Design of Cooperative Vehicle Safety Systems Based on Tight Coupling of Communication, Computing and Physical Vehicle Dynamics

Yaser P. Fallah
Institute of Transportation Studies, University of California at Berkeley
CA, USA

ChingLing Huang
Institute of Transportation Studies, University of California at Berkeley,
CA, USA

Raja Sengupta
Institute of Transportation Studies, CEE-Systems University of California at Berkeley, CA, USA

Hariharan Krishnan
Electrical and Controls Integration Lab, General Motors R&D Center,
Warren, MI, USA

ABSTRACT

One of the main characteristics of a Cyber Physical System (CPS) is the tight coupling of the computing and communications aspects of the system with its physical dynamics. In this paper, we examine this characteristic for a cooperative vehicle safety (CVS) system, and identify how the design and operation of such CPSs should consider this tight coupling. In CVS systems, vehicles broadcast their physical state information over a shared wireless network to allow their neighbors to track them and predict possible collisions. The physical dynamics of vehicle movement and the required accuracy from tracking process dictate certain load on the network. The network performance is directly affected by the amount of offered load, and in turn directly affects the tracking process and its required load. The tight mutual dependence of physical dynamics of vehicle (physical component), estimation/tracking process and communication process (cyber components) require a new look at how such systems are designed and operated. We consider these factors and propose methods to simplify the design procedure for such tightly coupled systems. The method includes modeling the subcomponent of the CPS and devising interaction and control algorithms to operate them. The proposed methods are compared with methods based on separate design of components that deal with physical and cyber aspects. Through simulation experiments we show significant gains in performance when CPS design considerations are respected.

Categories and Subject Descriptors

C.2.4 [**Computer-Communication Networks**] Distributed Systems - *distributed applications*

Keywords

Cyber Physical Systems, Cooperative Vehicle Safety, Estimation, Vehicular adhoc network, DSRC.

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1. INTRODUCTION

Embedded wireless devices are the main components of evolving cooperative active safety systems for vehicles. These systems, which rely on communication between vehicles, deliver warning messages to drivers and may even directly take control of the vehicle to perform evasive maneuvers. The cyber aspects of such applications, including communication of safety messages and detection of threats are tightly coupled with physical dynamics of vehicles and drivers' behavior. Recent research on such cooperative vehicle safety (CVS) systems has shown that significant performance improvement is possible by coupling the design of the components of the systems that are related to vehicle dynamics with the cyber components that are responsible for tracking other cars and detecting threats [11][15][16].

In this paper we describe the design of such safety systems from a cyber physical system (CPS) standpoint, and provide a new view into how interaction between different components of a CPS can be modeled and used in designing different components of the CPS of interest. Traditional methods of building such cooperative safety systems relied on separate design of the cyber and physical components. Even in the design of cyber components, there is a tendency towards separation of concerns, thus designs, of different elements of computation and communication. Such separation is indeed one of the reasons behind successful and quick development of many technologies and solutions; nevertheless, the success of such designs is quickly overturned if resources are limited to a level that tight coupling between cyber and physical components and sub-components leads to significant performance degradation. To elaborate on this issue we examine the case of CVS in more details in this paper.

In the next section we review the recent developments and activities with regards to CPS design and operation, and more specifically discuss the design of cooperative vehicle safety systems. In section III, the design of the CVS system is elaborated from a CPS standpoint. In sections IV, the sample designs are evaluated using OPNET and SHIFT simulations. Section V concludes the paper and outlines our view on future CPS research relevant to cooperative vehicle safety systems.

2. EXISTING KNOWLEDGE

Cyber physical systems have existed for a long time; however, their scale, complexity and pervasiveness have been very limited due to the limitations of technology (e.g., sensing, computing and communication technologies). With the recent leap in design of networked computing systems such as wireless sensor actuator networks, CPS is becoming a new reality of a different size and scale. As a result, existing ad hoc methods of developing CPS's are not adequate anymore. Some of the general challenges and research directions in CPS design and operation have recently been described in papers such as [1] and [2].

Similar to other evolving CPSs, cooperative vehicle safety systems have also been in development for few years. The current designs either do a separate design of the components that deal with physical and cyber aspects [8], or follow an informal or ad-hoc method of integrating physical and cyber aspect of the system [16]. In this paper we re-examine the design issues and present a new look at how CPS concepts should be followed when such integration is being done.

Traditional implementations of systems that include interaction with physical world follow the computational model design for implementing the computing and communication modules, while relying, separately, on analytical models for the physical processes [1]. In our approach, we bring in the effect of physical processes in the models that characterize the behavior of the communication and computing parts. This method allows a range of new designs that consider both cyber and physical aspects of a CVS system. Nevertheless, this method is only one of the choices for integrating all components in one design process, and a more general method for integrating the cyber and physical aspects through a common description framework is still highly desirable and not available yet.

In fact, the science of modeling and designing computing or communication based systems already exists, but describing a CPS in a single framework that streamlines design optimization and verification is still an open problem. For example, for CVS systems, abstract level models exist that describe the control of dynamical systems over multi-access channels [3]; also behavior of networks that these systems work on has been asymptotically studied (e.g., partly in [14]). However, efficient design and operation of CVS systems is not possible using the developed models, and a description framework or model that is closer to physical realities is still required. In particular, the exact behavior of the vehicular ad-hoc network (VANET) used in CVS, the effect of network performance on tracking process, and the effect of physical vehicle dynamics and the estimation process on the performance of the network are not captured by the existing models.

