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Version	Date	Author (Unit)	Description
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2.1 Daimler Models

Introduction

The basic settings of the DAIMLER's use-case [1] are as follows. Let us suppose we are driving our car, which will be referred as the EGO vehicle, in a highway. This EGO vehicle is equipped with a video camera, radar and some on-board sensors. Using the data provided by these sensors, the challenge consists in the early recognition of a manoeuvre either of the EGO or another relevant car in the traffic scene (OBJ). In total, the system is expected to recognised the following set of manoeuvres (a visual description of them is given below in Figure 1):

1. **Object-CutOut**: A vehicle that was driving in front of us is leaving the EGO lane.
2. **Object-CutIn**: A vehicle is moving to the lane where the EGO vehicle is placed.
3. **EGO-CutOut**: The EGO vehicle is leaving the lane where it was driving.
4. **EGO-CutIn**: The EGO vehicle is moving to a new lane already occupied by another vehicle.
5. **Object-Follow**: There is no lane change. The EGO is driving and there is some other vehicle in front.
6. **Lane-Follow**: There is no lane change. The EGO is driving and there is not any other vehicle in front.

Instead of working with the raw data from the video, radar and on-board sensors, the manoeuvre recognition system uses the so-called "object data", which contains "high level" representations or features describing the "traffic scene" such as EGO's speed, distance between EGO and another vehicle in front, etc.

Figure 2 contains a visual description of the current data flow used to create this "object data". As can be seen in this figure, in a first step the raw data coming from the video, radar and sensors is preprocessed. In a second step this preprocessed data is fused and the high-level or "object data" describing the traffic scene is obtained.

Using the resulting "object data", Daimler has developed a probabilistic graphical model [2] which is able to recognize an ongoing manoeuvre around 0.6 seconds before the manoeuvre really takes place. This probabilistic approach is based on modelling the problem in different layers as shown in Figure 3.

The sensor data is modelled in the first step. Using this layer, a new layer is created on top with the goal of detecting a lane change behaviour. The detection of a lane

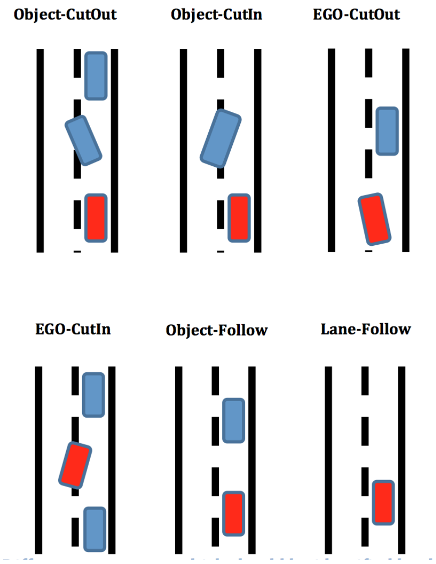

Figure 1: Different maneuvers which should be identified by the AMIDST system. Red blocks represents the EGO vehicle and blue blocks represents other vehicles in the scene. In the first four maneuvers, there is a lane change event or, under Daimler's terminology, a "Lane Marking Crossing" (LMC) event.

