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A ROBUST NAVIGATION MODEL FOR AN AUTONOMOUS MOBILE ROBOT

Simon J. Egerton, Vic L. Callaghan, Paul Chernett

Department of Computer Science,
University of Essex,
Wivenhoe Park, Colchester, C04 3SQ,, England

Abstract: This paper reports on preliminary work with an adaptive multi-representational approach to modelling the real world. The proposed method operates in real time, accounts for low accuracy in the robots sensors, requires minimal computational resources and leads to the implementation of efficient path planning algorithms. Experiments are currently being conducted on a mobile indoor robot. In the longer term, this work will be extended to an outdoor farm vehicle.

Keywords: Neural Networks, Quadtrees, Robot Navigation, Self Location, Environment Modelling

1. INTRODUCTION

A "really useful" mobile robot should be autonomous and be able to adapt its behaviour to its current environment. The world of our "really useful" robot should be unmodified i.e. no markers, beacons or any external position references, and the robot should not be given any a priori map or knowledge of the world structure. Exploring the world the robot should build its map from scratch using only its sensory impressions or "perceptions" of its current environment. These perceptions fall into two broad categories and using the terminology of (Duckett and Nehmzow, 1997) they are:

A. Exteroception. The robots perceptions of the outside world i.e. from a TV camera, laser range finders, ultrasound.

B. Proprioception. The robots perception of its internal state within the world i.e. its perceived position derived for example from wheel encoders, or its current heading from say an internal compass, or the reported state of any limbs it may have.

Many of the popular mapping methods make use of both perception categories. However, they rely on accurate proprioceptive perceptions especially the robots internal position information. For example, the "traditional" geometric approaches, or quantitative methods, such as (Elfes, 1989; Darwin et al., 1985; Hoppen, 1990; Pagac and Nebot, 1995) are based on the accumulation of accurate geometric information about the world. However, this dependency on sensor accuracy makes these methods impractical for autonomous robots in the real world.

A more flexible approach to robot mapping uses qualitative methods. Rather than trying to map the environment explicitly the robots exteroceptions are used more directly to form a map. The notion of the robot having a global position or any kind of geometric reference does not seem necessary. As long as the Exteroception perceptions are rich-enough in context to be different at places the robot will visit in the environment. If every place in the world is unique then the robot can use this information alone to build a navigable map. However this is not the case and we have an effect known as "Perceptual Aliasing" (Duckett and Nehmzow, 1997). This is an effect where similar Exteroception perceptions occur in more than one place in the environment. This problem is approached by adding context to the exteroceptions, commonly by adding positional information. Examples of qualitative mapping methods range from maps constructed using a set of explicit rules (Kuipers and Byun, 1988) to more recent examples using statistical methods (Zimmer, 1995; Kurtz, 1996). In the recent work of (Duckett and Nehmzow, 1997) the "Lost Robot Problem" is tackled, i.e. the basic problem of the robot being able to find itself on the map it has already built. After all a map can only be useful to the robot only if it knows where it is in relation to it. An interesting question is how might the robot autonomously decide that it is lost?

The above work has some disadvantages such as overfitting the environment with the mapping structure, updating in dynamic environments and representing the environment with low degrees of accuracy.

The world modelling method proposed here integrates some of the qualities of the above work, while avoiding some of their disadvantages. The modelling method aims for the robot to autonomously produce, in real time, a map that models the world with a higher degree of resolution, without overfitting with the mapping structure. The model readily being used for localisation and for path

planning tasks, with the path planning algorithms exploiting the proposed models structure for computational efficiency. Incidentally, the notions of the mapping method proposed here finds support in the biological literature (Cheng, 1986).

In the remainder of this paper, we outline the details of the robot used in the experiments and the environments the robot will be situated in. A description of the proposed mapping model is given along with some implementation details. Some experiments are then described to evaluate the robustness of the model. The paper concludes with a summary of the work.

2. THE ROBOT

All the experiments are performed using an indoor laboratory robot. Figure 1 shows the robot. The robot has a number of sensors. The robots wheels are driven by two stepper motors. Internal position information is derived from the number of steps taken by the stepper motors. This crude method ensures the internal position information is never very accurate and accumulates error if unchecked. A measure of the mapping models robustness is the amount of positional error tolerated before the map becomes unreliable. A set of touch sensors surrounds the robot perimeter and provides positive feedback when the robot bumps into objects. The robot has a set of eight simple ultrasound sensors distributed evenly around its perimeter. These sensors provide range distances relative to the robots current position. This is achieved by recording the time-of-flight of an ultrasound pulse at a single frequency. The readings are subject to the typical noise associated with ultrasound measurements i.e. reflections from surfaces, environmental temperatures, surface textures. The robot has an onboard 68030 processor with 1MB of memory and runs the real time operating system VxWorks. Due to these limited resources, all of the processing is performed on a host workstation. Control and perception information flows along an Ethernet connection between the robot and host. This arrangement allows off-line development.

3. THE ENVIRONMENT

The experiments initially performed with the model will be in engineered indoor environments. Environments are constructed from various low level wall sections and obstacles of simple shape, all surfaces are generally smooth as well. The environments are unmodified with no markers, beacons or any external position references. However, there should be enough variation in the world for the robot to distinguish various places with its sensors, so giving the robot enough information to localise itself.
The initial experiments are concerned with proving the model in static environments, but later progressing to dynamic environments. In the dynamic environment, two classes of dynamic objects are defined. The first class are those objects which are picked up and moved to another location, or just removed altogether, or are added to the environment. The second class are those which appear mobile relative to the robot. This may be the case if other robots, or indeed people, are working in the same environment. Indeed it would be interesting to have other robots using the same model within the environment, this idea could lead onto experiments developing co-operative mapping techniques.

The long-term goal of this work is to experiment with the model on an outdoor robot based around a farm vehicle situated in a farm environment.

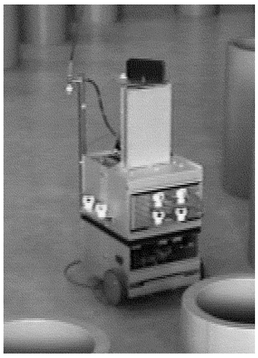

Fig. 1 *Photograph of the indoor robot used in the experiments.*

4. THE PROPOSED MODEL

The aim of this model is to allow a robot with inaccurate sensors to construct a map of an unmodified environment autonomously and without any a priori knowledge. To achieve this topological and geometric methods are brought together to produce a method that is robust, efficient, modular, and adequate for path planning and localisation tasks. Moreover, we think this method achieves this more elegantly than the other methods reviewed. To explain the model we introduce two concepts firstly the notion of a “Perception Space” and secondly the notion of a “Geometric Space”.