The models that need to be developed and integrated for CVS must include communication/networking and control models, as well as models describing physical processes, in one framework. In the context of CPS, an early work, [12], studies issues of network control in CPS and presents a feedback based scheduling scheme. This paper deals with the question of how QoS in networks that form the backbone of CPS should be managed. In our paper, we deal with how physical processes affect the way network should be controlled with the purpose of serving the cooperative safety systems. QoS in our case is not defined traditionally; rather an application level statistical metric is used to ensure that the performance of the CPS is adequate.

The work in [4] considers a more abstract view of a CPS, and studies co-design of scheduling and control schemes used in a CPS under power constraints. The paper presents a control theory perspective on a class of CPS applications that can be modeled as control of multiple inverted pandulums. The scope of the paper, however, is restricted to the interaction of scheduling and control algorithms, and a characterization of the communication component or programming frameworks are not included.

In general, due to the very wide spectrum of issues that naturally rise in CPS design, no work, including our current work, can portray a complete picture; a comprehensive solution for CPS design and operation can only be derived through collection of several solutions addressing different, sometimes orthogonal, issues. A unifying framework for such CPS modeling and system design theory is thus highly desirable. The research community is still not at a stage to present such a framework; nevertheless, CPSs are being analyzed from different perspective in order to derive their properties and eventually converge the models under one unifying theory.

In an effort to better understand CVS systems, which are a class of medium scale CPSs, we briefly review the particular features of CVS in the next subsections.

2.1 Existing Knowledge on Cooperative Vehicle Safety

The types of possible actions and warnings in vehicle safety systems range from low-latency collision avoidance or warning systems (active safety systems) [8] to moderate-latency systems (situational awareness) that provide heads up information about possible dangers in the non immediate path of the vehicle [9][10]. The main differences of these systems are the sources and means of information dissemination and acquisition.

In active safety systems, vehicles are required to be continuously aware of their neighborhood of few hundred meters and monitor possible threats. This task may be achieved by frequent real time communication between vehicles over dedicated short range communication (DSRC) channels [6] (see Figure 1). In addition to inter-vehicle communication, roadside devices may also assist vehicles in learning about their environment by delivering traffic signal or pedestrian related information at intersections. The main requirement of these active safety systems is the possibility of delivering real-time acquired information to and between vehicles at latencies of lower than few hundred milliseconds [8][13]. Prototypes of such systems are being developed by many automotive manufacturers.

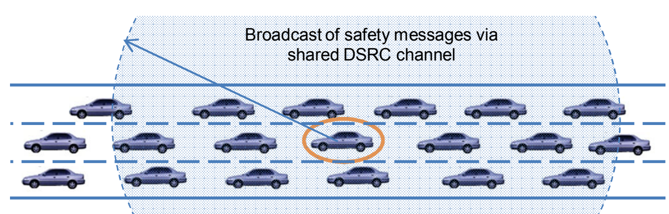

Figure 1 V2V CVS Communications

On the other hand, in situational awareness safety applications, a vehicle is presented with information about possible hazards at locations that may be 30-60 seconds ahead of the vehicle. For example, in areas where road curve prevents visibility of the end of a traffic queue, these soft safety messages can be delivered to drivers at the distance of a kilometer and warn them to slow down to avoid suddenly running into the end of a queue. An example of such a system is the networked traveler warning system developed at UC Berkeley [9][10]. In this system, vehicles communicate with a central server over 3G cellular networks to acquire road information (Figure 2). The central server gathers information from a sensor network of approximately 600 roadside sensors and fuses that with data from other traffic feeds (such as traffic.com) to produce traffic information and warning messages for vehicles. Since current 3G communication technologies cannot guarantee low latencies (few hundred milliseconds) and the roadside sensors we use are only updated at tens of seconds intervals, the overall system works at a latency beyond that of the active safety systems and is categorized as a situational awareness safety system. In fact, the physical requirements of active safety for vehicles requires very low latencies which are not provided by the cyber part in the case of the NT warning system. Improvements to this system requires significant improvement to the cyber part, which may force a design based on DSRC as described in the first example.

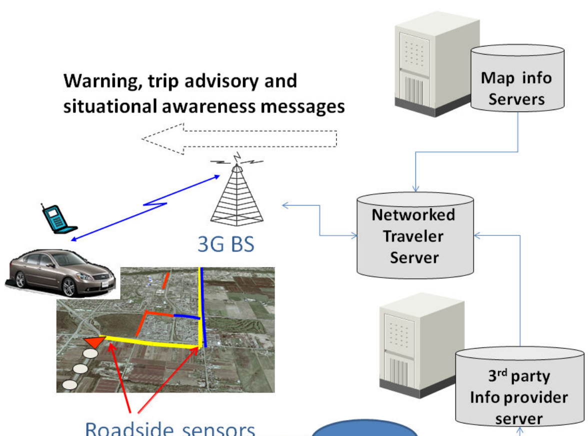

Figure 2 Network Traveler soft safety warning system

In DSRC based safety systems, the cyber components are selected so that they meet the requirements of active safety. Nevertheless, the existing designs fall short of supporting a full-fledged CVS in which a large number of vehicles communicate and cooperate with each other. The main reason behind the issues with the current designs is the level of separation in the design of different components. Later in this paper we describe methods to achieve better performance by further cooperation of the physical and cyber sub-components. In the next subsection we describe existing active safety CVS systems and their designs.

