Effective Assessment of AmI Intervention in Traffic Through Quantitative Measures

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1 Introduction and Related Work

In this chapter, we seek to quantify the benefit of Ambient Intelligence (AmI) within a complex system, specifically a motorway traffic system made up of agents with or without an AmI system. In addition to the potential autonomy of the individual AmI 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 can be 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. For a formal definition of the self-organizing properties, see the appendix.

There are many possible approaches to establish whether a given self-organizing, AmI-driven system at work in society is having a desired or undesired effect. We could perform longitudinal studies that try to tie societal changes to new

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technologies. Or questionnaires could be used to establish users' attitudes and use of a device. In the area considered here (vehicle traffic), instrumented vehicles or video recordings can be used to try and understand traffic effects. All of these assume that the device already exists and/or is at work in traffic at large. If we only have an idea of what the device could or should do, modeling approaches come into play, and the question of what manner and level to measure needs to be answered.

One recent approach for the analysis and evaluation of such system is quantitative measures [1–3]. In the micro-level model, measures are defined for the evaluation of global properties like emergence, target orientation, adaptivity, autonomy or global state awareness. These measures are described in detail in the appendix and have the advantage that they are comparable across scenarios and systems because of normalization. In addition, some of the measures (when proposed) were novel in the sense that they quantified for the first time various qualitative properties of self-organizing systems. In this chapter, we concentrate on the measure for target orientation. In some sense this is more traditional than some of the other measures: it describes how well the system is performing, which of course is the usual goal of any system evaluation. However, due to normalization we can describe the systems success along a scale of worst possible state to best possible state with a single number. For the measure of target orientation, the goals have to be defined in advance in the 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. The analysis and optimization of system parameters can then be made in accordance with predefined goals encapsulated in the target orientation measure.

The measures (including target orientation) and fitness function are generically defined for any system. The main problem considered here is how to make them domain specific. The domain at hand is vehicle traffic on a motorway, and the specific problem that of vehicle breakdowns and crashes on motorways. These 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 it was traditionally possible. Hence, it is now technically plausible that 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 action. This could happen without the aid of any infrastructure. For a longer introduction to the problem, please see [4]. We begin by giving a short overview of the system and its goals (Sect. 2) which motivates the choice of measures made in Sect. 3. The measurement process through simulation is also briefly covered in Sect. 3. Results are presented in Sect. 4 followed by a discussion and conclusions in Sects. 5 and 6 respectively. The background information on the quantitative measures themselves is contained in an appendix to the chapter.

2 System Overview

Two broad types of system 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 [5]. 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 [5]. 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. [6]). 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 AmI system, 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 an infrastructure-based system that is fixed in position (e.g. variable speed limit signs), but the microscopic interactions between the drivers may be different. This makes an evaluation based on individual agent experience more appropriate.

The second system is an adaptive cruise control (ACC) system that, when following another vehicle in range, is that of Kesting and colleagues in a special configuration for being upstream of a bottleneck [7]. Here, the acceleration is set in order to maintain a certain time headway. The ACC system when no preceding vehicle is in following range is a simple ACC that applies acceleration or deceleration within limits ($\pm$ 1.4 m/s^2) until the desired speed is reached. Both systems feature a common danger point detection algorithm that decides whether alerts are generated, forwarded, and whether a system is activated. Thereafter the control of the vehicle is governed by the HAR algorithm or ACC algorithm until the origin of the alert is passed. Full details on both systems can be found in [4].

3 Measurement Definition and Simulation Testing

To establish what measurements should be made, the target(s) of the system should be agreed upon. Derived from this, we can define which of the system states are safe or desirable and which not. These should then be assigned concrete numbers from a quantity that can be measured from the system entities. This facilitates normalization, which can either be explicit (a chosen relevant maximum and minimum) or taken from the properties of the data (both approaches are taken below).

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 the vehicle data (including simply averaging measures like headway or deceleration). 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 [8]. 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. This approach is included in our application of quantitative measures to try and directly assess the success of supposed system functionality (rather than indirect benefits).

Target orientation is a time dependent measure, which describes how good the current situation is. For this purpose, a fitness function g: $S \to [0, 1]$ has to be defined on the set S of all possible states of the system. Then the level of target orientation $TO_t = E(g(s(t)))$ 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.

