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Ant-based vehicle congestion avoidance system using vehicular networks

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ABSTRACT

Vehicle traffic congestion leads to air pollution, driver frustration, and costs billions of dollars annually in fuel consumption. Finding a proper solution to vehicle congestion is a considerable challenge due to the dynamic and unpredictable nature of the network topology of vehicular environments, especially in urban areas. Instead of using static algorithms, e.g. Dijkstra and A*, we present a bio-inspired algorithm, food search behavior of ants, which is a promising way of solving traffic congestion in vehicular networks. We have called this the ant-based vehicle congestion avoidance system (AVCAS). AVCAS combines the average travel speed prediction of traffic on roads with map segmentation to reduce congestion as much as possible by finding the least congested shortest paths in order to avoid congestion instead of recovering from it. AVCAS collects real-time traffic data from vehicles and road side units to predict the average travel speed of roads traffic. It utilizes this information to perform an ant-based algorithm on a segmented map resulting in avoidance of congestion. Simulation results conducted on various vehicle densities show that the proposed system outperforms the existing systems in terms of average travel time, which decreased by an average of 11.5%, and average travel speed which increased by an average of 13%. In addition, AVCAS handles accident conditions in a more efficient way and decreases congestion by using alternative paths.

1. Introduction

Over the last decade, vehicle population has dramatically increased all over the world. This large number of vehicles leads to heavy traffic congestion, air pollution, high fuel consumption and consequent economic issues (Narzt et al., 2010). In 2010, the American people faced a lot of difficulties due to vehicle congestion which forced their government to spend 101 billion dollars on the purchase of extra fuel (Schrank et al., 2012). Based on a report by Texas A&M Transportation Institute (Schrank et al., 2012), it is estimated that fuel consumption will rise up to 2.5 billion gallons (from 1.9 billion gallons in 2010) with a cost of 131 billion dollars in 2015. Accordingly, finding effective solutions with reasonable cost for congestion mitigation is one of the major concerns of researchers and industries in recent years. Building new, high-capacity streets and highways can mitigate some of the aforementioned problems. Nevertheless, this solution is very costly, time consuming and in most cases, impossible because of space limitations. On the other hand, optimal usage of the existing roads and streets capacity can lessen the congestion problem in large cities at a lower cost.

Intelligent Transportation System (ITS) (Dimitrakopoulos and Demestichas, 2010) is a newly emerged system which collects real-time data for congestion monitoring using road side units (e.g. video cameras, radio-frequency identification (RFID) readers and induction loops) and vehicles as mobile sensors (i.e. in-vehicle technologies or smart phones). These data are used by car navigation systems (CNSs) to find the shortest path or optimal path from a source to a destination. Previous researches (Noto and Sato, 2000; Yue and Shao, 2007; Nazari et al., 2008) concentrated on using static algorithms (e.g. Dijkstra, 1959) and A* (Hart et al., 1968) to find the shortest path in CNSs. Conversely, current studies primarily focus on finding the optimal paths, considering various criteria by utilizing dynamic and meta-heuristic algorithms (Liu et al., 2007; Salehinejad and Talebi, 2008; Boryczka and Bura, 2013). This trend happens due to the dynamic nature of vehicular environments which depends on both predictable and unpredictable events and also because of the

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multi-criteria nature of CNSs. Multi-criteria means that distance is not the only objective of CNSs and the drivers. Other key factors include congestion, number of traffic lights, number of route lines, accident risk and travel time. Hansen proved that the multi-criteria shortest path problem is an NP-problem since it requires enumerating all the possible routes (Hansen, 1980).

Recently, Google and Microsoft have predicted vehicle congestion and its duration by performing an advanced statistical predictive analysis of traffic information (Pan and Khan, 2012). This traffic information was provided by the existing infrastructures (e.g. Road Side Units) in order to propose a traffic-aware shortest path for users and drivers. Therefore, this information is not only based on the current traffic information but is also based on other metrics such as weather and historical traffic information. It is worth noting that their system is reactive and avoids vehicle congestion implicitly, which is still not enough, due to the non-recurring congestion. These types of congestion include more than 50% of all vehicle congestion (Coifman and Mallika, 2007). Moreover, the same path is suggested to users by this system and similar to static algorithms, congestion will be switched from one route to another if a significant number of drivers utilize this system. Swarm intelligence algorithms are proposed to solve the aforementioned drawbacks.