2.2 DSRC based Cooperative Vehicle Safety Systems

DSRC based CVS systems are designed to work by having each vehicle broadcast a set of safety messages in its neighborhood. The DSRC channel set aside for this purpose is a single 10Mhz channel, which is available for safety messages at pre-assigned times (according to IEEE 1609 standard [7]). CVS systems use two types of safety messages: 1) even driven emergency messages, 2) frequent vehicle tracking and collision avoidance messages. Event driven messages are only sent if a sudden change of state happens for a vehicle, for example as a result of a hard braking, or a crash. These messages are high priority, but are a small fraction of the messages that need to be sent.

Periodic vehicle tracking messages make up the bulk of safety messages that are transmitted over the shared DSRC channel in a vehicle's neighborhood. These messages are designed to include vehicle location and speed information, amongst other possible measures. Vehicles that receive these messages will parse them and form a map of their neighborhood to track their neighboring cars; the embedded CVS system in each car continuously analyzes the neighboring cars positions and predicts possible collisions. If an imminent threat is detected the driver is warned. Such collision warning messages are only useful if they are delivered within a few hundred milliseconds. Therefore, the objective of vehicle tracking is to accurately track neighboring vehicles in real-time.

The main issue with the current designs is that the DSRC channel may become quickly saturated and the performance significantly reduced if the network is highly crowded (e.g. in a congested highway). This situation makes accurate real-time tracking difficult with current designs. To understand where the problem is originated and how to redesign the system to combat this issue, we examine how components of a CVS system are put together and what are the possible avenues of improvement. The general architecture of an in-vehicle CVS system is depicted in Figure 3.

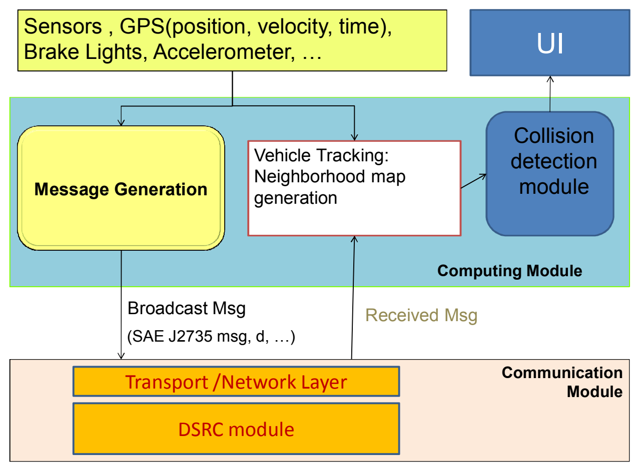

Figure 3 CVS in-vehicle system architecture

In this architecture, a communication subcomponent is responsible for sending and receiving safety messages, a computing subcomponent is responsible for tracking neighboring vehicles (estimation process), generating safety messages and managing communication time (Transmission Control Logic) and issuing warning indicators to the user-interface subcomponent (collision detection module). Traditional designs would follow a separate design process for each subcomponent. However, it turns out that in the case of CVS, acceptable performance requires that the design of computing subcomponent be tied to the design of the communication module.

The traditional design of the CVS system, based on the structure depicted in Figure 3, is a straightforward design following the recommendations of an early report by vehicle safety communication consortium (VSCC) [8]. According to this report, it is suggested that vehicles should transmit tracking messages every 100ms, to a distance of at least 150m (avg. 250m). Therefore, the message generation module in Figure 3 becomes a periodic process that outputs a sample of the current state of the vehicle in a message every 100msec. The DSRC radio power is set to reach the suggested distance.

Given the issues of the above design in crowded networks, several enhancements have recently been proposed to improve the performance of CVS systems beyond the early solutions set forth by VSCC [8].

One such method is the work in [22] that proposes to fairly allocate transmission power across all cars in a max-min fashion; this method helps reduce the load at every point of a formulated 1-D highway and thus reserves bandwidth for emergency messages with higher priorities. This method assumes a predefined maximum load as the target. In another work, [23], a message dispatcher is proposed to reduce required data rate by removing duplicate elements, here, the idea is that many applications require the same data elements from other vehicles. The message dispatcher at the sender side will group data elements from application layer (i.e., the source) and decides how frequently each data element should be broadcast.

The above methods focus on the computing module, as defined in this section, and try to improve its performance through observing the behavior of the application [22], or by incorporating limited physical process information in the design of the computing module. While the above improvements do enhance the performance of CVS systems, these designs do not consider the mutual effects of computation, communication and physical processes on each other. In this article we try to identify such mutual effects and propose a design that uses the knowledge of the tight coupling of cyber and physical processes to the benefit of a CVS system. Our proposed method and the rationale behind our design, depicted in Figure 4, are described next.