4.1 *Overall View*

In the introduction we defined the term perception and further defined two categories of perception, Exteroceptions and Proprioceptions. The notion of a “Perception Space” here is only concerned with the exterceptions and may be illustrated graphically with the use of some set theory. Letting the universal set be the set of all perceptions perceivable by any sensory means, then individual sensors form subsets of this universal set. Each sensor can be seen as acting as a filter, only allowing through perceptions that are specific to it (Wilson, 1991). So each sensor has its own associated set of perceptions as depicted in figure 2.

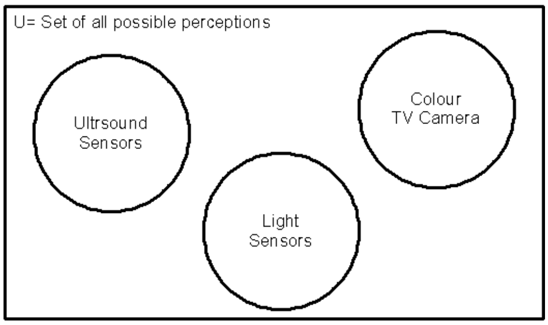

Fig. 2 *Each sensors set of perceptions*

The sensors space of perceptions is further constrained by the type of environment the sensor is situated in, forming an "environmental subset". This environmental subset of perceptions is constrained further, forming another subset, which depends on how much of the environment the sensor gets to see. It is this subset which forms the "Perception Space". Within this space, perceptions are categorised for their similarity relating to similar "Perception Areas" in the environment. For example, if the robot finds itself in a farm environment equipped with a camera then its environmental subset of perceptions are all things perceivable with the camera on the farm. However the robot spends its days trudging around the fields and its perception space only consists of things like fences, hedges, wooden poles, bales of hay etc. Therefore, as the robot explores the environment perceptions are categorised and perception spaces formed for each type of sensor it has. The perception space starts as an empty set, growing as more of the environment is seen and should stabilise once the entire set of perceptions in environment have been seen. However, if new parts of the environment are discovered then the perception space should accommodate the potentially new set of perceptions.

The "Geometric Space" is a geometric framework and its purpose is to simply relate geometric areas to perception areas in the environment where they occur. This is needed since it is unlikely that a perception area will be unique to one area of the environment i.e. "Perceptual Aliasing". The geometric space addresses the perception space to relate geometric areas to perceptual areas. A perception area may be referenced more than once by the geometric space. In our farm environment for example, there may be more than one bale of hay lying around in the field. As explained later in this article inexpensive path planning algorithms can be implemented with careful consideration to the representation of the geometric space. In addition, the robot should expect to see a certain sequence of perceptions along any planned path. This allows the robot to check its progress along the path and not be entirely dependent on its kinematics.

While the perception space should stabilise once the entire set of perceptions in the environment have been seen the geometric space may continue to expand as the robot explores more of the world. For example in our farm environment after exploring an entire field, the perception space will be stable. Now there may be a number of similar fields requiring the robots attentions. Therefore, the geometric space expands to accommodate the new fields as the robot explores them, but the perception space remains unchanged since all the fields contain similar objects and appear similar. However, should the robot then go to explore the barn where the hay is stored the perception space should accommodate the potentially new set of perceptions. The combination of the perception space and the geometric space is illustrated in Figure 3.

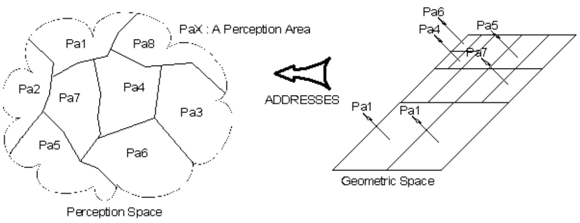

Fig. 3 *The Geometric Space referencing the Perception Space. This combination provides navigation information and a context for the robots perceptions forming the overall mapping model. The Perception Space has been partitioned into Perception Areas.*

The key to this model is the partitioning of the perception space into perception areas. It is not important what the perception areas relate to in the physical world, all that matters is that there are a set of areas in the environment which are distinguishable by the robots sensors. Since it is the ability to distinguish different perception areas that allow the geometric space to be constructed and allow path planning and localisation tasks to be performed. Using our farm environment for example, Pa1 could relate to open field, Pa4 could relate to bales of hay and Pa3 could relate to a fenced area, etc. On the other hand, they could relate to something far more abstract. Again, the importance lies with the robot being able to distinguish various perception areas in the environment. Whether or not the perception areas relate to objects "humans" can identify with does not matter, although of course this would be convenient. Perception areas are simply labelled by number, anything more meaningful requires the robot to have an "understanding" of what it perceives. Alternatively a human operator could observe the robot and try to match perception areas with some appropriate label.

If the robot becomes lost, for whatever reason, the robot can derive its location using the map it has built. Moreover, it can do this without referencing any positional information by making use of the perceptual space. When the robot is lost, it may be in any one of a set of possible locations. In this situation, the robot should wander around gathering evidence to find out where it is. The localisation procedure is formalised by the algorithm below. It

relies on neighbourhood information in the geometric space to reduce the robots set of possible locations.

Location Algorithm:

1. Note the current perception area.
2. Create a set of locations from the geometric space that share the above perception area.
3. Initialise the localisation hypothesis set with the set produced in step 2.
4. Repeat
5. Wander around until the perception area changes.
6. Create a set of locations from the geometric space that share the above perception area and neighbour a location in the current location hypothesis set.
7. Set the location hypothesis set with the locations created in step 6.
8. Until location hypothesis set contains only one element.

Here the robot will wander around the environment until it finds a particular sequence of perceptions that can be identified uniquely in the map. For example, in our farm environment if there is only once place where the robot would pass a gate followed by a hedge then by a fence, the robot can locate itself on the map after this sequence of perceptions. Successful localisation depends on the environment being varied enough to allow the robot to reduce the set of possible locations to one location. Figure 4 gives a simple example to illustrate the localisation process with a sequence of abstract perceptions.

It should be noted the location algorithm does not account for all eventualities. For example, if the robot encounters a new perception that does not have a neighbour in the current hypothesis set? This may be the result of three events.

1. Firstly and the most critical, the map was incorrectly built. This should not be allowed to happen.

2. The robot has moved out of the mapped area. In this case, the robot really is lost.

3. The environment has changed. In this case, either one or both of the above facts could be true as well.

We are aware of these problems and do not have any solutions to them now. Currently with the model, the only solution if this situation occurs is to restart the location process. However, are these location problems any different to those "humans" would have in similar situations? Would solving these problems result in a system out performing human capabilities?

