Propagation prediction in urban road network during accident

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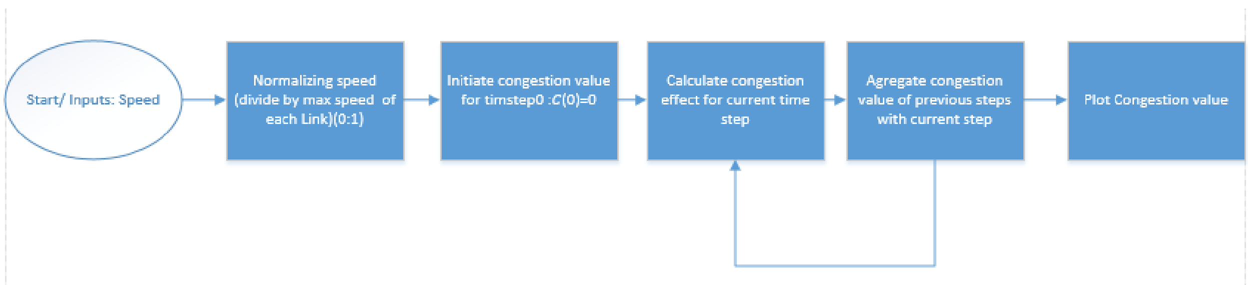
Transportation systems are literally the road map to our community. Roads move us from where we are to where we are going; connecting us to our institutions, our families, our lives. Yet, everyday traffic collisions and the resulting congestion result in lost lives, severe injuries, lost productivity, air pollution and wasted energy. Motor vehicle crashes cost Canada alone almost $20.62 billion in 2010 (Canada Department of Transportation, 2011). In an urban network, in the event of a collision, a bottleneck starts forming from the affected road segment and propagates to adjacent roads segments; possibly blocking intersections and forming gridlocks. The impact of a collision is thus not limited to only the upstream and downstream road segments, its impact rather disperse forming an impact area in the vicinity of the link subject to the incident. Predicting propagation of such congestion patterns provides the tools to proactively alleviate its impact with a real-time remedial traffic response.

The majority of collision-related literature focused on incident detection. Several studies in the literature have employed deep learning techniques such as Convolution neural networks (CNN), autoencoders & long short-term memory networks (LSTM) to solve anomaly detection problems ([1], [2], and [3]). Other studies have focused on estimating the spatiotemporal impact of collisions on freeways, focusing only on the impact of congestion on the upstream links along the same corridor [4]. While, several papers in the literature predicted congestion propagation resulting from recurrent congestion at the network, to the best of our knowledge, no research examined the problem of congestion propagation during a collision at the network level. This paper develops different algorithms to understand and predict traffic propagation patterns forming as the result of a collision. The analysis capitalizes on observed traffic time and reported collisions data as well as weather information. Deep learning techniques are used to capture the complex traffic dynamics of congestion during collisions. Incidents are first detected when the observed traffic data in real-time behaves significantly different from its historical traffic patterns. Then, congestion propagation patterns are predicted at the network level to identify the impact area and quantify the resulting congestion effects.

