Soft Computing Technique for Simultaneous Localization and Mapping of Mobile Robots

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***Abstract*—Because traditional approaches for solving the simultaneous localization and map building (SLAM) problem have the limitation of computational complexity, imprecision of filter algorithm and fragile data association, soft computing technique has been used to solve the problem. In this paper, we reviewed the state of the art of the application of evolutionary algorithm, fuzzy logic and neural networks in SLAM.**

Keywords- soft computing; SLAM; evolutionary algorithm; fuzzy logic; neural network

I. INTRODUCTION

In recent years, many approaches have been proposed to solve the simultaneous localization and map building (SLAM) problem. The main methods can be divided into two categories: the ones based on probabilistic models and the ones based on non-probabilistic models. The former includes, extended *Kalman* filter (EKF), unscented *Kalman* filter (UKF), particle filter, fastSLAM, and so on. The latter includes data fusion, scan matching, set membership SLAM (SM-SLAM) [1], fuzzy logic based, and so on. Currently, although most SLAM algorithms are based on EKF, they still have some shortages to overcome. The EKF requires time quadratic in the number of features in the map, for each incremental update. This means the large computational complexity for the SLAM problem. It was hardly used in large-scale environments. Another problem of EKF is the fragile data association. This means EKF lacks the capability of self-recovery. The fastSLAM algorithm requires time logarithmic in the number of features in the map. The computational complexity is reduced, but the algorithm needs a stable feature extraction of environment and data association. It depends linearly on a particle filter specific parameter (the number of particles), whose scaling with environmental size is still poorly understood.

Soft computing is a practical alternative for solving computational complexity and mathematically intractable problems [2]. It includes neural networks, evolutionary algorithm and fuzzy inference systems. Soft computing provides a more flexible processing method for the uncertain problems and it has described by the term of parallel processing, default tolerance and processing uncertainty. Aiming at the computational complexity and uncertain factors of SLAM, the soft computing methods have been used.

In this paper, we review the recent results of the application of soft computing in SLAM and give some comparisons. The rest structure of the paper is as follows. Section 2 describes the state of the art for the application of evolutionary algorithms in mobile robots SLAM. The methods based on fuzzy logic for SLAM are described in Section 3. Section 4 describes some approaches to solve SLAM problems using neural network. Finally the conclusions are given in Section 5.

II. SLAM BASED ON EVOLUTIONARY ALGORITHMS

In recent years, the evolutionary algorithms are widely used to solve the SLAM problems [3-12]. In [3], a genetic algorithm was used to solve the SLAM problem which was defined as a global optimization problem. The fitness values are obtained with a heuristic function that measures the consistency and compactness of the candidate maps. The procedure of treating SLAM as a continuous global optimization problem was shown by Fig.1.

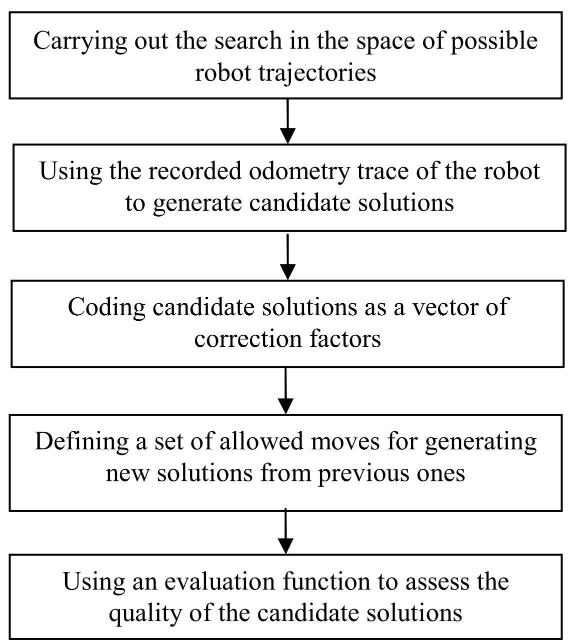

Figure 1. The transform from SLAM to a global optimization problem

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The solving procedure for the global optimization was shown by Fig.2

