Applied Soft Computing 38 (2016) 269–280

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

Multi-channel Bayesian Adaptive Resonance Associate Memory for on-line topological map building

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ARTICLE INFO

Article history:
Received 6 June 2015
Received in revised form
25 September 2015
Accepted 25 September 2015
Available online 22 October 2015

Keywords:
Adaptive resonance theory
Bayesian
Robot navigation
Simultaneous localization and mapping
Topological map

ABSTRACT

In this paper, a new network is proposed for automated recognition and classification of the environment information into regions, or nodes. Information is utilized in learning the topological map of an environment. The architecture is based upon a multi-channel Adaptive Resonance Associative Memory (ARAM) that comprises of two layers, input and memory. The input layer is formed using the Multiple Bayesian Adaptive Resonance Theory, which collects sensory data and incrementally clusters the obtained information into a set of nodes. In the memory layer, the clustered information is used as a topological map, where nodes are connected with edges. Nodes in the topological map represent regions of the environment and stores the robot location, while edges connect nodes and stores the robot orientation or direction. The proposed method, a Multi-channel Bayesian Adaptive Resonance Associative Memory (MBARAM) is validated using a number of benchmark datasets. Experimental results indicate that MBARAM is capable of generating topological map online and the map can be used for localization.

1. Introduction

With growth in robotics research, it is possible for autonomous robots to move in complex, unknown environments and execute assigned tasks with little or no human intervention. A human-friendly autonomous guided robot with little knowledge about its whereabouts can navigate safely within its environment in order to achieve certain goals [1]. It can construct a map of the environment based on its position and posture (mapping), and estimating its position and posture using a built environment map (localization). Building the representation of the map is crucial to autonomous navigation for improving map maintenance, map-based localization, and path planning in any given environment.

In mobile robotics, representations of the world fall into three broad groups, i.e. metric maps [2], topological maps [3], and hybrid models [4,5] that combine both metric and topological information. In the metric mapping framework, the environment is represented as a set of objects with coordinates in a 2D space. The construction of the map is based on a grid occupancy or feature map approach [6]. In the grid occupancy approach, the environment is mapped as an array of cells. This approach however requires complex computation for feature matching which is not reliable for large environments. Pure metric map methods are vulnerable to inaccuracies in both map building and robot position estimation [7].

In the topological framework, the environment is described by a collection of places linked by path [8]. Places are defined by information gathered from sensors placed in the environment, which is then stored in nodes. Some of the robot's odometry information, which is gathered while it travels from one place to another is stored in the links of the map. Therefore, a topological map is a sparse representation of the environment that only includes important places used for navigation gathered from sensor information, and connections between these places gathered from the robot's odometry information.

One of the advantages of topological maps is they do not require a metric sensor model to convert sensor data into a 2D frame of reference [9]. However, topological maps lack the details found in an environment. To overcome these problems, hybrid approaches [10,11] that combine the topological and metric paradigms have been proposed to compensate for the weakness of each approach. A crucial aspect that restricts the practice of topological maps is the absence of consistence semantics associated with them. For example in [8], nodes are represented as places distinguished by sensor

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http://dx.doi.org/10.1016/j.asoc.2015.09.031
1568-4946/

data, and edges as paths between places distinguished by control strategies. On the other hand, maps are constructed by partitioning a probabilistic occupancy grid into regions isolated by narrow paths based on a measure of local clearance [12]. In [13], grid map is transformed into a greyscale image and analyzed for retrieving the topological information. This method however requires massive memory allocation for the grid map storing. As an alternative, the generation of a straightforward topological map using the generalized Voronoi graph (GVG) is presented in [13,14].

GVG is however susceptible in dynamic, large-scale environments with sharp-edged obstacles and it requires high computational resources for node extraction and matching. A thinning approach to construct a topological map from a binary grid map is proposed in [15]. Although this method requires less computational resources than the GVG method, the method is based on an existing grid map that limits its application in online map building [16]. Another important factor that impedes the application of the topological map is the online detection and recognition of topological nodes. While artificial landmarks such as wireless beacons, visual patterns, or reflective tape provide reliable recognition of a specific location, we have to consider the possibility of the artificial landmarks not available in unknown environments.

Another area of research focused on emulating the biological systems thought to be the basis for mapping and navigation in animals. The hippocampus of rodents is one of the most studied brain regions of any mammal. Early work with rats identified place cells in their hippocampus that appears to respond to the animal's spatial location [17]. Some researchers have uncovered that beta oscillations occur during the learning of hippocampal place cell receptive fields in novel environments [18]. The aim of the Psikharpax project is to create an artificial robotic rat, driven by mapping and navigation algorithms that mimic place cells [19]. Other methods for biologically inspired navigation include RatSLAM [20,21], which builds a topological map with metric information by separating the topological and metric layer. This approach requires proper scaling of the map in advance and is unable to update efficiently during operation.

