Correction of Selection Bias in Traffic Data by Bayesian Network Data Fusion

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In this paper a method is introduced based on the concept of Bayesian Networks (BNs), which is applied to model sensor fusion. Sensors can be characterised as real time variant systems with specific physical functional principles, allowing to determine the value of a physical state of interest within certain ranges of tolerance. The measurements of the sensors are affected by external, e.g. environmental conditions, and internal conditions, e.g. the physical life of the sensor and its components. These effects can cause selection bias, which yields corrupted data. For this reason, the underlying process, the measurements, the external and internal conditions are considered in the BN model for data fusion. The effectiveness of the approach is underlined on the basis of vehicle classification in traffic surveillance. The results of our simulations show, that the accuracy of the estimates of the vehicle classes is increased by more than 60%.

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1. INTRODUCTION

Bayesian Data Fusion (BDF) is a well-established method in decision-level fusion to increase the quality of measured data of several equal or different sensors, e.g. [7], [13]. Although the method is powerful, the results of the fusion process are only (1) as good as the sensors are; (2) as good as the a priori knowledge about the sensors is and (3) as good as the a priori knowledge about the underlying process is. For instance, in case of vehicle classification for traffic surveillance by several more or less accurate sensors (item 1), accurate relative frequencies of correct and wrong classifications (phantom detections, incorrect classified vehicles) are required to achieve beneficial fusion results (item 2). This statement is supplemented by an adequate characterisation and quantification of the underlying unknown traffic process (item 3).

For an adequate traffic management, there is a particular need for highly accurate traffic data, measured by accurate and reliable sensors, yielding a high degree of acceptance and credibility concerning the significance of the measured traffic parameters. There are a lot of different sensor technologies with different physical functional principles, different performance, problems and thus, differing operational areas [18], [19]. Two currently important coexisting sensor technologies are for instance the inductive loop detectors and video sensors. Loop detectors measure the traffic process temporally, while video sensors enable temporal and wide area measurements, yielding more comprehensive data about the underlying traffic process than loop detectors. Both sensors provide a data quality in accordance with their physical functional principle and in accordance with the influences of the affecting surrounding environment. For instance, an inductive loop detector works properly under fluid traffic conditions, whereas the measurements are not accurate, if there is stop-and-go traffic. Furthermore, vehicle detection and classification may be problematic in case of overtaking procedures, when the loops are overrun only partly, [11], [12]. That means an inductive loop detector is a sensor, which is influenced by the traffic process itself. In contrast to loop detectors, it is a well-known fact, that the most currently employed video sensors usually work poorly under bad weather conditions (e.g. heavy rain, fog, etc.), changing illuminations (e.g. reflections on the road surface) and traffic process dependent problems (e.g. occlusions among the vehicles on the road). Although new methods have recently been developed to overcome the addressed problems [11], the detection errors of currently used video sensors increase to more than 1000%, if the weather and illumination conditions are bad [6]. In contrast, they perform much better (they can reach even the same accuracy as an inductive loop detector), if the conditions for an optimal operation are maintained.

Not only weather and illumination conditions affect the accuracy of the measurements, but also other environmental conditions (e.g. temperature, luminosity, hygrometry, etc.) and systematic causes (e.g. the installation of the sensor for overhead or sidefire detection) may distort the detection. Without consideration of particular sensor properties and dependencies and the influences of the environmental conditions on the sensor, the data are manipulated by selection bias. Consequently, physically and environmentally affected sensors must be considered in the (probabilistic) fusion model to correct selection bias and to decrease the frequency of faulty sensor data.

In this paper, the concept of BNs is applied to merge biased traffic sensor data, which are affected by the surrounding environment. The conditions affecting the sensors are modelled in the BN data fusion model. It will be shown that the correction of selection bias can improve the accuracy of data fusion by more than 60%.

The paper is structured as follows: In section 2 some background on BNs is given. Subsequently, in section 3, the naive (classical) concept of BDF is introduced and then, extended to Bayesian Network Data Fusion (BNDF) considering additional nodes containing additional information, which are important for the fusion process. In section 4, a BNDF model is developed for the qualification of traffic data. Thereby, some environmental conditions (e.g. weather conditions, reflections on the road surface) and some traffic process related conditions (e.g. occlusions among the vehicles, the dependency on the traffic state) are modelled as additional nodes in the considered network. Then, in section 5, simulation results are presented. Finally, in section 6, conclusions and and future prospects are given.

2. BAYESIAN NETWORKS (BNS)

A Bayesian Network (BN) is a graphical formalism of handling and processing uncertain and incomplete knowledge in causal reasoning. BNs consist of a set of discrete random variables or nodes and a set of directed links or arrows. Each node is described by a set of mutually exclusive states. Some of the nodes are connected with other nodes by arrows. The arrows characterise the conditional dependencies among the nodes. So for instance, in the BN shown in Fig. 1, there is an arrow from node X to node Z_1, this indicates X causes Z_1. In this case, X is called a parent node, because it is the cause and Z_1 is the child node, because it describes the effect. The cause-and-effect relationships are modelled by the quantification of conditional probability tables (CPTs) to each single node. The nodes together with the arrows form the directed acyclic graph (DAG) [5].

Neapolitan [22] gives an adequate mathematical definition of BNs: (1) Let $\mathcal{P} = P(\mathbf{x})$ be the joint probability distribution (JPD) of the space of all possible state values $\mathbf{x}$ of the random variables in some set $\mathbf{X} = \{X_1, \ldots, X_n\}$, which are connected by a set of arrows

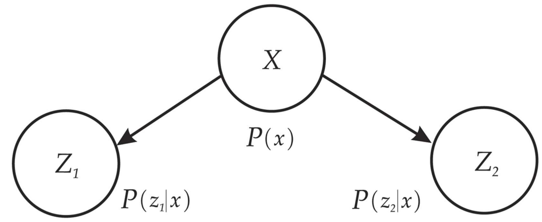

Fig. 1. A simple BN, which consists of three nodes. The variables Z_1 and Z_2 are effects of the common cause X. The (conditional) probabilities are given.

$\mathbf{A} = \{(X_i, X_j) \mid X_i, X_j \subset \mathbf{X}, i \neq j\}$ and the arrows pointing from X_i to X_j. (2) Let $\mathcal{G} = (\mathbf{X}, \mathbf{A})$ be a DAG. Then, (3) $(\mathcal{G}, \mathcal{P})$ is a BN, if $(\mathcal{G}, \mathcal{P})$ satisfies the Markov condition, i.e. a variable is conditionally independent of its nondescendents given its parents. Thus, the JPD $P(\mathbf{x})$ is characterised by

$$P(\mathbf{x}) = \prod_{x_i \in \mathbf{x}} P(x_i \mid \mathbf{pa}(X_i)) \tag{1}$$

with $\mathbf{pa}(X_i)$ denoting the set of the parents states of node X_i. If node X_i has no parent nodes, then $\mathbf{pa}(X_i) = \emptyset$. If X_i is a node with $m_i = |X_i|$ states, i.e. $X_i = \{x_{i,1}, \ldots, x_{i,m_i}\}$, $P(X_i = x_{i,k})$ denotes the probability of the certain state $x_{i,k}$. The conditional probability $P(x_i \mid x_j)$ denotes the conditional probability table of all conditional probabilities $P(x_{i,k} \mid x_{j,l})$, with $k = 1, \ldots, m_k$ and $l = 1, \ldots, m_l$.

