Proceedings of KFIS 2002 Spring Conference, 2002. 5. 25

Decision Support Method in Dynamic Car Navigation Systems by Q - Learning

홍수정 · 홍언주 · 오경환*
* 서강대학교 컴퓨터학과

Soo-Jung Hong, Eon-Joo Hong, and Kyung-Whan Oh
*Dept.of computer science and Engineering , Sogang University
E-mail : orchid@ailab.sogang.ac.kr

ABSTRACT

오랜 세월동안 위대한 이동수단을 만들어내고자 하는 인간의 꿈은 오늘날 눈부신 각종 운송 기구를 만들어 내는 결실을 얻고 있다. 자동차 네비게이션 시스템도 그러한 결실중의 한 예라고 할 수 있을 것이다. 지능적으로 판단하고 정보를 처리할 수 있는 자동차 네비게이션 시스템을 부착함으로써 한단계 발전한 운송수단으로 진화할 수 있을 것이다.
이러한 자동차 네비게이션 시스템의 단점이라면 한정된 리소스만으로 여러 가지 작업을 수행해야만 하는 어려움이다. 그래서 네비게이션 시스템의 주요 작업중의 하나인 경로를 추출하는 경로추출(Route Planning) 작업은 한정된 리소스에서도 최적의 경로를 찾을 수 있는 지능적인 방법이어야만 한다.
이러한 경로를 추출하는 작업을 하는 데 기존에 일반적으로 쓰였던 두 가지 방법에는 Dijkstra's algorithm과 A* algorithm이 있다. 이 두 방법은 최적의 경로를 찾아 낸다는 점은 있지만 경로를 찾기 위해서 알고리즘의 특성상 각각, 넓은 영역에 대하여 탐색작업을 해야 하고 또한 수행시간이 많이 걸린다는 단점과 또한 경로를 계산하기 위해서 Heuristic function을 추가적인 정보로 계산을 해야 한다는 단점이 있다.
본 논문에서는 적은 탐색 영역을 가지면서 또한 최적의 경로를 추출하는 데 드는 수행시간은 작으며 나아가 동적인 교통환경에서도 최적의 경로를 추출할 수 있는 최적 경로 추출방법을 강화학습의 일종인 Q- Learning을 이용하여 구현해 보고자 한다.

Keyword : Case-based Reasoning, Clustering

1. Introduction

Human being has been dreaming about creating a great mobility. One of the results is vehicle navigation system. With the assistance of the vehicle navigation system driver can do many intelligent works that once those never be concerned as a possible task.
But, there are still several obstacles to overcome. In particular, the route planning task that is one of goals of navigation systems need to have intelligent method to determine the optimal route.

There are two well-known methods to find the optimal route. One is Dijkstras algorithm and the other is A* algorithm. Those two methods find the optimal route but both of them have disadvantages, respectively.

According to the Dijkstras algorithm, it has to visit all the nodes in a given map, therefore it needs long execution time. In case of

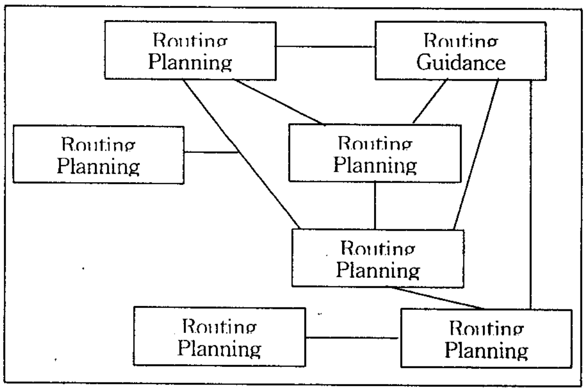
A*-algorithm, it has to maintain extra knowledge to calculate the heuristic cost.
These facts can be the critical matters to be applied in a navigation system, which faces not only static environment but also dynamic environment.

This paper proposes the new method to find the optimal route in navigation system. Proposed method is implemented based on the idea of Q-Learning.

2. Background

2.1 Autonomous car navigation systems

Human beings have never stopped pursuing the dream of great mobility. Thousands of years of civilization have led to the modern vehicle location and navigation systems of today. There are, and always will be, a range of systems from the very low and to the very high end. Figure 1 illustrates the building modules of a navigation system. Main modules are route planning, route guidance, digital map database, positioning and map matching.



<Figure 1> Basic module for a navigation system

2.2 Optimal route planning in navigation system

Route planning is the process of helping vehicle drivers to plan a route prior to or during their journey, based on a given map provided by the map database module, if available, along with real-time traffic information received via, i.e. wireless communications network. A commonly used technique is to find a minimum-travel-cost route based on criteria such as time, distance, and complexity.

