Novel assessment of a peer-peer road accident survival system

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***Abstract*—Vehicle breakdowns and crashes on motorways can create a sudden drop in traffic speed and make driving conditions dangerous through the requirement of many braking and merging manoeuvres within a confined region. Modern vehicle communications technologies will soon allow drivers to be alerted much sooner to an accident, and voluntarily take action to ensure smoother and safer traffic flow without any assistance from the road infrastructure. Here we address the question of how to evaluate the system outcome in order to assess success of the system intervention. Such an assessment is necessary to specify how the agents (e.g. on-board vehicle units) of the system should be configured such that the overall system improves the situation over the no-system case. We apply quantitative measures in order to directly address this question.**

***Keywords*-AmI; Quantitative Measures; Target Orientation; Emergence; Traffic Simulation; Traffic Safety; Vehicle Communication; Accident Warning**

I. Introduction and related work

Vehicle breakdowns and crashes on motorways have direct and indirect impacts on traffic flow (e.g. efficiency and economy) and traffic safety. The loss of a lane available to traffic can create a sudden drop in traffic flow and make driving conditions dangerous through the sudden change in traffic speed and the requirement of many braking and merging manoeuvres within a confined region. These changes often result in follow-on accidents.

In recent years, a large amount of development effort has been invested in vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication technologies which will allow incident information and driving instruction to be delivered to motorists far more rapidly than was traditionally possible. A vehicle-communication based system could allow even a small number of equipped and compliant drivers to rapidly improve the driving situation for others by taking appropriate driving actions and setting an example for non-equipped vehicles.

Unlike infrastructure-based systems that provide information to all vehicles at the same place, a peer-to-peer system delivers information at a time and place largely dependent on the success of the communication. The information can be interpreted by the vehicle differently depending on other (e.g. conflicting) information and its own location. While systems based around variable message signs (VMS) can only ask drivers to slow down, use a particular lane or divert to another road, systems within the vehicle have the chance to actually guide the vehicle through or around a difficult situation.

In previous work, it has been shown that reducing traffic speed approaching a disturbance in traffic flow through vehicle communication improves the harmonization of the flow of traffic approaching the blockage [1]. Harmonization in this context means the reduction of sudden changes in traffic speed over time and/or space (i.e., at a macro level), that are thought to be responsible for micro changes in vehicle speed that result in accidents. Indeed, the experience of motorway operators has shown that overhead, variable message signs bring an improvement on safety (e.g. [2]). However, in these systems speed is changed (or attempted to be changed) more-or-less at the macro level directly. In a peer-to-peer Ambient Intelligence system (AmI), we derive these changes from many drivers changing behavior at different places and times. The danger is that one 'informed' driver may react suddenly to information that an 'uninformed' driver does not have. Hence, the macroscopic changes in traffic speed might appear similar to those obtained using a VMS-based system, but the microscopic interactions between the drivers may remain dangerous. Aware of this issue, we want to examine the effectiveness of the various potential systems by looking not at average speed but the interactions of individual drivers. Furthermore, we no longer need to constrain ourselves to the translation of infrastructure (e.g. speed-limits through VMS) systems for peer-to-peer use, but rather also consider autonomous or semi-autonomous systems that can act directly on the received information.

In addition to the potential autonomy of the individual vehicle systems, the overall system of traffic is autonomous in general, because no external control is needed for the interaction between the devices. It is completely decentralized: although the rules are pre-installed in the vehicles, the decisions about when to activate them are induced by the local interactions, so no central instance is needed for controlling or for the configuration of the system. Such systems are adaptive with respect to changes in the environment (e.g. presence of an accident or not) and to changes in the system itself, e.g. a change in car density or a change in the equipment rate r, which is the percentage of all cars having the AmI device.

Because of the decentralization, there is no single point of failure, so a breakdown of a device has only a small influence on the behavior of the system. Under these conditions we have a self-organizing system. In this paper we turn to the field of self-organizing systems for inspiration for an evaluation methodology for a peer-to-peer road accident "survival" system. By survival we mean the passing of the road incident with the least possible detriment to safety.

In recent years, much research has been done in the field of evaluation methods for self-organizing systems. One evaluation method is based on quantitative measures [3], [4], [5]: In the micro-level model measures are defined for the evaluation of global properties like emergence, target orientation, adaptivity, autonomy or global state awareness.