3. CPS DESIGN: TIGHTLY COUPLED CVS SYSTEM ARCHITECTURE

Our design attempts to resolve the issues of the traditional design by considering the mutual effects of communication, computation and physical processes. The first step is to consider the physical processes which are being estimated in the computing module. If we consider the state of the vehicle (location, speed) to be the physical process which is being estimated, in the traditional design the solution is to sample this state and broadcast it at 100msec intervals. However, it has been shown in [11] that this process which follows the physical laws of vehicle dynamics can be more efficiently estimated using a model-based estimator. The model used in the estimation can be a constant speed model, which assumes vehicle's speed remains constant between sampling times. Thus, as depicted in Figure 4, each CVS device should contain a bank of estimators for the cars it is tracking. To prevent the model's estimate from drifting away and reporting wrong positions, the sender of the information will also run a local estimator of its own position using the same model that is used at remote estimators. The results from the self position estimator is constantly compared with the actual position of the vehicle and if the error is found to be large, the transmission logic (see Figure 4) will generate a new message and broadcast it to other cars. The new message corrects the estimated position at the other cars.

While the above design has been shown to provide significant improvements [11], it only considers the physical dynamics of a vehicle. In cases where packet loss in the network is too high, the performance of the above method may degrade quickly [15]. To deal with such issues and to further improve the performance of the CVS system, the interaction of computing and communication components, under the model based estimation process, should also be considered in the design. In particular, it is shown that in crowded networks, packet loss ratios and delays in the network are high due to congestion in the network. Resolving this issue requires a joint design that considers characteristics of all elements of the design. We next describe these characteristics and then lay out a design and operation (control) process for the cyber physical system that enables CVS.

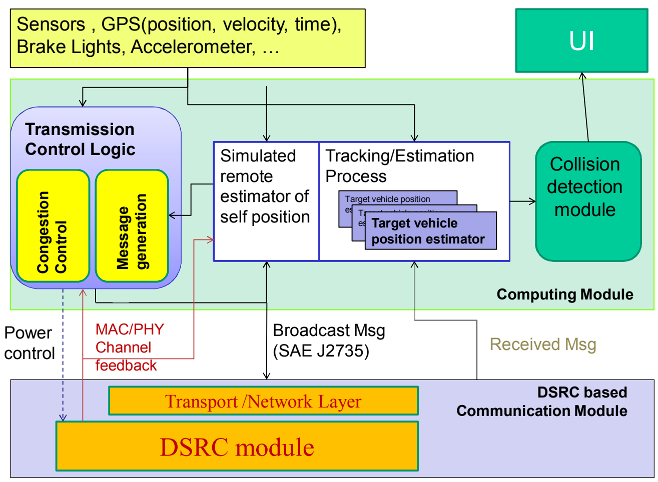

Figure 4 Enhanced CVS system architecture

3.1 CPS Component Modeling: Effect of Computation/ Physical Processes on Communication

To see how computing component should interact with the communication component, we examine how the controllable settings and operation of the computing module and the characteristics of the physical process affect the performance of the communications module; then, using this knowledge we will design the computing processes and the controllers for the communication module. The design in Figure 4 includes a transmission control logic unit that controls some parameters in the communications module, allowing for optimal overall performance of the CVS system.

We note that the service requested from the communication process is the transmission of packets; what is controllable is the time or frequency of packets (sent at rate R packets/sec) and their length (L bytes), as well as the power and some MAC layer settings of the DSRC radio (such as contention window size). In the CVS application, the size and format of packets and the channels over which packets (messages) are sent are predetermined according to the safety standards (e.g., [7]); therefore the controllable parameters are restricted to the rate of packet transmission and DSRC settings such as power level. Thus, modeling the behavior of the communication service requires identifying the relationship between these controllable parameters and a measurable performance metric.

As a performance metric we can use the broadcast throughput achieved by each vehicle in the neighborhood. We show in the next sections how this metric relates to the overall objective of the system in tracking other cars. The broadcast throughput, also called information dissemination rate (IDR), measures how many packets of a sender are received by the receivers in its locality per second. Clearly, in a network with infinite capacity, the higher the rate or power of transmission are, the higher the broadcast rate will be. However, this statement does not hold for a real vehicular ad-hoc network which has limited capacity and is accessed in a collision prone manner.

We have studied the effect of controllable parameters on broadcast throughput of a DSRC based VANET through simulation experiments. For this purpose we simulated the VANET behavior under heavy hidden node interference, which is typical of VANETs. We considered a highway with different traffic densities, rates and ranges of message transmission. The simulated network was a close implementation of the MAC layer of the 802.11 standard (DSRC), which is the standard used for inter-vehicle communications. The PHY layer issues are later included in our final simulations, and were excluded in this experiment. Here, we restrict our experiment to MAC issues and limit the PHY to a simple path loss model, in order to understand the effect of parameters on the network performance. The radio bitrate in this experiment was set to 3Mbps, and packets were of length 212B; other parameters were set according to the standard [5] default values.

From these experiments we observed the information dissemination rate (*IDR*) for different choices of transmission rate (*R*) and ranges (*D*). Figure 5 and Figure 6 shows how *IDR* changes for different choices of *R* and *D*.