Based on the two properties we are seeking from the systems (traffic harmonization and safety in general), we examine three measures (expressed formally below). With measure #1, bad states are situations where velocities have a high variance coefficient, because a high variance of velocities implies that many different speeds are present in the system. 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 using a simple safety 'proxy' indicator, Time-To-Collision [9] (TTC, time until collision if one vehicle is closing in on another).

Measure #1: Link Velocity Harmonization This measure 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,

$\mu_t = \frac{1}{n_t} \sum_{i=1}^{n_t} v_i(t)$ 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 This measure 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,

$\mu_t = \frac{1}{n_t} \sum_{i=1}^{n_t} \Delta v_i(t)$ 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 This measure is based on the mean of all finite Time-To-Collision (TTC) values.

$TO_t^3 = 1 - K \cdot \frac{\sigma_t}{\mu_t}$ where K is a normalizing constant,

$\mu_t = \frac{1}{n_t} \sum_{i=1}^{n_t} TTC_i(t)$ is the mean TTC,

$$TTC_i(t) = \begin{cases} \frac{dist(i, succ(i))}{v_i(t) - v_{succ(i)}(t)} & \text{for } v_i(t) > v_{succ(i)}(t) \\ 3 & \text{if } v_i(t) \le v_{succ(i)}(t) \text{ or } succ(i) \text{ does not exist} \end{cases}$$

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 at time t,

$\sigma_t^2 = \frac{1}{n_t - 1} \sum_{i=1}^{n_t} (TTC_i(t) - \mu_t)^2$ is the empirical variance of TTC.

Measure #3 represents an improvement over our previous work [4] where all TTC values were considered. Here we define a threshold of 3 s [9] to represent a safe state; hence any values above 3 s are quantized to this value for the analysis.

Although the level of target orientation TO_t is defined analytically (see appendix), 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 [10]. We use the results of simulations to approximate the level of target orientation.

For such a simulation, we require the ability to model vehicles in detail (because the measures used require detailed data concerning the vehicle interactions) and the ability to simulate the system and its communication needs in an integrated fashion. For our simulations, the vehicle traffic simulation VISSIM [16] (version 5.30, PTV AG, Karlsruhe) has been used, but there are several other possibilities (e.g. ITETRIS, VSIMRTI). Generally speaking, all approaches (including ours) utilize an application programming interface (API) whereby a logic for the system and communication can be defined for when messages are sent, and what action should be taken by the driver when they are received [5]. How the communication is modeled is usually flexible depending on the level of detail required and in the event of a large amount of detail being required, the exact properties of the

Table 1 Examined system parameters

Parameter	Description	Values
thw_{f0}	Time headway desired (ACC only) (s)	{1.5, 1.8, 2.1}
f	Input traffic flow (veh/h)	{500, 1,000, 1,500}
r	Equipment rate (%)	{0, 10, 50, 100}

communication system (e.g. medium type and bandwidth). We use a specialized version of the VCOM communication model [11].

The simulation tests used a simple straight road length where one vehicle equipped with a system is stationary and broadcasts accident alerts. More details can be found in [4]. This tests the system in a generic way, but for many use-cases it may be more appropriate to use a specially calibrated simulation for a specific road stretch [12].

Table 1 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_{f0} 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_{f0}. All other parameters are constant. This leads to a total of $36 + 12 = 48$ configurations for the evaluation of target orientation.

Each configuration is tested for a simulation time of 1,800 s, with simulation time steps of 0.1 s (although the analysis is performed utilizing data from every tenth time step, i.e. 1 s intervals). This is both to reduce computational effort, but also to provide some aggregation of acceleration (which fluctuates highly) differences in Measure #2, as suggested in [4]. The analysis is performed over a relevant stretch of the road where communication takes place. The simulation scenario file, application/control script and evaluation scripts are available from the authors upon request.

4 Results

Although for some cases it may be useful to examine the change in Target Orientation over time, we examine here only the mean values (Fig. 1a–c). These show the target orientation measures #1–#3 (see Sect. 3) calculated from simulation results in dependency of the system variant (HAR or ACC with variable thw_{f0}, f and r). The overall level of target orientation of the system is

$$TO^i = \frac{1}{s}\sum_{i=1}^{s} TO_t^i$$

for $i \in \{1, 2, 3\}$, where s is the number of analyzed steps in a simulation run.