The simple BN shown in Fig. 1 consists of three nodes, the parent node X and its child nodes Z_1 and Z_2. The states of each node are characterised by small letters x, z_1 and z_2 respectively. The causal relationships are given by directed links and the JPD of this BN is computed by equation (1), which can be rewritten as:

$$P(x, z_1, z_2) = P(x)P(z_1 \mid x)P(z_2 \mid x). \tag{2}$$

The BN in Fig. 1, which is characterised by the JPD in equation (2), satisfies the Markov condition.

For further reading in general theory on BN the reader is referred to [4], [22], [23].

3. BAYESIAN NETWORK DATA FUSION (BNDF)

In the following section 3.1, the naive or classical Bayesian approach for data fusion is introduced and then, in 3.2, extended to the more generalised Bayesian Network Data Fusion (BNDF).

3.1. Naive Bayesian Data Fusion (BDF)

Bayesian Data Fusion (BDF) makes use of Bayes' rule and combines objective and/or subjective knowledge of the underlying and possibly unknown process—its a priori probabilities and likelihoods—in a probabilistic model. The method can principally be characterised as:

$$P(x \mid z) = \alpha \cdot P(x)P(z \mid x) \tag{3}$$

to infer $x \in X$, which is the unknown state among $|X|$ possible states by the observation $z \in Z$ among $|Z|$ possible observations, which are also called evidences. All the Ps are discrete probability distributions, but can be considered in the continuous world as well. $P(z \mid x)$ is the conditional probability distribution (likelihood function) of a sensor measurement z given the true state x. It reflects the correct and false measurements, which can be characterised as the quantification of the accuracy of the sensor. $P(x)$ is the prior distribution of x describing our expectation of the unknown variable X. $P(x \mid z)$ is the inference distribution (a posteriori distribution) of the unknown state x given a specific measurement z. It can be characterised as the trust in a specific measurement $P(z \mid x)$ expecting the prior $P(x)$. α is a normalising constant, which ensures, that $\sum_i P(x_i \mid z) = 1$.

When the a priori probabilities and likelihoods are determined, the given measurements z allow to infer the unknown state x according to equation (3). That means knowledge, which is based on evidences from the observable variable Z is propagated towards the unknown variable X. For more information on BDF see [7], [13], [15], [25].

The BN in Fig. 1 is the simplest BN, which models naive BDF according to equation (3). The shown BN consists of the variable X, which represents the unknown process of interest and the two sensor variables (evidence nodes) Z_1 and Z_2. However, the advantage of BNDF is to extend the naive Bayesian model by a more detailed or more characteristic modelling of the sensor nodes and/or the underlying process. This problem is addressed in the following section.

3.2. From BDF to BNDF

Remind the BN in Fig. 1 for naive BDF. Imagine the two sensor variables Z_1 and Z_2 model an inductive loop detector and a video based sensor respectively, measuring the vehicle classes on a road of interest. Then, the variable X represents the underlying and unknown traffic process. Now, imagine, that some properties of the detectors are influenced by their surrounding environment, which might yield selection bias in the measurements, resulting in faulty or corrupted data usually being undesirable for an adequate traffic management. But, if we know more about the underlying process, the applied sensors and their properties and their surrounding environment, we can include this knowledge in a BN, which contains additional nodes, modelling these influences. Consequently, the advantage of BNDF is to extend the naive BDF model by a more detailed, more characteristic and more realistic modelling of the sensor nodes and/or the underlying process. This results in a data fusion model, which is capable of correcting selection bias. As a consequence, the resulting merged data are more accurate.

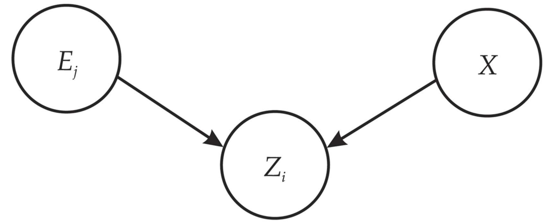

Fig. 2. An extended BN for data fusion according to Fig. 1 with an arbitrary sensor node Z_i and an environmental influence node E_j. The causal dependence between the environment E and the measurement Z is shown by the directed link connecting them. Without loss of generality, the sensor and environment nodes can be connected several times with the traffic node X, depending on how many sensors are in use and how many environmental dependencies affect the performance of the sensor.

The application of these particular BNs for traffic surveillance is a novel solution for the correction of selection bias in manipulated traffic data. Comparable, but different investigations were done for landmine detection, e.g. [5], and in case of the detection of acoustic signals, e.g. [16].

In Fig. 1, the environmental dependencies affecting the performance of the sensors are not yet considered. A more realistic and thus, more complex BN for data fusion considering environmental influences is shown in Fig. 2. According to Fig. 2 and the text above, equation (3) has to be modified to equation (4), which enables an improved data fusion:

$$P(x \mid \mathbf{z}, \mathbf{e}) = \alpha \cdot P(x) P(\mathbf{z} \mid x, \mathbf{e}) \tag{4}$$

with x representing the unknown vehicle class, $\mathbf{e}$ describing the set of the environmental influences on the performance of the sensor and $\mathbf{z}$ the affected measurements of a set of sensors. The calculation of equation (4) yields a correction of selection bias by the influence of the sensors' surrounding environment and hence, the improvement of the estimates of the unknown state variable X under these conditions.

In the following section, the influences of the affecting environment on a video based traffic detector are more specified. Later, a comparison between the performance of a weather independent inductive loop detector and a weather dependent video sensor is made. The correction of selection bias and thus, the improvement of the fusion process are shown on the basis of synthetic traffic data.

4. BNDF TO CORRECT SELECTION BIAS IN TRAFFIC DATA

In this section, the BN according to Fig. 2 and its inherent fusion equation (4) are applied to merge traffic data and to improve the accuracy of the fusion process. In the following paragraphs the modelling of the prior probability distribution, the likelihood probability of the environmental affected sensor, the resulting BNDF model and the inference of the unknown state values for the traffic process are discussed.

