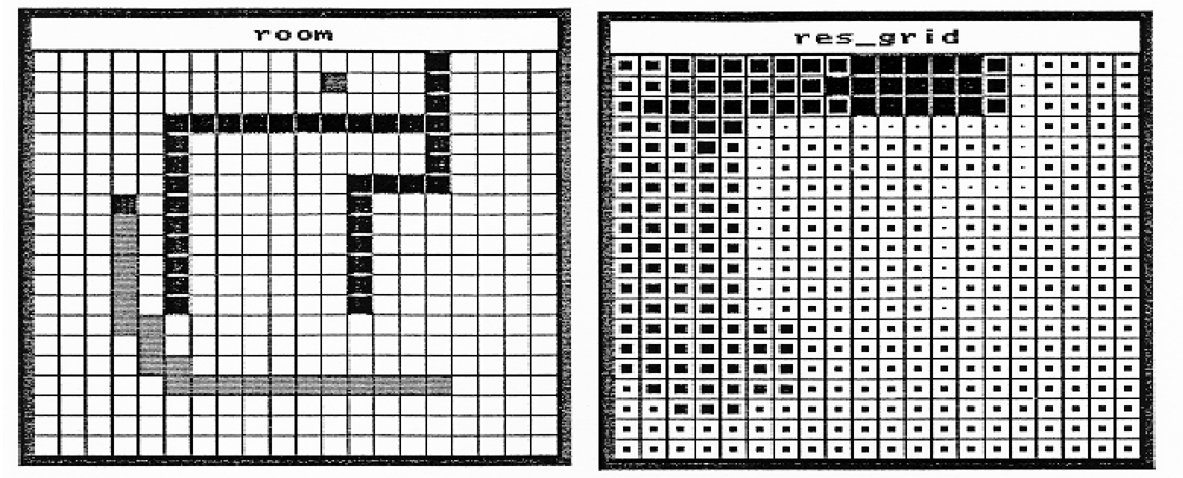


Fig. 1 Principle of memory/sensor completion.

The basic principles of the proposed system are outlined in figure 1. Instead of a room based map, a polar egocentric map is used. The radial axis represents **r'**, an exponentially compressed transformation of the distance ($r' = 1-\exp(-r/r_o)$), so that even obstacles located at infinite distance can be represented. However, in this work aimed at investigating the interaction with the spatial memory, we have used a simple Cartesian egocentric sensory-map. This map comprises an area corresponding to the "visible space" which is continuously fed with new information from sensors covering a limited range and possibly a limited observation angle, for instance as provided by a frontal array of ultrasound scanners. The remaining area of the map is fed with information provided by an invariant spatial memory. This memory is addressed by partial information on the environment and returns the stored information to the remainer of the map. A transformation **f** transforms sensory information in the egocentric reference frame into the invariant representation used in memory. A pseudo-inverse transformation $\mathbf{f^{-1}}$ transforms the stored invariant information into the egocentric reference frame. Using this interplay between invariant spatial memory and egocentric reference frame, most of the problems mentioned above are solved (see section 3). For instance, the robot localisation becomes an irrelevant question because the robot is always in the centre of the map. Indeed, the correct positioning of information from memory replaces the self-localisation problem. It is described in detail in section 4. The problem of incomplete knowledge is solved by progressively adding new information to the invariant memory. There is no need for explicitly designing an exploration strategy: As paths planned with incomplete knowledge are followed, invisible obstacles become visible and are added to the memory. These are then taken into account in future plannings and new paths are created. When the knowledge in memory is complete, a partial view of the obstacles suffices to retrieve the complete map of the room and optimal path planning can be achieved. We use a form of spatial memory which allows the storage of a number of obstacle configurations in different rooms or even to link rooms together so that navigation in complex environments is theoretically possible. As memory based and sensory based information is represented in the same map, spatial information produced solely by memory could be used for "mental exploration". This potential of our system is described in section 5. So far, we have realised a simulation of a robot moving in a single room and reaching a target using a combination of information originating from sensors an memory. Details of this simulation are given in section 6. Possible improvements or alternative options are discussed in section 7. The conclusion follows in section 8.