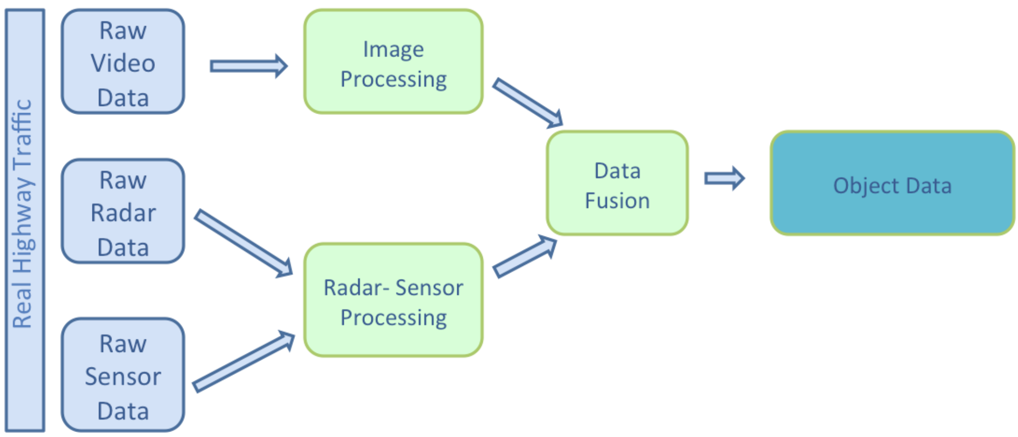

Figure 2: Daimler's Data Flow.

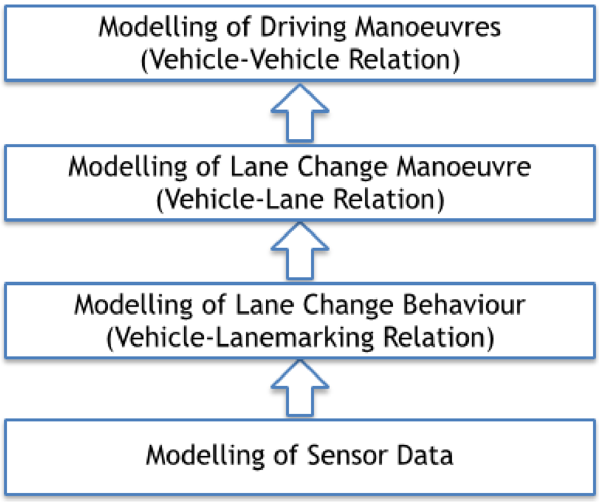

Figure 3: Hierarchical layers for the recognition of driving manoeuvres.

change behaviour allows the system to model the lane change manoeuvre in a higher layer. Finally, with this information, the system is able to identify the kind of driving manoeuvre which is taking place between a pair of vehicles.

The static-OOBN model

As commented above, this model will work with the so-called "object data". This data mainly consists of a set of measured and/or computed signals or situation-features denoted by S (e.g.. EGO speed, EGO lateral velocity, speed of a car in-front, etc., see [2] for further details) describing the traffic scene. The whole modelling is structured in hierarchical layers as detailed in Figure 3 and it has been previously implemented [2] using an object-oriented Bayesian network (OOBN) [3].

The general structure of this OOBN model consists of a number of abstraction levels (see Figure 4): all measured and/or computed signals S_MEAS are handled with their uncertainties S_SIGMA. These are represented as object classes at the lowest level (class S) of the OOBN. The real values S_REAL of evidence signals are then used at the next level of the hierarchy to evaluate the hypotheses (class H in Figure 4). The combined evaluation of several hypotheses results in the prediction of events, class E. In our case, the events are modelling traffic manoeuvres of the own and neighbour vehicles.

As commented above, the observations characterising a situation are acquired from sensors and computations (see Figure 2) and, in consequence, they are regarded as *measured data*. If the measurement instrument is not functioning properly (due to sensor noise or fault), then the sensor-reading (S_MEAS) and the real variable (S_REAL) under mea-

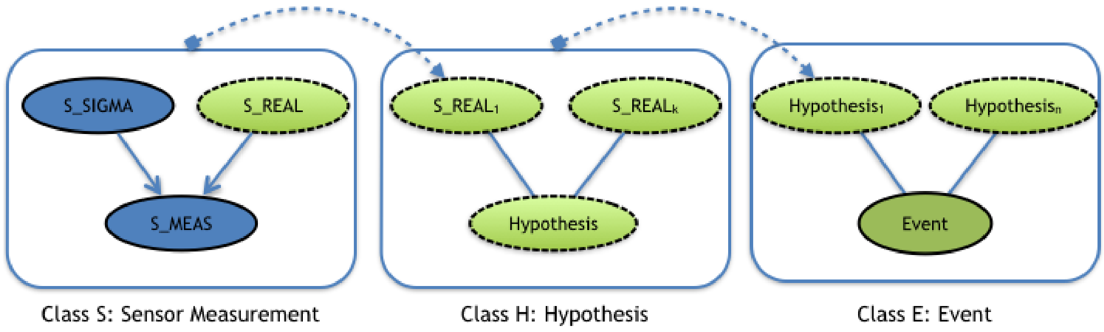

Figure 4: Static-OOBN model for the prediction of an event (maneuver) [4].