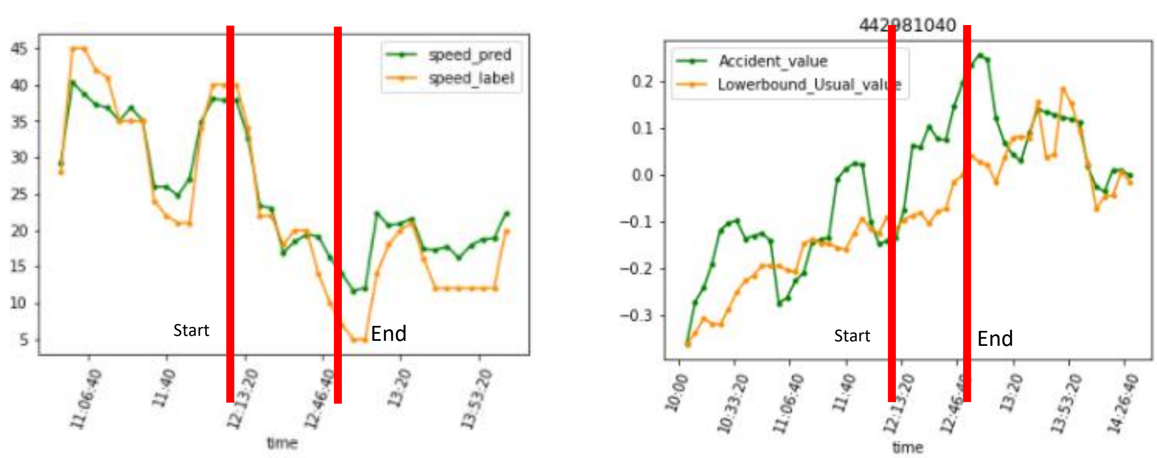
The contributions of this study are three folds. First, the congestion propagation pastern is predicted not only for road segments along the same corridor as the link subject to the incident but also on other links in the vicinity of the target link; thereby identifying an impact area. Second, in contrast to the common binary approach in the literature (congested/not congested), we quantify the severity level of congestion patterns, which enables us to what extend different links are affected by the collision. This is done by detecting the start time of collision, identifying the effect of collision, and identifying the time when different road segments recover from the incident. Third, the proposed framework is formulated in a more generic fashion that make it applicable to predict the congestion propagation not only on freeways but on other types of roads.

Our methodology is divided into two parts. In the first part, the combination of two deep learning methods is employed to predict future speed for all roads in the impact area. Then, a congestion identification algorithm is conducted to represent different phases of congestion. In the first part of methodology, we develop a graph of roads around the road segment subject to collision. Speed data of these roads is extracted by intervals of 5 min from INRIX datasets. The graph adjacency matrix and the speed information for each timestep are sent to the GCN (Graph Convolution Neural Network). Outputs of this layer are entered into the Long short-term memory (LSTM) layer. In addition, accident type, weather condition, and day of the week are joined the LSTM result as new features to make forecasting more interpretable. While the GCN layer captures the hidden spatial interaction of speeds among roads, the LSTM layer discovers the temporal pattern of speeds in consecutive time steps.

In the second part, the predicted speeds from phase one are passed to the congestion detection algorithm in order to forecast the future status of congestion patterns and quantify congestion level using a new variable that we call congestion value. This recursive algorithm employs previous congestion value and both current normalized speed value and its deviation in two consecutive time steps to update the current congestion value. By using normalized speed values, congestion value can be standardized among all roads of networks which makes it possible to find which road gets affected more severely in comparison to other roads by the collision. This algorithm depicts the trend of congestion (i.e. bottleneck formation or dissipation) ; thereby detecting the time when the congestion propagation starts, is at the maximum level, and is totally resolved. The congestion algorithm also incorporates an idea from Hypothesis testing in order to distinguish between non-recurrent-congestion and recurrent-congestion which makes the model capable of identifying accident congestion effect in arterials. Therefore, in each time step, our model forecasts both speed and congestion patterns for all roads in the collision impact area of the network.



Our results indicate that our model is able to predict which roads are affected by the collision and when and how much it will. In the other words, our model can fully map the congestion propagation in the network. The results of this analysis portray that, in the first phase, the Mean Absolute Error (MAE) for the speed prediction is only 3.37 and the standard deviation of the error is 0.20. In the second phase, our model completely captures the congestion trend and detects the start-time, congestion duration, and recovery time. In addition, the model was shown to be successful in distinguishing the recurrent congestion from non-recurrent congestion for each road. This model was implemented in the downtown Calgary as a case study and two phases results are shown in Fig. 1.



(a) (b)

Fig. 1. (a) prediction vs label speed is shown during accident for one specific road during accident. (b) Non recurrent (during accident) congestion value with green line and non-recurrent congestion value with yellow line are shown. In both cases, reported start time and end time of the accident is shown with red vertical line.

Moreover, the congestion detection algorithm shows the intensity of the impact of the collision on each road in the impacted area. This information not only is helpful for real-time response to manage traffic congestion but also provides maximum effectiveness for the emergency system in responding to an collision and reducing response time. The output of this research can thus be used to also provide improved proactive real time traffic information for navigation systems.

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