2A)



2B)

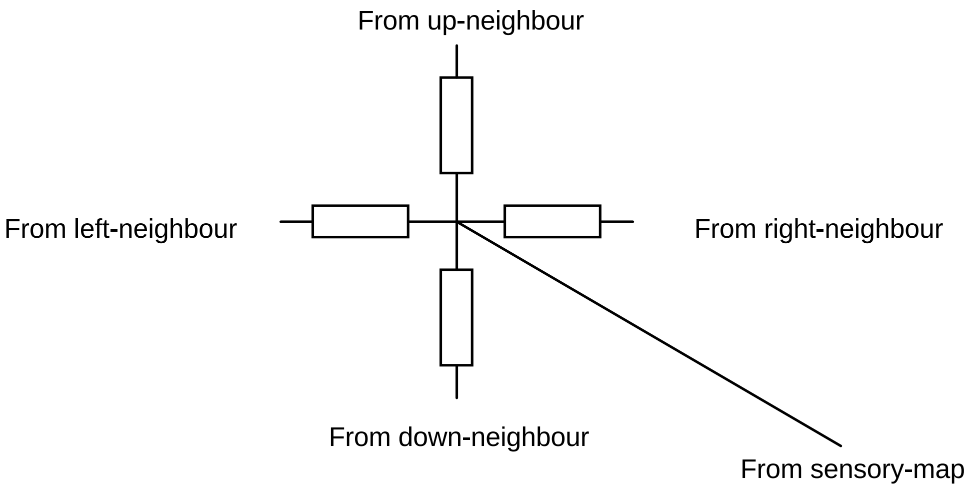


Fig. 2a) *Left*: Room divided into squares for the use of the resistive grid path planning technique. The obstacles are shown in black, the initial position of the robot is indicated by the beginning of its track (down to the right), and the position of the target is indicated by a single square towards the top. *Right*: Potential distribution using a neural network simulation of a resistive grid operating in the room based reference frame. Black nodes have the highest potential.

2b) Detail of a node in the resistive grid.

2) Path planning with a resistive grid

To use the resistive grid technique, the room is divided into small squares of equal size, as in figure 2a. To each square corresponds a node in the resistive grid. This node is a point where four electrical resistance's are connected together, each originating from a node corresponding to one of the four up, down, right or left neighbours (figure 2b). The node corresponding to the position of the target is set to a potential 1 and the nodes corresponding to obstacles are set to a potential 0. As the electric current in the grid flows from nodes with high potential to nodes with low potential, it is sufficient to measure, at the node corresponding to the robot's position, in which direction the current flows to know in which direction the robot should move to approach the target. Unlike potential methods, this technique has no problems with local minima. This is because electric current cannot flow through obstacles and must necessarily take a possible path to reach the position of the robot. In a sense, the electric current does the exploration of all possible paths leading from the obstacles to the target.

We have simulated the resistive grid using a simple neural network where each node is a neuron receiving inputs from 4 neighbours with weights 0.25. Each node realises a simple function, setting its output to the average value the outputs of it four neighbours. Such a neural network is a cellular automaton. The right figure 2a shows the distribution of output values for the configuration of the left figure 2a.

To set the desired activities in the obstacle and target nodes in the resistive grid, we use a sensory-map of the same size as the resistive grid with nodes connected one-to-one to the corresponding nodes in the resistive grid (figures 1 and 3). Sensory information provided by the robot, is used to set the target node to +1 and the obstacle nodes to -1 in the sensory-map. The nodes in the resistive grid have linear transfer functions saturating at +1 and 0. In this way, the obstacles nodes in the resistive grid, receiving a negative input from the obstacle nodes in the sensory-map, set their output to zero and act as if they were grounded. The node corresponding to the target receives an input +1 from the sensory-map added to the input from its neighbours in the resistive grid and saturates at +1, providing a permanent source of current into the resistive grid.

