Neural Networks for Mobile Robot Navigation: A Survey

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Abstract. Nowadays, mobile robots have attracted more and more attention from researchers due to their extensive applications. Mobile robots need to have the capabilities of autonomy and intelligence, and they pose a challenge to researchers, which is to design algorithms that allow the robots to function autonomously in unstructured, dynamic, partially observable, and uncertain environments [1]. Navigation is the key to the relative technologies of mobile robots and neural networks are widely used in the field of mobile robot navigation due to their properties such as nonlinear mapping, ability to learn from examples, good generalization performance, massively parallel processing, and capability to approximate an arbitrary function given sufficient number of neurons. This paper surveys the developments in the last few years of the neural networks with applications to mobile robot navigation.

1 Introduction

In recent years, mobile robots have attracted more and more attention from researchers since they have been widely used in various fields, such as space exploration, under water survey, industrial and military industries, and service and medical applications, and so on. The robots need to have the capabilities of autonomy and intelligence, and they force the researches to deal with key issues such as uncertainty (in both sensing and action), reliability, and real-time response [2]. Therefore, a key challenge in robotics is to design algorithms that allow the robots to function autonomously in unstructured, dynamic, partially observable, and uncertain environments [1].

The problem of mobile robot navigation, which includes four fundamental matters of mobile robots: map building, localization, path planning, and obstacle avoidance, refers to plan a path with obstacle avoidance to a specified goal and to execute this plan based on sensor readings, and is the key to the robot to perform some designated tasks. Neural networks, motivated by how the human brain works, are increasingly being employed in various fields, including signal processing, pattern recognition, medicine, speech production and recognition, and business. In the last few years, neural networks including feedforward neural network, self-organizing neural network, principal component analysis

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(PCA), dynamic neural network, support vector machines (SVM), neuro-fuzzy approach, etc., have been widely used in the field of mobile robot navigation due to their properties such as nonlinear mapping, ability to learn from examples, good generalization performance, massively parallel processing, and capability to approximate an arbitrary function given sufficient number of neurons. The objective of this paper is to present the status of the applications of neural networks to mobile robot navigation. The rest of this paper is organized as follows: The methods of neural networks and hybrid approaches for mobile robot navigation are described in Sections 2 and 3, respectively, and conclusions are given in Section 4.

2 Neural Networks for Mobile Robot Navigation

2.1 Neural Networks for Interpretation of the Sensor Data

Sensors are necessary for a robot to know where it is or how it got there, or to be able to reason about where it has gone. The sensors can be flexible and mobile to measure the distance that wheels have traveled along the ground, to measure inertial changes and external structure in the environment. The sensors may be roughly divided into two classes: internal state sensors, such as accelerometers, gyroscope, which provide the internal information about the robot's movements, and external state sensors, such as laser, infrared sensors, sonar, and visual sensors, which provide the external information about the environment. The data from internal state sensors may provide position estimates of the robot in a 2D space; however, cumulative error is inevitable.The data from external state sensors may be used to directly recognize a place or a situation, or be converted to information in a map of the environment. The laser, infrared, and sonar sensors can provide distant and directional information about an object. Visual sensors can obtain rich-information of the environment that can be very expensive to process. In most cases, the sensor readings are imprecise and unreliable due to the noises. Therefore, it is important for the mobile robot navigation to process the sensor data with noises. Since neural networks have many processing nodes, each with primarily local connections, they may provide some degree of robustness or fault tolerance for interpretation of the sensor data.

Feedforward multi-layer perception neural network, which is trained by the back-propagation algorithm, has been used for classification, recognition and function approximation. Kim *et al.* proposed an approach to build environmental map where the nonlinearity error of range data from infrared sensors was corrected by using a feedforward neural network [3]. Thrun has used a feedforward neural network to "translate" the sonar readings of sonar sensors into occupancy values of each grid cell for building metric maps [4]. Meng and Kak presented a NEURO-NAV system for mobile robot navigation [5]. In the NEURO-NAV, a feedforward neural network, which is driven by the cells of the Hough transformation of the corridor guidelines in the camera image, is employed to obtain the approximate relative angles between the heading direction of the robot and the orientation of the hallway in order to drive the robot to move in the middle of the hallway [5]. In [6], a neural network based camera calibration method was presented for the global localization of mobile robots using monocular vision. Since every type of sensors have their own limitations for collecting the environmental information of a robot, sensor fusion is necessary for the mobile robot navigation. A sonar and infrared sensors fusion algorithm based on a feedforward neural network to obtain reliable data is studied in [7].

