# Distributed Learning Automata based Route Planning

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## ABSTRACT
Distributed Learning Automata is automata based modelling approach for solving stochastic shortest path problems. The DLA can be applied to road networks to find shortest path that provides a spatial approach to bottom-up modelling of complex geographic systems that are comprised of infrastructure and human objects. Route finding is a popular Geographical Information System (GIS) application under Intelligent Transportation Systems (ITS). TheITS reduce traffic congestion and improve road network performance. They provide real time traffic information and route recommendation to road users, to increase their ability to choose the best alternative path.In recent years, DLA models for urban growth simulation are gaining popularity because of their ability to incorporate the spatial and temporal dimensions of the processes. The usage of DLA in route finding has not been explored to its fullest. In this work, a routing finding algorithm is proposed on road networks using DLA. The Distributed Learning Automata based Route Planning (DLARP) algorithm based on two dimensional automata is proposed. Transition rule of automata are proposed in such a way that at each step time the user cell is exchanged with best goal directing cell. DLARP algorithm achieves a proper solution to route finding in spatial road networks.

## Keywords
Distributed Learning Automata, Cellular Automata, Multi-Agent Systems, Route Planner, Intelligent Transportation Systems, Spatial Databases, GIS, Nearest Neighbor, GPS, Location based services, Path Planning.

## 1. INTRODUCTION
The integration of GIS and GPS made mobile users to search for point of interest like nearest restaurant, hospitals etc. These are location based nearest neighbor spatial queries on road networks. The route finding to point of interest is another popular application under GIS. With advances in spatial databases, finding nearest neighbor and shortest paths are vastly studied under Euclidean space[16] and road network distances[24]. Learning automata (LA) are simple mathematical systems that exhibit very complicated behavior. Recently the Learning automata are used in urban applications like traffic simulation, regional-scale urbanization to land-use dynamics, historical urbanization, and urban development. The integration of GIS and LA accelerates GIS's ability of simulating geographical process greatly. The integration of GIS and LA shows tremendous capability in simulating spatial-temporal dynamic process in geography world.

To sum up the following are the contributions:

1. Representation of road network based on Distributed Learning Automata System.
2. DLARP algorithm for route finding in spatial road networks.

The reminder of this paper is organized as follows. In section 2, we review the related work of Cellular automata, Distributed Learning Automata Systems in Intelligent Transportation Systems. In section 3, we formally defined Distributed Learning Automata System on Spatial Road Networks. In section 4, an DLARP algorithm for finding the route in spatial road networks using Distributed Learning Automata System. Finally section 5 concludes the paper with future research.

## 2. RELATED WORK
### 2.1 Automata in Urban Studies
The idea of cellular automata (CA) is introduced by J. von Neumann who was working in the 1940s at the Los Alamos National Laboratory on self-replicating systems. Later on the development is done by E. F. Codd and S. Wolfram. The classification of CA dependent on their behaviour is proposed by the latter. The most common definition of a cellular automaton describes it as a four-tuple:

$$CA = (L, S, N, f)$$

where L is a cell lattice, S is a finite set of states, N is a neighborhood of the given cell and f is a function which assigns a new state to a cell depending on the states of all its neighbors indicated by N [21].

For modelling biological self-reproduction, Cellular Automata were originally introduced by von Neumann and Ulam[19][20]. In the field of traffic study, Creamer and Ludwig [9] were first to introduce cellular automata. Boolean simulation of traffic flow is the basis of their model. It represents individual vehicles by 1-bit variables in computer memory. In [14], Nagel-Schreckenberg introduced a well established method of modelling traffic flow. The roadway is represented by a uniform cell lattice in their model where each cell belongs to a discrete set of states. The state of the cells is updated at discrete time steps. The update rules help to combine the vehicle motion models that are governed by a small set of parameters. The Models in [13][5][6] are simple to implement CA and easily deals with different aspects of traffic.

In [2] it was illustrated that an efficient computation method can be developed by cellular automata. The collision free path from initial to goal configuration on a physical space occupied by obstacles in arbitrary locations is found. The multilayered cellular automata is presented by Marchese[11] where a reactive path-planning method for a non-homonymic mobile robot is proposed. CA has become a popular modelling system and computational tool in mathematics, natural science, computer science and technologies. Training CA to perform image processing [15], design of reconfigurable robots [12], prediction of protein sub-cellular location [22] modeling phenomena of urban growth [10] and modelling earthquake activity features [8] are some examples.

In [17], for path planning a cellular automata based algorithm in multi-agent systems with a common goal is introduced. In [1], a novel Cellular Automata based Real Time Path Planning Method for Mobile Robots is developed. In [23], describes the modelling language for interacting hybrid systems in which we will build a new hybrid model of cellular automata, multi-agent technology and rough set theory.