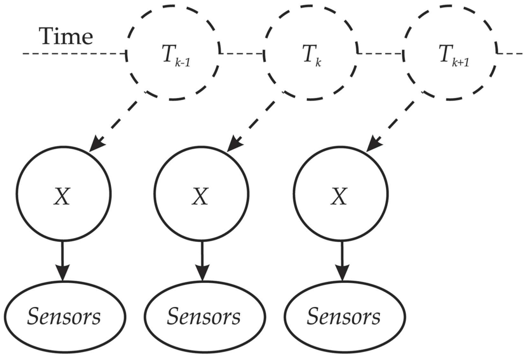

Fig. 3. A BN modelling the time dependence of the traffic process (node X). For each point in time T_k another BN characterises the traffic process with different probability distributions $P(x \mid T_k)$.

4.1. Modelling the Prior Probability

The prior $P(x)$ represents the knowledge about the underlying traffic process. If we do not know anything about it, it is legitimate to model the prior as a uniform probability distribution, weighting each state value equally. But if we know more, the process can be modelled considering different objective (physical) or subjective (Bayesian) assumptions. So, for instance, the prior can be modelled as a probability distribution containing all the relative frequencies of the most expected vehicle on a road

- depending on the ratio of actual vehicles counted in the referred area, city, country, etc.,
- depending on the time of the day,
- depending on the type of the observed road (e.g. it can be distinguished between play streets and transit roads),
- depending on incidents, events and structural measures, stoppages, etc.,
- or even mixtures of some of the mentioned dependencies.

An example for modelling the traffic process depending on the time of day is given in Fig. 3. The time dependence can be modelled as additional control nodes (which are not BN nodes) resulting in a different BN at each point in time. These kinds of BNs are called Dynamic Bayesian Networks (DBNs), but shall not be considered throughout this paper. See [21], [26] for deeper information.

The formalism of BNs, introduced in section 2, allows one to model the prior probability distribution of the traffic process and its dependencies with additional nodes and attached known or learned probability tables to manipulate the a posteriori probability by the given assumptions and information in a useful way.

The necessary data for the quantification of the probability tables can be learned, adapting the underlying traffic process. Adaptive learning methods, e.g. for learning time variant prior probabilities and CPTs are addressed in, e.g. [3], [10], [24].

Fig. 4. Reflections on the road surface usually make the determination of relevant traffic data difficult.

4.2. Modelling the Influenced Sensors

As already stated in section 1, the performance of a sensor is dependent on its functional principle, the surrounding environment and other phenomena. Here, a traffic state dependent sensor and an environmental affected sensor are modelled.

1) *Modelling the Environmental Influenced Sensor*: A video detector, as an example for an environmental influenced sensor, can be characterised by the following dependencies [2], [6], [14], [20]:

- Different or changing weather conditions (e.g. heavy rain, fog, snow, etc.) mainly cause false, multiple and phantom detections.
- Different or changing illuminations, e.g. darkness, at nightfall, glare of the sun, sun rise and sundown, shadows of moving or immobile objects, reflections on the road, e.g. as shown in Fig. 4, etc., usually cause false, multiple and phantom detections.
- Camera motion and camera vibrations can be caused by heavy winds. Particularly in wide area traffic surveillance erroneous detections occur.
- Particular traffic conditions can cause partial or even total occlusions among the vehicles, yielding an underdetection of some or even all vehicle classes.
- Video sensors are mounted for overhead, sidefire and wide area detection. Depending on the installation height partial and total occlusions occur, yielding an underdetection of some vehicle classes.
- The physical environment, e.g. temperature, luminosity, hygrometry, etc., can have a great influence on the measurements, because the sensor is built within a specific range of tolerance.
- The driver behaviour, e.g. overtaking and turning procedures, can lead to multiple or false detections, when the vehicles pass through several fixed detection areas partly. Usually specific vehicle classes are overcounted, some others are undercounted.

- The wear and tear of the sensor and the components during its operating life (Mean Time Between Failure—MTBF) can cause corrupted data, lack of data or even data terminations.
- A bad calibration of the camera, particularly of the detection areas, cause wrong vehicle classifications, because of multiple or underdetections and faulty velocity and length measurements.

Some of the effects are time-dependent (e.g. shadows of moving or standing objects, because of sun rise), some occur by accident (rain, reflections on the road surface) and some have systematic causes (calibration of a camera for overhead or side fire detection).

2) *Modelling the Traffic State Influenced Sensor*: An inductive loop detector, as an example for a traffic state dependent sensor, is an LC-oscillator, which is buried underneath the road surface. Its resonance frequency changes, if there is an metallic object in working area of the loop. These changes are evaluated and compared with known pattern, thus, a vehicle classification is possible. Besides environmental and other affecting dependencies, an inductive loop detector can be characterised by, e.g. [11]:

- Free flow conditions usually yield optimal detection results, while stop-and-go traffic distorts the measurements. Usually, there occur overdetections, misclassifications of the vehicles, enduring occupancies, yielding for instance false estimations of the traffic density.
- The driver behaviour in different traffic conditions, e.g. if loop detectors are overrun only partly, can lead to multiple or false detections and misclassifications of the detected vehicles.

3) *Comments on Modelling the Considered Sensors*: The most effects, which have an influence on the sensors' performance and the quality of the measured data, are not methodical, but stochastical uncertain and can be considered and quantified in the BNDF model. The quantification of the influences of the most physical conditions for an optimal sensor performance is possible by studying the data sheets, for instance, delivered by the original end manufacturer. In contrast, the quantification of the performance of the sensor under different environmental conditions is difficult, because extensive field tests with highly accurate sensors or manual references need to be realised. So for instance, by means of a rain or weather sensor, the current weather situation can be determined and relative frequencies of correct, false and phantom vehicle classifications could be made to decide whether the sensor is more or less influenced by weather conditions. Then, the values for the likelihood $P(z \mid x, \mathbf{e})$ of the considered sensor can be used for inference.

4.3. Inference and Sensor Data Fusion

The resulting BNDF model can be used to compute the state values of the unknown traffic process X within the surrounding known (or even unknown) environment (data $\mathbf{e}$). The sensors provide measuring data (evidences) $\mathbf{z}$, allowing the vehicle class x to be inferred from the BNDF model according to the Markov condition of the JPD in equation (1) and the extended Bayes' rule in equation (4).

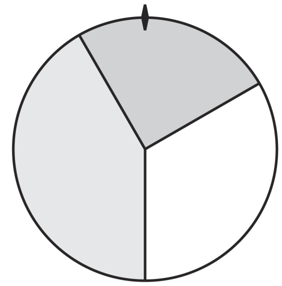

Fig. 5. The probability wheel (from Heckerman [8]).

In general, the computation and evaluation of a BN is NP-hard [22], [23]. Depending of the number of nodes, the number of states of each node and the algorithm used, the evaluation of a BN can be quick or time-consuming. The consideration of these facts and the requirements, defined by the user, e.g. concerning the real-time applicability, the accuracy of the fusion results, etc. determine the structure (e.g. the number of nodes and states) and the computation methods of the BN in question (e.g. exact or approximate inference algorithms).