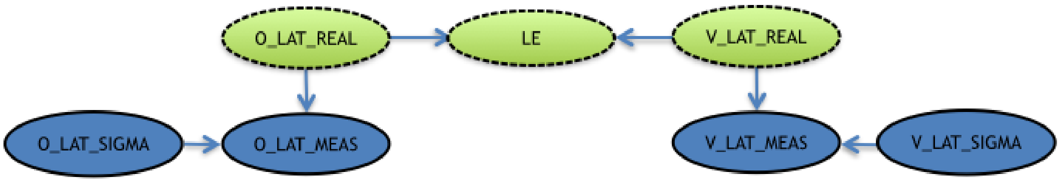

Figure 5: Static BN fragment for the LE hypothesis.

surement need not to be the same. This fact imposes the causal model structure as shown in the first part on Figure 4. The sensor-reading of any measured variable is conditionally dependent on random changes in two variables: real value under measurement (S_REAL) and sensor fault (S_SIGMA).

The situation features used for manoeuvre recognition are structured along three main dimensions: lateral evidence (LE), trajectory (TRAJ), and occupancy schedule grid (OCCGRID). They represent the three hypotheses (see Figure 4), which are modelled by the corresponding OOBN-fragments [2]. The BN fragment for the hypothesis LE is shown in Figure 5. Its conditional probability distribution is represented by a sigmoid (logistic) function. This is used to model the growing probability for the lateral evidence to cross the lane marking, based on the vehicle coming closer to the lane marking (modelled by O_LAT_MEAS) and the increase of its lateral velocity (modelled by V_LAT_MEAS).

The right-hand square on Figure 4 abstractly shows how these hypotheses are combined into events (right-hand square), which in our automotive scenario correspond to the different driving manoeuvres: lane follow, lane change (cut-in, cut-out), expressed for ego and surrounding objects [2].

The dynamic-OOBN model

The above described static OOBN is able to detect a manoeuvre 0.6s before execution. The goal is to extend the prediction horizon for manoeuvre recognition at least to 1-2 seconds (max. 4-5 seconds ahead) before the actual lane marking crossing, which is of advantage for the adaptive cruise control. Most precisely, and as indicated on Daimler's use cases [1], the area under the ROC curve (AUC) should be greater than 0.96 for 1 second and greater than 0.9 for 2 seconds.

Figure 6 shows an example of the current performance, and limitations, of the static-OOBN model. In these figures we plot the evolution on different time-steps for lateral velocity and lateral offset to a lane marking in an ongoing Object-CutOut and Object-Cutin manoeuvres (see Figure 1). The vertical black bar in these figures indicates the moment in which the manoeuvre has been recognised by the static-OOBN. The manoeuvre is finished at the end of the series, which coincides with the actual moment of changed lane. The black line corresponds to the lateral offset and lateral velocity of the EGO car, which is following the lane (LF), and the green line to the values of the Object car performing the Object-CutOut/Object-Cutin manoeuvres. As expected for lane follow (LF), the lateral velocity of the EGO fluctuates around zero (i.e. EGO car is just driving inside its lane) and the lateral offset of the lane marking is almost constant all the time. However, when we look at the lane change behaviour of the OBJ car (green lines) we easily see a quite different behaviour. Firstly, we observe that the lateral velocity is much higher indicating a lateral movement. Similarly, we also observe how the lateral offset steadily increases, what clearly indicates that the Object car is leaving its current lane in both manoeuvres.