## 2.2 Distributed Learning Automata Systems

Geo-simulation is concerned with automata-based methodologies for simulating discrete, dynamic, and action-oriented spatial systems, combining cellular automata and multi-agent systems in a spatial context[2][3].

# 3. SYSTEM MODEL

## 3.1 Learning Automata

The determination of an optimal action from a set of allowable actions is an automaton approach to learning. The abstract object that has finite several actions forms an automaton. It selects an action from its finite set of actions. This action is applied to a random environment. The random environment evaluates the applied action and gives a grade to the selected action of automata. The response from environment is used by automata to select its next action. By continuing this process, the automata learn to select an action with best response. The learning algorithm used by automata to determine the selection of next action from the response of environment. An automaton acting in an unknown random environment and improves its performance in some specified manner, is referred to as learning automata (LA). Learning automata can be classified into two main families: fixed structure learning automata and variable structure learning automata.

Distributed Learning Automata (DLA) DLA is a network of automata which collectively cooperate to solve a particular problem. In DLA, the number of actions for any automaton in the network is equal to the number of outgoing edges from that automaton. When an automaton selects one of its actions, another automaton on the other end of edge corresponding to the selected action will be activated. For example in figure 1, every automaton has two actions. If automaton a1 selects action1 then automaton a3 will be activated. The activated automaton a3 chooses one of its actions which in turn activate one of the automata connected to a3. At any time only one automaton in the network will be active. Formally, a DLA with n learning automata can be defined by a graph (A; E), where A = {A1; A2; ; An} is the set of automata and E is the set of edges in the graph in which an edge (i; j) corresponds to action j of automaton Ai.

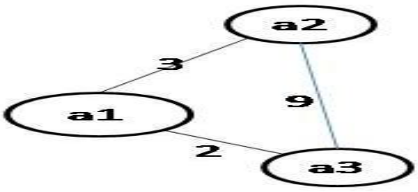


**Fig:1DLA Network**

Formally, a DLA may be defined as consisting of seven components:

G ~ (K; S, TS; L, ML; R, NR)

Here K denotes a set of types of automata featured in the DLA, S set of states, set of state transition rules TS, L denotes the geo-referencing conventions that dictate the location of automata in the system and ML denotes the movement rules for automata, governing changes in their location. R represents neighbors of the automata and NR represents the neighborhood transition rules that govern how automata relate to the other automata in their vicinity.

## 3.2 Algorithm for DLARP

The algorithm uses Dist_Tb and Direct_Tb for processing route information. The Dist_tb consists of minimum distances between each cell and the goal. The Direct_Tb consists of optimal direction(s) for each cell (following the optimal directions a user can take its shortest diagonal path(s) toward the goal from an arbitrary location). Each cell state is added to Resultset to get the route to reach the goal.In this algorithm, the stochastic graph plays the role of random environment for DLA. The output of DLA is a sequence of actions that represent a particular path in the stochastic graph. The environment uses the length of this path to produce its response. This response, depending on whether it is favorable or unfavorable, causes the actions along this path be rewarded or penalized. In the proposed algorithm, at first a network of learning automata which is isomorphic to the input graph is created.

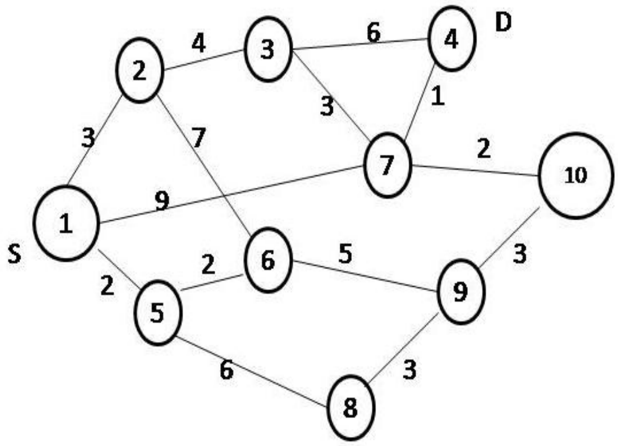


**Fig:2 DLA based Graph (G)**

**Algorithm 4.4 GARP**
GDNNQ (upos,goal)

/* upos: query origin (latitude,ongitude) , goal: point of interest*/

1. Construct DLA from graph G

2. Find the nearest vertex for the query origin upos

u←StartVertex(Upos)

3. while true do until step 9

4. minnode←TRule(u) /* for all adjacent nodes of u, apply the transition rule to find minimum cost node basing on direction of travel*/

5. Resultset←minnode

6. if (minnode=goal) then

7. Disp(Resultset)

/* display DLARP */

8. end if

9. u ←minnode

10. while end

In this network each node is a learning automaton and each outgoing edge of this node is one of the actions of this learning automaton. The algorithm then traverse the graph until the shortest path is found. In the first step, the source automaton As chooses one of its actions, say m.This action activate automaton Am on the other end of the edge. The process of election of an action and activating an automaton is repeated until destinationautomaton Ad is reached or for some reason moving along the edges of the graph is not possible or the number of visited nodes exceeds thenumber of nodes in the graph. After the Ad is reached, the length of the traversed path and optimalare computed. The edges towards the goal are considered for automata to be generated. The edges in opposite direction are not explored as it will lead to increase in automata generation and will not result in shortest path. This decreases the total number of automata being generated. Hence the DLA based route finding towards the goal decreases the computation cost.