Computing equation (4) by the use of exact or approximate inference algorithms, the probability distribution of the inferred state $x \in X$ is estimated. Typically, the unknown value x is determined by a maximum a posteriori estimation (MAP) of the a posteriori probability

$$\hat{x} = \arg\max_x P(x \mid \mathbf{z}, \mathbf{e}) \tag{5}$$

by maximising the confidence in the measurement. Another method to calculate $\hat{x}$, which keeps the principle of probability alive, is the so called probability wheel, introduced in [8]. In this method, the probabilities of the states of a variable are considered as regions of different percent areas on a symmetric wheel (see Fig. 5). The symmetry assumption implies, that any position where the wheel can stop is equally likely. Consequently, the probability of which state $\hat{x}$ will be chosen, depends on the percent area where the wheel will stop. Hence, in comparison to MAP estimation the probability wheel may stop at the percent area for even very unlikely states, which is particularly advantageous in case of flat probability density functions, that characterise a higher degree of uncertainty. The application of the probability wheel can be expressed by

$$\hat{x} = \arg\underset{x}{\mathrm{PW}}\, P(x \mid \mathbf{z}, \mathbf{e}) \tag{6}$$

where PW labels the probability wheel operator. There are different methods and algorithms for realising exact or approximate inference, which are not discussed in this paper. Good descriptions can be found in [21]–[23].

5. RESULTS

In this section simulation results for BNDF in comparison with the naive BDF in the case of vehicle classification are presented. Thereby, on the one hand, the influence of environmental conditions on the performance of a video sensor and on the other hand, the influence of the traffic conditions on the performance of an inductive loop detector are investigated. In the case of BNDF these influences, which affect the measurements of the sensors, are considered as additional nodes in the BN model. The inference of the resulting BNDF model yields a correction of selection bias in the merged traffic data. In contrast, naive BDF is not capable of correcting bias, yielding manipulated data.

The investigations were made on the basis of a data base (video based measurements) containing 65,000 measurements generated synthetically and additionally, real 24-hour traffic data [27] containing approximately 120,000 measurements. The real traffic data were recorded with an ASIM TT 298 combination detector[1] and an ordinary inductive loop detector at an intersection between a federal road and a less frequented city road (Radeburger Strasse/Meinholdstrasse) in Dresden, Germany, on 20 May 2005. This data base is characterised by peak traffic in the morning and in the evening and was used for learning the prior probability $P(x)$.

The BNDF model, developed in the last two sections and the given data base are used for learning and validation of cases with sensor data. The real data set is not used for validation. For simulations, the tools Mathematica 4.0 and Netica 3.19 were used. The results are compared with the naive approach of BDF without correction of selection bias.

5.1. State Declaration and Assumptions

In the following, the states of the traffic process node X and the sensors Z_1 (loop detector) and Z_2 (video sensor) are represented by different nine vehicle classes, which are given by the following set of symbols:

$$X = \{\mathrm{C}, \mathrm{C+}, \mathrm{V}, \mathrm{L}, \mathrm{L+}, \mathrm{D}, \mathrm{B}, \mathrm{M}, \mathrm{N}\}$$

representing C (car), C+ (car with a trailer), V (van), L (lorry), L+ (lorry with a trailer), D (double train), B (bus), M (motorcycle) and N (not classifiable). One more virtual class Ø, representing the case *nothing detected*, was used to decide, whether a sensor did not detect anything, although a vehicle was present. Thus,

$$Z_1 = Z_2 = \{X, \text{Ø}\}.$$

[1] A final report about testing the ASIM TT 298 detector in accordance with the German TLS standard [1], developed by Munich University of Technology is available on http://www.asim.ch/traffic/pdf/report_tt298_d.pdf [17].

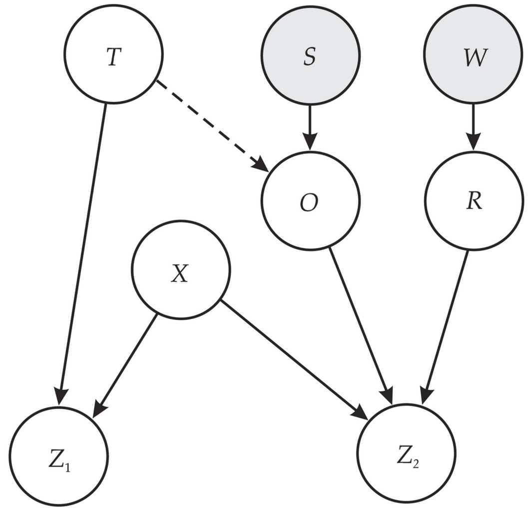

Fig. 6. Qualified data fusion with the two affected sensors Z_1 and Z_2. In contrast to the classical BDF model according to Fig. 1 the BN contains the environmental nodes W and R, modelling the Weather conditions and the Reflections on the road surface; the traffic process dependent nodes T and O, modelling the Traffic state and Occlusions among the vehicles on the road; as well as the node S, modelling the Sensor installation for sidefire or overhead detection. The grey coloured nodes and the dashed directed link are inconsequential, if the the nodes O, R and T are evidence nodes.

The quantification of the prior $P(x)$ was made by EM- (expectation maximisation) learning of the real 24-hour data [27]. The vehicle class C was expectedly strongly overrepresented by approximately 85%, while the other eight classes share the remaining 15%. The relative frequency of the most rare class N reached only 0.1% (see equation (8) in the appendix).

We chose the simple BN in Fig. 6, which is the result of the following assumptions and determinations made:

- The loop detector Z_1 is affected only by the traffic state T, which is characterised by the states t_1 (free flow) and t_2 (stop-and-go traffic), i.e. $T = \{t_1, t_2\}$. It works optimally in the case of $T = t_1$. There should be an explicit underdetection of the vehicle classes C+, L+ and D in the case of $T = t_2$ (see equation (10) in the appendix). All other classes should be slightly underdetected. The influence set for sensor Z_1 thus is $\mathbf{E}_1 = T$.
- In contrast, the video sensor Z_2 should be affected by reflections on the road surface R and current occlusions among the vehicles O. Reflections on the road surface should be caused by the current weather conditions W. Occlusions should be caused by the sensor installation S and the traffic state T. Since we consider the nodes O and R as evidence nodes, the influences of T, S and W on Z_2 are "explained away" [22], [23]. Thus, the influence set for the video detector is given by $\mathbf{E}_2 = \{R, O\}$.
- The resulting influence set is given by $\mathbf{E} = \{\mathbf{E}_1, \mathbf{E}_2\} = \{T, R, O\}$.
- The nodes O and R are binary nodes, which are characterised by the states o_1 (there are not any occlusions among the vehicles at all) and o_2 (heavy

occlusions) and r_1 (there are not any reflections on the road surface) and r_2 (heavy reflections).