Although the manoeuvre is clearly identified before it completes in both cases (approx. 0.6 seconds in advance), it is desired to predict it 1-2 seconds in advance. This is one of the basic piece of evidence that motivated us to develop the dynamical version of the static-OOBN model. More generally, it is clear that this problem has an inherent dynamic component. So, our main assumption is that the use of the dynamic model will allow us to build a more accurate and reliable system for manoeuvre recognition.

Note however that the prediction horizon for manoeuvre recognition is limited in order to avoid false positives. In case of a false positive, such as an erroneously Object-CutIn for instance, the adaptive cruise control would react with an unnecessary break, so they ought to be avoided.

In general, each manoeuvre can be considered as a process, developing in time, i.e., as data stream given by a time sequence of the transition from lane follow into lane change manoeuvre. The dynamic extension involves copies of the static OOBN for different number of time steps in the time window, Fig. 7 shows an example for the LE hypothesis, where the two top nodes are temporal clones defining the share belief state between consecutive time steps, and hence creating a first order Markov process.

A good starting point to model the dynamics of the data involves the variables that

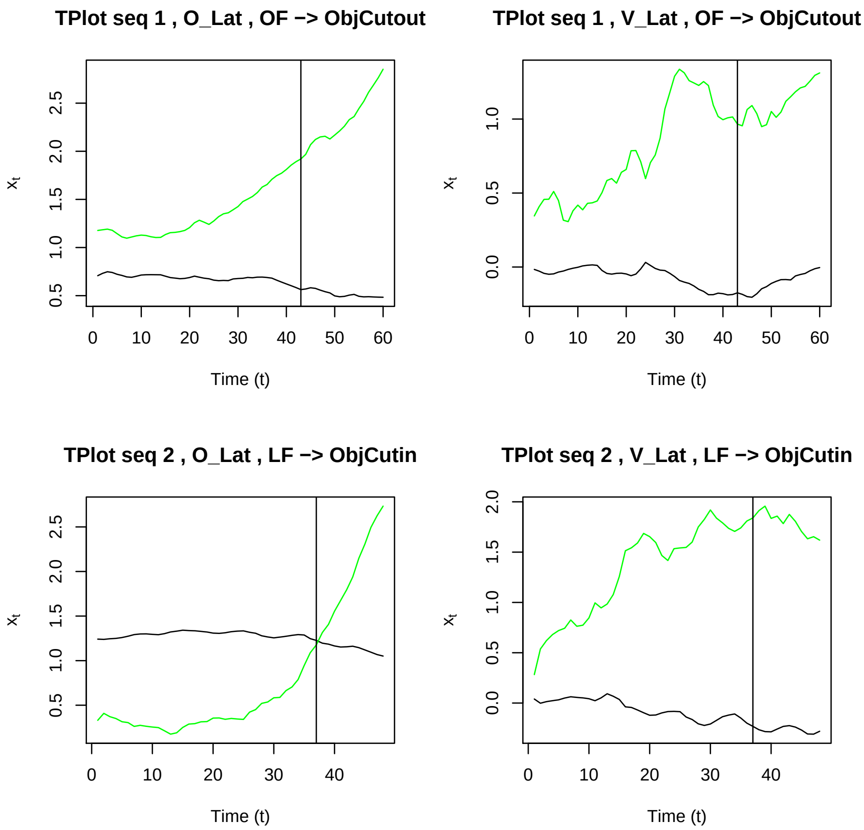

Figure 6: Daimler Time Plot

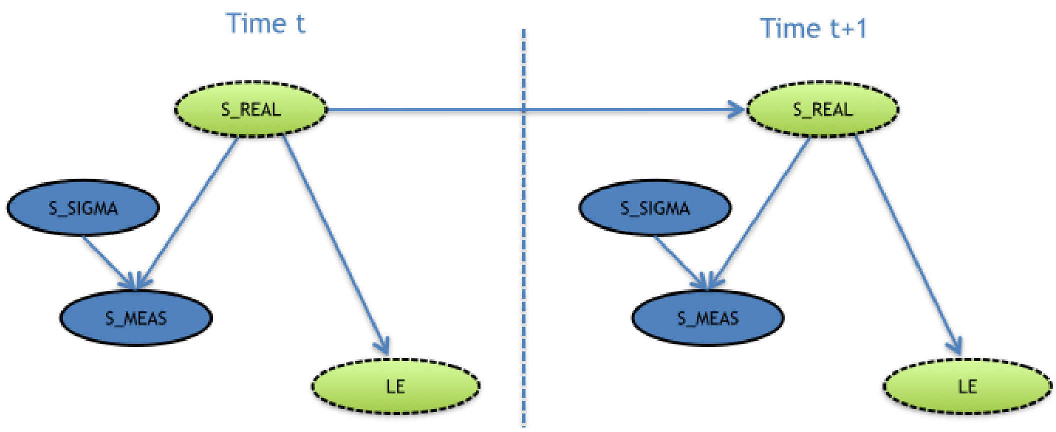

Figure 7: Daimler Temporal fragment for the LE hypothesis.

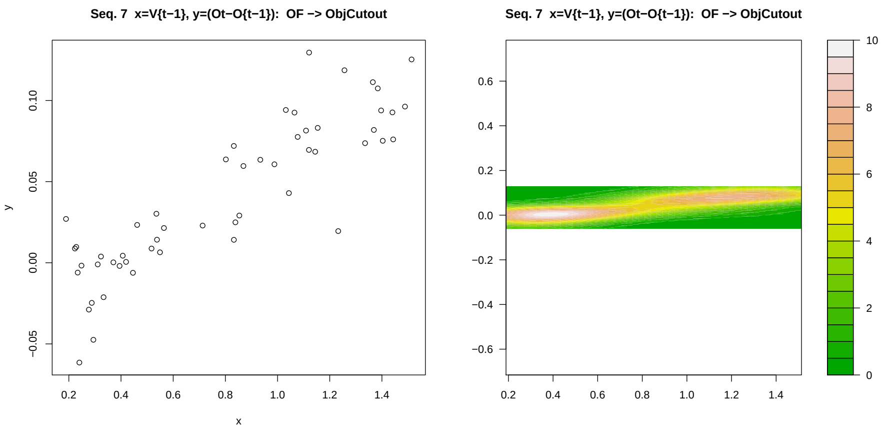

Figure 8: Time plot for $v(t-1)$ vs $O(t)-O(t-1)$. Linear correlation can be observed.

