

From Mammals to Machines: Towards A Biologically Inspired Mapping Model For Autonomous Mobile Robots

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Abstract: In this paper we introduce a mapping approach that allows an autonomous mobile robot to model its environment. It is designed to do this autonomously in unknown, unstructured and unmodified environments without any a priori knowledge. Its modular multi-representational approach allows flexibility in sensor integration and is readily used for self-localisation and navigation tasks. Experiments have been conducted with indoor and outdoor robots, some results from the outdoor experiments are given.

Keywords: Robots, Mammals, Spatial Integration

1.0 Introduction

The goal of Artificial Intelligence is to understand the nature of intelligence and produce a complete computational model of intelligence through such an understanding. The magnum opus of this experimental science is the embodiment of this complete computational model of intelligence into a robot of humanoid form. We are of course a long way from achieving this goal.

To model intelligence we must make observations of intelligence and primarily this is achieved through observing behaviours, generally in animals, including humans. These behaviours are a result of a complex set of processes that map sensory perceptions to actions; it is these computational processes which are of interest and we are interested in the processes that deal with spatial representation and spatial reasoning. These processes deal with environment modelling and environmental tasks such as exploration, localisation, navigation and pilotage [3]. The term navigation has a broad meaning and we define it as the task of “navigating” to a goal where the route to the goal is unknown. Exploration can usefully be combined with navigation tasks. The term pilotage is defined as the task of finding ones way to the goal though a familiar environment by using familiar landmarks. These notions will seem familiar since we are used to the notion of maps and their use. For example, when using a street map, we will first perform a localisation process to locate ourselves within the map; we may then plan a route and then navigate our way to the destination. If we became lost we initiate the localisation process again and once we are familiar with the area we then pilot our way to the destinations. If we did not have the street map then we would explore the area and after some time be able to perform the other tasks.

A great deal of effort has been devoted into realising the above notions in autonomous mobile robots, since these notions are recognised as being very desirable and useful behaviours. In this paper we propose a generalised spatial model that has the potential of achieving the above notions, using a mobile robot as a test-bed for these proposals. We have chosen to look towards the biological literature for our inspiration, which lead to the spatial model we propose in this paper, which is a practical interpretation of a biological theory. We take the view that nature has a habit of solving problems in the most elegant of

ways. Moreover, since biological computational resources are very costly to produce and maintain we also assume such solutions are the most simple and efficient.

In the remaining of this paper we introduce our proposed model, show some experimental results and discuss further research ideas.

2.0 Environment Models

We believe that the environment has a key role in the development of any spatial model. Indeed animals have evolved both physically [20] and mentally according to their environmental niches. So we will also define the class of environment the proposed model and the robot are expected to deal with. We are interested in environments that are unknown, unstructured and unmodified. These three environmental ‘*U*’ factors present interesting and challenging environments for the model and the robot to deal with. For added flexibility we also specify that the environment modelling process should construct the representation from scratch, with no a priori knowledge of the target environment. The modelling process should only use sensory perceptions of, in our case, the exploring robot.

Many environment modelling strategies, or mapping strategies, have been suggested. These mapping methods can be broadly categorised. The first, are those methods which are the “traditional” geometric or qualitative methods, such as [6, 4, 14]. These methods are based on the accumulation of accurate geometric information about the world. This dependency on accurate sensor information makes these methods impractical for robots situated in the above types of target environments. The second category of methods is the topological, or qualitative, methods, such as [22, 23]. Rather than using rigid geometric information these types of methods use the robots sensory impressions more directly to construct an environment map. The third category of methods is formed from using both geometric and topological methods. In these methods the quantitative and qualitative information is clearly separated. Good examples of this hybrid approach are [11, 18]. Each of these three categories may be divided into a further two categories [21]. The first subcategory contains those methods that are object-based methods. With these methods the environment model is a description of the relationships between its objects. The second subcategory contains those methods in which the environment model is a description of the environment space. The description of the space is used to hold or place the object within the environment. The model we introduce in this paper is classed as a hybrid that models a description of the environment space.

2.1 Biological Models

Animals are said to have a “cognitive map” a term first loosely defined by Tolman [19] and in general refers to the spatial representation an animal has of the environment. However, the use of this term has become confused [4] probably because the term has not been precisely defined, Thinus [17] suggests an alternative term “Spatial Integrating System”. This definition is more encompassing since it stresses the spatial representation process as a dynamic structure, which the “cognitive map” term does not capture [17].