For the measure of target orientation, the goals have to be defined in advance in form of a fitness function. The target orientation of the system is a value in the interval $[0, 1]$ indicating how "good" the system behaves: It is the mean value of the fitness function applied to the system. The analysis and optimization of system parameters can then be done in accordance with predefined goals encapsulated in the target orientation measure. In addition, the level of emergence is measured to assess the degree of self-organization.

Section II specifies the tested device models of the vehicles. Section III describes the methodology and the target orientation measures applied. In Section IV the details of the simulation implementation and the values for the system parameters are given. Section V contains the results of the simulations and Section VI discusses and interprets these results. Section VII concludes the paper.

II. Proposed System

Two broad types of systems are tested for the AmI devices. The first is a fine-grained speed reduction system (also known as harmonization (HAR) or speed 'funnel') where the (desired) speeds of vehicles are set individually by an on-board system according to the distance from a point of danger. This is inspired by traditional overhead, sign-based systems but differs in having the ability to communicate a speed at any place and hence with smaller increments. A similar system is investigated in [1]. The second is an adaptive cruise control system (ACC) [6] whereby acceleration is set in order to maintain a certain time headway[1]. In the first system, the approach towards the target speed is assumed to be made by the driver (i.e. it is a hard speed limit). In the ACC system, full control of the vehicle is taken over by the system. An exception to this is that the system does not control lane changing acceleration behavior (driver controls acceleration), but lane changes are prevented after the time of system activation and first stable lane position (i.e. lane holding is activated first after a single lane is occupied), until the vehicle reaches the merging point, where it may be required to change lane in order to continue. This is the case also for the HAR system.

[1]The current time headway of a car is the time needed to overcome the distance to the car in front.

Both systems feature a common danger point detection algorithm that decides whether alerts are generated, forwarded, and whether a system is activated (Figure 1). Thereafter the control of the vehicle is governed by the HAR algorithm or ACC algorithm as follows, until the origin of the alert is passed:

HAR System: At a distance of 1000m from the alert and below, target speed is set to $100km/h$. For every decreasing $150m$ this target speed is reduced by $10km/h$ except for the final speed ($< 100m$) where it is $42.5km/h$. This speed is chosen because the desired speed distribution of the simulated unequipped drivers travelling through the accident area is linearly distributed between 40.0 and $45.0km/h$.

ACC System: Here, the acceleration set by an ACC system when following another vehicle in range is that of Kesting and colleagues in a special configuration for being upstream of a bottleneck [6]. The system maintains a target time headway (system parameter thw_{f_0}), a maximum acceleration a_0 of $1.4m/s^2$ and a 'comfortable' deceleration, b_0 of $1.4m/s^2$ (corresponding to the suggested value of b of $2.0m/s^2$ multiplied by the bottleneck-approach factor of 0.7) [6]:

$$a = a_0 \left[(1 - (\frac{v}{v_d}))^4 - (\frac{s_0 + v \cdot thw_{f_0} + \frac{v(v-v_p)}{2\sqrt{0.7 \cdot a_0 b}}}{s})^2 \right] \tag{1}$$

where v_d represents desired speed, s represents headway (distance) to the vehicle in front, v_p represents the speed of the vehicle in front and s_0 represents the minimum distance to be maintained (only significant for low velocities) [6].

The ACC system when no preceding vehicle is in following range is a simple ACC that applies acceleration or deceleration within the same limits ($\pm 1.4m/s^2$) until the desired speed is reached.

III. Evaluation Methodology

For the evaluation and analysis of the system we use quantitative measures [3], [4]. The measure for target orientation is a time dependent measure, which describes how good the current situation is. For this purpose, a fitness function $b : S \to [0, 1]$ has to be defined on the set S of all possible states of the system. Then the level of target orientation