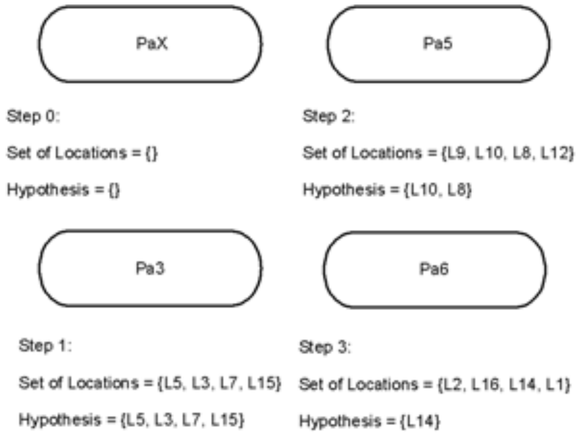

Fig. 4 *Illustrating the self-location abilities of the model. Each time a new perception area is encountered the hypothesis set is updated based on which locations of the new perception neighbour those of the previous hypothesis set. Note that no positional information is used in the process.*

5. IMPLEMENTATION

The function of the perception space module is to partition a perception space into suitable perception areas. This partitioning function is a data classification problem. A "Growing Cell Structure" neural network (Fritzke, 1993) is used for this classification process. The growing cell network is a self-organising neural network and works on the same principles as the well-known Kohonen neural network (Kohonen, 1988). The structure of the Kohonen network is fixed. The structure of the Growing Cell network is not fixed and is able to evolve with the data, growing and shrinking to best categorise the data. These are desirable features since the robot will be exploring an environment that is of unknown size, shape and complexity. The other desirable feature is the statistical element to these types of network, this will allow for some inconsistency in the robots sensors. Figure 5 gives the general idea how the growing cell structures will model perception spaces. The cells of the network represent the perception areas and the connections between them express their topological similarity.

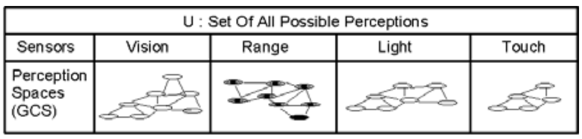

Fig. 5 *Each type of sensor has its own perception space and is modelled by a growing cell structure.*

The geometric space module relates perception areas to geometric areas in the environment where they occur. An "Area Quadtree" (Samet, 1984) is used to implement the geometric space. The quadtree is based around the principle of recursive decomposition. Areas are viewed as quadrants, and quadrants are recursively decomposed until quadrants are either homogeneous or the minimum quadrant

size has been reached. In our case, homogeneous areas represent areas with the same perception area. Hence uniform areas are mapped with the minimum of quadrants and the resolution of the represented area is defined by the minimum quadrant size.

Quadtrees offer a dynamic and efficient method for representing areas, the resolution to which an area is represented can vary as well. In addition, the tree structure of the quadtree allows the represented area to be efficiently searched. This property has been exploited to produce efficient path planning algorithms for the structure (Kambhampati and Davis, 1986; Zelinsky, 1992).

6. EXPERIMENTS

The experiments proposed are designed to evaluate the robustness of the world modelling method. The first set of experiments involves using place markers, in particular a “home” marker, to measure the performance of the model in general. The robot will be instructed to explore the environment and given enough time to build a reasonable map. Then the robot will be instructed to go “home”. The accuracy and the types of paths chosen will be measured. The second set of experiments will measure the effectiveness of the localisation algorithm under varying conditions. Again the robot will be allowed to explore the environment long enough for it to build a reasonable map. The robot will then be picked up, placed in a random location within the mapped environment, and with its positional sensors switched off, instructed to “go home”. This will be an essential test for the performance of the Perception Space and Geometric Space for localisation and navigation.

7. CONCLUSION

This paper has presented preliminary work on a multi-representational approach to the modelling of the real world. The approach is designed for a “really useful” robot that is autonomous and able to adapt to the surrounding environment. It is assumed the robots environment is unknown, unstructured and unmodified. The robot explores its new environment gathering perception information to construct the Perception Space and the Geometric Space. The Geometric Space will continue expanding as more of the environment is explored, while the Perception Space will converge to a stable stage when all the perceptions in the environment become identifiable. The Perception Space and the Geometric Space together can be used for self-localisation and path planning tasks. The presented localisation algorithm does not rely on the robots positional information. The model is currently being experimented with on an indoor mobile robot. Conclusive results are expected soon and will be presented at the conference and in future publications. In the longer term, experiments will include a mobile outdoor farm robot.

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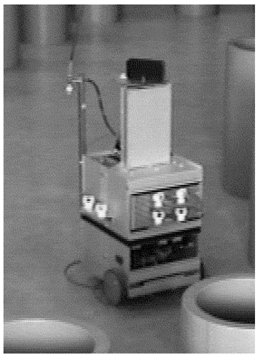

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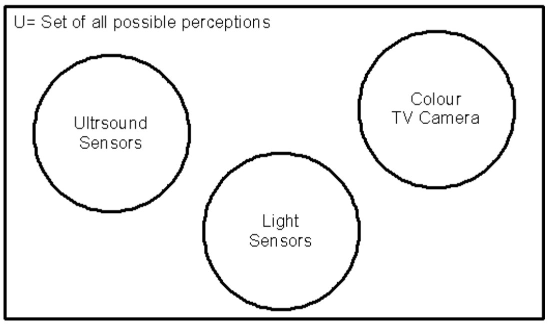

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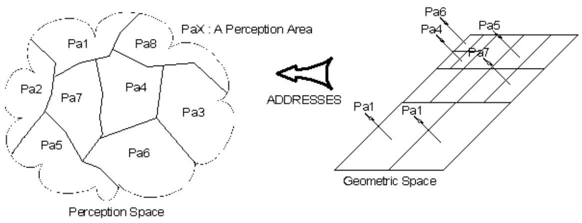

Fig. 3 *The Geometric Space referencing the Perception Space. This combination provides navigation information and a context for the robots perceptions forming the overall mapping model. The Perception Space has been partitioned into Perception Areas.*

The key to this model is the partitioning of the perception space into perception areas. It is not important what the perception areas relate to in the physical world, all that matters is that there are a set of areas in the environment which are distinguishable by the robots sensors. Since it is the ability to distinguish different perception areas that allow the geometric space to be constructed and allow path planning and localisation tasks to be performed. Using our farm environment for example, Pa1 could relate to open field, Pa4 could relate to bales of hay and Pa3 could relate to a fenced area, etc. On the other hand, they could relate to something far more abstract. Again, the importance lies with the robot being able to distinguish various perception areas in the environment. Whether or not the perception areas relate to objects "humans" can identify with does not matter, although of course this would be convenient. Perception areas are simply labelled by number, anything more meaningful requires the robot to have an "understanding" of what it perceives. Alternatively a human operator could observe the robot and try to match perception areas with some appropriate label.

If the robot becomes lost, for whatever reason, the robot can derive its location using the map it has built. Moreover, it can do this without referencing any positional information by making use of the perceptual space. When the robot is lost, it may be in any one of a set of possible locations. In this situation, the robot should wander around gathering evidence to find out where it is. The localisation procedure is formalised by the algorithm below. It

relies on neighbourhood information in the geometric space to reduce the robots set of possible locations.