## 4. EXPERIMENTAL SIMULATION

The experiment is conducted for three sample graphs and results are shown as follows. The metrics adopted are No. of Nodes processed, No. of edges processed for each graph. The goal directed learning automata technique reduces the No. of automata generated. From the figure 4.30, the automata generated are by DLARP are as follows:

1---->2----->3---->4

1---->7---->4

1---->7--→10

Out of the three automata generated, the shortest path from source to destination I,e from node 1 to node 4 is given by route 1--→7--→4 which of cost 10 where as the cost of route 1--→2--→3--→4 is 13 and route 1-→7--→10 is not the correct destination. Hence the DLARP reduces the automata generation instead exploring all possible paths.

### 4.1 Impact of No. of Edges Processed

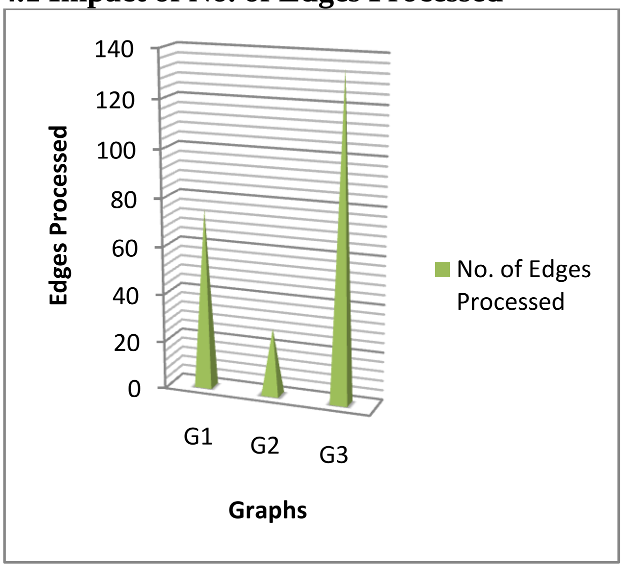


**Fig: 3 Edges processed**

Figure 3 shows the impact of edges processed in three graphs.

### 4.2 Impact of No. of Automata generated

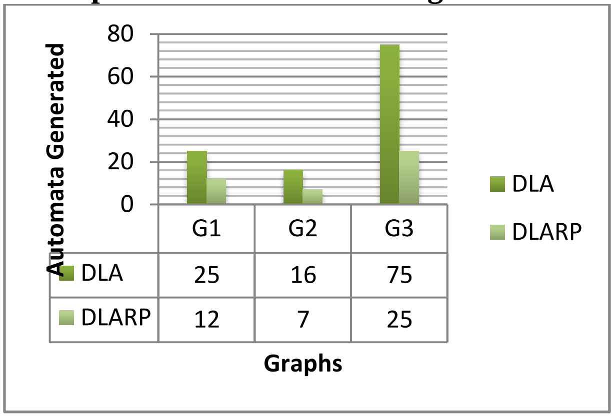


**Fig: 4 No. of Automata Generated**

Figure 4 shows the impact of reduction in automata generated in three graphs.

### 4.3 Impact of No. of nodes Processed

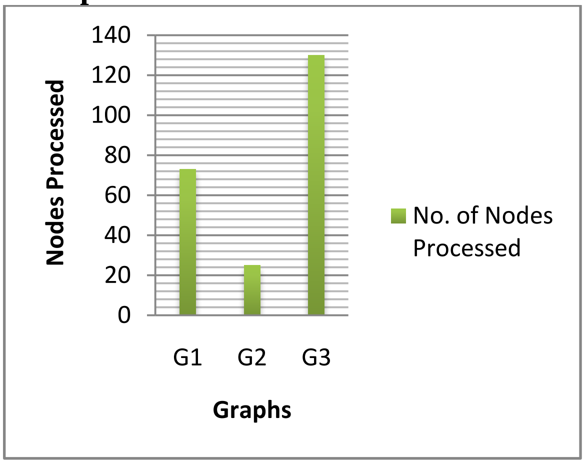


**Fig: 5 Nodes Processed**

Figure 5 shows the impact of nodes processed in all the three graphs.

## 5. CONCLUSION

A new Distributed Learning Automata based route finding algorithm in spatial road networks is developed. The main contribution is that it is a useful attempt to study the spatial and temporal resolutions of DLA in building Intelligent Transportation Systems.

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