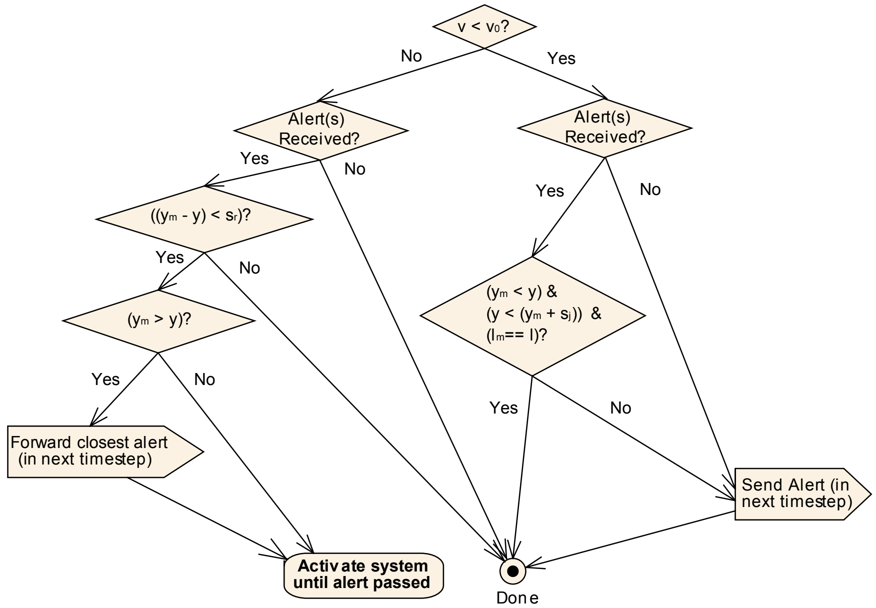


Figure 1. Detection of need to send or forward messages, and whether to activate a system. A jam speed threshold v_0, a 'relevance distance' within which the message is considered relevant s_r, and a jam break distance s_j, within which it assumed jammed vehicles are part of the same traffic jam for the system are set. In general, any equipped vehicle traveling with a speed below v_0 will send an alert to the surrounding traffic, unless they themselves receive an alert from behind the vehicle in the same lane within the jam break distance, whereupon it will be blacklisted from sending alerts itself for the next sending period. This is to reduce unnecessary communication traffic and attempts to only have alerts being sent from the back of the jam. Otherwise, if an alert is received from ahead, the location of the sender is stored. If the alert is from a closer location than other received alerts, the originating location is updated. This closest alert received from in front, with the originating location preserved, is forwarded. y refers to the road position of the vehicle, y_m to the road position of the message (i.e. originating vehicle). l refers to lane and l_m to the lane of the message.

$TO_t = E(b(s(t)))$ at time t is the mean value of the fitness of the current state $s(t)$, where in a stochastic system $s(t)$ is a random variable. Although TO_t is defined analytically, it is usually impossible to evaluate the level of target orientation analytically, because the set S of all global states is very large. Therefore approximation methods are needed [7]. The mean value of the random variable can be approximated by using the mean value calculated from simulation runs: Each simulation run yields a value $b(s(t))$ for the fitness function, and the level of target orientation TO_t at time t is the mean value.

Considering the goal of the system, i.e. reducing the risk of accidents, we want to test for the most stable possible system state, where variations in vehicle interaction states are minimized, while maintaining traffic flow. A number of possibilities exist for utilizing vehicle trajectory data (including simply averaging measures like headway or deceleration). Going further, simple safety indicators like average Time-To-Collision [8] (TTC, time until collision if one vehicle is closing in on another) or more complicated ones like deceleration rate needed to avoid a crash (DRAC) [9] can be used. One useful methodology [8], is to detect conflicts that fall below one or multiple thresholds of an indicator. The number of such incidents will then be counted and/or averaged. Specific to speed harmonization evaluation, we know of no measures applied to individual vehicle data to assess the degree of harmonization. One recent approach applied to single-point detection data is to measure the variation coefficient of the data [10]. This normalizes the standard deviation of the data (e.g. speed) by the average, hence removing 'disharmony' that is only due to the magnitude itself. We include this approach in our application of quantitative measures to try and directly assess the success of supposed system functionality (rather than indirect benefits). Of the three measures for target orientation presented here, two attempt to examine the level of harmonization, and one examines the traffic safety more directly.

Measure #1: Link velocity harmonization: Measure #1 is based on the variance coefficient of velocities $\{v_i(t) \ : \ i \text{ vehicle}\}$ at each point in time t.
$TO_t^1 = 1 - K \cdot \frac{\sigma_t}{\mu_t}$, where K is a normalizing constant,
$\mu_t = \frac{1}{n_t} \cdot \sum_{i=1}^{n_t} v_i(t)$ is the mean velocity,
$n_t =$ number of cars in the system at time t,
$\sigma_t^2 = \frac{1}{n_t - 1} \sum_{i=1}^{n_t} (v_i(t) - \mu_t)^2$ is the empirical variance of velocity.