Location Algorithm:

1. Note the current perception area.
2. Create a set of locations from the geometric space that share the above perception area.
3. Initialise the localisation hypothesis set with the set produced in step 2.
4. Repeat
5. Wander around until the perception area changes.
6. Create a set of locations from the geometric space that share the above perception area and neighbour a location in the current location hypothesis set.
7. Set the location hypothesis set with the locations created in step 6.
8. Until location hypothesis set contains only one element.

Here the robot will wander around the environment until it finds a particular sequence of perceptions that can be identified uniquely in the map. For example, in our farm environment if there is only once place where the robot would pass a gate followed by a hedge then by a fence, the robot can locate itself on the map after this sequence of perceptions. Successful localisation depends on the environment being varied enough to allow the robot to reduce the set of possible locations to one location. Figure 4 gives a simple example to illustrate the localisation process with a sequence of abstract perceptions.

It should be noted the location algorithm does not account for all eventualities. For example, if the robot encounters a new perception that does not have a neighbour in the current hypothesis set? This may be the result of three events.

1. Firstly and the most critical, the map was incorrectly built. This should not be allowed to happen.

2. The robot has moved out of the mapped area. In this case, the robot really is lost.

3. The environment has changed. In this case, either one or both of the above facts could be true as well.

We are aware of these problems and do not have any solutions to them now. Currently with the model, the only solution if this situation occurs is to restart the location process. However, are these location problems any different to those "humans" would have in similar situations? Would solving these problems result in a system out performing human capabilities?

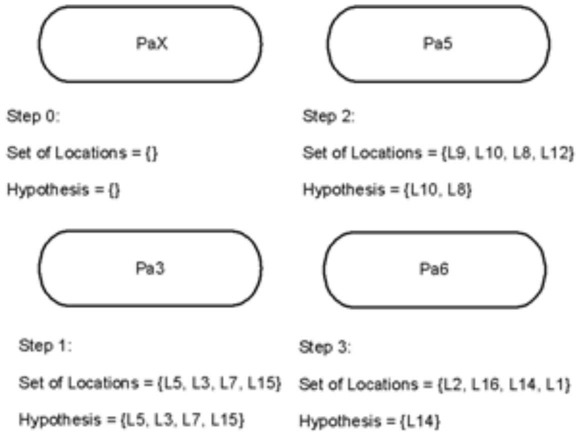

Fig. 4 *Illustrating the self-location abilities of the model. Each time a new perception area is encountered the hypothesis set is updated based on which locations of the new perception neighbour those of the previous hypothesis set. Note that no positional information is used in the process.*

5. IMPLEMENTATION

The function of the perception space module is to partition a perception space into suitable perception areas. This partitioning function is a data classification problem. A "Growing Cell Structure" neural network (Fritzke, 1993) is used for this classification process. The growing cell network is a self-organising neural network and works on the same principles as the well-known Kohonen neural network (Kohonen, 1988). The structure of the Kohonen network is fixed. The structure of the Growing Cell network is not fixed and is able to evolve with the data, growing and shrinking to best categorise the data. These are desirable features since the robot will be exploring an environment that is of unknown size, shape and complexity. The other desirable feature is the statistical element to these types of network, this will allow for some inconsistency in the robots sensors. Figure 5 gives the general idea how the growing cell structures will model perception spaces. The cells of the network represent the perception areas and the connections between them express their topological similarity.

U : Set Of All Possible Perceptions				
Sensors	Vision	Range	Light	Touch
Perception Spaces (GCS)				

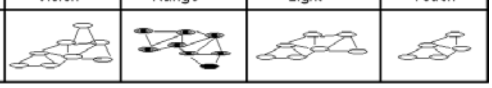

Fig. 5 *Each type of sensor has its own perception space and is modelled by a growing cell structure.*

The geometric space module relates perception areas to geometric areas in the environment where they occur. An "Area Quadtree" (Samet, 1984) is used to implement the geometric space. The quadtree is based around the principle of recursive decomposition. Areas are viewed as quadrants, and quadrants are recursively decomposed until quadrants are either homogeneous or the minimum quadrant

size has been reached. In our case, homogeneous areas represent areas with the same perception area. Hence uniform areas are mapped with the minimum of quadrants and the resolution of the represented area is defined by the minimum quadrant size.

Quadtrees offer a dynamic and efficient method for representing areas, the resolution to which an area is represented can vary as well. In addition, the tree structure of the quadtree allows the represented area to be efficiently searched. This property has been exploited to produce efficient path planning algorithms for the structure (Kambhampati and Davis, 1986; Zelinsky, 1992).

6. EXPERIMENTS

The experiments proposed are designed to evaluate the robustness of the world modelling method. The first set of experiments involves using place markers, in particular a “home” marker, to measure the performance of the model in general. The robot will be instructed to explore the environment and given enough time to build a reasonable map. Then the robot will be instructed to go “home”. The accuracy and the types of paths chosen will be measured. The second set of experiments will measure the effectiveness of the localisation algorithm under varying conditions. Again the robot will be allowed to explore the environment long enough for it to build a reasonable map. The robot will then be picked up, placed in a random location within the mapped environment, and with its positional sensors switched off, instructed to “go home”. This will be an essential test for the performance of the Perception Space and Geometric Space for localisation and navigation.

7. CONCLUSION

This paper has presented preliminary work on a multi-representational approach to the modelling of the real world. The approach is designed for a “really useful” robot that is autonomous and able to adapt to the surrounding environment. It is assumed the robots environment is unknown, unstructured and unmodified. The robot explores its new environment gathering perception information to construct the Perception Space and the Geometric Space. The Geometric Space will continue expanding as more of the environment is explored, while the Perception Space will converge to a stable stage when all the perceptions in the environment become identifiable. The Perception Space and the Geometric Space together can be used for self-localisation and path planning tasks. The presented localisation algorithm does not rely on the robots positional information. The model is currently being experimented with on an indoor mobile robot. Conclusive results are expected soon and will be presented at the conference and in future publications. In the longer term, experiments will include a mobile outdoor farm robot.

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A ROBUST NAVIGATION MODEL FOR AN AUTONOMOUS MOBILE ROBOT

Simon J. Egerton, Vic L. Callaghan, Paul Chernett

Department of Computer Science,
University of Essex,
Wivenhoe Park, Colchester, C04 3SQ,, England

Abstract: This paper reports on preliminary work with an adaptive multi-representational approach to modelling the real world. The proposed method operates in real time, accounts for low accuracy in the robots sensors, requires minimal computational resources and leads to the implementation of efficient path planning algorithms. Experiments are currently being conducted on a mobile indoor robot. In the longer term, this work will be extended to an outdoor farm vehicle.