The inspiration for the model we present below is derived from an interpretation of the biological literature [1, 2, 4, 9]. Presented in this literature is experimental evidence that mammals compute and make use of geometric information in their spatial integrating system [2]. Experimental evidence is presented showing that topological information is also computed. These two types of information are brought together by a “Geometric Frame Module” and a set of “Feature Modules” [1]. The Geometric Frame module models the shape of the environment. The geometrical information to do this is derived from the senses, for example, optic flow calculations [4]. The non-geometric information is located

on the Geometric Frame by addressing the appropriate Feature Module. For simplicity a Feature Module can be seen as detecting a specific non-geometric feature. These notions are illustrated in figure 1. Also, it suggested that the complexity of the Feature Modules increase with the complexity of the animal, however the Geometric Frame Module remains the same. The hippocampus is known to play a role in the animal's spatial integration system [10, 17, 19], although it is not clear exactly how. It is suggested the hippocampus "recognises" places through sensory features presented to it. There is evidence, which shows that the hippocampus is larger in those animals that put a greater demand on spatial knowledge [10]. However, it is not clear if the hippocampus could be related to the role of Feature Modules in such a direct way.

The model we now present is an interpretation of this biological model. To explain the model we introduce two concepts. Firstly the notion of a "Perception Space", this is analogous to the "Feature Modules". Secondly the notion of a "Geometric Space", this is analogous to the "Geometric Frame Module".

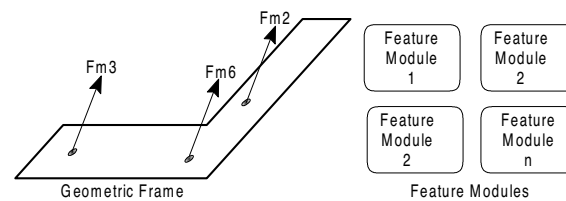


Figure 1 Illustrating the Geometric Frame Module and the Feature Modules. The geometric frame is featureless, and addresses the feature modules. For example, feature module one may equate to food, feature module two may equate to a burrow.

3.0 Towards A Biologically Inspired Model

A robot can be equipped with a range of sensors through which to sense the world that surrounds it. This is analogous to the mammal, which is equipped with its senses, although perhaps more sophisticated. Exploring the world the robot should build its map from scratch using only its sensory impressions, much like a mammal would in an unfamiliar environment. These sensory impressions are sensor element activation's relating to some fixed physical location in the environment (generally not directly equatable to objects in the "human" perception domain) and we term these "Perception-Signatures". To illustrate this notion, let 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 [20]. By this, each sensor has its own associated set of perceptions. These perception-signatures are categorised for their similarity relating to similar "Perception Areas" in the environment. The "Perception Space" is the collection of these perception areas.

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". Indeed, if every place in the world visited by the robot appears unique to its sensors, then the robot can use this information alone to build a navigable map.

The notions of the "Perception Space" and the "Geometric Space" are illustrated by figure 2, which gives a complete description of the model's architecture. Also illustrated is the notion of sensor fusion within the model. Sensor information is combined through adding the geometric spaces together. This process can be selective of the sensors used based on some performance measure or other criteria. The model is readily used for path planning. Paths are generated in the combined geometric space, which is the navigable map. The robot can then navigate along the planned path with a set of expectations. These

expectation are what it should expect to “see along the way” in terms of perception areas. This feedback from the perception space can be used to check if the planned path is being followed.

The perception space module is implemented as a classification algorithm, which algorithm depends on the type of input perception signatures. The geometric space is implemented as a quadtree structure [16]; [7] has a fuller description of the model.