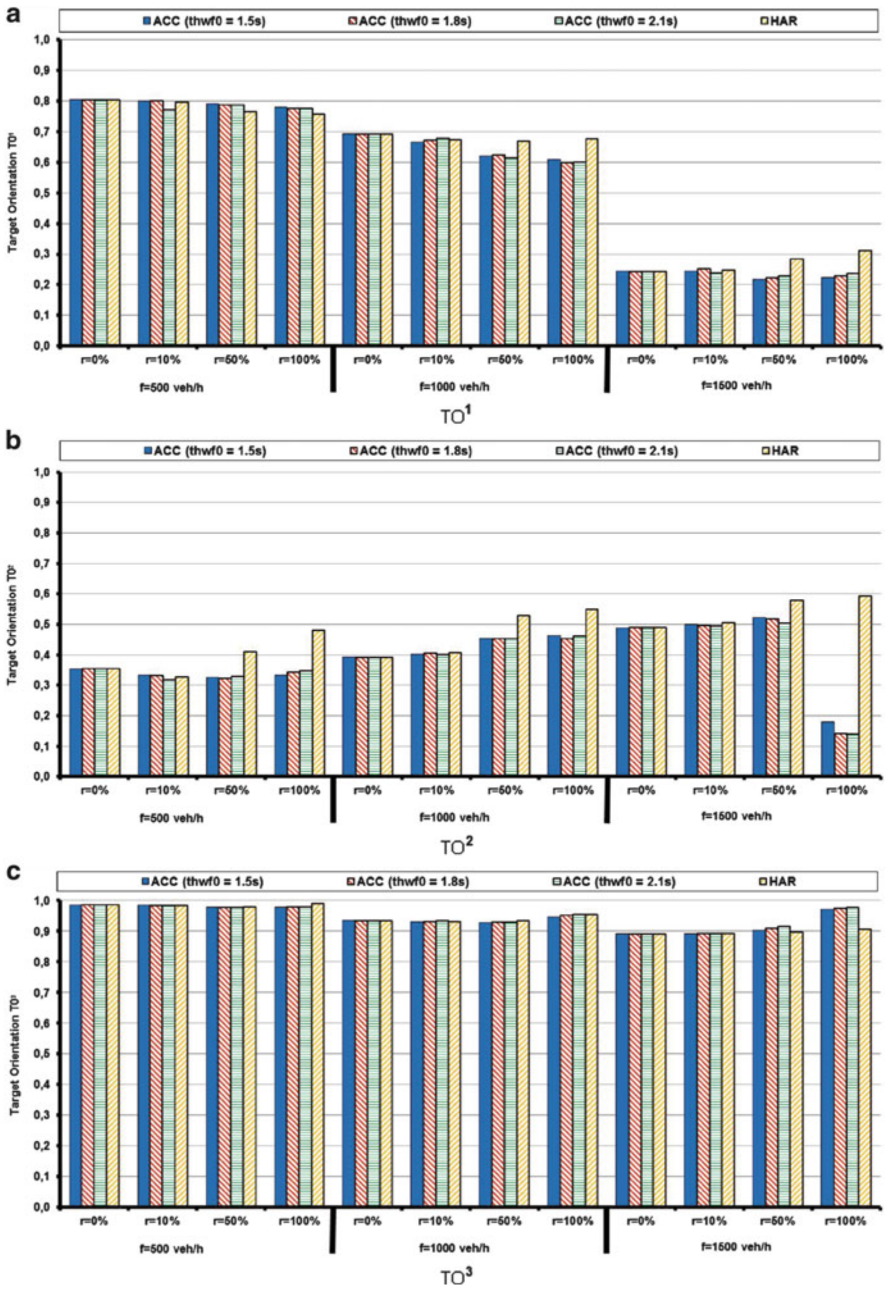

Fig. 1 Target orientation TO^1–TO^3 measured within the relevance area of the three ACC system variants (thw_{f0} = 1.5, 1.8 or 2.1) and HAR system separated by input traffic flow f in veh/h and equipment rate r in %, according to (**a**) the variance coefficient of the speed of all vehicles, (**b**) the variance coefficient of the speed change of all vehicles between time steps and (**c**) the mean of all