A neural network implementation of a resistive grid has also been proposed by Tarasenko and Blake [1991]. We have been unable to obtain a copy of their paper in time so that our knowledge on their system is only based on a remark in [Connolly, 1992]. The form of their resistive grid seems to be different from the one described above in the sense that the weights between nodes code for the local potential rather than the activity of the nodes. With our approach of the resistive grid, no learning of the connections in the resistive grid occurs. The resistive grid only processes information set into the sensory-map.

The resistive-grid technique ensures that a path is found when it exists, it can be realised cheaply in hardware and is then extremely rapid. For path planning in this case, a two dimensional grid is used but the techniques can be extended to any high dimension although, above three dimensions, a hardware realisation becomes very complicated. Using a neural network implementation there are no restrictions in dimensionality as any number of neighbours to a node can be defined. The possible existence in biological systems of structures analogue to resistive grids is discussed in Connolly and Burns [1993].

3) Egocentric versus room-based maps

Using a room based resistive grid, the exact position of the robot has to be known in order to read the potential gradient (opposite to the direction of the current flow) at the corresponding node. As mentioned in the introduction, such an accurate information is usually unavailable. Further, it is necessary to redirect the connections to the gradient reading unit at each robot displacement. Using a robot centred resistive grid, the node corresponding to the robots position has always the same position and the four neighbouring nodes used to determine the gradient are always the same.

When path-planning is done in the room reference frame, any obstacle found for instance by an ultrasound scanner has to be positioned on the map at its correct position, requiring a transformation from the egocentric reference frame to the room centred reference frame. However, when the exact position of the robot in the room is not known, this is impossible. Using a robot-centred map, the scanned obstacle are simply positioned on the map at the angle and the distance where they are found.

Regarding memory and accumulation of knowledge, the room based map has an advantage over the egocentric map. New obstacles found during exploration can be stored in the map at their fixed position so that eventually the map contains a complete knowledge on the obstacle configuration. Whereas, in the case of a robot centred map, the position of the obstacles on the map is different after each displacement of the robot so that the knowledge on the spatial organisation in the room must be stored in a way which is independent of the position or the orientation of the robot and must be retrievable and replaced on the egocentric map after each displacement of the robot. Biology does not give us clear hints on the possible form of an invariant spatial memory. We present here the form we have developed. It is however realisable with biological hardware.

4) Invariant spatial memory

When we observe a group of obstacles, whatever our position, what does not change is the spatial relation between the obstacles, the distances and angles separating them. Therefore, our form of invariant memory encodes the view of other obstacles when an observer is "sitting" on one of them. Practically, the robot does first a 360^{o} scan of the environment over a limited range. The information on the position of the found obstacles is placed in an egocentric sensory map (Figure 3 and 4). This map is then searched internally by the focus point selection unit of figure 4, for remarkable features which are used as focus points from which the distances and angles of all other found obstacles are determined. In our simulations we have chosen corners as focus points. If all obstacles had been used as focus points, a unnecessarily large memory space would have been used for storing the spatial information. As the sensory-map is a map internal to the robot, one may see the focus point as a target for internal attention.