Keywords: Neural Networks, Quadtrees, Robot Navigation, Self Location, Environment Modelling

1. INTRODUCTION

A “really useful” mobile robot should be autonomous and be able to adapt its behaviour to its current environment. The world of our “really useful” robot should be unmodified i.e. no markers, beacons or any external position references, and the robot should not be given any a priori map or knowledge of the world structure. Exploring the world the robot should build its map from scratch using only its sensory impressions or “perceptions” of its current environment. These perceptions fall into two broad categories and using the terminology of (Duckett and Nehmzow, 1997) they are:

A. Exteroception. The robots perceptions of the outside world i.e. from a TV camera, laser range finders, ultrasound.

B. Proprioception. The robots perception of its internal state within the world i.e. its perceived position derived for example from wheel encoders, or its current heading from say an internal compass, or the reported state of any limbs it may have.

Many of the popular mapping methods make use of both perception categories. However, they rely on accurate proprioceptive perceptions especially the robots internal position information. For example, the “traditional” geometric approaches, or quantitative methods, such as (Elfes, 1989; Darwin et al., 1985; Hoppen, 1990; Pagac and Nebot, 1995) are based on the accumulation of accurate geometric information about the world. However, this dependency on sensor accuracy makes these methods impractical for autonomous robots in the real world.

A more flexible approach to robot mapping uses qualitative methods. Rather than trying to map the environment explicitly the robots exteroceptions are used more directly to form a map. The notion of the robot having a global position or any kind of geometric reference does not seem necessary. As long as the Exteroception perceptions are rich-enough in context to be different at places the robot will visit in the environment. If every place in the world is unique then the robot can use this information alone to build a navigable map. However this is not the case and we have an effect known as “Perceptual Aliasing” (Duckett and Nehmzow, 1997). This is an effect where similar Exteroception perceptions occur in more than one place in the environment. This problem is approached by adding context to the exteroceptions, commonly by adding positional information. Examples of qualitative mapping methods range from maps constructed using a set of explicit rules (Kuipers and Byun, 1988) to more recent examples using statistical methods (Zimmer, 1995; Kurtz, 1996). In the recent work of (Duckett and Nehmzow, 1997) the “Lost Robot Problem” is tackled, i.e. the basic problem of the robot being able to find itself on the map it has already built. After all a map can only be useful to the robot only if it knows where it is in relation to it. An interesting question is how might the robot autonomously decide that it is lost?

The above work has some disadvantages such as overfitting the environment with the mapping structure, updating in dynamic environments and representing the environment with low degrees of accuracy.

The world modelling method proposed here integrates some of the qualities of the above work, while avoiding some of their disadvantages. The modelling method aims for the robot to autonomously produce, in real time, a map that models the world with a higher degree of resolution, without overfitting with the mapping structure. The model readily being used for localisation and for path

planning tasks, with the path planning algorithms exploiting the proposed models structure for computational efficiency. Incidentally, the notions of the mapping method proposed here finds support in the biological literature (Cheng, 1986).

In the remainder of this paper, we outline the details of the robot used in the experiments and the environments the robot will be situated in. A description of the proposed mapping model is given along with some implementation details. Some experiments are then described to evaluate the robustness of the model. The paper concludes with a summary of the work.

2. THE ROBOT

All the experiments are performed using an indoor laboratory robot. Figure 1 shows the robot. The robot has a number of sensors. The robots wheels are driven by two stepper motors. Internal position information is derived from the number of steps taken by the stepper motors. This crude method ensures the internal position information is never very accurate and accumulates error if unchecked. A measure of the mapping models robustness is the amount of positional error tolerated before the map becomes unreliable. A set of touch sensors surrounds the robot perimeter and provides positive feedback when the robot bumps into objects. The robot has a set of eight simple ultrasound sensors distributed evenly around its perimeter. These sensors provide range distances relative to the robots current position. This is achieved by recording the time-of-flight of an ultrasound pulse at a single frequency. The readings are subject to the typical noise associated with ultrasound measurements i.e. reflections from surfaces, environmental temperatures, surface textures. The robot has an onboard 68030 processor with 1MB of memory and runs the real time operating system VxWorks. Due to these limited resources, all of the processing is performed on a host workstation. Control and perception information flows along an Ethernet connection between the robot and host. This arrangement allows off-line development.

3. THE ENVIRONMENT

The experiments initially performed with the model will be in engineered indoor environments. Environments are constructed from various low level wall sections and obstacles of simple shape, all surfaces are generally smooth as well. The environments are unmodified with no markers, beacons or any external position references. However, there should be enough variation in the world for the robot to distinguish various places with its sensors, so giving the robot enough information to localise itself.
The initial experiments are concerned with proving the model in static environments, but later progressing to dynamic environments. In the dynamic environment, two classes of dynamic objects are defined. The first class are those objects which are picked up and moved to another location, or just removed altogether, or are added to the environment. The second class are those which appear mobile relative to the robot. This may be the case if other robots, or indeed people, are working in the same environment. Indeed it would be interesting to have other robots using the same model within the environment, this idea could lead onto experiments developing co-operative mapping techniques.

The long-term goal of this work is to experiment with the model on an outdoor robot based around a farm vehicle situated in a farm environment.

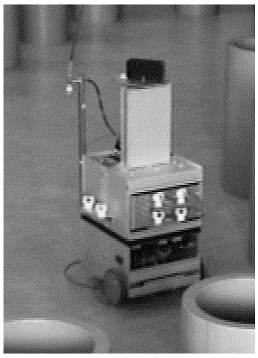


Fig. 1 *Photograph of the indoor robot used in the experiments.*

4. THE PROPOSED MODEL

The aim of this model is to allow a robot with inaccurate sensors to construct a map of an unmodified environment autonomously and without any a priori knowledge. To achieve this topological and geometric methods are brought together to produce a method that is robust, efficient, modular, and adequate for path planning and localisation tasks. Moreover, we think this method achieves this more elegantly than the other methods reviewed. To explain the model we introduce two concepts firstly the notion of a “Perception Space” and secondly the notion of a “Geometric Space”.

4.1 *Overall View*

In the introduction we defined the term perception and further defined two categories of perception, Exteroceptions and Proprioceptions. The notion of a “Perception Space” here is only concerned with the exterceptions and may be illustrated graphically with the use of some set theory. Letting the universal set be the set of all perceptions perceivable by any sensory means, then individual sensors form subsets of this universal set. Each sensor can be seen as acting as a filter, only allowing through perceptions that are specific to it (Wilson, 1991). So each sensor has its own associated set of perceptions as depicted in figure 2.