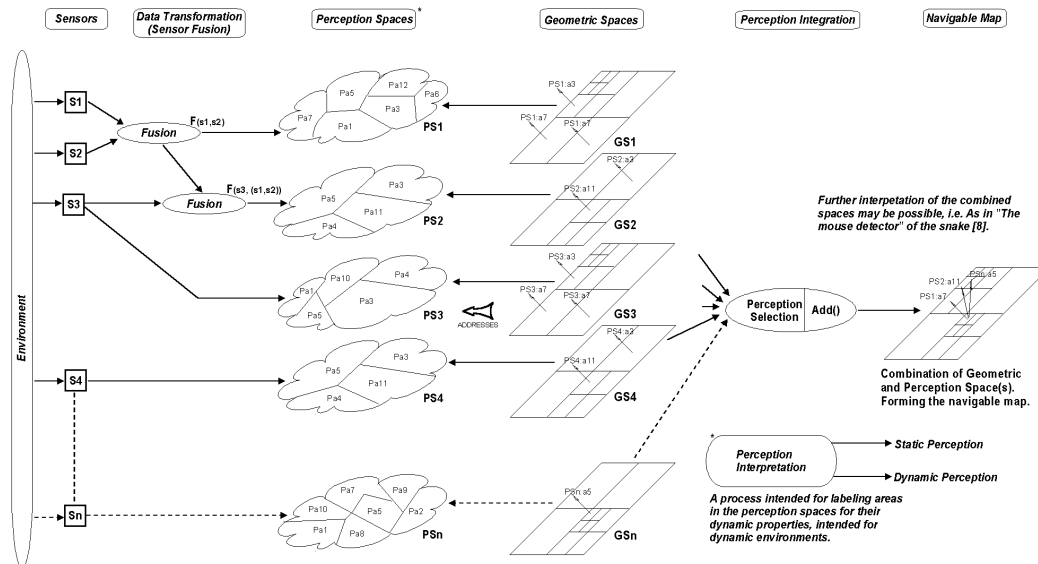


Figure 2 Illustrating the architecture of the mapping model we have proposed. The environment is sensed and the information may then be pre-processed and fused to form the Perception Signatures. The Perception Spaces are based around a set of classification methods, each classification method being suited to its corresponding Perception Signature input. The Geometric Spaces may be derived from geometric data directly or from other sources. For example we may use vision processing to derive an Absolute Space Representation [21] of the local environment which may then be converted to the Geometric Space representation.

3.0 Perception Space Results

The outdoor robot used to conduct some of the experimentation is shown in figure 3a. It is equipped with a panoramic vision sensor and the configuration is shown in figure 3b. A typical view from the arrangement is shown in figure 3c.

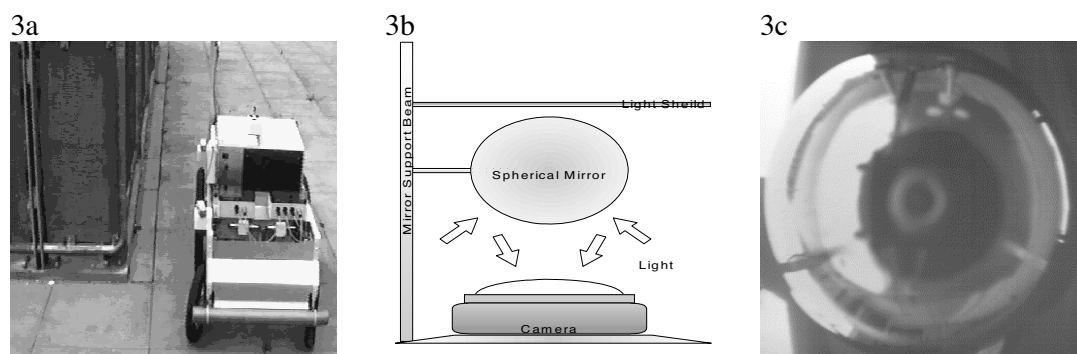


Figure 3a Illustrating the outdoor robot in an outdoor test environment which is unknown, unstructured and unmodified. 3b Illustrating the panoramic camera configuration, which consists of a grey-scale CCD camera focusing on a spherical mirror, ideally the mirror should be hyperbolic [15]. 3c A typical view from the camera with the robot situated in a typical environment, these views form a raw perception signature.