Route planning is a process that helps vehicle drivers to plan a route prior to or during a journey [1]. A variety of route optimization criteria (planning criteria) may be used in route planning. We refer to all these factors as the 'travel cost'. Some drivers may prefer the shortest distance. Others may prefer the shortest travel time. Thus the evaluation function chosen to minimize this cost depends on the system design and user preference.

2.3 The Dijkstras algorithm & The A*-algorithm

The Dijkstra's algorithm is one of the main representatives of shortest path algorithms [5-6]. This algorithm is a general method to solve the single-source shortest path problem. The Dijkstras algorithm is a prime example of a greedy technique, which generally solves a problem in stages by doing what appears to be the best thing at each stage.

The A*-algorithm is one of the most popular heuristic search methods [3]. In general, there are different search strategies to realize a heuristic search method. A heuristic is a technique for improving the efficiency of a search process by possibly sacrificing claims of completeness. The merit of using heuristic information is that this information helps to determine which is the "most promising" node, which successors to generate, and also it tells which irrelevant search branches to prune [2].

In the A*-algorithm this heuristic evaluation function enables the algorithm to search the most promising nodes first. In other words: to find the most promising node, the evaluation function is used [1].

2.4 Q-Learning

Reinforcement learning is learning from positive and negative rewards [2]. One of the most important breakthroughs in reinforcement learning was the development of Q-learning [4]. As can be seen from Figure 2, Q-learning consists of a termination checking step (line 2) and action selection step (line 3), an action execution step (line 4), and a value update step (line 5). For the moment, the initial Q-values stay unspecified.

The action selection step implements the exploration rule ("which state to go to next").

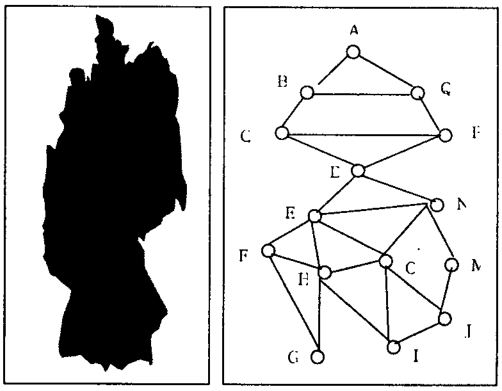
It is constrained to look only at information local to the current state s of the system.

```
For each state  and action  , initialize the Q-value to zero.
Observe the current state
1. Set s:= the current state.
2. If s∈G̅ , then stop. (G̅ is goal state).
3. Select an action a∈A̅(s).
4. Execute action a./* As a consequence, the agent receives reward γ̅(s,a) and is in state succ̅(s,a). Increment the number of steps taken, i.e. set t := t+1*/
5. Set Q(s,a) := γ̅(s,a) + γU(succ̅(s,a)).
6. Go to 1.
where total reward U(s) := max a∈A̅(s)Q(s,a) at every point in time.
```

<Figure 2> The Q-learning algorithm

3. Decision Support method in car navigation systems by Q- learning

This part describes how a method for decision support to optimize route planning in car navigation system is constructed. The proposed method for route planning is implemented based on Q-learning. The reason for using the Q-learning algorithm for route planning is that this method can improve the performance on-line, while the system and the environment interact. A car navigation system faces a real-time traffic environment, thus Q-learning provide proper way to adapt to a dynamically changing environment.



<Figure 3> Partial map of digital map database and corresponding graph

Q-learning estimates the values of each state and its action pairs. In the case of navigation system, this 'state' is the vertex the system considers at the moment. When the system's current state is 'i', then the system considers the vertex 'i'. The state is not in the time domain, thus there is no time related order between states. An 'action' of the system is movement to the next vertex.

One restriction on the actions in route calculation is: if that a vertex has already been visited before, then there is no action that moves to that vertex again

4. Experimental results

when a navigation system is trying to find the route requiring the minimum travel time, then time is the criterion being applied. And when the system wants to find the shortest path, then distance is the criterion being applied. These two criteria are commonly used for finding an optimal route.