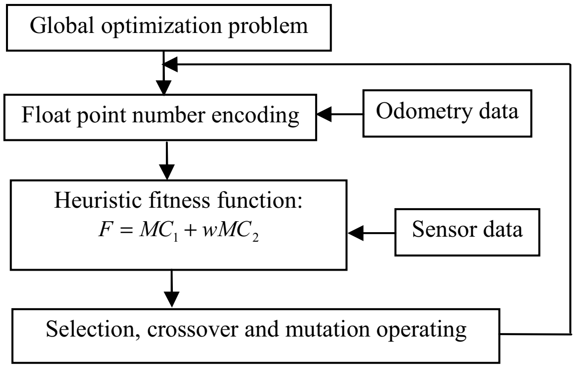

Figure 2. A solving method based on genetic algorithm

where $MC_1 = \sum_i \min(occ_i, emp_i)$, occ_i is the number of laser readings which indicate that the cell is occupied, emp_i is the number of readings which indicate that the cell is empty. $MC_2 = (x_{\max} - x_{\min}) \times (y_{\max} - y_{\min})$, $x_{\max}$, $x_{\min}$, $y_{\max}$, $y_{\min}$ are the maximum and minimum coordinates of the bounding box which measured in number of grid cells.

The resulting maps obtained are very accurate, but the approach is computationally expensive. The search space of maps and paths are extremely large because they are high dimensional data structures. In order to decrease the number of dimensions in search space, an evolutionary algorithm and particle swarm optimization (PSO) has used to solve the problem of SLAM for mobile robots in [4]. With a proper representation of problem parameters in chromosome, the dimensionality of search space is reduced. Two different fitness function based on map cell are proposed that is computationally efficient and the evolutionary algorithm used the parent selection, uniform crossover, survivors selection and mutation which used the method of taking place for each offspring column. An island model genetic algorithm for SLAM of mobile robots was proposed in [5]. The algorithm searches for the most probable maps such that the underlying robot's pose provides a robot with the best localization information. The algorithm processes sensor data incrementally and has the capability to work online. A steady-state genetic algorithm with the elitist crossover and adaptive mutation strategy is applied to update the estimated the self-position of the robot by using the measured distance and topological map in [6]. The measured distance is obtained by laser range finder. The topological map building method based on a growing neural network which can add neurons and their connections to the network. If the difference between the measured distance and its corresponding map data is large, the robot updates the self-location by using the steady-state genetic algorithm.

In order to improve the precision of SLAM based on particle filter, a few of evolutionary algorithms are presented. A PSO method is proposed in [7] for increasing the FastSLAM precision. This method used the equations of speed and situation of PSO to update the predicting pose of the robot. It can reduce the particle number and the computational time complexity. In [8, 9], a genetic algorithm was used to optimize the particles set. It can improve the capability of the particles set and enhance the accuracy of estimating. The evolution strategies were applied in Rao-Blackwellized particle filter by using the adaptive re- sampling scheme to implement indoor mobile robot SLAM in [10]. It used the evolution operation to optimize system status expressing by particles.

Data association is critical for SLAM. Incorrect data association will cause the map feature estimating divergence and the inaccurate of feature location. An ant colony algorithm (ACA) was proposed to solve this problem in [11]. The math model of data association is evolved to combinatorial optimization model. The ACA is used to solve the problem of combinatorial optimization. In order to overcome the difficulties of data association, the SLAM problem can also be translated to a multi-objective optimization problem. In [12], an evolutionary algorithm with immunity is proposed to deal with multi-objective optimization problem. The algorithm used the float point numbers encoding, vaccination and immune selection operation. A comparison of the optimization algorithms application in SLAM is given by Table 1.