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_{f0} and f and variable values for r we observe:
  - For the ACC system measure #1 is generally decreasing as r increases. For the HAR system the picture is similar except for f = 1,500 veh/h where it is increasing
  - For the ACC and HAR systems measure #2 is generally increasing as r increases except for f = 500 veh/h and f = 1,500 veh/h with r = 100 % (outlier)
  - For the ACC and HAR systems measure #3 is generally increasing with r but values are very similar. As the base case gets worse with increasing f, these differences become bigger.
- For fixed values f and r and variable values for thw_{f0} in the ACC system the only pattern is that measure #3 slightly increases with thw_{f0}. This difference is larger with increasing f.
- For fixed values thw_{f0} and r and variable values for f we observe:
  - Measure #1 decreases as f increases
  - Measure #2 increases as f increases (except for the ACC system at f = 1,500 veh/h)
  - Measure #3 decreases as f increases (except for the ACC system at f = 1,500 veh/h and r = 100 %)

5 Discussion

The measures were tested for varying parameters, which can be freely set (under simulation conditions). Whereas the time headway thw_{f0} can be chosen for the system, the equipment rate r and the input traffic flow f cannot be controlled at the individual system level. However, the variables can still either be used to understand what system rules should be employed, or an infrastructure operator could 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

Fig. 1 (continued) finite Time-To-Collision values of all vehicles. To assess a system benefit in a given situation, one should generally compare within the three f-value blocks against the “base case” of r = 0 %

controlled by the road operator where diversion or ramp metering facilities exist. These factors must be borne in mind when discussing the results.

The results of Sect. 4 show that the influence of the system parameters differs according to the measure used, even though ideally all measures, which are examining desirable states, should show similar results. Intuitively, a higher equipment rate should lead to a situation, which is safer. But the simulation results show, that while this often works for measure #2, which pertains to individual driver experience, it rarely holds for measure #1, which examines the entire analyzed area. For measure #3, we observe large improvements only for the $r = 100\ \%$, $f = 1{,}500$ veh/h case. Measure #1 showed little system success except for the HAR system at higher equipment rates for the largest input traffic flow. Specific to 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 here also, when there is less congestion (lower f), higher r values do not improve the 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.

Measures #1 and #2 suggest that the HAR system is often better than the ACC system, especially for a high input traffic flow. For measure #3 there is so little improvement to be made that the use of any of the systems usually seems unnecessary.

Overall, the results are mixed. In this case they cannot be used to choose one measure as the ideal or one system is better or worse than the other. While there is evidence to show that speed harmonization based on variable message signs (VMS) improves safety (e.g. [6]), we cannot automatically assume that the same will be true of a peer-to-peer system, or show (via measure #3) that any large safety benefit is present. None of the measures bring a noticeable benefit at low equipment rates. This may serve as a warning: Systems that seem sensible for a single driver may only bring about benefits for all traffic when we ensure high equipment rates.

6 Conclusions and Future Work

In this work, we have discussed how a self-organizing AmI-based system may be evaluated in a targeted and comparable fashion using the quantitative measure of target orientation. The system was designed to increase safety on a section of highway in the event of one lane being blocked by an accident. It can be seen that quantitative measures are a useful evaluation tool, which can be used for the design, analysis and optimization of a complex decentralized system, in this case 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 understand when the system performs well and when not.

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. The traffic situation and road network were artificial (constant input traffic flow) and hence the base driver model, while validated in general [13] is not calibrated to real data. This may have led to overly ‘safe’ driving demonstrated through measure #3. Obviously the examined scenario needs to be plausible and valid for the measures, no matter how suitable they may be, to be of any use. Indeed, the measures can be used to augment traditional calibration techniques whereby (if data is available) the measure from reality and an “as-is” simulation is compared. Overall, the results should not be used for the recommendation for or against the implementation of any particular system in traffic. Only one simulation per case was used for this analysis. This prohibits plotting standard error which can inform as to the likely significance of differences. We are currently performing additional simulations to make this possible. The systems are also somewhat simplistic in nature and have not been tested with real drivers.