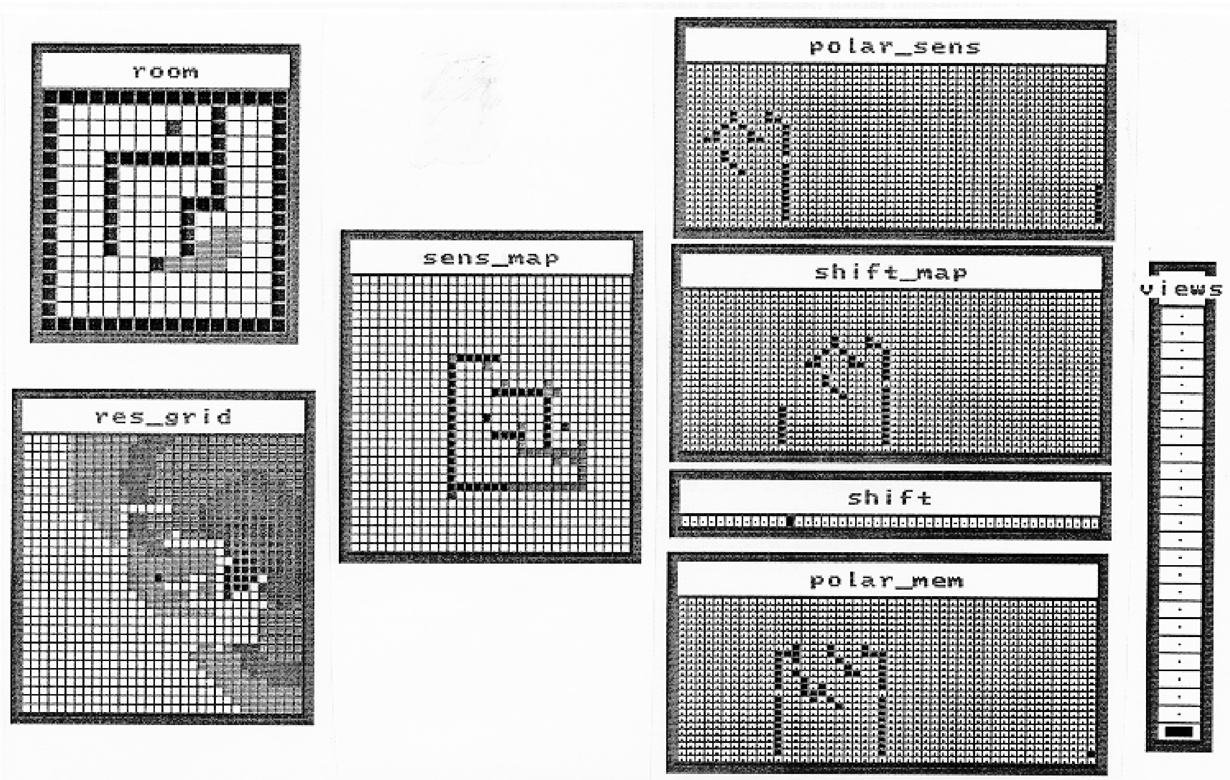


Fig 3. Copy of part of the screen seen during simulation using the CORTEX-PRO simulator. The grid on the top right shows the polar representation of a group of obstacles as seen from the bottom right hand corner of the room used as focus point in the sensory-map. The leftmost column corresponds to a small angle of $2\pi/48$. The rightmost column corresponds to and angle 0 or 2π. The robot is oriented towards 9 O'clock. Therefore, obstacles in the left of the room are in front of the robot and appear on top in the egocentric sensory map. The obstacles in black are those found by scanners. The obstacles in grey are those retrieved from memory. The position of the robot can be seen in the room at the end of its track. The state of the resistive grid correspond to the previous position of the robot. Details of the simulation are given in section 6

For each focus point on the sensory-map, a circular anti-clockwise scan is performed. The angles and distances of all the obstacles in the sensory map are measured and placed, using a polar representation, in a polar-sensory map. In this representation, the x-axis represents angles between 0 and 2π, the y-axis, distances from the focus point. The origin of the angles is determined by the current orientation of the robot. Its right hand side corresponds to an angle zero. An obstacle placed at the right of a focus point would be recorded at an angle zero, an object placed on a line parallel to the line of sight of the robot and beyond the focus point would be recorded with an angle of $\pi/2$. The right hand side of the egocentric sensory-map, corresponds always to the right hand side of the robot.