Measure #2: Acceleration harmonization: Measure #2 is based on the variance coefficient of velocity change (acceleration) $\{|v_i(t+1) - v_i(t)| \ : \ i \text{ vehicle}\}$ from the current point in time t to the next time step.

$TO_t^2 = 1 - K \cdot \frac{\sigma_t}{\mu_t}$, where K is a normalizing constant,
$\mu_t = \frac{1}{n_t} \cdot \sum_{i=1}^{n_t} \Delta v_i(t)$ is the mean velocity change,
$\Delta v_i(t) = |v_i(t+1) - v_i(t)|$,
n_t = number of cars in the system at time t,
$\sigma_t^2 = \frac{1}{n_t - 1} \sum_{i=1}^{n_t} (\Delta v_i(t) - \mu_t)^2$ is the empirical variance of velocity change.

Measure #3: Individual safety: Measure #3 is based on the mean of all finite Time-To-Collision (TTC, see above) values.
$TO_t^3 = K \cdot \mu_t$, where K is a normalizing constant,
$\mu_t = \frac{1}{n_t} \cdot \sum_{i=1}^{n_t} TTC_i(t)$ is the mean TTC,
$TTC_i(t) = \frac{dist(i, succ(i))}{v_i(t) - v_{succ(i)}(t)}$ for $v_i(t) > v_{succ(i)}(t)$,
$succ(i)$ = car driving in front of car i,
$dist(i, succ(i))$ = distance between car i and the car driving ahead,
n_t = number of cars in the system with finite TTC at time t.

In addition to the three variants of target orientation, we use the measure of emergence [3] for the identification of global patterns appearing in the communication. The measure for emergence is based on the statistical entropy, which is defined by $H(X) = -\sum_{w \in W} P(X = w) \log_2 P(X = w)$ for a discrete random variable X with value set W. Note that the simulated system is a stochastic system, which uses a random number generator for a number of driver parameters [11] and the success of communication messages [1]. For each point in time $t \geq 0$ let $Conf_t$ be the random variable describing the global state of the system, i.e. all internal states of the entities and all values on the communication channels between the entities. In our scenario all communication channels can be seen as broadcast channels: For the sender it is irrelevant, by which other entity the alert signal can be received. Let K be the set of all these (broadcast) communication channels and $\mathrm{Conf}_t|_K$ be random variable describing the values on these channels at time t. For a single communication channel $k \in K$ let $\mathrm{Conf}_t|_{\{k\}}$ be the random variable describing the value on this channel at time t. The level of emergence at time t is defined by [3]

$$\varepsilon_t = 1 - \frac{H(\mathrm{Conf}_t|_K)}{\sum_{k \in K} H(\mathrm{Conf}_t|_{\{k\}})}. \quad (2)$$

This measure compares the information of all communication channels with the information contained in each single edge, so it can be used to identify global dependencies in the communications: A high value of emergence indicates many dependencies in the communication, while a low value indicates the independence of communications. Since the system is too complex to calculate the statistical entropy analytically, approximation methods are needed [7]: We use the relative frequencies of simulation values for the approximation of the corresponding probabilities to compute the entropies.

IV. Simulation Implementation

Recently, with the interest in vehicle communication technologies, the traffic microsimulation package VISSIM (PTV AG, Karlsruhe) has been extended in order to allow a vehicle's normal action to be supplemented with new information through the modeling of communication processes. For further information, see [1], [12]. An application programming interface (API), accessible through C++ or Python, allows a logic to be defined for when messages are sent, and what action should be taken by the driver when they are received [1].

The scenario is implemented in VISSIM 5.30 with a specialized version of the VCOM communication model [12], using a 5250m long straight section, consisting of a 5000m link for queue storage, a 100m section for merging, a 25m section representing the blockage and 125m section for outflow.

One equipped vehicle, supplied to a short link at the predefined accident point, is programmed using the communications interface to stop throughout the simulation. Hence the vehicle broadcasts jam alerts.