In scenarios where there is a tradeoff between different goals that should be achieved, the corresponding measures for target orientation may be combined into a single measure. A methodology for deriving such a combination and the corresponding evaluation is left for future work. Elsewhere [4] we have considered the measure of emergence, to examine the appearance of global patterns arising from the local interactions between the entities. It is also worthwhile to investigate other quantitative measures like global state awareness [3] to answer questions like “Which system parameters can increase the global state awareness of all drivers?” Finally, we wish to stress that the evaluation methodology used in this chapter is not restricted to the special scenario of an accident on a highway, but can be used in any other context of self-organizing systems where input data can be measured. The critical steps are to define what the target(s) of the system should be, which of the states safe or desirable states are and which not, and to assign these concrete numbers from a quantity that can be measured from the system entities.

Appendix

Model of Socio-technical Systems

For modelling socio-technical systems, we use the methods of [1], which are based on the ideas of [14]: A directed graph $G = (V, K)$ describes the entities V of the system and their network topology, i.e. each node $v \in V$ in the graph corresponds to an entity and each edge $(v, w) \in K$ is used to model the interaction (e.g. transfer of data) between the entities. For modelling the external influence of the environment we use special vertices (external nodes) $E \subseteq V$ in the graph, where the edges from these vertices represent the channels for the input into the system, and the edges to these vertices represent the output of the system. All other nodes $v \in V \backslash E$

are called *internal nodes*. We distinguish between user data (data from the environment that is processed by the system) and control data (data from the environment to change the behaviour of the system).

In the real world, not all properties are known in all detail (e.g. it would be very difficult to describe a deterministic behaviour of an animal), but there are many things, that can better be described by probabilities. Therefore, a stochastic behaviour is more adequate than a deterministic one. We use stochastic automatons to describe the behaviour of the entities. These concepts allow the modelling of a wide variety of complex systems of the real world, e.g. systems that appear in biology, physics, computer science or any other field.

For an edge $k = (v, w) \in K$ the starting vertex v is denoted by $k-$ and the ending vertex w is denoted by $k+$. For a vertex $v \in V$ the set of edges ending in v is denoted by $v-$ and the set of edges starting at v is denoted by $v+$. Analogously for $T \subseteq V$ the sets $T-$ and $T+$ are defined by $T-: = \{k \in K | k+ \in T\}$ and $T+: = \{k \in K | k- \in T\}$. The *input edges* are E+ and the *output edges* are E−. All other edges are called *internal edges*. For the input coming from the environment, we distinguish between control data and user data. A subset of the input edges $C \subseteq E+$, which elements are called *control edges*, are used for change the behaviour of some nodes, while the other input edges (called *user edges*) are used for the data, that should be processed by the system. For the communication between entities we need a finite set A, which is used as alphabet for communication, i.e. each value transmitted by a node to another node is in A. For modelling the behaviour of a node v, we use a stochastic automaton $a_v = (A^{v-}, A^{v+}, S_v, P_v)$, where

- $A^{v-} = \{(x_k)_{k \in v-} | x_k \in A, k \in v-\}$ are the *local input values*,
- $A^{v+} = \{(x_k)_{k \in v+} | x_k \in A, k \in v+\}$ are the *local output values*,
- S_v is the set of states,
- $P_v: S_v \times A^{v-} \times S_v \times A^{v+} \to [0,1]$ is a function, such that $P_v(q, x, \cdot, \cdot): S_v \times A^{v+} \to [0,1]$ is a probability mass function on $S_v \times A^{v+}$ for each $q \in S_v$ and $x \in A^{v-}$. The value $P_v(q, x, q', y)$ is the probability, that the automaton moves from state q into the new state q' and gives the local output y when it receives the local input x.

This model allows us to describe socio-technical systems of the real world: Assume that we would like to analyse a system, e.g. a network of AmI devices. Then each node of the network corresponds to a vertex of the graph. If one node of the network is able to communicate with another node, then we draw an edge between the vertices in the graph. The behaviour of each node is modelled by a (stochastic or deterministic) automaton, which describes, how the internal state changes for each input, which it gets from the other nodes.

