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A Generalized Stochastic Petri Net model of route learning for emergency egress situations

S.N. Danial *, F. Khan, B. Veitch

Centre for Risk, Integrity and Safety Engineering (C-RISE), Faculty of Engineering & Applied Science, Memorial University of Newfoundland, St. John's NL, Canada

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ABSTRACT

Route learning is an essential activity for a person visiting a new environment. The element of forgetting a location (called decision point) along a route, where a change in direction is needed, is of immense importance especially during emergency evacuation scenarios. It is this element that has not been given the attention it deserves in developing a route learning algorithm. This work proposes a model of route learning in a new environment based on landmarks using generalized stochastic Petri nets because landmarks based route learning has been observed as a method natural to humans. The model takes information about landmarks along a route and associated navigation commands and then chooses whether to save this information as part of the learned route or not. The selection is made by exploiting stochastic transitions for which the firing rates are dependent on the type of landmark encountered at a decision point. The final output is a route having some decision points missing; resembling the situation that humans encounter after they visit a route in a new environment. The model results closely match empirical results obtained with human subjects.

1. Introduction

Representing human-like intelligent behavior is an active research area in artificial intelligence (AI). Today, technological advances seem to support the idea that some mental modalities may be modeled as AI constructs. Speech recognition on ordinary cell phones, and a recent defeat of Lee Sedol, the world champion of Go[1] by AlphaGo (Lien and Borowiec, 2016) – a computer program – are to mention but a few. This work considers learning as a mental modality and considers only one type, viz., the *route learning* in a new environment, to construct a model based on empirical understanding of the human route learning process. The purpose is to have a model that can be used by a software agent so that the agent can produce human-like behavior, such as forgetting a portion of escape route, in a training simulator for emergency egress.

How people learn routes in a new environment is a classical problem. Route learning falls under a broader subject area of *Environmental Knowing* where people collect different landmarks as cues to build their own mental representation of the environment (Golledge, 1977). This mental representation is often called a cognitive map and it is this representation that a person uses to find routes from one place to another in the environment (Tolman, 1948).

Learning a route becomes of prime importance when one considers emergency evacuation situations. People need training to egress through designated routes in a facility, such as an offshore petroleum platform. In this regard, a high fidelity virtual environment (VE) is considered a suitable training environment compared to traditional classroom type training using video tapes or presentation-based methodology. A serious limitation of VEs is the general unavailability of reasonably intelligent agents to support various training tasks. For example, if a human participant watches an agent performing a typical task, like moving to a muster station in the case of a fire alarm and corresponding public announcement (PA) call for evacuation, it is hard to show the human participant cases where the agent goes astray, because the agent is typically given access to a complete map of the environment and a related path finding algorithm, such as A* (Hart et al., 1968; Buckland, 2004), and so can use this map to perfectly retrieve the desired route information. This enables the agent to always find a correct path for the desired destination instead of making it possible to expose the agent to the dangers of taking a wrong route. One way to get around this problem

* Corresponding author.
E-mail addresses: snd804@mun.ca (S.N. Danial), fikhan@mun.ca (F. Khan), bveitch@mun.ca (B. Veitch).

[1] Go is an ancient Chinese abstract strategy adversarial two player board game that aims to occupy more space on the board than the opponent. Due to shear complexity of the game, the one who is better in intuition, creativity and strategic planning will most likely win.

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is to model remembering and forgetting of landmarks, because it is observed that missing a landmark results in forgetting needed turn along a route to a destination (Beusmans et al., 1995). Although remembering and forgetting can be seen as functions of knowledge retrieval mechanisms, such as similarity matching and frequency biases (Reason, 1990 pp. 13, 97–98, 125–126), they can also be modeled as functions of an information gathering mechanism, where an agent does not remember a landmark due to lack of practice or retention time-out. The behavior of these naïve agents is important in the assessment of difficulties of learning a route due to physical properties of the environment. If given more than one exposure to a route, people tend to adapt to these difficulties because of practice (Kyritsis et al., 2014).

The form of route learning the present work involves is like ant colony optimization (ACO) algorithms (Dorigo and Stutzle, 2004) in the sense that ACOs are inspired by pheromone trails and use the trails as landmarks to guide the search of finding the best route — just as people use landmarks to remember certain moves such as *move left, move right, go straight* along their route. We refer to such moves as *navigation commands* (NC) in this work. This paper presents a Generalized Stochastic Petri Net model of route learning based on remembering landmarks along the route. This means that the model allows storing some landmarks, while at the same time producing the effect of forgetting by not storing some of the landmarks. The GSPN model of route learning is explained by describing parts of the model with the help of algorithms presented in Section 4. However, the main contribution of this study is the GSPN model of route learning.