Initial driver desired speeds are set from a VISSIM default distributions around 120km/h (range 85km/h - 155 km/h) and driver behavior parameters are set to the VISSIM defaults. Driver speeds traveling through the blockage zone are set around $42.5 km/h$.

Table I specifies the values for the system parameters. Two parameters are variable for both systems: The input traffic flow f (unit: vehicles per hour) and the equipment rate r (unit: %) of the AmI device. For the ACC system, there is another variable system parameter thw_{f_0} for the target time headway (unit: seconds). For all variations of f and r, the HAR and ACC systems were tested, with the ACC system in addition being subject to the three variations of thw_{f_0}. All other parameters are constant. This leads to a total of $36 + 12 = 48$ configurations for the evaluation of target orientation. The emergence is evaluated for the ACC system with the following two parameter configurations:

- $thw_{f_0} = 1.5,\ f = 1000,\ r = 100\%$
- $thw_{f_0} = 2.1,\ f = 1000,\ r = 100\%$

Each configuration is tested for a simulation time of $1800s$, where the time is discretized into steps of $0.1s$.

The simulation scenario file, application/control script and evaluation scripts are available from the authors upon request.

V. Results

Figures 2a-2c show the mean values of the target orientation measures #1 $-$ #3 (see Section III) calculated from simulation results in dependency of the system variant (HAR

Parameter	Description	Values
s_r	relevance distance (m)	1000
s_j	jam-break distance (m)	100
thw_{f_0}	time headway desired (ACC only) (s)	$\{1.5, 1.8, 2.1\}$
v_0	jam speed threshold (km/h)	30
f	input traffic flow (veh/hour)	$\{500, 1000, 1500\}$
r	equipment rate (%)	$\{0, 10, 50, 100\}$
a_0	ACC (AmI) vehicle max acceleration (m/s^2)	1.4
b_0	ACC (AmI) vehicle desired braking (m/s^2)	1.4
s_0	Min spacing to vehicle in front (m)	2.0

Table I
SYSTEM PARAMETERS

or ACC with variable thw_{f_0}, f and r). The overall level of target orientation of the system is $TO^i = \frac{1}{s}\sum_{t=1}^{s} TO_t^i$ for $i \in \{1, 2, 3\}$, where s is the number of steps in a simulation run. Analogously the overall level of emergence is calculated by $\varepsilon = \frac{1}{s}\sum_{t=1}^{s} \varepsilon_t$, where ε_t is shown in Figure 3.

For a first analysis of these figures, we can examine the values of the measures for one variable parameter and two constant parameters:

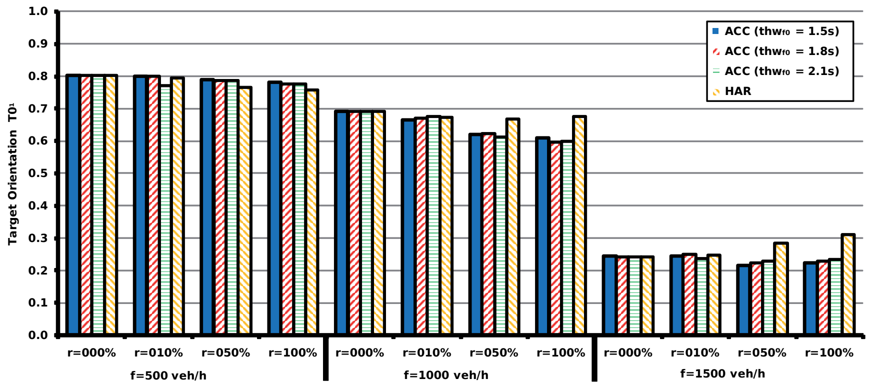
- For fixed values thw_{f_0} and f and variable values for r we observe: In the system ACC, measure #1 is often decreasing for increasing equipment rate r. For the system HAR this only holds for $f \leq 1000$, while for $f = 1500$ measure #1 is increasing for increasing equipment rate r. For $f \geq 1000$, measure #2 is monotone increasing with the equipment rate, so in this case, a high equipment rate yields a higher level of target orientation. For measure #3 no monotone behavior can be seen, but it mostly yields a strong increase for $r = 100\%$ compared to lower equipment rates.
- For fixed values f and r and variable values for thw_{f_0} in the ACC system we observe: While for the measures #1 and #3 no monotone behavior can be seen, the measure #2 is often increasing with thw_{f_0}, so usually a higher value for this system parameters leads to a higher value for the level of target orientation
- For fixed values thw_{f_0} and r and variable values for f we observe: The measure #1 is decreasing for increasing input traffic flow f. The measure #2 is increasing for increasing input traffic flow f. No monotone behavior can be seen for measure #3.
- We evaluated the measure of emergence, for two values of the parameter thw_{f_0} in ACC. For both cases we used 20 simulation runs for the calculation of the level of emergence. For $thw_{f_0} = 1.5$ the average level of emergence is $\varepsilon = 0.8843$. For $thw_{f_0} = 2.1$ the average level of emergence is $\varepsilon = 0.8866$. In both cases the emergence is low at the beginning of the simulations, when only few cars are in the system, and then it jumps up to a high value and stays over 0.9 until the end of the simulations.