If we consider the global view on the system at a point in time, then we see a current local state inside each automaton and a current value on each edge, which is transmitted from one node to another node. Such a global view is a snapshot of the system: A *configuration* $c = (c_V, c_K)$ consists of

- A tuple $c_V \in \prod_{v \in V} S_v$, which defines the current states of the automatons,
- A map c_K: $K \rightarrow A$, which defines the current symbols on the edges,

The set of all configurations is denoted as Conf. For a configuration $c = (c_V, c_K)$ and a set $T \subseteq K$ of edges the assignment $c_K|_T$: $T \rightarrow A$ of the edges in T is also denoted by $c|_T$. The restriction of c to the external nodes is defined by $c|_{ext} = (c_V|_E, c_K|_{E+})$. The restriction of c to the internal nodes is defined by $c|_{int} = (c_V|_{V\setminus E}, c_K|_{(V\setminus E)+})$. An *initialization* is a pair (Γ, P_Γ), where Γ is a set of configurations and $P_\Gamma : \Gamma \rightarrow [0, 1]$ is a probability mass function on Γ, which describes, with which probability the system starts in a certain configuration $c \in \Gamma$. A configuration $c' = (c_V', c_K')$ is a *successor configuration* of $c = (c_V, c_K)$ with probability p (notation: $P(c \rightarrow c') = p$) if

- $$p = \prod_{v \in V} P_v(c_V(v), (c_K(k))_{k \in v-}, c_V'(v), (c_K'(k))_{k \in v+})$$

For a configuration c let succ(c) be the corresponding random variable with the probability distribution $P(\mathrm{succ}(c) = c') = P(c \rightarrow c')$ for each successor configuration c' of c. This concept of successor can be extended in a canonical way to arbitrary sequences $(c_0, c_1, \ldots, c_j)$ of configurations to get the probability, that c' is reached from the configuration c, where the steps are considered as independent. For a given duration t let $P(c \rightarrow^t c')$ be the probability, that c' is active t time units after the time of c. Let $P(\Gamma \rightarrow^t c)$ be the probability, that c is active at time t. Define $\Gamma_t = \{c | P(\Gamma \rightarrow^t c) > 0\}$, i.e. Γ_t is the set of all configurations that may be active at time t, where we assume that the initialization of the system is at time $t_0 = 0$. Let Conf_t be the random variable taking values in Γ_t with the probability distribution $P(\mathrm{Conf}_t = c) = P(\Gamma \rightarrow^t c)$ for $c \in \Gamma_t$.

To analyze the behaviour of a system, we initialize it at time $t_0 = 0$ by choosing a start configuration $c_0 \in \Gamma$ and then the behaviour of the system, which is induced by the automatons in all nodes, is the sequence $s = (c_0, c_1, \ldots)$ of configurations during the run of the system. When we do a snapshot of the system at time t, we see a current configuration $c \in \Gamma_t$. Since the automatons and the initialization are not deterministic, the sequence s is not uniquely determined by the system, but it depends on random events. So for each time t, we have a random variable Conf_t, which describes, with which probability $P(\mathrm{Conf}_t = c)$ the system is in a given configuration c at time t.

For measuring the information in a system we use the statistical entropy: For a discrete random variable X taking values from a set W the *entropy* H(X) of X is defined by [15] $H(X) = -\sum_{w \in W} P(X = w) \log_2 P(X = w)$.

The entropy measures, how many bits are needed to encode the outcome of the random variable in an optimal way. In the following sections we use this concept to define quantitatively some properties of a system. Another concept that we need for the quantitative definitions in the following sections is the average value of a function: Let f: $\mathbf{R}^{+}{}_0 \rightarrow \mathbf{R}$ be a real function, which is integrable on every finite interval. For points of time s > r the average value of f in the interval [r, s] is defined by $Avg_{[r,s]}(f) = \frac{1}{s-r}\int_r^s f(t)dt$. The average value of f is defined by $Avg(f) = \liminf_{t\rightarrow\infty} Avg_{[0,t]}f$.

In this micro-level model we can now specify self-organizing properties like adaptivity, emergence or autonomy by using quantitative measures. In the following, let S be a system and (Γ, P_Γ) be an initialization.

Autonomy

To compute the level of autonomy [1], we compare the information contained in the control data with the information of the whole system. For a point in time t, the value H($Conf_t$) measures the system entropy at time t, i.e. H($Conf_t$) is the average number of bits that are needed to encode the information of the configuration at time t in an optimal way. By restricting the configuration to a set of edges, we can analogously measure the information of the values on these edges. For example the control entropy H($Conf_t|_C$) is the average number of bits that are needed to encode the control information.