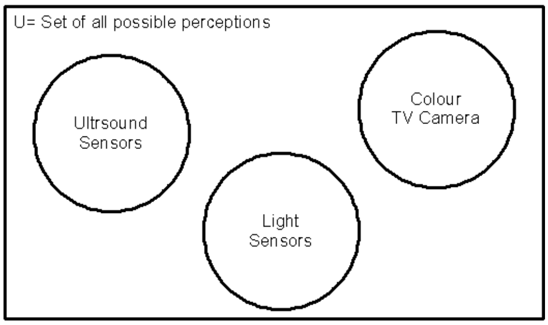
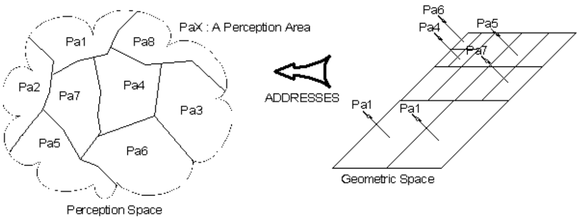


Fig. 2 *Each sensors set of perceptions*

The sensors space of perceptions is further constrained by the type of environment the sensor is situated in, forming an "environmental subset". This environmental subset of perceptions is constrained further, forming another subset, which depends on how much of the environment the sensor gets to see. It is this subset which forms the "Perception Space". Within this space, perceptions are categorised for their similarity relating to similar "Perception Areas" in the environment. For example, if the robot finds itself in a farm environment equipped with a camera then its environmental subset of perceptions are all things perceivable with the camera on the farm. However the robot spends its days trudging around the fields and its perception space only consists of things like fences, hedges, wooden poles, bales of hay etc. Therefore, as the robot explores the environment perceptions are categorised and perception spaces formed for each type of sensor it has. The perception space starts as an empty set, growing as more of the environment is seen and should stabilise once the entire set of perceptions in environment have been seen. However, if new parts of the environment are discovered then the perception space should accommodate the potentially new set of perceptions.

The "Geometric Space" is a geometric framework and its purpose is to simply relate geometric areas to perception areas in the environment where they occur. This is needed since it is unlikely that a perception area will be unique to one area of the environment i.e. "Perceptual Aliasing". The geometric space addresses the perception space to relate geometric areas to perceptual areas. A perception area may be referenced more than once by the geometric space. In our farm environment for example, there may be more than one bale of hay lying around in the field. As explained later in this article inexpensive path planning algorithms can be implemented with careful consideration to the representation of the geometric space. In addition, the robot should expect to see a certain sequence of perceptions along any planned path. This allows the robot to check its progress along the path and not be entirely dependent on its kinematics.
While the perception space should stabilise once the entire set of perceptions in the environment have been seen the geometric space may continue to expand as the robot explores more of the world. For example in our farm environment after exploring an entire field, the perception space will be stable. Now there may be a number of similar fields requiring the robots attentions. Therefore, the geometric space expands to accommodate the new fields as the robot explores them, but the perception space remains unchanged since all the fields contain similar objects and appear similar. However, should the robot then go to explore the barn where the hay is stored the perception space should accommodate the potentially new set of perceptions. The combination of the perception space and the geometric space is illustrated in Figure 3.



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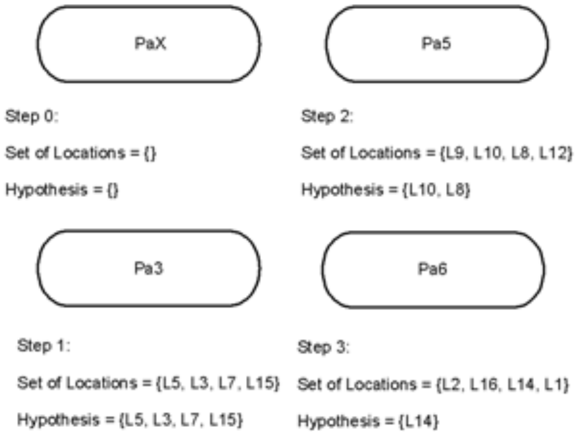

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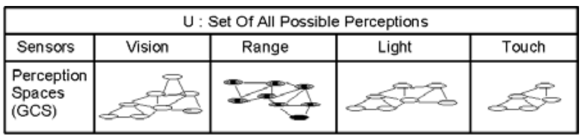

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1. INTRODUCTION

A “really useful” mobile robot should be autonomous and be able to adapt its behaviour to its current environment. The world of our “really useful” robot should be unmodified i.e. no markers, beacons or any external position references, and the robot should not be given any a priori map or knowledge of the world structure. Exploring the world the robot should build its map from scratch using only its sensory impressions or “perceptions” of its current environment. These perceptions fall into two broad categories and using the terminology of (Duckett and Nehmzow, 1997) they are:

A. Exteroception. The robots perceptions of the outside world i.e. from a TV camera, laser range finders, ultrasound.

B. Proprioception. The robots perception of its internal state within the world i.e. its perceived position derived for example from wheel encoders, or its current heading from say an internal compass, or the reported state of any limbs it may have.

Many of the popular mapping methods make use of both perception categories. However, they rely on accurate proprioceptive perceptions especially the robots internal position information. For example, the “traditional” geometric approaches, or quantitative methods, such as (Elfes, 1989; Darwin et al., 1985; Hoppen, 1990; Pagac and Nebot, 1995) are based on the accumulation of accurate geometric information about the world. However, this dependency on sensor accuracy makes these methods impractical for autonomous robots in the real world.

A more flexible approach to robot mapping uses qualitative methods. Rather than trying to map the environment explicitly the robots exteroceptions are used more directly to form a map. The notion of the robot having a global position or any kind of geometric reference does not seem necessary. As long as the Exteroception perceptions are rich-enough in context to be different at places the robot will visit in the environment. If every place in the world is unique then the robot can use this information alone to build a navigable map. However this is not the case and we have an effect known as “Perceptual Aliasing” (Duckett and Nehmzow, 1997). This is an effect where similar Exteroception perceptions occur in more than one place in the environment. This problem is approached by adding context to the exteroceptions, commonly by adding positional information. Examples of qualitative mapping methods range from maps constructed using a set of explicit rules (Kuipers and Byun, 1988) to more recent examples using statistical methods (Zimmer, 1995; Kurtz, 1996). In the recent work of (Duckett and Nehmzow, 1997) the “Lost Robot Problem” is tackled, i.e. the basic problem of the robot being able to find itself on the map it has already built. After all a map can only be useful to the robot only if it knows where it is in relation to it. An interesting question is how might the robot autonomously decide that it is lost?

The above work has some disadvantages such as overfitting the environment with the mapping structure, updating in dynamic environments and representing the environment with low degrees of accuracy.

The world modelling method proposed here integrates some of the qualities of the above work, while avoiding some of their disadvantages. The modelling method aims for the robot to autonomously produce, in real time, a map that models the world with a higher degree of resolution, without overfitting with the mapping structure. The model readily being used for localisation and for path

planning tasks, with the path planning algorithms exploiting the proposed models structure for computational efficiency. Incidentally, the notions of the mapping method proposed here finds support in the biological literature (Cheng, 1986).

In the remainder of this paper, we outline the details of the robot used in the experiments and the environments the robot will be situated in. A description of the proposed mapping model is given along with some implementation details. Some experiments are then described to evaluate the robustness of the model. The paper concludes with a summary of the work.