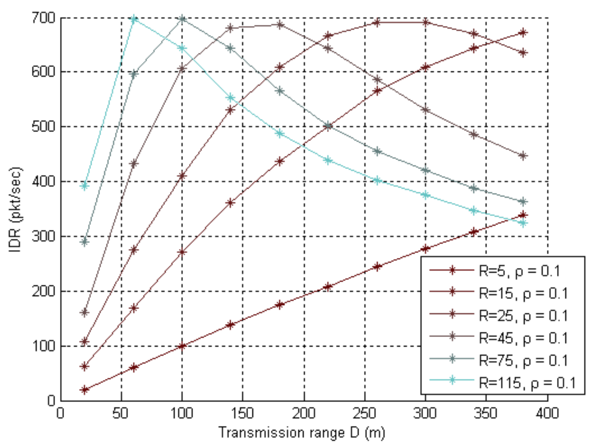

Figure 5 IDR vs. range of transmission for different transmission rates, ρ=.1

It is observed that for given values of rate *R* and traffic density ρ, there exists a value of *D* which yields maximum *IDR*. Here, ρ is the traffic density in vehicle/meter of highway; ρ=0.1 means 1 vehicle every 10 meters, which for a 4-lane highway is one vehicle every 40 meters. From Figure 5 and Figure 6, it is also observed that the maximum IDR is the same for all different choices of *R*. Similarly the same argument is true if value of *D* was fixed and we had varied *R*. This observation suggests that an optimal operation point exists for each selected value of *R* (or *D*), and the optimal point is reachable by adjusting the other controllable parameter *D* (or *R*). However, it must be noted that the optimal value of the controllable parameter is sometimes outside the range of meaningful or useful values of *R* or *D*.

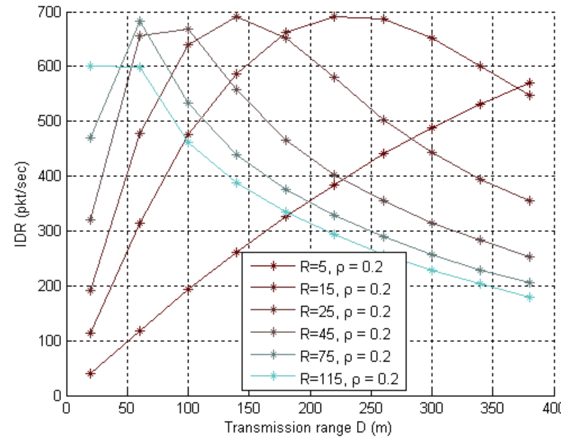

Figure 6 IDR vs. range of transmission for different transmission rates, ρ=.2

In addition to the effect of *R* and *D* on broadcast throughput, we observed how channel occupancy (*U*) is affected by different choices of *R* and *D*. This quantity, *U*, is of special interest since it can be observed locally by each vehicle and later used as a network feedback which is used for controlling the communication component. The relationship between *U* and *D* and *R* is shown in Figure 7. This relationship is in fact characterizing how controllable parameters affect the measurable network feedback, and is later used in devising control algorithms.

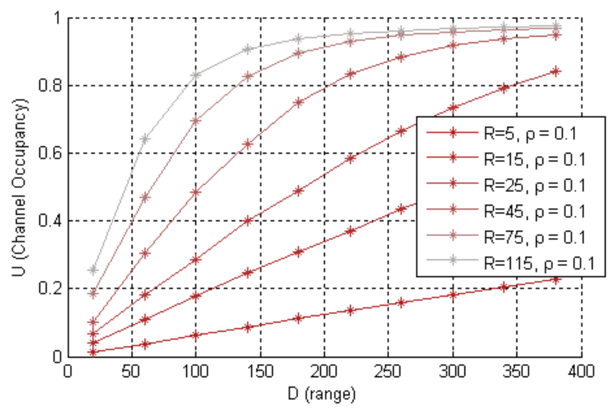

Figure 7 The effect of transmission range (D) and rate (R) choices on channel occupancy (U)

Given that *IDR* is the network measure that corresponds to the performance of the computing subcomponent (estimation and tracking process), we observed the relationship between *IDR* and *U*, which is depicted in Figure 8 for different values of *R*, *D*, and network density ρ. An interesting fact from this relationship is observed, here all different choices of *R, D*, and ρ result in an *IDR* value that falls on a single curve, which characterizes how *IDR* and *U* are related. This observation greatly simplifies the design of the controllers that rely on channel occupancy as network feedback. In simple terms, a controller should be designed in a way that maintains the value of channel occupancy around its optimal value, where *IDR* is maximized. The relationship between IDR and U depicts one of the models that characterize the communication component in the CPS of interest.

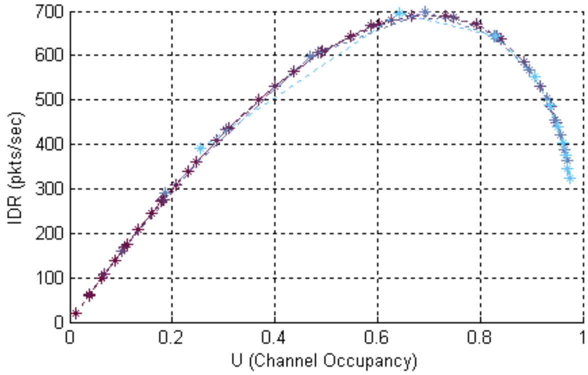

Figure 8 IDR vs. channel occupancy for different values of R(5-115 msg/sec), D(20-400m), and ρ (0.1-0.2 vehicle/m)Relationship

These observations and a characterization of how network performance is affected by the different choices of the controllable parameters (e.g., *R* and *D*), provides us with a view or model of the communication subcomponent behavior and reaction to the choices that are made by the computation subcomponent and due to the physical process dynamics. In the next section we develop a view of how computation subcomponent makes such choices based on the observed communication performance and physical process dynamics.