VI. DISCUSSION

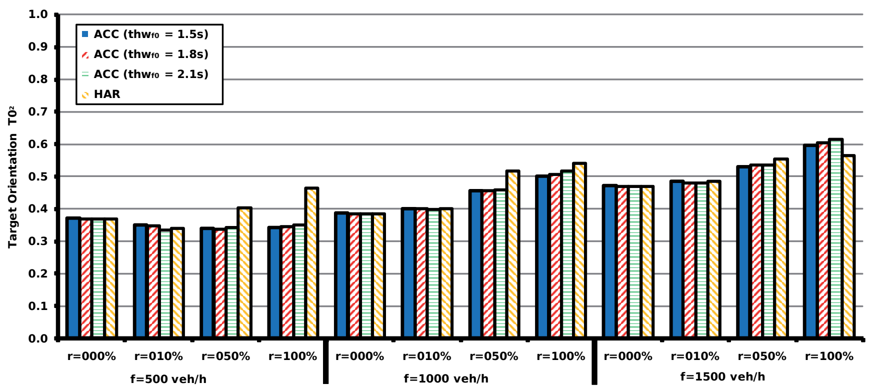
The measures specified in Section III can be used for the design, analysis and for the optimization of a system to increase the safety in traffic. Whereas the time headway thw_{f_0} can be freely set or even adjusted for the system, the equipment rate r and the input traffic flow f are less controllable. Here, the variables can either be used to understand what system rules should be employed, or an infrastructure operator can use them to exert some control over the traffic system. For a nominally high equipment rate r, the possibility could exist to deactivate the AmI device in a certain number of vehicles (in case of undesired effects at high equipment rate). Unfortunately, the opposite problem, of too low equipment rate, can only be solved in the longer term by market take-up, and hence is only useful for market and policy-making decisions. Regarding the input traffic flow f, the variable can be somewhat controlled by the road operator where diversion or ramp metering facilities exist. The different measures defined in Section III can be used to specify different criteria for “safe states” in the system. With measure #1, the bad states are situations where the velocities have a high variance coefficient, because a high variance of velocities implies that many different speeds are present in the systen (not harmonized). Analogously, measure #2 specifies a good state by a low variance coefficient for the velocity changes that each vehicle makes from one time step to the next. These measures express the “system” goals of motorway speed management, namely to see less variance in the overall speed, and to prevent drivers from having to adjust the speed suddenly. Measure #3 attempts to examine the safety effects more directly by applying a ‘proxy’ safety assessment measure, Time-To-Collision (TTC).

The results of Section V show that the three measures do not tell an identical story about the benefits of the system. Intuitively, a higher equipment rate should lead to a situation, which is safer. But the simulation results show, that while this works for measure #2, which pertains to individual driver experience, it rarely holds for measure #1, which examines the entire link. For measure #3, we observe large improvements only for the $r = 100\%$ case.