The self-organizing Kohonen neural network is known for its ability to perform classification, recognition, data compression and association in an unsupervised manner [8]. The self-organizing Kohonen neural networks are employed to recognition the landmarks using the measurements from laser sensors in order to provide coordinates of the landmarks for triangulation in [9]. Janet *et al.* proposed a global localization algorithm using self-organizing Kohonen neural networks [10]. By using the self-organizing Kohonen neural networks, the robot can determine the room where it is according to the sonar sensor data.

PCA, which has been applied to data compression, pattern recognition, and so on, is a statistical technique and is well known as one of the effective methods to extract the principal features from high-dimension data and decrease the dimension of the data. Crowley *et al.* presented an approach to estimate position of a mobile robot based on PCA of laser ranger sensor data [11]. Vlassis *et al.* proposed an approach for mobile robot localization where PCA was employed to decrease the dimensions of sonar sensor data [12]. PCA has been used to extract features of images for mobile robot localization in [13], [14]. Though PCA is an appropriate model for data generated by a Gaussian distribution, or data best described by a second order correlation; however, the distribution of natural images is highly non-Gaussian. Therefore, kernel PCA is used to extract features from image for mobile robot localization [15]. In the work reported in [15], kernel PCA has a higher localization rate than that of conventional PCA, whereas, the conventional PCA is faster than the kernel PCA.

SVM, which was proposed by Vapnik, is based on the statistical learning theory [16]. In [17], seat numbers were used as landmarks for mobile robot localization because the seat number could be employed to distinguish the landmarks, and SVM was adopted to segment number regions from images.

Hopfield neural network can be used as associative memory or to solve optimization problems [8]. In [18], [19], an improved neural network based on Lagrange programming method was presented for hierarchical optimization of nonlinear large-scale systems. Djekoune and Achour proposed a localization algorithm using stereo vision where the correspondence problem for a set of segments extracted from a pair of stereo images is formulated as minimization of a cost function that is performed by means of a two-dimensional Hopfield neural network [20].

2.2 Neural Networks for Obstacle Avoidance

In the environment, there are always static and non-static obstacles. Therefore, the robots need to autonomously navigate themselves in the environment with obstacle avoidance. The neural networks for obstacle avoidance of mobile robots should take the sensor data from the environment as the inputs, and output the direction for the robot to proceed. Fujii *et al.* proposed a multilayered model for collision avoidance of a mobile robot through reinforcement learning [21]. Silva *et al.* presented the MONODA (modular network for obstacle detection and avoidance) architecture for obstacle detection and avoidance of a mobile robot in an unknown environment [22]. This model consists of four modules that are three-layered feedforward neural networks (each detects the probability of obstacle in one direction of the robot). Ishii *et al.* developed an obstacle avoidance method for underwater vehicle based on self-organizing Kohonen neural networks [23]. Gaudiano and Chang studied an approach to avoid obstacle using a neural network model of classical and operant conditioning based on Grossberg's conditioning circuit [24] [25].

2.3 Neural Networks for Path Planning

The path planning problem, which may consist of two subproblems, path generation and path tracking, refers to determining a path between an initial pose of the robot and a final pose such that the robot does not collide with any obstacles in the environments and that the planned motion is consistent with the kinematic constraints of the vehicle. The existing path planning methods include A* algorithm [26], potential fields [27], BUG2 algorithm [28], and methods using intelligent control technique. The A* algorithm assumes that paths are made of a series of points in the free space. Each segments given a value that is the cost of that particular portion of the path. The drawback of the A* algorithm is that the generated path is made of a series of connected straight lines, which makes its curvature radius discontinuous, resulting in wheel slippage. Potential field methods were first introduced by Khatib [27]. The drawbacks of this approach are that convergence is not guaranteed and it requires very heavy calculation power. The A* algorithm and potential fields are employed in the static environment and assume that the map of the environment is known *a prior*. BUG2 algorithm is one of behavior based techniques, which divides the goal-seeking task into several dependent subtasks. Though it is simple and efficient, it does not always generate the optimal path. The methods using intelligent control such as neural networks, neuro-fuzzy, do not plan a global path for mobile robots and can be employed in an unknown environment. The input pattern of the neural network for path planning of mobile robots should consider the following data: robot's actual position and velocities; robot's previous positions and velocities; target position and sensor data, and then output the commands to drive the robot to follow a path towards the target with obstacle avoidance according to these data.