3.2 CPS Component Modeling: Computing module and physical process estimation

The estimation process, i.e., the computing module in Figure 4, relies on messages delivered through the network to make accurate predictions. The accuracy of the tracking process is also dependent on how fast vehicle position and state changes. In fact, if vehicle dynamics are fast changing, a higher rate of message transmission is required for maintaining accuracy levels [20]. In traditional designs this concept is missing and transmission rate is preset to a value like 10Hz. At an abstract level, the vehicle dynamics can be sampled and approximated as a linear system. The connection between information rate and tracking accuracy for LTI processes is studied in [19][20]. In such formulation, the minimum rate to track the process with finite distortion is *log2|a* (where *a* is the amplification factor of the LTI system)|; as |*a*| increases, the LTI system evolves faster and thus a higher rate is required by the remote estimator to track the process in real time.

In this section we characterize the effect of physical process dynamics and communication subcomponent performance (seen as the rate of message reception) on the performance of the computing subcomponent. For this purpose we ran a set of simulations. We observe how the rate of successful reception of messages (which is rate of transmission multiplied by success probability) affects tracking accuracy. The results are shown in Figure 9 and Figure 10 for a typical scenario (Highway speed 30m/s, constant acceleration between samples, but acceleration changing to a new value according to a normal distribution (0,1), creating an autoregressive process for speed). Here, we are considering one receiver only and assuming several rates of message arrival from senders at the receiver. Packet transmission is controlled by either randomly selecting whether the message should be transmitted (probabilistic policy), or using an estimation error dependent policy that controls the rate based on perceived tracking error, according to [19] and similar to our method [15]. Here we only consider the rate of message arrival at the receiver to exclude network effects and ensure that only estimation and physical processes are involved. We observe that an estimator that follows a first order dynamical system model (assumes constant speed between received samples) can produce results with accuracy as shown in Figure 9 and Figure 10. In Figure 9 we show the MSE of tracking, while in Figure 10 a measure called 95% cut-off error is depicted. 95% cut-off error is the value below which 95% of the error histogram lies. This measure gives a statistical sense of the worst case behavior. The reason behind choosing this measure is the fact that worst case error in wireless networks is unbounded and a statistical measure must be used to get a sense of worst case behavior.

The rate of transmission in probabilistic policy is controlled by changing the probability of transmission at each sampling time (here set to 20msec to examine higher rates, but normally set to 50msec), whereas the rate of transmission of error dependent policy is controlled by adjusting an error-sensitivity parameter α (0.1-100) in the algorithm that sets the probability of transmission as a function of estimation error *e*: $1-exp(-\alpha.e^2)$. As expected, it is seen from these plots that higher rate of message arrival results in higher tracking accuracy (lower tracking error). However, the shape of the rate distortion curves for these cases are different. This observation is consistent with well known results [18][19]. Moreover we observe that the error saturates after a certain rate.

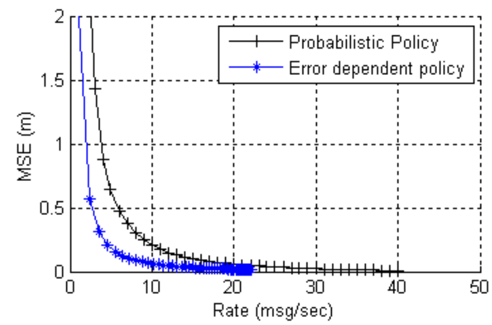

Figure 9 Relationship between message arrival rate and tracking MSE

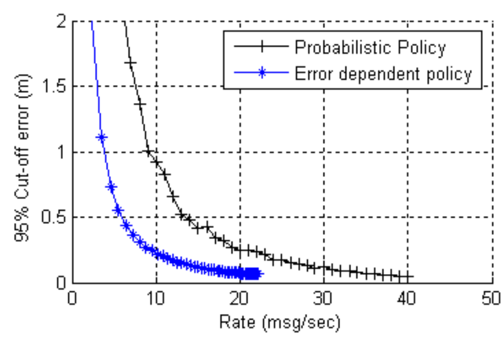

Figure 10 Relationship between message arrival rate and 95% tracking error

In general, different communication policies have different rate-distortion curves. Conceptually, with the same data rate, some policies are more "efficient" in the sense that they deliver information in a timely manner to the estimator to eliminate large tracking errors. The more the correlation of arrival information with the tracking error magnitude is, the lower the resulting tracking error will be. For example, from Figure 9 and Figure 10, the rate-distortion curve for a probabilistic policy is seen to be considerably higher (worse performance) than the curve of error dependent policy. Our choice for the communication policy is the error dependent policy. As it is observed from the rate distortion curve for this policy, the error drops quickly as message rate increases, but then saturates. It can be deduced that the performance of the estimator does not improve after a certain rate, at which the error is already low. At this point, it might be more useful to use the network resources to reach farther nodes, rather than sending more packets to closer nodes. This fact is used in the next section where we describe the CPS design.

3.3 CPS Component Interaction and Tightly Coupled Design

Following the modeling of the subcomponents of a CPS, we need to describe the interaction between these subcomponents, in order to construct a modular design that can maintain some levels of separation in design of subcomponents without completely disregarding the mutual effect of the subcomponents. In the case of CVS systems, the communication subcomponent provides an interface which for example allows control of the range of transmission *D* (through setting radio power level), and provides feedback on the measured channel occupancy *U*. The flow of control information in and out of the communication module is shown in Figure 4.