Swarm intelligence algorithms are newly emerged algorithms which simulate the behavior of different animals in nature such as ants, bees, fish and birds (Merkle and Blum, 2008; Ahmed and Glasgow, 2012; Yang et al., 2013). These algorithms are able to produce fast, multi-criteria, low cost and robust solutions for various problems such as routing, scheduling and assignment (Merkle and Blum, 2008; Panigrahi et al., 2011). Among these heuristic algorithms, the use of ant-based algorithms has been reported as promising and one of the best approaches for congestion control and traffic management in many research projects (Tatomir and Rothkrantz, 2004; Liu et al., 2007; Dhillon and Van Mieghem, 2007). This paper moves one step forward by presenting a multi-objective ant-based vehicle congestion avoidance system (AVCAS) for proactive congestion avoidance based on real-time traffic information. Our main goal in AVCAS includes proposing the shortest path with the least congestion and travel time, as well as higher vehicle speed. Moreover, non-recurring congestion (e.g. accident, working zones, weather conditions) are also implicitly considered and handled in AVCAS. AVCAS periodically computes n shortest paths, where n is the number of alternative paths, based on the average travel speed prediction and vehicle density for various Origin–Destination (OD) pairs instead of computing these paths for each vehicle (i.e. the number of vehicles is much bigger than the number of OD pairs) and re-routes the vehicles through the least congested path based on their destinations. Implicitly, air pollution and fuel consumption are decreased by this system.

The remainder of this paper is organized as follows: an overview of the ant-based algorithm and its various types and applications are presented in Section 2. Section 3 discusses the ant-based algorithm usage in vehicle congestion control systems. AVCAS and its operation are presented in Section 4, while Section 5 includes the simulation results and system evaluation. Finally, Section 6 concludes the paper and suggests the direction for future research.

2. Ant-based algorithms: definition, types, and applications

How do real ants communicate with each other in finding food sources and accumulate food in their nest using the shortest path, considering the fact that they are blind insects? This question has attracted the attention of many researchers and scientists for many years. The answer is that the ants release a chemical liquid, called pheromone, on their traversed paths based on the quality of the food resource found while moving from their nest to the food source and vice versa. This pheromone trail helps other ants to find the food resources by sniffing the pheromone. The pheromone intensity decreases (pheromone evaporation) over time in order to increase the probability of finding new paths. This phenomenon forms the infrastructure of an Ant System (AS) and Ant Colony Optimization (ACO) algorithms proposed by Dorigo et al. (1991, 1999) and Dorigo (1992) to simulate real ant behaviors by using artificial ants.

Most of the characteristics of real ants are mimicked by artificial ants in order to simulate the behavior of an ant colony for the solution of optimization and distributed control problems. The most common characteristics of real and artificial ants are discussed as follows:

- *Pheromone trail based stigmergy communication*: Pheromone trails assist ants to find the shortest path from nest to food source. While stigmergy communication is a self-organizing behavior of ants which is required to interact with each ant (Theraulaz and Bonabeau, 1999). This communication occurs in an indirect manner which means that an ant alters its surrounding environment by laying pheromone on its traversed paths and the other ants respond to this modification at a later time (Bonebeau et al., 1999). Stigmergy can be transferred to artificial ants by assigning numerical information to the problem space variables and by giving the artificial ants local access to these variables (Dorigo et al., 1999).
- *Implicit shortest path finding*: An implicit shortest path finding happens by reinforcement on the shortest path for both real and artificial ants. More pheromone is laid on the shortest paths because they are completed more faster than longer paths (Di Caro, 2004).
- *Concurrent and independent iterations*: The artificial individual ant, similar to the real one, is able to find a path from nest to food, but it is not the only ant that does this task. The other ants do the same task concurrently and independently in order to converge to the optimal path in a short time (Dorigo and Birattari, 2010).
- *Discrete world*: Artificial ants, unlike real ants, live in a discrete world which means that their actions are transitions from one discrete condition to another (Dorigo et al., 1999).
- *Synchronized vs. desynchronized system*: Artificial ants move from their nest to the food source and vice versa in each iteration. Therefore, they move in a synchronized way unlike real ants which move in a desynchronized pattern (Blum, 2005).
- *Memory*: The artificial ant utilizes an embedded memory to store the traversed path information. It is used for building and evaluating possible solutions, for backtracking from destination to source and for updating the pheromone value on the found path. In comparison, real ants do not have memory but use their sensing capability for this purpose.
- *Pheromone evaporation strategy*: Pheromone evaporation happens very slowly in nature and its rate is constant (Deneubourg et al., 1990). This mechanism and its evaporation rate vary from one problem to another in the simulation environment for artificial ants.
- *Extra capabilities*: Artificial ants use extra capabilities to increase the efficiency of the whole system that can be augmented with capabilities such as future prediction, local optimization, and backtracking, while these capabilities cannot be found in real ants.

2.1. Ant colony optimization (ACO)

In this section, we describe the procedure of ACO algorithm. Even though many changes have been applied to the ACO