2. THE ROBOT

All the experiments are performed using an indoor laboratory robot. Figure 1 shows the robot. The robot has a number of sensors. The robots wheels are driven by two stepper motors. Internal position information is derived from the number of steps taken by the stepper motors. This crude method ensures the internal position information is never very accurate and accumulates error if unchecked. A measure of the mapping models robustness is the amount of positional error tolerated before the map becomes unreliable. A set of touch sensors surrounds the robot perimeter and provides positive feedback when the robot bumps into objects. The robot has a set of eight simple ultrasound sensors distributed evenly around its perimeter. These sensors provide range distances relative to the robots current position. This is achieved by recording the time-of-flight of an ultrasound pulse at a single frequency. The readings are subject to the typical noise associated with ultrasound measurements i.e. reflections from surfaces, environmental temperatures, surface textures. The robot has an onboard 68030 processor with 1MB of memory and runs the real time operating system VxWorks. Due to these limited resources, all of the processing is performed on a host workstation. Control and perception information flows along an Ethernet connection between the robot and host. This arrangement allows off-line development.

3. THE ENVIRONMENT

The experiments initially performed with the model will be in engineered indoor environments. Environments are constructed from various low level wall sections and obstacles of simple shape, all surfaces are generally smooth as well. The environments are unmodified with no markers, beacons or any external position references. However, there should be enough variation in the world for the robot to distinguish various places with its sensors, so giving the robot enough information to localise itself.
The initial experiments are concerned with proving the model in static environments, but later progressing to dynamic environments. In the dynamic environment, two classes of dynamic objects are defined. The first class are those objects which are picked up and moved to another location, or just removed altogether, or are added to the environment. The second class are those which appear mobile relative to the robot. This may be the case if other robots, or indeed people, are working in the same environment. Indeed it would be interesting to have other robots using the same model within the environment, this idea could lead onto experiments developing co-operative mapping techniques.

The long-term goal of this work is to experiment with the model on an outdoor robot based around a farm vehicle situated in a farm environment.

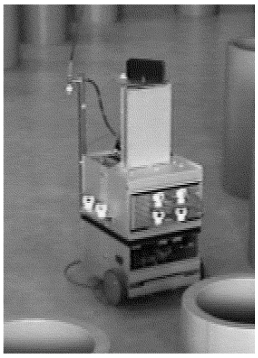


Fig. 1 *Photograph of the indoor robot used in the experiments.*

4. THE PROPOSED MODEL

The aim of this model is to allow a robot with inaccurate sensors to construct a map of an unmodified environment autonomously and without any a priori knowledge. To achieve this topological and geometric methods are brought together to produce a method that is robust, efficient, modular, and adequate for path planning and localisation tasks. Moreover, we think this method achieves this more elegantly than the other methods reviewed. To explain the model we introduce two concepts firstly the notion of a “Perception Space” and secondly the notion of a “Geometric Space”.

4.1 *Overall View*

In the introduction we defined the term perception and further defined two categories of perception, Exteroceptions and Proprioceptions. The notion of a “Perception Space” here is only concerned with the exterceptions and may be illustrated graphically with the use of some set theory. Letting the universal set be the set of all perceptions perceivable by any sensory means, then individual sensors form subsets of this universal set. Each sensor can be seen as acting as a filter, only allowing through perceptions that are specific to it (Wilson, 1991). So each sensor has its own associated set of perceptions as depicted in figure 2.

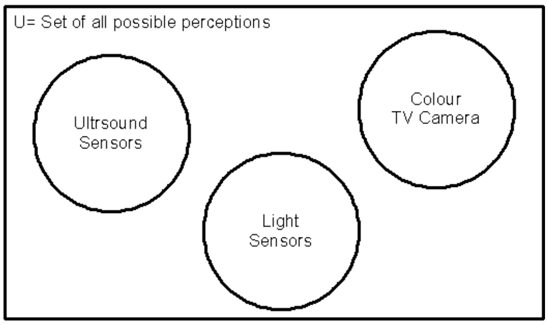


Fig. 2 *Each sensors set of perceptions*

The sensors space of perceptions is further constrained by the type of environment the sensor is situated in, forming an "environmental subset". This environmental subset of perceptions is constrained further, forming another subset, which depends on how much of the environment the sensor gets to see. It is this subset which forms the "Perception Space". Within this space, perceptions are categorised for their similarity relating to similar "Perception Areas" in the environment. For example, if the robot finds itself in a farm environment equipped with a camera then its environmental subset of perceptions are all things perceivable with the camera on the farm. However the robot spends its days trudging around the fields and its perception space only consists of things like fences, hedges, wooden poles, bales of hay etc. Therefore, as the robot explores the environment perceptions are categorised and perception spaces formed for each type of sensor it has. The perception space starts as an empty set, growing as more of the environment is seen and should stabilise once the entire set of perceptions in environment have been seen. However, if new parts of the environment are discovered then the perception space should accommodate the potentially new set of perceptions.

The "Geometric Space" is a geometric framework and its purpose is to simply relate geometric areas to perception areas in the environment where they occur. This is needed since it is unlikely that a perception area will be unique to one area of the environment i.e. "Perceptual Aliasing". The geometric space addresses the perception space to relate geometric areas to perceptual areas. A perception area may be referenced more than once by the geometric space. In our farm environment for example, there may be more than one bale of hay lying around in the field. As explained later in this article inexpensive path planning algorithms can be implemented with careful consideration to the representation of the geometric space. In addition, the robot should expect to see a certain sequence of perceptions along any planned path. This allows the robot to check its progress along the path and not be entirely dependent on its kinematics.

While the perception space should stabilise once the entire set of perceptions in the environment have been seen the geometric space may continue to expand as the robot explores more of the world. For example in our farm environment after exploring an entire field, the perception space will be stable. Now there may be a number of similar fields requiring the robots attentions. Therefore, the geometric space expands to accommodate the new fields as the robot explores them, but the perception space remains unchanged since all the fields contain similar objects and appear similar. However, should the robot then go to explore the barn where the hay is stored the perception space should accommodate the potentially new set of perceptions. The combination of the perception space and the geometric space is illustrated in Figure 3.

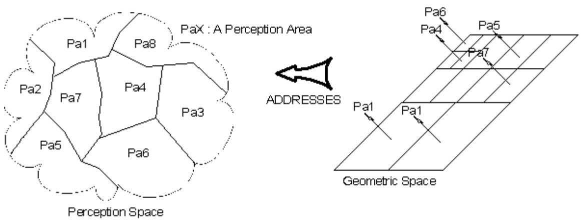


Fig. 3 *The Geometric Space referencing the Perception Space. This combination provides navigation information and a context for the robots perceptions forming the overall mapping model. The Perception Space has been partitioned into Perception Areas.*

The key to this model is the partitioning of the perception space into perception areas. It is not important what the perception areas relate to in the physical world, all that matters is that there are a set of areas in the environment which are distinguishable by the robots sensors. Since it is the ability to distinguish different perception areas that allow the geometric space to be constructed and allow path planning and localisation tasks to be performed. Using our farm environment for example, Pa1 could relate to open field, Pa4 could relate to bales of hay and Pa3 could relate to a fenced area, etc. On the other hand, they could relate to something far more abstract. Again, the importance lies with the robot being able to distinguish various perception areas in the environment. Whether or not the perception areas relate to objects "humans" can identify with does not matter, although of course this would be convenient. Perception areas are simply labelled by number, anything more meaningful requires the robot to have an "understanding" of what it perceives. Alternatively a human operator could observe the robot and try to match perception areas with some appropriate label.