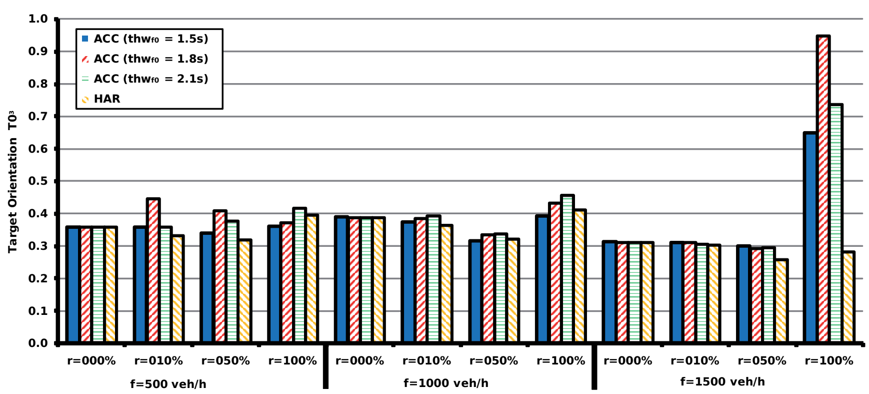
Measure #1 showed little system success except at high equipment rates and input traffic flow. Considering the HAR system, this can be explained partly by noting that the velocity of the whole system is inherently unlikely to be ‘harmonized’ when not all vehicles are controlled and furthermore those that are controlled are not controlled in a synchronized way. Interestingly also, when there is less congestion (lower f), higher r values do not improve the



(a) TO^1



(b) TO^2



(c) TO^3

Figure 2. Target orientation, measured within the relevance area of the three ACC system variants ($thw_{f_0} = 1.5, 1.8$ or 2.1) and HAR system separated by input traffic flow f in veh/h and equipment rate r in $\%$, according to (a) the variance coefficient of the speed of all vehicles, (b) the variance coefficient of the speed change of all vehicles between time steps and (c) the mean of all finite Time-To-Collision values of all vehicles.

outcome. This may be because more cars can drive at their desired speeds such that the arrival of speed reduction instructions results in (relatively) more diversity of speeds in the system.

Ignoring 100% cases (which are in reality highly unlikely to occur), measures #1 and #2 suggest that the HAR system is better than the ACC system; whereas for measure #3 the reverse is usually true. This would suggest that if we want to improve velocity harmonization as has traditionally been attempted on real roads, we can indeed attempt to

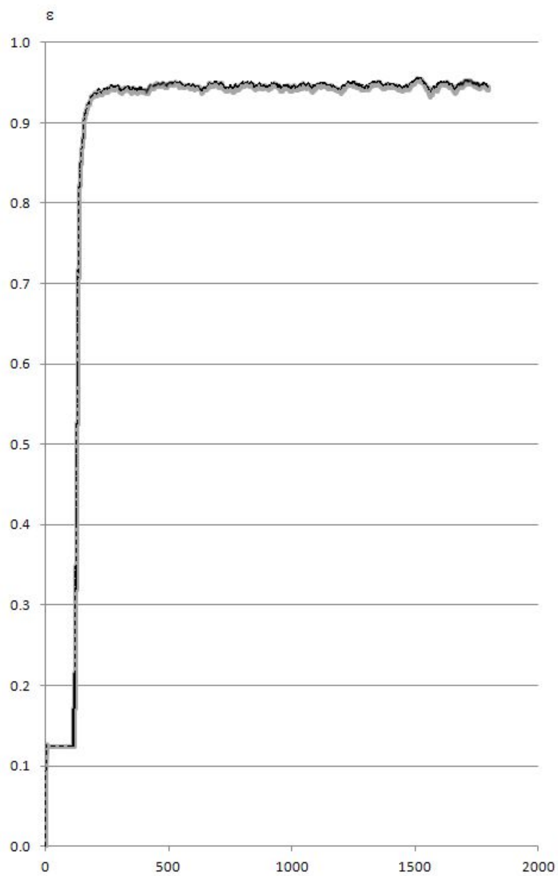


Figure 3. Emergence ε of the ACC system in dependency of the time $[sec]$ for $f = 1000, r = 100\%$ and $thw_{f_0} = 1.5$ (solid light grey line) and $thw_{f_0} = 2.1$ (dotted black line).

translate VMS-based systems for peer-to-peer use. However, if we want to directly influence the safety of drivers, a more advanced system that governs the time headway would be more appropriate.

Regarding measure #2, larger values of the system parameter thw_{f_0} almost always lead to better states for cases where the system is observed to actually be improving anything over the no-system case ($r = 0\%$). If this were taken as the only outcome measure, designing the system with a large value of thw_{f_0} would be sensible. The picture is more complicated for measure #3. Here, the result can be used for optimization: when knowing the parameters r and f, a different value of thw_{f_0} can be set, or the system can be turned off completely.