In a static environment, each of the three routing methods Dijkstra, A*- algorithm, Q-values finds the optimal route regarding travel distance or travel time.

pair	Dijkstra's	A*	Q-learning
A - B	0.990	0.060	< 0.001
A - C	0.770	0.050	< 0.001
A - P	0.610	0.060	< 0.001
A - D	0.660	0.050	< 0.001
A - E	0.550	0.050	< 0.001
A - O	1.100	0.060	< 0.001
A - F	0.710	0.050	< 0.001
A - H	0.660	0.060	< 0.001
A - M	0.770	0.050	< 0.001
A - J	0.710	0.050	< 0.001
A - I	1.200	0.060	< 0.001
A - G	1.100	0.060	< 0.001

<Table 1> Average execution times in a static environment

	Average execution Time	Normalized Time	Improvement Row by row
Dijkstra	0.8192	100 %	0 %
A*	0.0550	6.71 %	93.29 %
Q-learning	<0.001	0.23 %	98.2 %

<Table 2> Average execution time of each method in static environment

The accuracy of Dijkstra's algorithm, A*-algorithm and Q-learning method in dynamic environment is the same as before. Table 3 shows the execution time to get the optimal route in dynamic environment. The execution time in Table 3 is obtained from the experimental result when the starting vertex is 'A' on the map

	Dijkstra's	A*	Q-learning
A - B	0.940	0.220	0.050
A - C	1.100	0.220	0.100
A - P	0.820	0.170	0.110
A - D	0.990	0.220	0.060
A - E	0.710	0.220	0.110
A - O	1.100	0.170	0.060
A - F	1.150	0.160	0.110
A - H	0.770	0.220	0.060
A - M	0.880	0.280	0.110
A - J	0.830	0.160	0.060
A - I	1.150	0.160	0.110
A - G	1.250	0.330	0.120

<Table 3> Average execution time in the dynamic environment

	Average execution Time	Normalized Time	Improvement Row by row
Dijkstra	0.9742	100 %	0 %
A*	0.2108	21.64 %	78.36 %
Q-learning	0.0750	9.06 %	64.42 %

<Table 4> Average execution time of each method in the dynamic environment

5. Conclusion and Prospects

One of the objects in car navigation systems is to provide the optimal route information for the user. This task for route planning is done in the car navigation system's module called 'Route Planning' (Figure 1). This paper proposes a new decision support method for route planning in car navigation systems. The proposed method is implemented by using the Q-learning algorithm. The proposed method shows an outstanding performance in the experiments in static and in dynamic environments In the future the method proposed in this thesis will be applied to further experiments on larger area of the digital map database. Moreover, based on this method using Q-value, a personalized routing algorithm will be constructed. The personalized routing is finding the route with personal preference.

Acknowledgement : 본 연구는 2001학년도 서강대학교 교내연구비 지원에 의해 수행 되었음.

7. References

[1] Yilin Zhao, Vehicle Location and Navigation Systems, Boston: ARTECH HOUSE, Inc., 1997) pp. 1~6, p. 105~112.

[2] Richard S. Sutton, Andrew G. Barto, Reinforcement Learning, Cambridge Massachusetts : The MIT Press, 1998, pp. 3~6, pp.148~150.

[3] A.V. Aho, J.E.Hopcroft and J.D. Ullman, Data Structures and Algorithms, MA : Addition-Wesley, 1983.

[4] Sven Koenig and Reid G. Simmons, "Complexity Analysis of Real-Time Reinforcement Learning Applied to Finding Shortest Paths in Deterministic domains", Carnegie Mellon Univeristy, December 1992.

[5] R. Agrawal, S.Dar and H.V. Jagadish, "Direct Transitive Closure Algorithms: Design and Performance," ACM Trans. Database Systems, vol.15, no.3, pp 427-458, Sept.1990.

[6] T. Cormen, C. Leiserson, and R.L. Rivest, Introduction to Algorithms, MIT Press, 1993.

[7] Ning Jing, Yun-Wu Huang, Elke A. Rundensteiner, "Hierarchical Encoded Path Views for Path Query Processing: An Optimal Model and Its Performance Evaluation" IEEE transactions on knowledge and data engineering, vol.10, 1998

[8] Hinrich Claussen, "Status and Directions of Digital Map Databases in Europe" IEEE-IEE Vehicle Navigation and Information Systems Conference, Ottawa, 1993

[9] S. Shekhar, A. Kohl and M. Coyle, "Path Computation Algorithms for Advanced Traveler Information Systems," Proc. Ninth Int'l Conf. Data Eng., pp.31-39, 1993.

[10] Y. W. Huang, N. Jing, and E.A. Rundensteiner, "A Semi-Materialized View Approach for Route Maintenance in Intelligent Vehicle Highway Systems," Proc. Second ACM Workshop Geographic Information Systems, pp 144-151, Nov.1994

[11] Elaine Rich, Kevin Knight, Artificial Intelligence, Second Edition, New York, McGraw