Section 2 discusses related work and explains different concepts in the human route learning process, along with some artificial intelligence aspects. Section 3 covers topics in the human route-learning process and presents some definitions related to the types of Petri nets used in this work. In Section 4, the proposed model is presented with elements of training and learning. Section 5 describes an experiment whose data are used to test the validity of the model. The model results are compared with the empirical results. The mathematical verification of the model is also presented in this section. Results and future directions are discussed in Section 6.

2. Related work

The subject of *Environmental Knowing* has an important role in situation awareness (Endsley, 1995). Lehtonen et al. (2017) show how learning about an environment increases situation awareness and thereby decreases possible accidents of child bicyclists. Beusmans et al. (1995) determine how a route learning process is involved in one's continues effort to stay aware of the surrounding environment during driving on a road. The authors performed an experiment in a VE where sixteen participants were used as paid volunteers. The participants were given verbal navigation commands, such as take the next left or right, without pinpointing the landmarks and asked to remember the route, which was a 1770 m long complex road map. The authors found that some participants developed the skill of navigating using landmarks and some of them went further as they developed a mental image of the environment. The latter showed less situation awareness between intersections on roads and the former showed situation awareness as their ubiquitous property irrespective of their location on route.

Gale et al. (1990) performed an experiment with children of ages 9–12 to investigate spatial knowledge acquisition. Their general result about the mode of learning supports active exploration through field trips in the real environment. However, the use of video tapes also proved to be fairly effective in terms of representing fundamental components in spatial learning. The authors found that children learned more at intersections where they needed to make decisions about their move, rather than in between the intersections. These intersections are termed decision points. They also suggest that during a route learning task, knowledge about the features of the surroundings starts being stored concurrently as a background process. Another important finding was that successful navigation does not require extensive knowledge about the route, rather route navigation seems to be parsimonious, i.e., the modeling of route learning may be simpler than other types of learning tasks. Plank et al. (2014) used a large immersive VE to investigate human memory about remembering positions of 39 distinct objects in the VE. The experiment started by making the subjects explore the positions on day 1. On day 2, the positions of some of the objects were changed and the subjects needed to recognize that. The subjects correctly identified 87% of times that the objects were moved or not. The authors also suggest that these findings could help understand neurocognitive stages related to an early first-pass allocentric space processing, followed by integration of the objects' locations in the spatial cognitive map. An allocentric spatial representation expresses location of an object in an environment with reference to other objects, provided the environment with all the objects takes an arbitrary orientation that defines left/right and up/down positions (Grush, 2000). On the contrary, the egocentric spatial representation considers the self as the reference point.

Studies of rats show that the brain creates multiple cognitive maps, each representing a different segment of the environment (Derdikman and Moser, 2010). The study (Eilam, 2014) details exploration of an unfamiliar environment using home-base and looping behavior in mice. The author gives a detailed account of the path integration, retracing, and wall-following mechanisms, and describes analogies between humans and other animals in biobehavioral mechanisms. Eilam (2014) also suggests that the three important phases in spatial learning, viz., the path integration phase, the place recognition (or landmark recognition) phase, and the reorientation phase that works while using representations of a surface layout (Wang and Spelke, 2002), may be explained in terms of looping being a way to do path integration, home-base behavior being an expression for place recognition, and wall-following being moving with reference to a surface layout.

The use of AI techniques in matters related to emergency situations is an important area of investigation. Ramchurn et al. (2016) develop a disaster response system called *Human Agent Collectives-Emergency Response* (HAC-ER) system. The HAC-ER serves as a mediator between humans and agents and provides a platform where humans and agents can develop a social relationship to address a number of evolving phenomena in an emergency situation, such changing demands. The authors develop a novel way to team up agents and humans to act more effectively in emergency situations. Sud et al. (2007) propose a multi-agent navigation graph for real-time path planning for a dynamic VE. The agents use this graph as a global data structure to compute, in parallel, the maximal clearance paths without using a separate path planning data structure for individual agents. Kang et al. (2010) deploy a Region of Interest (ROI) in a VE to enable the system to detect abnormal shortest routes selected by different users. The ROI with the highest level is selected and a discretized path graph (DPG) is constructed using the data sampled in the selected ROI. The VE's existing navigation-graph is then integrated with the DPG using Delaunay triangulation. Nonetheless, in real emergencies, several risks related to human factors are in play. This means it is possible that some trained personnel become overwhelmed by mental stress and make mistakes (Reason, 1990). Musharraf et al. (2013) assess human reliability during emergencies on offshore petroleum platforms. They use four major factors that influence stress, which in turn deteriorates human performance. Norazahar et al. (2016) present a method based on Bayesian networks to identify critical human and organizational factors in escape and evacuation systems.

3. Background concepts

3.1. Human route learning process

Route learning is defined as a phenomenon in which a navigator recognizes an origin and a destination location, and identifies route