This polar representation of the relations between obstacles as seen from one of them, used as a focus point, is invariant modulo a shift of the x-axis. When such a group of obstacles is seen for the first time, the angles are recorded with their origin determined by the robots orientation at that time. If the robot is observing the same group of obstacles a second time but having an opposite orientation, he will record the same picture on the polar sensory map but shifted by π.

For each view from the obstacles seen from a different focus point, a neuron in a "views-layer", as seen in figure 4, is trained such that if the same view is seen again with the same orientation of the robot, i.e. has the same polar representation, this neuron will have an output value near to 1. Training is described in section 6. There is only one view-neuron per focus point. As later observations of the same group of obstacles from the same focus point but with different robots orientations will lead to shifted polar representations, the polar representation must be shifted back until the configuration initially learned by the corresponding view-neuron is met. For that purpose, the content of the polar sensory map is copied in the "shift-map".

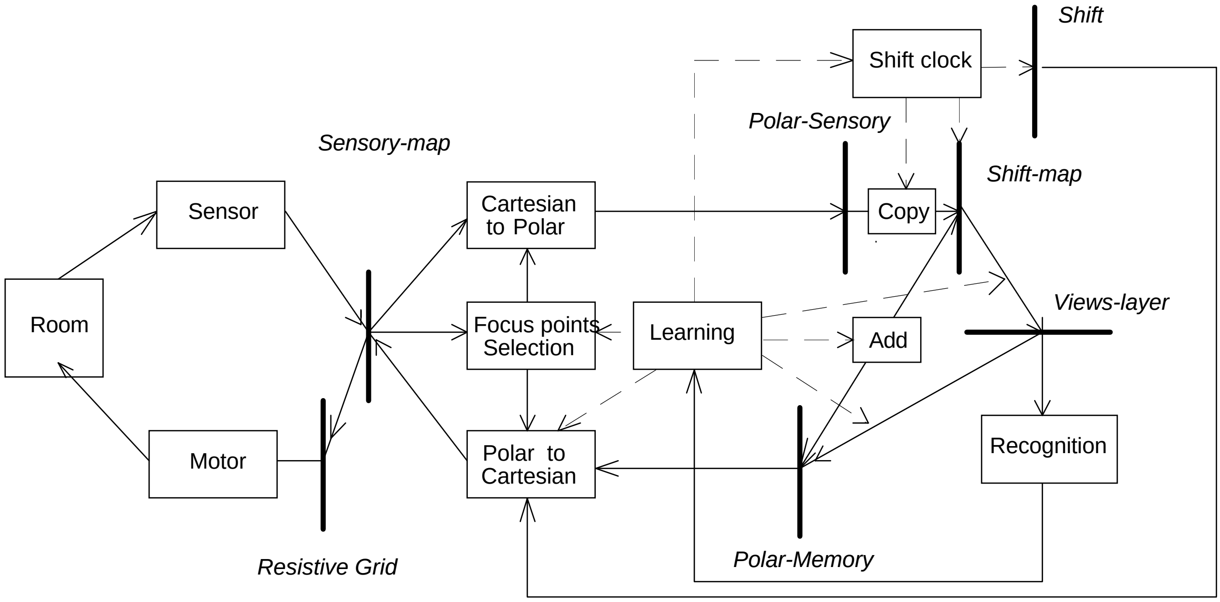


Fig 4. Diagram of the complete path planning system. The thick lines represent layers of neurons. The boxes represent functions realised by subroutines written in C. Information communicated between units is represented by full lines. Some of the control signals are also represented with dashed lines.

The shift-map is a neural network where each neuron is connected only to its neighbour to the right. Each neuron in the views-layer is connected to all neurons in the shift-map. The input weights of the view neurons are set such that they respond maximally when the pattern of activity in the shift-map corresponds to the view of a given group of obstacles seen from a given focus point under a given orientation. When all the neurons in the shift-map are updated synchronously, the whole pattern of activity is shifted by one column to the right. At each one-column shift, the activity of the view-neurons is monitored and, at the end of a whole 2π shift, corresponding to a scan of all possible orientations of observation, the neuron with the largest activity is noted.