- The video sensor has the same performance as the loop detector in the case of optimal conditions with no bias. Thus, the likelihood probability of the video sensor is given by $P(z_2 \mid x, o_1, r_1) = P(z_1 \mid x, t_1)$ yielding optimal fusion results (see equations (9) and (11) in the appendix). For this reason, the fusion process needs only to be simulated in the case of the worst conditions concerning the three nodes with the states o_2, r_2 and t_2, where the correction of selection bias is to be proved.
- In the case of reflections on the road surface, because of darkness and bad weather conditions and in the case of occlusions among vehicles, it often happens, that some vehicles are overcounted and some are undercounted [2], [6], [14], [20]. Here it is assumed, that larger vehicles, e.g. lorries and buses, are overcounted, while smaller vehicles, like cars, motorcycles and vans, are undercounted (see equations (13) and (14) in the appendix). This causes changes in the quantification of the likelihoods of the video sensor and the loop detector and yields different joint likelihoods $P(z_1, z_2 \mid x, t, o, r)$.
- Phantom detections should not be present.

With the assumptions and determinations made we simulated the naive BDF approach in comparison with the extended and qualified BNDF model, which considers the traffic state node, the occlusions node and the reflections node.

In the following paragraph the results for two sensor data fusion are presented.

5.2. BNDF vs. BDF

According to the learned a priori distribution $P(x)$ of the underlying traffic process and the modelled likelihoods of the the loop detector $P(z_1 \mid x, t)$ and the video sensor $P(z_2 \mid x, o, r)$, which consider the made assumptions of the preceeding paragraph 5.1, we simulated the fusion process with two sensors for the following cases (see equations (9) to (14) for the applied sensor likelihoods):

0. Both sensors work optimally, i.e. there are not any internal and external influences, which affect the measurements of the sensor. This case is only used for reference.
1. The inductive loop detector works optimally, but the video detector is affected
   a) by occlusions, i.e. $\mathbf{e} = \{o_2\}$.
   b) by reflections on the road surface, i.e. $\mathbf{e} = \{r_2\}$.
   c) by occlusions and reflections on the road surface, i.e. $\mathbf{e} = \{o_2, r_2\}$.
2. The video sensor works optimally, but the inductive loop detector is affected by the traffic state, i.e. $\mathbf{e} = \{t_2\}$.
3. Both sensors are affected, i.e the loop detector is influenced as in 2.) and the video sensor is influenced as in 1.) by:
   a) by occlusions, i.e. $\mathbf{e} = \{t_2, o_2\}$.
   b) by reflections on the road surface, i.e. $\mathbf{e} = \{t_2, r_2\}$.
   c) by occlusions and reflections on the road surface, i.e. $\mathbf{e} = \{t_2, o_2, r_2\}$.

In case 3.c) the conditions for the detection and classification of vehicles are the worst, because both sensors are affected by reflections on the road, heavy traffic conditions and occlusions among the vehicles.

The simulations were done with the same number of 65,000 measurements under the prevailing circumstances. Since the sensors have the same performance in the case of optimal conditions (see paragraph 5.1), yielding the best fusion results, it is necessary to investigate the fusion process for the cases 1.a) till 3.c). Case 0.) is used only for reference. We used the probability wheel, according to equation (6), for the estimation of the optimal state x, since highly influenced traffic sensor data are merged reflecting the expected higher degree of uncertainty of the data.

The tables I to VII show the achieved estimation errors of the vehicle classes with naive BDF (row BDF) according to equation (3) in comparison to the extended BNDF (row BNDF), which considers the the nodes T, O and R, according to equation (4) and Fig. 6.

We considered two kinds of estimation errors for the evaluation of the comparison between BNDF and BDF. The relative Class Related Error CRE(x) of vehicle class x is given by:

$$\mathrm{CRE}(x) = \frac{\mathrm{FDV}(x)}{\mathrm{CDV}(x) + \mathrm{FDV}(x)} \qquad \forall \quad x \in X,$$

with CDV(x) denoting the number of correctly detected vehicles of class x and FDV(x) denoting the number of false detected vehicles of class x. The calculation of the CREs of the vehicle class of interest informs us about the accuracy of the fusion process in a class related context. Since some vehicle classes can be detected more or less better than other, the CREs differ. The accumulation of FDV(x), $\forall x \in X$, in relation to the sum of all detected vehicles, yields the Total Classification Error (TCE):

$$\mathrm{TCE} = \frac{\sum_{x \in X} \mathrm{FDV}(x)}{\sum_{x \in X} (\mathrm{CDV}(x) + \mathrm{FDV}(x))} \tag{7}$$

which allows us to state something about how accurate and successful the fusion process is overall. Although the TCE can be decreased by far, it might happen, that there are vehicle classes, whose CREs increase by far or which cannot be determined anymore, i.e. their CREs reach 100%. Depending on the fusion task to be solved and the underlying operational areas of the applied sensors, the fusion process can be successful if the TCE decreases and some CREs increase. For instance, this might be the case for an average estimation of the travel times for traffic management. On the other hand, the fusion process can be unsuccessful, if there is at least one CRE increasing or reaching even 100%, e.g. in the case of enforcement at tollgates on motorways. Because of these facts, the two terms *CRE-successful fusion* and *TCE-successful fusion* are introduced to distinguish between the two error metrics above.

The relative discrepancies between the TCEs and the CREs in the case of BNDF and in the case of the naive BDF are given by ΔTCE and ΔCRE respectively.

In the following, the simulation results of the considered cases are given and interpreted. It is shown, that modelling the affecting conditions as additional nodes in a BN usually, but not generally, yield improvements of the vehicle class estimates. Although the TCEs decrease in any cases in BNDF, the CREs of some vehicle classes may increase.

1) *None Affected Sensors—Case 0.)*: As mentioned above, if both sensors work optimally, i.e. there is no affecting influence set **E**, optimal results for vehicle classification are obtained. In this case the results for BDF and BNDF are identical. 807 of 65,000 vehicle class estimates are erroneous (TCE = 1.24%). The CREs for each vehicle classes are the following: CRE(C) = 0.5%, CRE(C+) = 19.0%, CRE(V) = 2.6%, CRE(L) = 3.9%, CRE(L+) = 18.0%, CRE(D) = 5.3%, CRE(B) = 20.3%, CRE(M) = 18.3% and CRE(N) = 29.2%. These results are used for reference.