In this paper, we present the Multi-channel Bayesian Adaptive Resonance Associative Memory (MBARAM) for online topological map learning and generation. Each topological node represents a particular region of the environment with location of the robot, while edges connect nodes and stores the robot actions and relative positions of connecting nodes. MBARAM is developed from the Bayesian Adaptive Resonance Theory (Bayesian ART) framework [22]. Despite several optimization algorithms [23–26] being used to solve the SLAM problem, we chose the ART framework for its fast, online, unsupervised learning abilities, and it has been used in explaining place cell learning [27]. In addition, ART addresses the *stability-plasticity* dilemma [28], which explains how the brain can both quickly learn to categorize information in the real-world and remember it, without forgetting previously-learned knowledge. With these advantages, the proposed method overcomes the problem of online detection and recognition of topological nodes. In addition, MBARAM handles and learn multiple sensory information simultaneously during the mapping process. MBARAM does not require a metric map, it performs self-learning, and maintains the topological map that makes it suitable for work in natural environments.

The proposed method has a number of contributions. The first is an incremental and unsupervised learning method that enables map building with little to no human intervention. Next, it does not require high-level cognitive and prior knowledge to make it work in a natural environment. Third, it can process multiple sensory sources simultaneously in continuous space, which is crucial for real-world robot navigation. Finally, the ART architecture overcomes the *stability-plasticity* dilemma without forgetting previously-learned knowledge. This paper is organized as follows. Section 2 introduces the theoretical framework of the proposed online topological map building approach. The experimental setup and results are detailed in Section 3 with discussions in Section 4. Concluding remarks are finally presented in Section 5.

2. Multi-channel Bayesian Adaptive Resonance Associative Memory (MBARAM)

MBARAM integrates the Bayesian ART [22] and an incremental topology-preserving mechanism. Bayesian ART is used as a learning framework for its ability to reduce category proliferation with better classification accuracy. The topology-preserving mechanism was used to construct a topological mapping, in which nodes are connected by edges. In addition, we modified the ARAM network [29] in becoming a multi-channel architecture. This enable it to learn multiple mappings simultaneously across multi-modal feature patterns from multiple sensors.

The architecture of MBARAM consists of two layers, as shown in Fig. 1. The input layer is formed by multiple Bayesian ARTs to categorize multiple sensory sources as place regions (nodes) and transmit to the memory layer. In the memory layer, place regions (node) connects to one another by edge when transitions between regions are experienced. Each particular connection contains robot's orientation and bearing when the transition is happened whereas nodes represent distinct places of the environment.

As mentioned in Section 1, the nature of MBARAM learning process is biologically inspired, but different from other biologically inspired method, such as RatSLAM [20]. The work in [30] used different techniques for online topological map building. Table 1 shows the difference between MBARAM, RatSLAM and work in [30].

2.1. Building a topological map online with MBARAM

MBARAM learns in an environment that is perceived from continuous sensory information provided by multiple sensors. The *M*-dimensional sensory information is transmitted to the Bayesian ART and the map learning undergo three main processes, i.e. node competition, node matching, and node learning. Details of the learning process is detailed in Section 2.1.2.

In order to generate a topological map, a number of nodes are created that corresponds to the number of distinct regions determined by the robot, i.e. one node for each region. MBARAM incrementally produces nodes to represent the environment as multiple regions throughout the navigation. It is therefore possible to identify where the robot has already been through a simple comparison of the current sensory information with the nodes already in the topological map (online detection and recognition).

2.1.1. Node definition

In our topological map, nodes are defined as regions, in which perceptions are similar given the robot's position in the area. This method solves the point-of-view problem. The definition is obtained directly through Bayesian ART categorization of sensory information, the category of a perception corresponding to the place where the robot is positioned. Each node contains a multidimensional Gaussian distribution, with mean vector $\hat{\mu}_j$, covariance matrix $\hat{\Sigma}_j$, and a prior probability $\hat{P}(w_j)$. Table 2 summarizes the content of the node in topological map.

The network is initialized with three parameters: the maximal hypervolume S_{MAX}, the initial covariance matrix $\hat{\Sigma}_{\text{init}}$, and initial prior probability $\hat{P}(w_j)_{init}$. Such node definitions are based solely on the robot's perceptual capacities and does not rely on a human definition of the place it is supposed to be. This makes places easier to recognize from sensory information.