This most active view-neuron indicates that the focus point from which the scan has been done is most likely the same as the one used for the training of that view-neuron. By noting the position of a single active neuron in special one-dimensional layer "shift" updated simultaneously with the shift-map, one can determine by how much the present orientation of the robot has been rotated from the orientation under which the obstacles were seen at the time of the learning. As we also know where the focus point is located in the egocentric sensory map, we have all the needed information to replace on the sensory map obstacles which may have been part of the learned group but are not visible from the current position of the robot. In this way, once a focus point has been recognised, the memory associated with that point can be retrieved, placed on the sensory map and used for path planning in addition to current sensory information.

The information on the positions of the obstacles as seen from a given focus point is stored in the strength of the connections from the view-neurons to the neurons in a "polar-memory", a layer of same size as the shift-map. The weights to the polar-memory are such that the pattern of activation in the polar-memory reproduces the learned activity in the shift-map. When a given view-neuron has recognised its focus point, even with partial information, its output is set to 1 and the polar memory reproduces the complete learned information. This information and the noted angle of shift is then used to calculate the positions on the sensory-map where obstacles should be. These obstacles are then added to those placed by the sensors. For that purpose, a short-term memory property is given to the sensory-map. The addition process is described in section 6.

A number of focus points in the sensory map are investigated in this way. Either they are already known and are used to place additional spatial information on the sensory map, or they are not recognised by one of the view-neurons and a yet unused view-neuron is trained to recognise the view from this new focus point. As the robot moves in the room, new corners may appear behind other obstacles and constitute these new focus points.

When a focus point is recognised, it is often from a different position of the robot than at the time of the training. Some obstacles may no more be visible and new obstacles may have become visible. These new obstacles are incorporated into the knowledge associated with that particular focus point in the following way: The content of the polar-memory called by the recognised focus-point, is added to the shift-map in such a way that the shift-map now contains information from sensors and from memory. The configuration in the shift map is then relearned by the corresponding view neuron to enhance its recognition capabilities and is used to recalculate its weights to the polar-memory, which contains therefore more complete spatial information.

This loop involving transfer of information between polar-memory and polar-sensory layers is one way to increase the spatial knowledge. Another source of knowledge increase comes from the obstacles placed on the sensory-map by previously recognised focus points. These obstacles are incorporated into the knowledge of the next investigated focus point. In that way, knowledge acquired by the robot in one position of the room is transferred to focus points visible only from other positions. Progressively, each focus point acquires complete knowledge of the obstacle configuration in the room. In figure 3 we can see an example of how limited sensory information is completed with information associated with a given focus point retrieved from memory.

The response properties of the view neurons used for recognition and for activating the memorised patterns in the polar memory is reminiscent of those of the place cells in the hippocampus. These cells fire when the animal is in a given position in the room rather than when attention is given to a given focus point. In a sense, the animal is the focus point. These cells show intriguing variations of the phase of their firing relative to the hippocampal theta rhythm [Burgess et al., 1994]. In our model, the view neurons are connected to the shift-map where the learned configuration can appear only one time per complete cycling of the shift map. Therefore, if we assume an uninterrupted operation of the shift map, the view-neurons tuned to the current view will show periodic maxima in activity with the same period as the cycling time of the shift map, the phase of the maxima relative to the cycle varying as the orientation of the robot changes. We have introduced the shift-map in our form of invariant spatial memory purely to solve an engineering problem and its properties may, at most, bring some food for thoughts towards understanding the hippocampus.

5) Potential of the model

In our simulations, the reconstruction of the knowledge stored in memory, involving the recognition of successive focus-points is a relatively slow process. It may actually be much faster to use information from ego-motion sensors to reposition obstacles on the sensory map as the robot moves. Knowing the inaccuracy of the ego-motion information, this can indeed not be used alone, but it may provide a temporary information needed for short distance moves and can then be confirmed or re-calibrated using information from memory.

