Comprehensive Overview of V2X Communication Prediction Methods for Cooperative Vehicular Maneuver Coordination

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Abstract—This paper gives a brief overview of the current state of Quality-of-Service (QoS) prediction concepts in the evolving V2X technologies. Firstly, the relevant metrics for intelligent transportation systems are identified for which a prediction proves to be useful. The considered technologies include C-V2X with its key interfaces Uu for cellular communication and PC5 for direct communication between UEs as well as 802.11p.

For these technologies available and considered concepts are presented and a comparison is being drawn.

I. Introduction

In recent years, proactive communication between vehicles became a more prevalent matter of research. Today many manufacturers try to implement new technology into their vehicles, aiming at improved security and comfort for the passengers. The needed communication infrastructure is developing fast, with several technologies available to choose from depending on the use case.

One important use case of this new technology is the cooperative maneuver coordination, as this cooperation between vehicles enables an even higher degree of automation, leading to more efficient traffic and safety in complex driving situations.

Independently from the deployment, as a centralized or decentralized approach, this high level of cooperation has strict performance requirements of the communication links. Yet there is no guarantee if these requirements will be satisfied at all times due to poor network coverage or propagation conditions.

As a priori knowledge of the communication quality may serve to adjust and enhance the level of cooperation, this study performs a research in currently available communication prediction methods and evaluates these approaches in terms of their applicability to the use case of autonomous cooperative maneuver coordination.

The paper is structured as follows: First, it will give an overview of related works. Following that, Sect. 3 will introduce the concept of cooperative maneuver cooperation and analyze its requirements on communication. In Sect. 4 current research of prediction methods is being explored. The following discussion will evaluate the existing methods in terms of their applicability on cooperative maneuver coordination and lay the foundation for the conclusion.

II. Related Works

As this work tries to give a comprehensive overview of prediction methods with a given set of constraints, other works providing overviews of methods or constraits must not be neglected. These can be grouped into different categories based on the research topics they portray.

A. Network Basics

Existing studies give a great overview of the challenges faced in vehicular communication. While Mecklenbräuer et al, 2011 gives an overview the available technologies, its focus lies in the depiction of the communication channels, the various scenarios (V2V, V2I, cellular), the metrics (e.g. fading, path loss and doppler shift) as well as the models (e.g. raytracing or stochastic models) for their simulation.

For the estimation of the communication channel, traditionally pilot symbols are being used, which contain no data, but by which the receiver is able to estimate and equalize received data. This estimation is the key element in achieving low bit error rates (BER) but not trivial.

Existing pilot patterns such as the one from 802.11p were not designed for highly mobile networks, thus leading to decreased performance in these scenarios. Some of our the reviewed methods try to take the prediction as an advantage for channel estimation, as such it is crucial to understand and distinct these terms.

B. Communication Prediction

As by now, efforts in the standardization of vehicular communication prediction are undertaken, the 5GAA summarized the key concept of QoS prediction and its use cases and challenges. Notably, the whitepaper identifies possible deployment methods, namely Over-The-Top and Mobile Network Operator prediction, as well as

III. Cooperative Maneuver Coordination

Cooperative Maneuver Coordination is the aim of making automated vehicles influence the each others behaviour and enabling joint driving maneuvers, making road traffic safer and more efficient. The concept consists of multiple use cases, among others [1]:

- lane changing

- platooning
- cacc (cooperative adaptive cruise control)
- intersection control
- collision avoidance

Hereby different approaches exist, either as centralized [2] or decentralized cooperation [3, 4].

In a centralized cooperation, a central entity such as a RSU, gains global knowledge by the usage of its own sensor data and direct communication with the vehicles in its coordination range and thereby plans optimal maneuvers in terms of efficiency and safety.

The decentralized approach does not rely on a central entity, but rather leaves the planning to the vehicles, which adapt their maneuvers based on maneuver intentions shared by surrounding vehicles in order to achieve locally optimal traffic patterns.

Without going too much into the details of implementation methods for the coordination, we rather want to take a look at the aspect of communication. Several works investigated the requirements for the communication links. Typical KPIs (Key Performance Indicators) are end-to-end latency, reliability, data rate (per vehicle) and the communication range.

Boban et al. [1] suggest a latency of sub 3 to 100 ms, a required data rate of 1.3 to 25 MB/s, depending on the degree of sensor data dissemination, and a transmission reliability of over 99%.

As stated in [3], the number of exchange messages and their contained amount of data need to adapt dynamically in order to prevent channel congestion, as it is apparent that the aforementioned link requirements cannot be met at all times. Furthermore vehicles need to interact with their environment even without these cooperation messages.

The aim of this work is to evaluate existing communication prediction methods in terms of their applicability on the cooperative maneuver coordination. Therefore we first need to identify possible prediction scenarios and use cases.

If we take the use case of intersection control and collision avoidance for example, it is clear, that vehicles are approaching each other from different directions and the requirements on the reliability on the communication between these vehicles are of a higher priority than the communication with other vehicles of the area. While a global prediction is attractive, the close-to-mid range prediction is far more relevant in such use cases.

The most interesting parameters are the reliability, e.g. measured in packet loss, and latency, as they decide whether the communication is stable enough in order to be used for cooperation. Otherwise the predictions can be used to initiate safety measures such as increased distancing against the desire for perfect efficiency.

IV. Scope of the Paper

While there are many channel quality prediction approaches, not all are appropriate for our use case.

This paper lays its focus on higher level V2X communication prediction, hence methods aimed at replacing traditional pilot-based channel estimation will not be covered.

While these methods may use similar prediction models (e.g. autoregression and machine learning), their prediction horizon spans only several milliseconds, which enables adaptive transmission techniques such as adaptive modulation, channel coding or power control, but is conceptually inappropriate for the intended use case of adaptive coordination behaviour based on future connectivity.