We now describe some results obtained with the outdoor robot, the vision sensor and the perception space. For these experiments the robot was situated in an unknown, unstructured and unmodified outdoor environment and was let to wander along a straight-line path of 80 meters. The raw perception signatures were segmented concentrically into 360 segments. The light intensities in each segment were averaged to produce a perception signature with 360 elements. These perception signatures were used as input vectors to the perception space module, in this experiment the module was instantiated with a growing cell structure neural network [8]. The neural network trains on and categorises the perception signatures, each category relating to a perception area. This process operates in real-time at a rate of 4 frames per second; A set of perception signatures is illustrated in figure 4. After training, the robot was let to wander through the environment again and the recognised Perception Areas recorded. Figure 5 shows the results of a test run. It is clearly seen that locations in the environment have successfully been classified and then later recognised. These results are very encouraging and show that the perception space and vision sensor are working as expected.

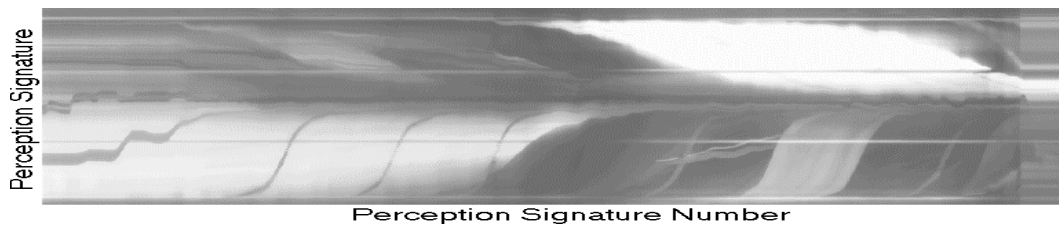


Figure 4 Illustrating the processed Perception Signatures from a test run with the outdoor robot in an outdoor environment along a straight-line path of 80 meters. For display purposes the signature elements are displayed in sequence forming a continuous grey level image. The solid strips seen across the signatures represents the fixings on the robot. Vision sensor parameters $P_e = 360$, $P_{rr} = [73..140]$.

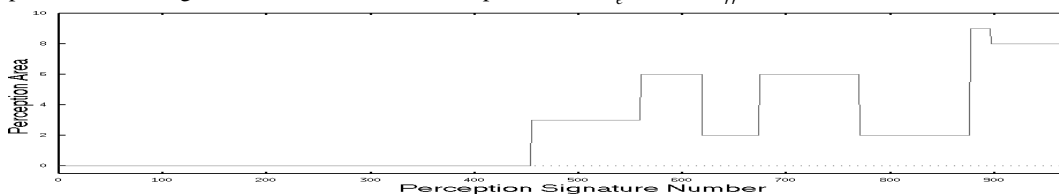


Figure 5 Perception Areas created from the above experimental; The areas just show difference and have not been labelled for environmental meaning; Cell structure parameters $\epsilon_{init} = 0.15$, $\epsilon_{nei} = 0.035$, $\Delta\epsilon_{bmu} = 0.01$, $d_{accuracy} = 0.10$, $B_{size} = 500$, $B_l = 5$, $N = 1$; Vision sensor parameters $P_e = 360$, $P_{rr} = [73..140]$;

4.0 Further

We have made several compromises in the construction of our spatial model above. These compromises are points for further research with the aim of expanding the generality of the model. Firstly we would like to derive the geometric data for the geometric space from the external sensors, perhaps from optic flow [15] as mammals may do [4].

Secondly, by using panoramic sensors we have simplified location recognition. Generally in mammals the senses they use to perceive their environment are directed. It maybe the case that the Head Direction cells [17] of mammals are used to integrate the directed perceptions from the same physical location of the environment, so forming a view similar to a panoramic view from that location. However, recognising a previously visited location without any geometric information does become more complex, which is of special concern when exploring a new environment.

Thirdly we have not addressed the issues involved when dealing with dynamic environments. We believe that a successful Spatial Integration System must somehow give

meaning to the sensory perceptions, perhaps by using some “higher” body of knowledge. This knowledge can then be used by the system to “decide” how best to use new sensory perceptions, if at all. This will be subject of much more research.

5.0 Conclusion

The model we have introduced in this paper forms the basis of a Spatial Integration System for an autonomous mobile robot. The notions of the robot being an ideal test-bed for biological spatial theories, from which our model is derived, is aimed at moving towards a complete theory and understanding of how the spatial integration system of mammals works. The grand goal of this work is to produce a spatial integration system that would endow a robot with the same spatial skills of any mammal.

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6.0 References

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