The use of ego-motion signals implies the addition of a mechanism for moving obstacles on the sensory-map. One can conceive that it may be even faster to use, not ego-motion signals, but an efferent copy of the motor command causing the motion. A model extended in such a way should be capable of purely mental exploration. Let us assume that a given scene is retrieved from memory and placed in the sensory map. This information can then be used for path planning and the issued control command used not for an actual motion but only to move the scene on the map. Obstacle configurations can be recognised and used to retrieve more information from memory and the mental walk can carry on. The information available in the sensory map could also be used by other units, for evaluation of potential dangers or benefits.

6) Simulations

The simulations are performed using the very flexible CORTEX_PRO neural simulation software. We have designed neurons of "linear-saturated" type, being linear between 0 and 1, saturating at 1 for weighted sums of the inputs large than 1 and saturating at 0 for weighted sums of inputs smaller than 0. Such neurons have the important properties of no negative output and an output equal to zero when there is no input. However, in the egocentric sensory map, neurons with positive an negative outputs are used. The room in which the robot moves is made of 16x16 nodes as in figure 3. The robot can only move in one of four directions, to one of its four neighbours (eight or more directions would technically be possible but would not be of any help in studying the principle of our system). The current orientation of the robot is determined by the direction of its latest movement.

In figure 1, we have proposed the use of polar representation in the sensory map coupled to a resistive grid operating in the same representation. This representation allows information gathered from distance scanners to be placed in the most straightforward way. However, to facilitate the observation of the quality of the information retrieval from memory, we have used instead a Cartesian representation. One of the four nodes at the centre of the sensory map is chosen to represent the position of the robot. Obstacles found in front of the robot, whatever its orientation, are placed on the upper part of the sensory-map. The sensory map has a size of 32x32 so that, whatever the position and orientation of the robot in the room, the found obstacles will always fit into the sensory map. The robot is assumed to have a "target-scanner" which informs only on the position of the target and can "see" it through obstacles.

The sensory map is searched (using non-neural classical programming techniques in the simulation package) for corners. Each found corner becomes then the focus point for a second scan (also non-neural) which activates neurons in the corresponding position in the polar-sensory grid. It would be possible to use neural techniques to perform such a transformation of representation [Grossberg et al, 1993] but there was no interest for us to implement them at this stage of the research. The polar view grid has 48 columns corresponding to an angular range of 7.5 degrees each and 23 rows for representing a maximal distance of 23 (in unit of nodes) along the diagonal of the room. Once, the focus-point centred scan is completed, the polar representation in the polar-view layer is copied into the shift-map. The recognition takes place as described in section 3.

Regarding learning, the connections from the shift-map to the selected view-neuron are a normalised copy of the current activity in the shift-map. The normalisation is such that the same pattern shown again would cause an output equal to 1 of the view-neuron. The connections from the view-neuron to the polar-memory map are a simple copy of the activity in the shift-map, so that a view neuron with activity 1 generates the learned activity in the polar-memory. The learning from shift-map to views-layer is Hebbian in the sense that nodes with the strongest activities in the shift-map have the strongest connections to the view-neuron. A copy of activities of nodes in the shift-map is made available in the polar-memory at the time of learning. Therefore, Hebbian learning can also be applied from views-layer to polar-memory.