For further research in this area of research please refer to [5–9].

V. Methods

This section covers the research projects of prediction methods, categorized by their used prediction models.

Of course these methods differ in many more aspects from each other, e.g. intended use case, target techology, time/distance horizon, KPIs, etc..

A. Connectivity Map Based Methods

We start off the examination of works with so-called connectivity maps as they present the most simple concept for prediction of future connectivity. Mobile nodes such as vehicles share their experienced network quality with a central back end using their data channels, which in turns aggregates all the received data in a map.

This concept differs from the related network coverage maps, which use mathematical models in order to determine network coverage and quality at a given place. The data aggregated for the connectivity map differs, as well as the processing that is performed when determining the network quality on a given location.

Kelch et al. [10] examine this concept in the vehicular application, focusing on the acquisition and matching of data, which includes CQI values queried for generated TCP/IP traffic on their cellular modem, as well as the coordinated gathered by a GPS module. In order to make good predictions for map segments, they examine a map segmentation method called Jump-P [], which outperforms simple fixed length segmentation in terms of the trade-off between the number of needed map segments and the RMSE of the pooled data. The CQI values shared to the sender determine the block size, as better channel conditions allow for a more optimized data transmission, thus enabling an estimation of the theoretical throughput for a given CQI value.

Summarizing, this method enables a prediction of the theoretical throughput by previously collected CQI values. Only a small range of CQI values lead to tolerably accurate predictions, as values below 20 rarely appeared and values above 25 were exceedingly inaccurate.

A similar approach is performed by Pögel et al. [11], but in contrast they are collecting different data in the form of RSSI (which is part of CQI) as well as used cells, actual bandwidth and latency at a given location. This leads to a more accurate prediction, but as the authors show, the accuracy is highly dependant on external factors such as average speeds, congestion and weather as they show in their tests performed on different weekdays. As the map simply delivers collected data, it is not self-adjusting to these external factors.

The only comparable measurement of connectivity maps is performed by Schmid et al. [12] predicting the Round Trip Time (RTT) in addition to the throughput. Laying their focus on the segmentation of such a connectivity map, their results showed that even for an optimal manual segmentation, the RMSRE between the measured and predicted values is at least 39.12% which leads them to conduct history based algorithms in order to predict future throughput.

All these methods have in common, that they only predict cellular communication quality.

B. Machine Learning

Machine Learning algorithms gained popularity with the first implementations conducted for communication prediction conducted in 2016.

The aim is to train neural networks to

Most works using Machine Learning algorithms focus on the prediction of various KPIs, most commonly the throughput, in cellular networks such as LTE or 5G.

The prediction methods further differ in their type of probing, either active or passive. In the active probing, the prediction algorithms requires an active transmission in order to predict the desired KPI, while for the passive approach available quality indicators are used like RSRP or RSRQ.

One of the earlier works for KPI prediction using Machine Learning algorithms was conducted by Xu et al. [13] using up to 20 seconds of historic data, such as throughput, packet loss or one-way delay, in a Regression Tree model without preceding offline training in order to predict the respective values for a time horizon of up to 20 seconds.

Tests were performed in 3G networks using mostly UDP traffic, as TCP has built-in congestion control and retransmission, influencing the measurements. As mobile nodes were not focus of the study, features such as velocity or location were not considered, making the work less applicable for V2X scenarios, but enabled following research using similar approaches.

Torres et al. [14] lay their focus on the readiness of MNOs to support V2X applications, including cooperative automated driving. Their prediction focused on end-to-end delay thresholds as an important factor for the required QoS. They selected the most important features, namely the average historic E2E delay, velocity, SINR, RSRP and RSSI, using the Maximum Dependancy algorithm in order to train a CNN. In a comparison against other Machine Learning algorithms such as Support Vector Regression, Random Forest or LSTM-RNN, only the latter achieved slightly better results but at a high computational cost.

Tested on real world data, the algorithm yields a false positive rate of about 15% resp. 39% for being within/beyond a 50 ms E2E delay, which can be balanced out to yield about 26% for both by adjusting the used data, however the overall prediction performance does not improve. The prediction horizon is not given.

Schmid et al. [15, 16] as well as Jomrich et al. [17] try to predict future throughput, both suggesting the usage of Random Forest algorithms but using different sets of features. While Schmid et al. include the usage of past throughput, making it an active approach, as well as OSM data for average number of buildings and the respective minimu heights, Jomrich et al. are performing a passive approach solely relying on network quality indicators and vehicle speed.

In order to overcome this influential feature and achieve good results they implement localized training for each cell, achieving much better prediction results, but making the prediction highly location dependant.

Other noteworthy works of throughput prediction are conducted in [18–21] upon which the aforementioned works are based, trying to improve these studies by extending the feature sets, improving the data collection or comparing the results to different ML algorithms.

C. Unsorted

Zeng et al. [] propose the usage of AR model-based prediction specifically for usage in V2X scenarios, enabling improved centralized scheduling compared to centralized scheduling techniques relying on collected real-time CSI. Their solutions is a channel prediction and scheduling scheme using RSUs and Control Servers which receive data for prediction of the best relay candidate of the connected vehicles. The prediction is achieved using current velocity and position which yields the respective distances between the nodes. Using a predetermined LS fading model, a value for the LS fading can be predicted and used in a computation of the SNR. Using that value, a centralized scheduling scheme is applied based on the best candidate. While this technique reduces the transmission overhead and delay and opens the doors for further use cases of the predictions, the simulations were performed using a static path loss model which doesn't account for parameters such as refraction or scattering.

VI. Conclusion

The conclusion goes here.

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