TABLE I. A COMPARISON OF OPTIMIZATION ALGORITHMS BASED SLAM

Ref.	***Optimization algorithms***	***Filter algorithms***	***Sensors***
[7]	PSO	FastSLAM	Laser
[8]	Genetic algorithm	Marginal-SLAM	
[9]		FastSLAM2.0	
[10]	Evolution strategies with adaptive crossover and mutation	Rao-Blackwellized Particle Filter	Visual
[11]	ACA	None	Sonar
[12]	Evolutionary algorithm with immunity		Laser

III. SLAM BASED ON FUZZY LOGIC

In [13], a fuzzy logic supervisor is used to solve EKF-based SLAM problem. The fuzzy system is employed to minimize the mismatch of the actual covariance of the innovation sequences and the theoretical covariance of the innovation sequences. The input to each fuzzy subsystem is employing three membership functions: negative, zero, and positive. The final output of each fuzzy system is calculated by employing the well-known weighted average technique. In order to training the parameters for the fuzzy systems, differential evolution method has been employed to learn the free parameters of the fuzzy system. In [14], a fuzzy-adapted EKF is proposed to prevent the filter divergence and improve the localization accuracy. Fuzzy logic and covariance-matching are adopted to adjust the measurement noise covariance in order to deal with the incomplete knowledge. Five fuzzy subsets (NL, NS, ZE, PS and PL) are used to achieve the algorithm. The structure of the algorithm was shown by Fig.3.

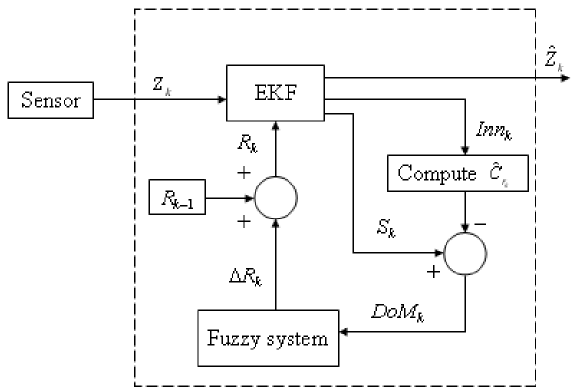

Figure 3. Fuzzy-adapted EKF structure

A fuzzy *Kalman* filter based on Takagi-Sugeno (T-S) fuzzy model is presents in [15, 16, and 17]. Using the *Kalman* filter theory, each local T-S model is filtered to find the local estimates. The linear combination of these local estimates gives the global estimate for the complete system. The fuzzy model proposed by T-S is described by fuzzy IF-THEN rules, which represent local linear input-output relations of a nonlinear system. The i^{th} rule of the T-S fuzzy model is of the following form:

$$\text{If } z_1(k) \text{ is } M_{i1} \text{ and } \ldots \text{ and } z_p(k) \text{ is } M_{ip}$$

$$\text{Then} \begin{cases} x(k+1) = A_i x(k) + B_i u(k) \\ y(k) = C_i x(k) \quad i = 1,2,...,r. \end{cases}$$

where M_{ij} is the fuzzy set of vehicle angel , $x(k) \in R^n$ is the state vector, $u(k) \in R^m$ is the input vector and $y(k) \in R^q$ is the measurement vector. Given a pair of $(x(k), u(k))$, the final outputs of the fuzzy system are inferred as follows:

$$x(k+1) = \frac{\sum_{i=1}^{r} w_i(z(k))\{A_i x(k) + B_i u(k)\}}{\sum_{i=1}^{r} w_i(z(k))}$$

$$= \sum_{i=1}^{r} h_i(z(k))\{A_i x(k) + B_i u(k)\}$$

$$z(k) = [z_1(k), z_2(k) \cdots z_p(k)],$$

$$w_i(z(k)) = \prod_{j=1}^{p} M_{ij}(z_j(k)) \text{ , } h_i(z(k)) = \frac{w_i(z(k))}{\sum_{i=1}^{r} w_i(z(k))},$$

$$\sum_{i=1}^{r} w_i(z(k)) > 0 \text{ , } w_i(z(k)) \geq 0 \text{ , } i = 1,2,\ldots,r.$$

Fuzzy Logic is often combined with the evolutionary algorithm to solve the SLAM problem. **In [18, 19],** a fuzzy-evolutionary algorithm is presented. It exploits the intelligent properties of two soft computing techniques (fuzzy logic and genetic algorithm) to develop a novel solution for SLAM. The algorithm utilizes the uncertainty handling capacity of fuzzy logic to infer the uncertainty in robot's pose. The search for the optimal robot's pose is performed by genetic algorithm. Knowledge on the problem domain is preprocessed by fuzzy logic system. The proposed fuzzy system has four input linguistic variables and five output linguistic variables.