Interaction with the physical process, i.e., vehicle dynamics and warning systems, is through the sensors and the alert UI. (Figure 4). The estimation function that tracks the physical process of neighboring vehicles, and controls the communications module and alert UI is the core computing module of the design and interfaces with the communication module and the physical process as shown in Figure 4. Considering the proposed architecture, the main design task is to identify how information from physical process and communication module should be used to control the communication module and the computing core. The collision detection process, within the computing module, that drives the UI does not require dynamic control or adjustments; other designs may look into the detail of this module and include further controls in the computing process for controlling this unit as well. However, this is outside the scope of the current paper.

We use the models and findings of the previous section and try to identify control algorithms and design criteria that allows better performance of the CPS. The objective here is to design algorithms that control the rate, *R*, and range, *D*, of transmission based on the observed network feedback *U*, and perceived tracking error *e*. A practical solution for such adaptive algorithm design is to consider the fact that the tracking accuracy, tied to the physical process, is directly related to the amount of data delivered to receivers (Figure 9). Thus, if for now we assume a method of congestion control exists for the network, this accuracy will be directly related to the rate of transmission, *R*. Congestion control can be achieved by throttling the range of transmission *D*, if network is found to be too crowded.

The above rationale is valid for CVS applications; although it may not be an acceptable strategy for applications with other objectives. The reason is that in CVS, vehicles are interested in tracking their closest neighbors as precisely as possible, while if extra capacity exists, it serves the safety purpose to also track farther nodes, albeit tolerating lower accuracy. This means that the range of transmission can be reduced in crowded networks, since neighbors are closer to the sender anyway; also, the rate of transmission should not be compromised for congestion control. Based on the above logic, we use two control functions as described below.

Rate of Transmission is controlled by:

$$R(t) = p(t)/T \quad , \quad p(t) = 1 - \exp(-\alpha \cdot |e(t) - e_{th}|^2) \qquad (1)$$

Where *p(t)* is the probability of transmission at every *T* seconds sampling time; α is the tunable sensitivity to error parameter and *e(t)* is the perceived tracking error at time *t*. e_{th} is a tunable error threshold. The perceived error includes the error measurement from the network. An early version of a similar controller for transmission rate is described in detail in [15]. The tunable parameter *α* specifies how sensitive the controller is to the perceived error. The value of this adjustable parameter is found to be around 30 and is not sensitive to the varying parameters of the network or physical process [15][16].

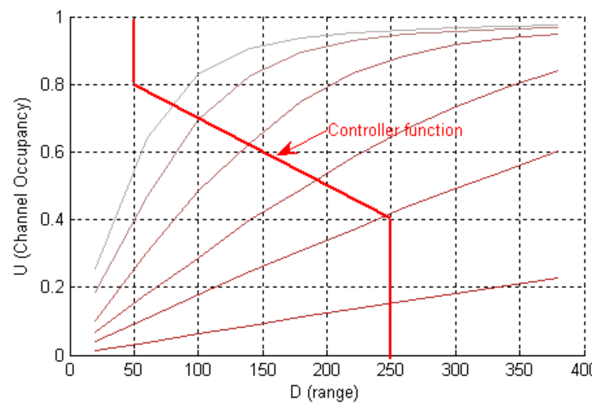

Figure 11 Communication characteristic curves, and feedback control function for transmission range control using channel occupancy (as network feedback)

The range control algorithm follows the rational that the range *D* should increase if channel occupancy, *U*, decreases, and it should decrease if *U* increases. There are many choices for functions *D=f(U)* that achieve this behavior, and each will have a different intersection point with the network characteristic curve *U=g(D),* shown in Figure 7. We introduced a range control function based on heuristics in [16], which is equivalent to the function we use here. In this paper we provide for the first time the rationale and justification behind this design and introduce the VANET network characteristics curves and their interaction with the proposed congestion control function.

It may seem ideal that the function should be designed in a way that the maximum *IDR* is always achieved, i.e., so that *U~0.7*. However, we note that the rate of transmission of other nodes, as well as the road density are not always known (thus we do not know which one of the network characteristic curves we are operating at). As a result, we have to opt for a solution that tries to keep the value of *IDR* near its peak value, while also respecting network and safety constraints. From Figure 8 it can be observed that if the controller maintains U between U_{min}=0.4 and U_{max}=0.8, good IDR performance can be expected. Thus, we can select a linear adaptation function, depicted in Figure 11,that maintains *U* between these values by adjusting *D* (other methods are also possible):

$$D = f(U) = \begin{cases} D_{max} & U < U_{min} \\ D_{min} + \frac{U_{max} - U}{U_{max} - U_{min}} (D_{max} - D_{min}) & U_{min} \le U < U_{max} \\ D_{min} & U_{max} \le U \end{cases} \quad (2)$$

The limits, D_{min} and D_{max}, in setting D come from the safety requirement (for example, minimum of 50-100meters, and maximum of interest around 250-300 meters). The above choice of the range controller, though not optimal, is a robust design which well tolerates the changes in network density and other nodes transmission rate changes.