For a configuration c the level of autonomy of c is defined by[1] $\alpha(c) = 1 - \frac{H(succ(c)|_C)}{H(succ(c)|_K)}$.

For a point in time t, the level of autonomy at time t is defined by the weighted mean value of all these autonomy levels of configurations, which may be active at time t, i.e. [2]

$$\alpha_t(S,\Gamma) = \sum\{\ P(\Gamma \rightarrow^t c)\,\alpha(c)\ |\ c \in \Gamma_t\}.$$

The level of autonomy of the system S is defined by $\alpha(S,\Gamma) = \mathrm{Avg}(t \mapsto \alpha_t(S,\Gamma))$. The system S is called autonomous if $\alpha(S,\Gamma) = 1$.

In this definition the value $\frac{H(succ(c)|_C)}{H(succ(c)|_K)}$ describes the relation between the entropy on the control edges and the entropy on all edges: A high value for this ratio means, that much control data is needed in the configuration c, and a low value for this ratio means, that the system behaves nearly autonomously in the configuration c. Therefore α(S, Γ) measures how much control data is needed relative to the data on all edges during the whole run of the system. Since α(S, Γ) ∈ [0, 1], a level of autonomy near 1 means, that the information contained in the control data will be

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[1] If H(succ(c)|K) = 0 then we define 0/0:= 0 and α(c) = 1.

[2] When we write a set after the sum symbol ∑, it should be considered as a multiset, i.e. in the following formula a value is added twice if it is contained twice in the multiset.

very low, i.e. the system behaves autonomously if we wait long enough. A level near 0 means, that it needs much control data to keep the system running, i.e. the system will not be autonomous even if we wait a very long time.

Emergence

In some systems, it may happen that some patterns or properties appear in the system as a whole, but do not appear in the single components. Such an appearance is called emergence. For a point in time t the level of emergence [1] at time t is defined by $\varepsilon_t(S,\Gamma) = 1 - \frac{H(Conf_t|_K)}{\sum_{k\in K} H(Conf_t|_{\{k\}})}$

The level of emergence of the system S is defined by $\varepsilon(S,\Gamma) = \mathrm{Avg}(t \mapsto \varepsilon_t(S,\Gamma))$. The system S is called emergent if $\varepsilon(S,\Gamma) = 1$.

For the level of emergence, the information of all edges is compared to the information contained in each single edge. Analogously to the level of autonomy, also the level of emergence is a value in the interval [0, 1]. If at the current point in time t there are large dependencies between the values on the single edges (which can be seen as patterns), the level of emergence is high: $\varepsilon_t(S,\Gamma) \approx 1$. If the values of nearly all edges are independent, there will be no pattern, so the level of emergence is low: $\varepsilon_t(S,\Gamma) \approx 0$. Therefore $\varepsilon(S,\Gamma)$ measures the dependencies occurring during the whole run of the system.

Target Orientation

Before a new system is designed, we have the goal of the system in our mind: The system should fulfil a given purpose. The behaviour of each node is defined in such a way, that this goal is reached, so the design of a system needs a *target orientation*. Let $b: \mathrm{Conf} \to [0, 1]$ be a fitness function for the configurations. For a point in time t the level of target orientation [2] of the system S at time t is defined by $TO_t(S,\Gamma) = E(b(Conf_t))$, where E is the mean value of the random variable. The level of target orientation of the system S is defined by $TO(S,\Gamma) = \mathrm{Avg}(t \mapsto TO_t(S,\Gamma))$. The system S is called target oriented with respect to b if $TO(S,\Gamma) = 1$.

For the target orientation, the fitness function b describes which configurations are "good": A high value $b(c) \approx 1$ means that the configuration c is a part of our goal which we had in mind during the design of the system. The level of target orientation measures the fitness b(c) of the configurations during the whole run of a system: A high level of target orientation ($TO(S,\Gamma) \approx 1$) means, that the mean valuation of the configurations during a run of the system often is nearly 1.