If the robot becomes lost, for whatever reason, the robot can derive its location using the map it has built. Moreover, it can do this without referencing any positional information by making use of the perceptual space. When the robot is lost, it may be in any one of a set of possible locations. In this situation, the robot should wander around gathering evidence to find out where it is. The localisation procedure is formalised by the algorithm below. It

relies on neighbourhood information in the geometric space to reduce the robots set of possible locations.

Location Algorithm:

1. Note the current perception area.
2. Create a set of locations from the geometric space that share the above perception area.
3. Initialise the localisation hypothesis set with the set produced in step 2.
4. Repeat
5. Wander around until the perception area changes.
6. Create a set of locations from the geometric space that share the above perception area and neighbour a location in the current location hypothesis set.
7. Set the location hypothesis set with the locations created in step 6.
8. Until location hypothesis set contains only one element.

Here the robot will wander around the environment until it finds a particular sequence of perceptions that can be identified uniquely in the map. For example, in our farm environment if there is only once place where the robot would pass a gate followed by a hedge then by a fence, the robot can locate itself on the map after this sequence of perceptions. Successful localisation depends on the environment being varied enough to allow the robot to reduce the set of possible locations to one location. Figure 4 gives a simple example to illustrate the localisation process with a sequence of abstract perceptions.

It should be noted the location algorithm does not account for all eventualities. For example, if the robot encounters a new perception that does not have a neighbour in the current hypothesis set? This may be the result of three events.

1. Firstly and the most critical, the map was incorrectly built. This should not be allowed to happen.

2. The robot has moved out of the mapped area. In this case, the robot really is lost.

3. The environment has changed. In this case, either one or both of the above facts could be true as well.

We are aware of these problems and do not have any solutions to them now. Currently with the model, the only solution if this situation occurs is to restart the location process. However, are these location problems any different to those "humans" would have in similar situations? Would solving these problems result in a system out performing human capabilities?

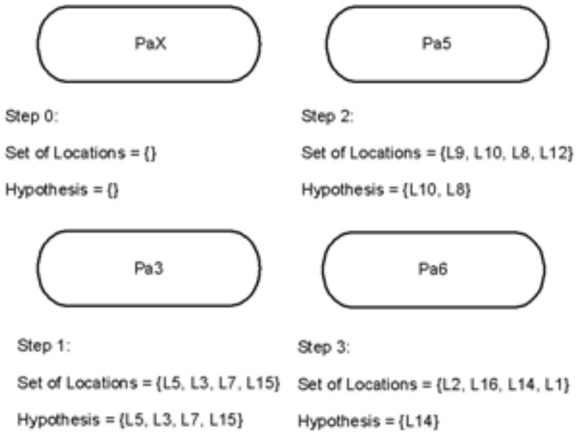


Fig. 4 *Illustrating the self-location abilities of the model. Each time a new perception area is encountered the hypothesis set is updated based on which locations of the new perception neighbour those of the previous hypothesis set. Note that no positional information is used in the process.*

5. IMPLEMENTATION

The function of the perception space module is to partition a perception space into suitable perception areas. This partitioning function is a data classification problem. A "Growing Cell Structure" neural network (Fritzke, 1993) is used for this classification process. The growing cell network is a self-organising neural network and works on the same principles as the well-known Kohonen neural network (Kohonen, 1988). The structure of the Kohonen network is fixed. The structure of the Growing Cell network is not fixed and is able to evolve with the data, growing and shrinking to best categorise the data. These are desirable features since the robot will be exploring an environment that is of unknown size, shape and complexity. The other desirable feature is the statistical element to these types of network, this will allow for some inconsistency in the robots sensors. Figure 5 gives the general idea how the growing cell structures will model perception spaces. The cells of the network represent the perception areas and the connections between them express their topological similarity.

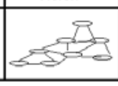
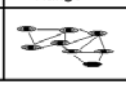
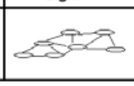
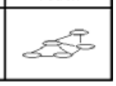
U : Set Of All Possible Perceptions				
Sensors	Vision	Range	Light	Touch
Perception Spaces (GCS)				

Fig. 5 *Each type of sensor has its own perception space and is modelled by a growing cell structure.*

The geometric space module relates perception areas to geometric areas in the environment where they occur. An "Area Quadtree" (Samet, 1984) is used to implement the geometric space. The quadtree is based around the principle of recursive decomposition. Areas are viewed as quadrants, and quadrants are recursively decomposed until quadrants are either homogeneous or the minimum quadrant

size has been reached. In our case, homogeneous areas represent areas with the same perception area. Hence uniform areas are mapped with the minimum of quadrants and the resolution of the represented area is defined by the minimum quadrant size.

Quadtrees offer a dynamic and efficient method for representing areas, the resolution to which an area is represented can vary as well. In addition, the tree structure of the quadtree allows the represented area to be efficiently searched. This property has been exploited to produce efficient path planning algorithms for the structure (Kambhampati and Davis, 1986; Zelinsky, 1992).

6. EXPERIMENTS

The experiments proposed are designed to evaluate the robustness of the world modelling method. The first set of experiments involves using place markers, in particular a “home” marker, to measure the performance of the model in general. The robot will be instructed to explore the environment and given enough time to build a reasonable map. Then the robot will be instructed to go “home”. The accuracy and the types of paths chosen will be measured. The second set of experiments will measure the effectiveness of the localisation algorithm under varying conditions. Again the robot will be allowed to explore the environment long enough for it to build a reasonable map. The robot will then be picked up, placed in a random location within the mapped environment, and with its positional sensors switched off, instructed to “go home”. This will be an essential test for the performance of the Perception Space and Geometric Space for localisation and navigation.

7. CONCLUSION

This paper has presented preliminary work on a multi-representational approach to the modelling of the real world. The approach is designed for a “really useful” robot that is autonomous and able to adapt to the surrounding environment. It is assumed the robots environment is unknown, unstructured and unmodified. The robot explores its new environment gathering perception information to construct the Perception Space and the Geometric Space. The Geometric Space will continue expanding as more of the environment is explored, while the Perception Space will converge to a stable stage when all the perceptions in the environment become identifiable. The Perception Space and the Geometric Space together can be used for self-localisation and path planning tasks. The presented localisation algorithm does not rely on the robots positional information. The model is currently being experimented with on an indoor mobile robot. Conclusive results are expected soon and will be presented at the conference and in future publications. In the longer term, experiments will include a mobile outdoor farm robot.

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