2) *Affected Video Detector—Cases 1.a) to 1.c)*: As expected, if there is only one sensor affected by some influence set **E**, the vehicle classification with BNDF yields much better results, than by BDF, which had already been stated in the underlying paper [9]. Here, the TCEs decrease from 8.7% (5,644 erroneous vehicles), 10.0% (6,517) and 10.9% (7,097) to 5.0% (3,241), 3.7% (2,430) and 4.2% (2,751) for the cases 1.a), 1.b) and 1.c) respectively. See the tables I, II and III for more results. In almost any case the CREs decrease by far, up to ΔCRE(M) = −88% in case 1.b), whereas there is exactly one significant increase of the CRE of vehicle class L in the case 1.c). Since the class C ist strongly overrepresented by the prior probability $P(x = C) = 85\%$, it is not surprising, that there can be achieved an enormous error reduction for this vehicle class up to ΔCRE(C) = −79% in case 1.c) as well. There are also some other cases, where the vehicle classes C+ and N cannot be detected at all, i.e. their CREs reached 100%. Furthermore, if the classification results achieved here are compared with the unaffected reference case 0., it can be ascertained, that there is an reduction of the CREs of the class M from 29.2% to 11.8%, i.e. we could even improve the unaffected fusion results by far. Considering the three cases, we can speak of a TCE-successful fusion and an almost totally CRE-succesful fusion for vehicle classification, if the sensor properties, affected by the modelled conditions are considered in the BNDF model. As a consequence, we are able to improve the measurements of environmental influenced sensors, whose properties and dependencies are modelled in a particular BN, by environmental independent sensors.

3) *Affected Loop Detector—Case 2.)*: If the video detector works optimally and the loop detector is affected by the traffic state, i.e. the influence set is $\mathbf{e} = \{t_2\}$, the simulation results of the cases 1.a) to 1.c) are mostly verified. Altogether, there is a reduction of the TCE from 3.5% (2,298 erroneous vehicles) to 3.1% (1,989). See table IV for results. The CRE for class L+ is decreased by far: ΔCRE(L+) = −62%. But there are also increases of the CREs for the vehicle classes V, L and N. As a result, vehicle class N cannot be correctly classified anymore. The fusion results can be said to be TCE-succesful and almost CRE-successful. Completely CRE-unsuccessful are the CREs for the classes L and N.

4) *Both Sensors Affected—Cases 3.a) to 3.c)*: If both sensors are affected by some influence set **E**, we have the worst conditions for detecting and classifying vehicles on the road. Here, the TCEs decrease from 17.4%, 27.1% and 26.3% to 10.2%, 8.8% and 9.5% in the cases 3.a), 3.b) and 3.c) respectively. That means the TCEs reduce by 41%, 67% and 64%, respectively. See table V, VI and VII for results. The overall results show incredible improvements, due to the consideration of the sensors' dependencies in the BNDF model, but there are also weightily drawbacks in accordance with the CREs of some vehicle classes. Since class C is strongly overrepresented by the prior probabiliy $P(x)$, the superposition of the influences make the correct classification of C much easier, thus the CREs of class C in BNDF are very low. In contrast, the CREs of other vehicle classes increase and some reach 100%. Noticable is for instance the increase of the CRE(L) by 184% and 44% in the cases 3.b) and 3.c) respectively.

If the fusion in these cases is evaluated, we can state, that we have very TCE-successful fusion, but CRE-unsuccessful fusion in almost any case and for almost each vehicle class, which is usually unacceptable. Due to the fact, that BDF also behaves poorly, we cannot even speak of good fusion results in general. Under such difficult circumstances and again, depending on the fusion task to solve in accordance with the underlying traffic related problem, one should think about the reduction of the nine vehicle classes to maybe two, for instance combining car similar vehicles to the first class and lorry similar vehicle to the second class.

5) *Summary of the Results in the Tables I to VII*: Summarising the seven tables, we can state, that usually BDF performs poorly, because of the inherent selection bias, yielding the addressed over- and undercounting of specified vehicle classes. In contrast, in the case of BNDF, the consideration of the sensors' surrounding environment and other phenomena like traffic process related dependencies, affecting the sensors' performance, in the fusion model, yielded an explicit

TABLE I

	C	C+	V	L	L+	D	B	M	N
CREs for Vehicle Classification in the Case 1.a) [%]									
BDF	3.8	94.0	26.1	25.4	86.3	39.7	88.1	99.5	98.9
BNDF	2.7	100	9.0	17.3	46.6	26.1	42.7	17.9	100
ΔCRE	−27	+6	−66	−32	−46	−34	−52	−82	+1
ΔTCE	By consideration of $\mathbf{e} = \{o_2\}$ in BNDF: −42.6%								

TABLE II

	C	C+	V	L	L+	D	B	M	N
CREs for Vehicle Classification in the Case 1.b) [%]									
BDF	8.6	98.3	7.9	8.3	63.4	14.1	66.9	95.8	92.4
BNDF	2.5	19.2	7.3	8.6	20.1	15.9	53.5	11.8	38.0
ΔCRE	−71	−81	−8	+4	−68	+12	−20	−88	−59
ΔTCE	By Consideration of $\mathbf{e} = \{r_2\}$ in BNDF: −62.7%								

TABLE III

	C	C+	V	L	L+	D	B	M	N
CREs for Vehicle Classification in the Case 1.c) [%]									
BDF	7.9	99.6	16.1	21.9	72.6	26.8	80.8	96.2	94.2
BNDF	1.7	37.1	8.5	35.2	34.5	32.2	32.0	35.9	100
ΔCRE	−79	−63	−48	+61	−52	−14	−60	−634	+6
ΔTCE	By Consideration of $\mathbf{e} = \{o_2, r_2\}$ in BNDF: −61.2%								

TABLE IV

	C	C+	V	L	L+	D	B	M	N
CREs for Vehicle Classification in the Case 2.) [%]									
BDF	1.6	71.3	5.9	8.6	79.2	28.0	36.2	30.7	88.6
BNDF	1.2	71.3	6.6	11.2	29.4	22.2	36.2	30.7	100
ΔCRE	−25	±0	+13	+31	−62	−21	±0	±0	+13
ΔTCE	By Consideration of $\mathbf{e} = \{t_2\}$ in BNDF: −13.4%								

TABLE V

	C	C+	V	L	L+	D	B	M	N
CREs for Vehicle Classification in the Case 3.a) [%]									
BDF	9.9	97.6	38.6	37.6	95.9	74.8	90.1	100	100
BNDF	2.8	100	36.4	44.3	100	100	100	100	100
ΔCRE	−76	+2	−6	+18	+4	+34	+11	±0	±0
ΔTCE	By Consideration of $\mathbf{e} = \{t_2, o_2\}$ in BNDF: −41.1%								

TABLE VI

	C	C+	V	L	L+	D	B	M	N
CREs for Vehicle Classification in the Case 3.b) [%]									
BDF	26.0	99.6	22.5	18.7	90.6	57.0	65.8	96.8	100
BNDF	3.9	73.7	21.8	53.1	100	46.2	65.8	59.3	100
ΔCRE	−85	−26	−3	+184	+10	−19	±0	−39	±0
ΔTCE	By Consideration of $\mathbf{e} = \{t_2, r_2\}$ in BNDF: −67.4%								