Once the polar-memory has been set to its new activity by an active view-neuron, its activity is read by a routine written in C performing the polar-to-cartesian transform as can be seen in figure 4. In order to determine the current position of the memorised obstacles, this routine uses information on the relative orientation of the robot found in the layer "shift" and on the position of the focus point provided by the focus point selection unit, as described in section 4. The knowledge retrieved from memory is then added to the sensory-map and stored temporarily in the following way: First the input activity is added to the current activity. The sum is then divided by 2. If the result exceeds 1, it is set to 1, if the result is smaller than a threshold of 0.25, it is set to zero. After that, a new scan of the obstacles in the room is done and the nodes in the sensory-map corresponding to the found obstacles are set to 1. In that way, real sensory information is always signalled with a maximum activity, while information from memory decays and eventually disappears if it is not refreshed, or in a sense, confirmed, by subsequent memory information generated by other focus points. The threshold of 0.25 prevents unconfirmed obstacles to affect later the potentials in the resistive grid. The short-term memory property of the sensory-map can easily be realized using neurons with self-feedback connections [Bugmann & Taylor, 1994]. Only activities larger than 0.75 are transferred to the polar-view layer during scans from focus points. In this way, relearning is carried out only on obstacles either of sensory origin, or which have been recalled from memory by several focus points.

At this stage of our work, as small imperfection in our program has prevented the robot of reaching the target. In a given position in the room, only the bottom left corner is visible. Unfortunately, from that position, the scanner which operates in discrete angular steps, misses also the cornerstone. Therefore, the robot is left without "typical" corner to be used as focus point and reverses its direction. When this small problem with the corner recognition routine is fixed, we expect the system to behave as well as the room-based system demonstrated in figure 2.

7) Possible improvements

Apart from those mentioned in section 5, related to the use of ego-motion and an efferent copy of motor commands, other improvements to the current system could be carried out. For instance, in our simulation, learning was centred on the problem of incorporating new obstacles into the memory, in order to provide the robot with complete information required by the resistive grid technique. However, a truly adaptive system should also be able to unlearn obstacles which have moved or have been removed. Such unlearning can only involve obstacles in currently visible parts of the space, because it is impossible to know if obstacles which the memory places in invisible portions of the room are actually still there. Such a restriction to unlearning requires the addition into the sensory polar representation of some form of information on the visible portions of the space. This is one of the improvements we will have to work on.

After a complete 2π shift of the shift-map, we decide that a view from a given focus point has been recognised by detecting the view neuron with the highest activation and measuring if there is sufficient difference with the activation of the second most active view neuron. However, limited sensory information of the room from a critical position of the robot, for instance, in alignment with a wall appearing thus as a single small obstacle, may sometimes lead to a focus point confounded with another and inadequate memory information placed on the map. To avoid such a problem one may have to use a recognition criteria based more on the consistency between information retrieved from a set of focus points, some of them predicted by the information in memory. This may require some changes in the diagram of the system.

The form of polar sensory map we use, having a finite set of columns corresponding to a discrete set of angles and a finite set of rows corresponding to a discrete set of distances, leads to quantization errors. For instance, an obstacle occupying a given grid node in the sensory map can activate two grid nodes after being learned and retrieved from memory. Such quantization errors can be see in the figure 3. As it is impossible to increase indefinitely the number of column and rows in the polar sensory map, one should consider a more refined coding of the angles and distances of obstacles, using possibly a more distributed representation, based on the activity pattern in local clusters of neurons.

In our simulation we have given noise-free values to sensory information. However, ultrasound scanners are noisy, sometimes misplacing obstacles, not detecting them or "inventing" them. This is very similar to the behaviour of the present form of our spatial memory. Therefore, similar confirmation techniques should be applied to the two types of information before learning and path planning.

We have assumed that the robot can, at any time, detect the position of the target. This is not always the case and we should assume, in future versions of the simulation, that the robot only receives an initial information on the position of the target and stores it in memory. This will involve to add to the system a extra group of neurons which keep track of the identity of objects as their positions change on the maps, a potentially interesting feature.

Conclusion

We have presented an initial approach towards the combined use of information from sensors and from memory for path planning in an egocentric reference frame. The method offers the potential of using map-based optimal path planning on-board of a real autonomous mobile robot. Several problems and possible improvements have been noted, which will the subject of future work.

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Note:
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