Kozakiewicz and Ejiri have used a human expert to train a feedforward neural network that reads inputs from a camera and outputs the appropriate commands actuators [29]. In [30], Sfeir *et al.* developed a path generation technique for mobile robot using memory neuron network proposed by Sastry *et al.* [31]. The memory neuron network is a feedforward neural network that uses memory neurons. A memory neuron is a combination of a classic perception and unit delays, which gives it memory abilities. Glasius, Komoda, and Gielen proposed a Hopfield-type neural network for dynamic trajectory formation without learning [32]. Fierro and Lewis studied a control structure that integrated a kinematic controller and a feedforward neural network computed-torque controller for nonholonomic mobile robot, and the neural network weights are tuned on-line, with no "off-line learning phase" needed [33], [34], [35]. Yang and Meng proposed a biologically inspired neural network approach for motion planning of mobile robots [36], [37], [38]. This model is inspired by Hodgkin and Huxley's membrane model [39] for a biological neural system and Grossberg's shutting model [40]. The proposed model for motion planning of mobile robots has the following properties: without any prior knowledge of the environment, without explicitly searching over the free workspace or the collision path, and without any learning procedure.

However, neural networks have also some drawbacks. For instance, a neural network can not explain its results explicitly and its learning is usually time-consuming. Further, the learning algorithm may not be able to guarantee the convergence to an optimal solution [41].

3 Hybrid Approaches for Mobile Robot Navigation

Though neural networks have some properties that are important for the mobile robot navigation, knowledge representation and extraction are difficult. Fuzzy systems are able to treat uncertain and imprecise information; they make use of knowledge in form of linguistic rules. Their main drawback is lack of systematic methodology for their design. The technology that combines or fuses the neural network with the fuzzy reasoning is being watched some very interesting architectures [42]. Several fuzzy neural networks have been presented and used for mobile robot navigation successfully [43-45, 47, 49-52].

Godjevac and Steele proposed a neuro-fuzzy controller based on Takagi-Sugeno design and a radial basis function for obstacle avoidance and wall following of a mobile robot [43]. Marichal *et al.* presented a neuro-fuzzy approach to guide a mobile robot with obstacle avoidance [44]. The proposed neuro-fuzzy strategy, which consists of a three-layer neural network along with a competitive learning algorithm, is able to extract the fuzzy rules and the membership functions according to the information provided by a set of trajectories that are obtained from a human guidance. Er and Deng studied a hybrid learning approach for obstacle avoidance of a mobile robot [45]. In [45], firstly, a neuro-fuzzy controller is developed from a pre-wired or innate controller based on supervised learning in a simulation environment. The fuzzy inference system has been constructed based on the Generalized Dynamic Fuzzy Neural Networks learning algorithm proposed by Wu and Er *et al.* [46], whereby structure identification and parameters estimation are performed automatically and simultaneously. Secondly, the controller is implemented on a real robot after the learning phase. A reinforcement learning algorithm based on the Fuzzy Actor-critic learning algorithm is employed so that the system can re-adapt to a new environment without human intervention.

Fuzzy Adaptive Resonance Theory (ART) and fuzzy ARTMAP were proposed by Carpenter and Grossberg *et al.* [47], [48]. Fuzzy ART is capable of learning stable recognition categories in response to both analog and binary input patterns, and fuzzy ARTMAP can rapidly learn stable categorical mapping between analog or binary input and output vectors. Araujo has used fuzzy ART neural network for on line map building from actual sensor data [49]. Later, this work has been extended. Prune-able Fuzzy ART neural network, which included the ability to selectively remove recognition categories, was introduced to build map of mobile robot in unknown environments [50]. The fuzzy ART based approach for map building of mobile robots has the following characteristics [50]: (1) Self-organization from perceived sensor data; (2) Multi-functionality for map building, motion planning; (3) Updatability: incremental, on-line update by learning separately each sensor data point, thus make the model available as soon as possible; (4) Compact geometric representation with small data requirements; (5) Low computational costs; (6) Possible application to higher dimensional space without adversely impacting on data size and complexity. Streilein *et al.* presented an approach to sonar-based object recognition using a fuzzy ARTMAP neural network for the mobile robot localization [51]. Azouaoui *et al.* proposed an approach for obstacle avoidance of mobile robot using fuzzy ARTMAP neural network [52]. This approach can provide robots with capability, after learning based on the supervised fast stable learning: Simplified fuzzy ARTMAP, to determine and use the rule allowing the robots to avoid collision.

4 Conclusions

In this paper, we have given a brief discussion on mobile robot navigation using neural networks. Although a great deal of progress has been made in the field of mobile robot navigation using neural networks, we have to go a long way to make the robot to have the capabilities of intelligence and autonomy truly, which will be possible when the neural hardware evolves and we get a better understanding of how the human brain works. In the mean time, perhaps the best approach is the hybrid approach that combines neural networks with other artificial intelligent algorithms such as fuzzy logic, knowledge-based systems and genetic algorithms.

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