TABLE VII

	C	C+	V	L	L+	D	B	M	N
CREs for Vehicle Classification in the Case 3.c) [%]									
BDF	23.5	99.6	29.0	31.9	92.8	64.3	84.8	98.5	98.0
BNDF	3.3	100	31.3	45.9	100	66.3	84.8	47.8	100
ΔCRE	−86	+0.4	+8	+44	+8	+3	±0	−52	+2
ΔTCE	By Consideration of $\mathbf{e} = \{t_2, o_2, r_2\}$ in BNDF: −63.8%								

TCE-successful fusion for any considered case. See Fig. 7 for the results. The best results were obtained, if the worst conditions were considered in the fusion model. In the case of two sensors, one traffic process dependent loop detector and one weather and traffic process affected video sensor, we achieved an improvement of the fusion process by more than 60%. Consequently, we are able to enhance environmental independent sensors by strongly environmental dependent sensors, whose properties and dependencies are modelled in a particular BN. That means since there is no single sensor, which is environmentally independent, the sensors should be affected in different ways and/or different domains.

On the other hand, the results show, that BNDF (and also BDF) is not CRE-successful in any case, particularly if the conditions for both sensors are bad. Depending on the fusion task to be solved and the underlying task in traffic management, it must be decided, whether the fusion results are beneficial or not. If necessary, the classification domain for vehicles must be reduced to two classes for instance.

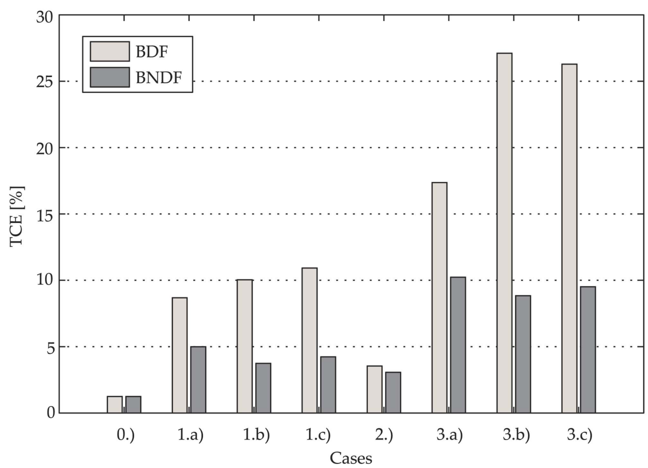

Fig. 7. The TCEs of the cases 0.) (for reference) to 3.c) are plotted for BDF and BNDF. The most improvements occur in 3.a) to 3.c).

The results show, what magnitude of improvements in data fusion can be achieved, if external and internal affects are considered in the fusion model. Nevertheless, the obtained error reductions of the vehicle class estimates must be interpreted in a correct manner, because the simulations were done on the basis of synthetic data (which was supplemented with real 24-hour traffic data). When using real traffic data, the fusion error reduction results are supposed to be slightly worse.

6) *Computational Performance*: The computation and evaluation of the simple BN in Fig. 6 can be done in real-time, since it is small and consists of mainly binary evidence nodes. However, if one wishes to consider more external and internal influences, which are characterised by more states, affecting the performance of the sensors, the computational complexity grows exponentially. Consequently, the use of larger, more realistic BN for data fusion in traffic surveillance, has to be investigated with regard to the accuracy and reliability of the traffic data, real-time applicability, etc.

6. CONCLUSIONS AND FUTURE PROSPECTS

In this paper a data fusion method was introduced, that is based on the concept of Bayesian Networks, called Bayesian Network Data Fusion (BNDF). Since sensors are time variant systems with particular functional principles, the measurements are as good as the a priori knowledge about the sensors and the underlying process are and as good as the measurements of the sensors are. The sensors are affected by the external, e.g. environmental conditions, and internal conditions, e.g. the physical life of the sensor, yielding selection bias in the resulting measuring data. Thus, the consideration of these dependencies in a BN model are indispensable to correct selection bias and thus, improve the fusion process and the resulting data.

The obtained results for vehicle classification show, that the BNDF model is able to infer vehicle classes by systematically taking into account sensor measurements (the vehicle evidences), environmental conditions (the environmental evidences) and traffic process related conditions (traffic state evidences and occlusions). By the combination of two heterogeneous sensors—here, a weather and traffic process dependent video sensor and a traffic process dependent inductive loop detector—the accuracy of the estimates of the vehicle classes is improved by up to more than 60%, i.e. the fusion process is TCE-successful in any case. The fusion results are also CRE-successful, if it can be ensured, that the sensors are affected by some differing influence sets. Under certain difficult circumstances, the fusion process is usually not CRE-successful, which means, the CREs increase by far or reach even 100%, i.e. the vehicles cannot be classified correctly at all. As a consequence, the applied sensors should differ in their internal and external influences. Furthermore, the sensors must be used carefully. Depending on the fusion task to be solved and the underlying traffic related application, one must decide, whether a not CRE-successful fusion is sufficently satisfied. The decisions of a traffic manager will differ in the case of simply measuring averaged travel times and in the case of the classifaction of vehicles for enforcment and monetary applications.

The obtained results must be interpreted carefully, because the simulations were done on the basis of synthetic traffic data, supplemented with real traffic data. Moreover, the conditions for an optimal performance of the video sensor were intentionally violated by the modelled bad conditions. Vice versa, if the conditions are optimal, the fusion results will be even better. The investigation of a two homogeneous sensor fusion was not of interest in this article. Since, homogeneous detectors are affected by the same internal and external conditions, selection bias cannot be corrected in general. Nevertheless, an improvement of the fusion process is obvious.

The results further show, what magnitude of improvements in data fusion can be achieved, if external and internal affects are considered in the fusion model. But, in case of real traffic data, the fusion results are supposably slightly worse.

Our current work is characterised by the application of the proposed method (using probability wheel and MAP estimation) to real traffic data. Thereby not only video sensors and their dependencies on weather conditions, but also other sensors, e.g. inductive loop detectors, infrared sensors, etc. and their influences by external and internal conditions need to be investigated and quantified in a BNDF model, because the concept of BNDF is not restricted to any particular sensor type, but generally valid. Thus, the creation and application of an adequate BN sensor model is supposed to improve the fusion results and to correct selection bias in general. In this regard it has to be stated, that the simulations done and the results achieved cannot be extrapolated, since they refer only on two specific sensors, with certain properties and applications.

Furthermore, the concept of adaptive probability learning is to be applied to the considered probabilistic sensor model to investigate the considered results for an instationary traffic process with time dependent prior probabilities [10]. This comes along with the coupling of the environmental nodes, e.g. the weather node, with meteorological models to achieve more sophisticated cases.