4. EVALUATION

To verify the performance gain of a CVS system due to the tight coupling of CPS components in the design process, we have conducted several simulation experiments in a relatively realistic setting. We compare the tracking accuracy for two designs, the traditional design, and the tightly coupled design (adaptive design). To evaluate tracking performance we measure the tracking error (of each estimation instance at sampling rate) of all neighboring cars in different neighborhood distance bins, and derive the error histogram (of all instances). The tracking measure is then defined as the 95% cut-off error that is the value below which 95% of error population lies. This measure is chosen since the objective of tracking is safety, for which the worst case performance is of more importance than average performance (i.e. MSE). But in wireless networks absolute worst case error would be infinity, and we have to settle for a measure like 95% cut-off error that captures a statistical sense of worst case behavior.

The simulations were carried using OPNET and SHIFT simulators for network and road traffic simulations respectively. A bi-directional highway, 4 lane in each direction, was simulated in SHIFT for several typical traffic scenarios. Vehicle trajectories were then fed to OPNET in which vehicles communicated over a DSRC (modified 802.11a) channel. DSRC PHY bitrate was set to 3Mbps (100% of channel dedicated to safety; this is equivalent of 6Mbps and 50% channel dedication [7]). Other parameters were set to default values. The scenarios tested are described in the following table:

Table1. Simulated Bidirectional Highway Traffic Scenarios

case	Direction1 status	Direction1 speed	Direction2 status	Direction2 speed
H1	congested	14mph	congested	14mph
H2	Low speed	30mph	Low speed	30mph
M1	congested	14mph	Free flow	74mph
M2	Low speed	30mph	Free flow	74mph

Results are depicted in Figure 12. As it can be observed, for crowded networks (congested highway) the adaptive method manages to keep the tracking error at much lower levels than the traditional design. It is also observed that when the network is lightly loaded (free flow on both sides), both traditional and adaptive methods perform well. It is seen that the adaptive method works well under all conditions. In certain bins of distance the adaptive method seems to work worse than the fixed range (traditional) method. However, this is in fact the desired behavior, since the network is crowded in those scenarios and the algorithm reduces the range of accurate tracking to a smaller domain as expected.

Simulation results confirm the significant performance improvement due to coupling the design of different components of a CPS system.

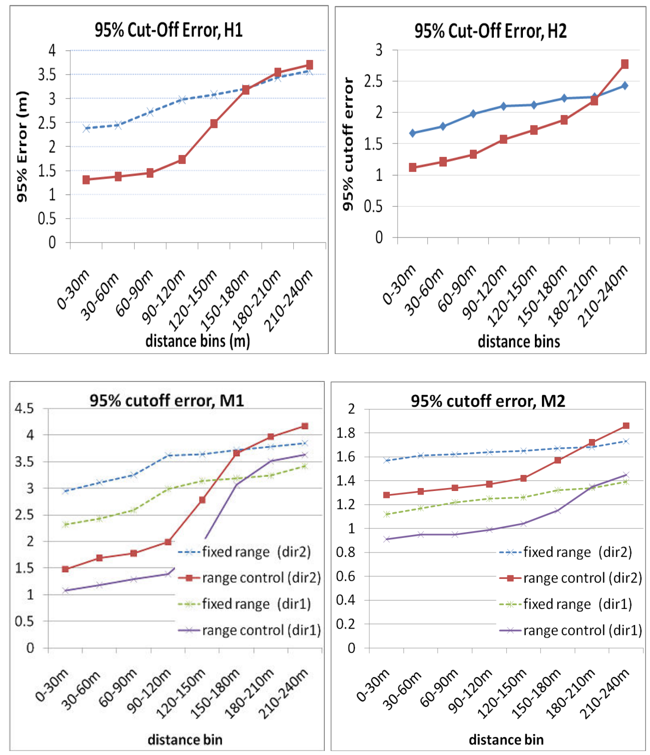

Figure 12 OPNET and SHIFT simulation results for different traffic scenarios, the proposed range control scheme vs. fixed range.

5. CONCLUSIONS

In this paper, we examined an automotive safety cyber physical system that operates based on cooperation and communication between vehicles. We investigated the interaction and mutual effects of different components of this system and characterized the tight coupling of computing, communication and physical dynamics of the CVS system. It was then shown that significant performance improvement is possible, if the design of the system is also based on tight coupling of its subcomponents.

We observed that in general, and specifically for a cooperative vehicle safety system, two levels of modeling for system design may be performed: 1) traditional method in which each component (computing, communication, physical process) is modeled separately and fixed non-parametric behavior is assumed for other components when designing each component. 2) tightly coupled method which models the behavior of each component as a function of the controllable parameters and measurable parameters of other components, and proposes control of each component in order to improve the overall system performance.

The above two methods are already used in many designs; in this paper we describe how the tightly coupled method can be applied to CVS systems. Through this effort, we identified that from a CPS perspective the second method could be done at many different levels of detail. In particular for a cooperative vehicle safety system, our current work is based on modeling the average behavior of the communication component (we derive long term throughput or success probability as a network measure), and link that to a model that describes the long term statistical behavior of the computing module in its interaction with the physical process (the model based estimator) and communication component.

Despite the significant improvement over traditional methods, our proposed method can still be improved if micro-level models for communication and computing/physical processes were available (to the best of our knowledge such models are not available yet); such models should specify at micro level (time durations shorter than 3-4 sampling period) how each component behaves, and tie the performance of different components together in one framework. This is indeed one of the grand challenges of CPS research. For a system similar to CVS, models such as stochastic hybrid systems [24][25] can help in identifying part of the system, but the overall system, in particular communication component still requires different modeling tools. Our future work involves extending the current models of the CVS application using existing and new mathematical models to achieve this objective.

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