The approach of fuzzy logic also can be applied in map building and information extraction. In [20], a map building method based on fuzzy logic is proposed for SLAM problem. This approach uses the fuzzy trapezoidal set as the basic geometric unit of map and employs the vertex localization method to achieve the self-localization. In [21], a fuzzy clustering algorithm is used to fusion line for improving the accuracy of SLAM. The algorithm of extracting line is divided into two phases. The first phase uses the fuzzy C-mean algorithm to compute cycle. The second phase uses adaptive fuzzy clustering algorithm. A comparison of the fuzzy logic application in SLAM is given by Table 2.

TABLE II. A COMPARISON OF FUZZY LOGIC BASED SLAM

Ref.	***Inference type and membership function***	***Filter algorithms***	***Sensors***
[13]	Mamdani ,Trapezoid	EKF	Laser
[14]	Mamdani , Triangle		Sonar
[15]- [17]	T-S, Piecewise function about cos(x)	Kalman filter	None
[18] -[20]	Mamdani ,Trapezoid	None	Laser
[21]	Fuzzy clustering algorithm	Particle filter	Ultrasonic

IV. SLAM BASED ON NEURAL NETWORKS

In recent years, the neural network methods have been developed to solve the localization problems of SLAM and improve the precision of SLAM based on filter algorithm.

A neural network aided EKF algorithm is proposed in [22]. The neural network will capture the un-modeled dynamics by learning on line. A sigmoid type function describes the difference between the true plant and the best model. In [23], an approach of model errors compensation based on neural network with EKF is proposed. In this proposed algorithm, the errors are replaced with neural network function and the network's weight coefficients are augmented to the system state. The augmented state is predicted and updated by the EKF algorithm continuously. A hybrid filter method is proposed to compensate the error of EKF in [24]. The proposed algorithm consists of two types of neural networks: the multi layer perceptions algorithm and the radial basis function algorithm. Neural network training is composed of two steps: first, the weights from the input to the hidden layer are determined; then, the weights from the hidden to the output layer are determined. The function of neural network is to increase the capability of filter algorithms.

The hybrid method of neural network and fuzzy logic approach is also used in SLAM problem. In [25], a neuro-fuzzy approach is proposed to supervise the performance of the EKF for SLAM problems and take necessary corrective actions by adapting the sensor statistics online, so that the degradation in system performance can be arrested. A self-organizing neural network was used to solve the problem of SLAM in [26]. This method has the advantages of both fuzzy reasoning and neural networks. It adopts self-organizing fuzzy neural networks to model the environment and to implement localization. A comparison of the neural network application in SLAM is given by Table 3.

TABLE III. A COMPARISON OF NEURAL NETWORK BASED SLAM

Ref.	***Network***	***Filter algorithms***	***Sensors***
[22] [23]	Three layers feed-forward network		
[24]	Multi-layer feed-forward network and RBF network	EKF	Laser
[25]	Multi-layer feed-forward network		
[26]	Five layers feed-forward network	None	Ultrasonic

V. SLAM BASED ON NEURAL NETWORKS

In this paper, we reviewed the state of the art of the applications of soft computing approaches in SLAM. The evolutionary algorithm, fuzzy logic and neural network methods are used to solve the problems of improving the precision of SLAM based on filter algorithm, overcoming fragile data association and extracting information.

Future work in the solution to the SLAM problem can be envisaged in several areas. High quantity map building and multi-sensor data fusion in SLAM problem are also important factors. SLAM in 3D dynamic and outdoor non-structured environments is another challenge for the mobile robot navigation. The soft computing methods have shown potential advantages in solving the problems.

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