APPENDIX

In the following the prior probability and the CPTs of the simulated inductive loop detector Z_1 and the video sensor Z_2 are given.

Prior Probability

$$P(x) = (.847\ \ .004\ \ .094\ \ .026\ \ .005\ \ .012\ \ .005\ \ .006\ \ .001)^T \tag{8}$$

CPTs of the Inductive Loop Detector Z_1

$P(z_1 \mid x, t_1)$

$$= \begin{pmatrix}
.91 & .01 & .01 & .01 & .01 & .01 & .01 & .01 & .01 & .01 \\
.01 & .91 & .01 & .01 & .01 & .01 & .01 & .01 & .01 & .01 \\
.01 & .01 & .91 & .01 & .01 & .01 & .01 & .01 & .01 & .01 \\
.01 & .01 & .01 & .91 & .01 & .01 & .01 & .01 & .01 & .01 \\
.01 & .01 & .01 & .01 & .91 & .01 & .01 & .01 & .01 & .01 \\
.01 & .01 & .01 & .01 & .01 & .91 & .01 & .01 & .01 & .01 \\
.01 & .01 & .01 & .01 & .01 & .01 & .91 & .01 & .01 & .01 \\
.01 & .01 & .01 & .01 & .01 & .01 & .01 & .91 & .01 & .01 \\
.01 & .01 & .01 & .01 & .01 & .01 & .01 & .01 & .91 & .01
\end{pmatrix} \tag{9}$$

$P(z_1 \mid x, t_2)$

$$= \begin{pmatrix}
.73 & .03 & .03 & .03 & .03 & .03 & .03 & .03 & .03 & .03 \\
.18 & .36 & .18 & .04 & .04 & .04 & .04 & .04 & .04 & .04 \\
.03 & .03 & .73 & .03 & .03 & .03 & .03 & .03 & .03 & .03 \\
.03 & .03 & .03 & .73 & .03 & .03 & .03 & .03 & .03 & .03 \\
.04 & .05 & .05 & .13 & .27 & .27 & .13 & .02 & .03 & .01 \\
.04 & .05 & .05 & .13 & .27 & .27 & .13 & .02 & .03 & .01 \\
.03 & .03 & .03 & .03 & .03 & .03 & .73 & .03 & .03 & .03 \\
.10 & .01 & .03 & .03 & .01 & .01 & .03 & .73 & .03 & .02 \\
.11 & .11 & .11 & .11 & .11 & .11 & .11 & .11 & .11 & .01
\end{pmatrix}. \tag{10}$$

CPTs of the Video Sensor Z_2

$P(z_2 \mid x, o_1, r_1)$

$$= \begin{pmatrix}
.91 & .01 & .01 & .01 & .01 & .01 & .01 & .01 & .01 & .01 \\
.01 & .91 & .01 & .01 & .01 & .01 & .01 & .01 & .01 & .01 \\
.01 & .01 & .91 & .01 & .01 & .01 & .01 & .01 & .01 & .01 \\
.01 & .01 & .01 & .91 & .01 & .01 & .01 & .01 & .01 & .01 \\
.01 & .01 & .01 & .01 & .91 & .01 & .01 & .01 & .01 & .01 \\
.01 & .01 & .01 & .01 & .01 & .91 & .01 & .01 & .01 & .01 \\
.01 & .01 & .01 & .01 & .01 & .01 & .91 & .01 & .01 & .01 \\
.01 & .01 & .01 & .01 & .01 & .01 & .01 & .91 & .01 & .01 \\
.01 & .01 & .01 & .01 & .01 & .01 & .01 & .01 & .91 & .01
\end{pmatrix} \tag{11}$$

$P(z_2 \mid x, o_2, r_1)$

$$= \begin{pmatrix}
.20 & .06 & .06 & .06 & .05 & .05 & .06 & .20 & .06 & .20 \\
.20 & .05 & .05 & .10 & .05 & .05 & .05 & .20 & .05 & .20 \\
.20 & .05 & .10 & .10 & .10 & .07 & .10 & .07 & .14 & .07 \\
.10 & .05 & .10 & .15 & .125 & .125 & .15 & .05 & .10 & .05 \\
.10 & .05 & .10 & .15 & .15 & .15 & .15 & .05 & .05 & .05 \\
.10 & .05 & .10 & .15 & .15 & .15 & .15 & .05 & .05 & .05 \\
.10 & .05 & .15 & .15 & .10 & .10 & .15 & .05 & .10 & .05 \\
.01 & .01 & .01 & .01 & .01 & .01 & .01 & .01 & .01 & .91 \\
.12 & .12 & .12 & .12 & .12 & .12 & .12 & .12 & .02 & .02
\end{pmatrix} \tag{12}$$

$P(z_2 \mid x, o_1, r_2)$

$$= \begin{pmatrix}
.01 & .01 & .01 & .91 & .01 & .01 & .01 & .01 & .01 & .01 \\
.01 & .01 & .01 & .07 & .40 & .40 & .07 & .01 & .01 & .01 \\
.01 & .01 & .22 & .70 & .01 & .01 & .01 & .01 & .01 & .01 \\
.01 & .01 & .01 & .40 & .07 & .07 & .40 & .01 & .01 & .01 \\
.01 & .01 & .01 & .07 & .40 & .40 & .07 & .01 & .01 & .01 \\
.01 & .01 & .01 & .07 & .40 & .40 & .07 & .01 & .01 & .01 \\
.01 & .01 & .01 & .40 & .07 & .07 & .40 & .01 & .01 & .01 \\
.55 & .05 & .05 & .05 & .05 & .05 & .05 & .05 & .05 & .05 \\
.10 & .10 & .10 & .10 & .10 & .10 & .10 & .10 & .10 & .10
\end{pmatrix} \tag{13}$$

$P(z_2 \mid x, o_2, r_2)$

$$= \begin{pmatrix}
.03 & .03 & .03 & .73 & .03 & .03 & .03 & .03 & .03 & .03 \\
.15 & .01 & .03 & .07 & .30 & .30 & .07 & .05 & .01 & .01 \\
.10 & .01 & .18 & .65 & .01 & .01 & .01 & .01 & .01 & .01 \\
.08 & .01 & .07 & .25 & .19 & .17 & .20 & .01 & .01 & .01 \\
.05 & .03 & .05 & .12 & .30 & .30 & .12 & .01 & .01 & .01 \\
.05 & .03 & .05 & .12 & .30 & .30 & .12 & .01 & .01 & .01 \\
.08 & .01 & .07 & .20 & .19 & .17 & .25 & .01 & .01 & .01 \\
.03 & .03 & .03 & .03 & .03 & .03 & .03 & .03 & .03 & .73 \\
.10 & .10 & .10 & .10 & .10 & .10 & .10 & .10 & .10 & .10
\end{pmatrix}. \tag{14}$$

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