Resilience

For socio-technical networks, there are different forms of resilience:

- Resilience with respect to malfunctioned nodes
- Resilience with respect to attacks by an intruder, who takes part in the network
- Resilience with respect to attacks by an intruder, who is outside the network
- Resilience with respect to natural disasters or other external influence, which might cause a breakdown of some nodes

Now we model these different forms of resilience: Let Θ be a set and p_Θ: $\Theta \rightarrow [0, 1]$ be a probability distribution. Let $(a_{\theta,v})_{\theta\in\Theta,v\in V}$ be a family of stochastic automatons. For $\theta \in \Theta$ let S^θ be the system S after replacing a_v by $a_{\theta,v}$ for all $v \in V$. Let $(\Gamma^{S^\theta}, P_{\Gamma^{S^\theta}})$ be an initialization of S^θ. Let $Conf^\theta$ be the set of the configurations of S^θ. Let $b = (b_\theta)_{\theta\in\Theta}$ be a family of fitness functions b_θ: $Conf^\theta \rightarrow [0, 1]$ for the configurations. For a point in time t let $Conf_t^\Theta$ be the random variable, which applies the random variable $Conf_t$ in the system S^θ after choosing $\theta \in \Theta$ randomly according to the probability p_Θ. The level of resilience [2] of S at time t is defined by $Res_t(S, \Gamma) = E(b(Conf_t^\Theta))$, where E is the mean value of the random variable. The level of resilience of the system S is defined by $Res(S, \Gamma) = Avg(t \mapsto Res_t(S, \Gamma))$. The system S is called resilient with respect to b if $Res(S, \Gamma) = 1$.

In this definition the automaton $a_{\theta,v}$ can be used to describe the malfunctioned behaviour of a node v. In a socio-technical network with AmI devices, this behaviour could be caused by hardware failure, it could be the behaviour of an intruder inside the network ($v \in V\backslash E$) or outside of the network ($v \in E$) or it does not send data to its successor nodes due to a breakdown. The system is resilient if despite the malfunctioned nodes the system still runs through many "good" configurations.

If there are only few malfunctioned nodes, then we can use $a_{\theta,v} = a_v$ for the other nodes. If the behaviour of a malfunctioned node v depends on the original behaviour a_v, then the automaton $a_{\theta,v}$ can be a modification of the original automaton a_v to describe the malfunctioned behaviour of v.

Adaptivity

Now we model the concept of adaptivity [2] of a system. Let Θ be a set and p_Θ: $\Theta \rightarrow [0, 1]$ be a probability distribution. Let $(a_{\theta,v})_{\theta\in\Theta,v\in C-}$ be a family of stochastic automatons. For $\theta \in \Theta$ let S^θ be the system S after replacing a_v by $a_{\theta,v}$ for all $v \in C-$. Let $(\Gamma^{S^\theta}, P_{\Gamma^{S^\theta}})$ be an initialization of S^θ. Let $Conf^\theta$ be the set of the configurations of S^θ. Let $b = (b_\theta)_{\theta\in\Theta}$ be a family of fitness functions b_θ: $Conf^\theta|_{int} \rightarrow [0, 1]$ for the configurations of internal nodes. For a point in time t let $Conf_t^\Theta$ be the random variable, which applies the random variable $Conf_t$ in the system S^θ after choosing $\theta \in \Theta$ randomly according to the probability p_Θ. The level of adaptivity of S at time t is defined by $Ad_t(S, \Gamma) = E(b(Conf_t^{\Theta}|_{int}))$, where E is the mean value of the random variable. The level of adaptivity of the system S is defined by $Ad(S,\Gamma) = Avg(t \mapsto Ad_t(S,\Gamma))$. The system S is called adaptive with respect to b if $Ad(S, \Gamma) = 1$.

The level of adaptivity measures the influence of the change of control data: A high value of $Ad(S, \Gamma)$ means that the mean valuation of the configurations during each run of the system with the new control data is nearly 1, so many "good" configurations are reached. If the system has no external nodes ($E = \emptyset$), then no automaton in replaced. In this case, the concept of target orientation can be seen as a special case of the concept of adaptivity: By choosing a one element set $\Theta = \{\theta\}$ we get $TO(S, \Gamma) = Ad(S, \Gamma)$. For $E = \emptyset$ with $|\Theta| > 1$ the level $Ad(S, \Gamma)$ is the weighted mean level of target orientation $TO(S, \Gamma)$ with respect to $\theta \in \Theta$: $Ad(S,\Gamma) = \sum_{\theta\in\Theta} p_\Theta(\theta) TO_\theta(S,\Gamma)$, where $TO_\theta(S, \Gamma)$ is the level of target orientation with respect to b_θ.

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