Hence, the system rules should actually adapt dynamically to the input traffic flow and surrounding equipment rate. Although, as described above, the simplest method for such changes might be intervention from the road operator, input traffic flow could be estimated autonomously (e.g. [13]), and this combined with received beaconing communication from other vehicles can be used to infer an equipment rate. However, it must be noted that input traffic flow can be well controlled in a simulation. In reality, there is no single input traffic flow, only a local traffic flow, which may be very different in terms of its effect on system performance.

As expected, the measure for emergence indicates a strong global pattern in the communications: Since alert signals are forwarded by other cars, there are many dependencies in the communications, which can be seen as an emerging global pattern induced by the local interactions between the cars. The tested values for the system parameter thw_{f_0} shows that there is only a very small influence of this parameter on the result of the measure of emergence. Note that emergence as a stand alone measure does not indicate how "good" or how "bad" a system behaves. There are many practical applications, where some undesired emergence might occur (e.g. a traffic jam can also be seen as an emergent property of a traffic flow), so the measure for emergence should be used in addition to the measures for target orientation for the identification of target oriented emergence in the system behavior.

Overall, the results as they stand cannot be used to choose one measure as the ideal or to decide, which system is better or worse than the other. While there is evidence to show that VMS-based speed harmonization improves safety (e.g. [2]), we cannot automatically assume that the same will be true of a peer-to-peer system, or show (via measure #3) that any safety benefit is present. We can show however, that the system usually does what it should (via measure #3). Measure #3 (and to a lesser extent, measure #1 for high traffic flow $f = 1500veh/h$) may serve as a warning: systems that seem sensible for a single driver may only bring about benefits for all traffic when we ensure very high equipment rates.

VII. Conclusion and future work

In this work a self-organizing AmI based system for increasing safety on a highway has been proposed. We considered the scenario, where one lane is blocked by an accident. Evaluations methodologies that consider the welfare of individuals in decentralized traffic systems are lacking. The main result of this paper is to show that quantitative measures, an approach from the field of self-organizing systems, are a useful evaluation tool which can be used for the design, analysis and optimization of a decentralized system in traffic. We have applied the measure for target orientation based on different fitness functions to analyze the system. The results were used to investigate the influence of system parameters on the safety in such a situation and to propose methods for optimizing the system with respect to predefined criteria.

There are several areas where the work can be extended upon both in terms of improving the analyses and understanding how to improve the systems themselves. Often it is the case that results for $r = 100\%$ differ strongly from other cases. It is not clear if this change is gradual while approaching $r = 100\%$ or if it these are special cases because all drivers drive with identical rules. Hence, more simulations, for example at $r = 90\%$ should be performed. In addition, it is not clear for measure #2 if simulation time steps are ideal or if some aggregation would be more effective. Therefore the effect of analyzing time step intervals larger than $0.1s$ should also be investigated. Measure #3 showed some positive system effects, but suggested that the rules or parameters (i.e. thw_{f_0}) of the system need to change according to the surrounding conditions. If approximate individual sensing of these conditions (defined by r and f) were added, the success of this approach could be evaluated by assessing the adaptivity of the system [4].

Furthermore, the results should not be used for the recommendation for or against the implementation of any particular system in traffic. Aside from the experiments concerning emergence, only one simulation per case was performed. This prohibits plotting standard error or testing results for significant differences. The systems are also somewhat simplistic in nature and have not been tested with real drivers. The traffic situation and road network were artificial (constant input traffic flow) and hence the base driver model, while validated in general [14] is not calibrated to real data.

In scenarios, where there is a trade-off between different goals that should be achieved, the corresponding measures for target orientation may be combined into a single measure. A methodology for how such a combination could be done and the corresponding evaluation is left for future work. It is also worthwhile to investigate other quantitative measures like global state awareness [5] to answer questions like "Which system parameters can increase the global state awareness of all drivers?"

For the analysis of emergent patterns in the vehicle communication, we have applied the measure for emergence for two different parameter settings. Both results indicate the appearance of global patterns arising from the local interactions between the entities.

The evaluation methodology used in this paper is not restricted to the special scenario of an accident on a highway, but it can be used in a broader sense. The defined measures for target orientation can also be used for arbitrary traffic jams and the defined measure for emergence can also be used for the evaluation of arbitrary vehicle communications.

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