capture the lateral evidence for the different vehicles, given its relevance and simplicity. The dynamic BN (DBN) incorporates the trend of change for the real values, where their physics relations are represented as causal dependencies between the time steps dt, e.g. in Fig. 7 the transition function of O_LAT at time t, $O(t)$, is modeled as a Gaussian distribution. Its mean is affected by $O(t-1)$, and by V_LAT at time $t-1$, $v(t-1)$:

$$O(t) = O(t-1) + v(t-1)dt + N \tag{1}$$

where N denotes a white noise $N(0, \sigma^2)$ which is assumed to be small.

The shaded nodes represent the development of the real values of observations over several time steps in the time window. Thus, their trend estimation contributes to the prediction of probability of transition from a lane follow to a lane change manoeuvre.

In order to corroborate the validity of this BN fragment, we have analysed the hypothesis $O(t)-O(t-1) = \Delta O = v(t-1)dt+N$ on our data. Figure 8 shows the plot and contour plots for v and ΔO, where we observe a linear correlation.

A DBN induces a number of constraints on the compilation of the network into a computational structure. One constraint relates to transferring the belief state from one time slice to the next where the belief state is the probability distribution over the variables shared by neighbouring time slices. In general, the belief state is transferred as a joint distribution. We have imposed limitations in our dynamic model so that the next state depends only on the current state, and not on the sequence of events that preceded it, i.e. first order Markov model. Although in principle this might seem as a strong limitation, we have reasons to believe that this property might hold in our data. Fig. 9 displays, at the top, the sample correlograms for lateral velocity and offset, that is, the correlation of the data with lagged values of themselfves. The partial correlogram (bottom figures) is used to remove the common linear effect of the data in between samples. In our example,

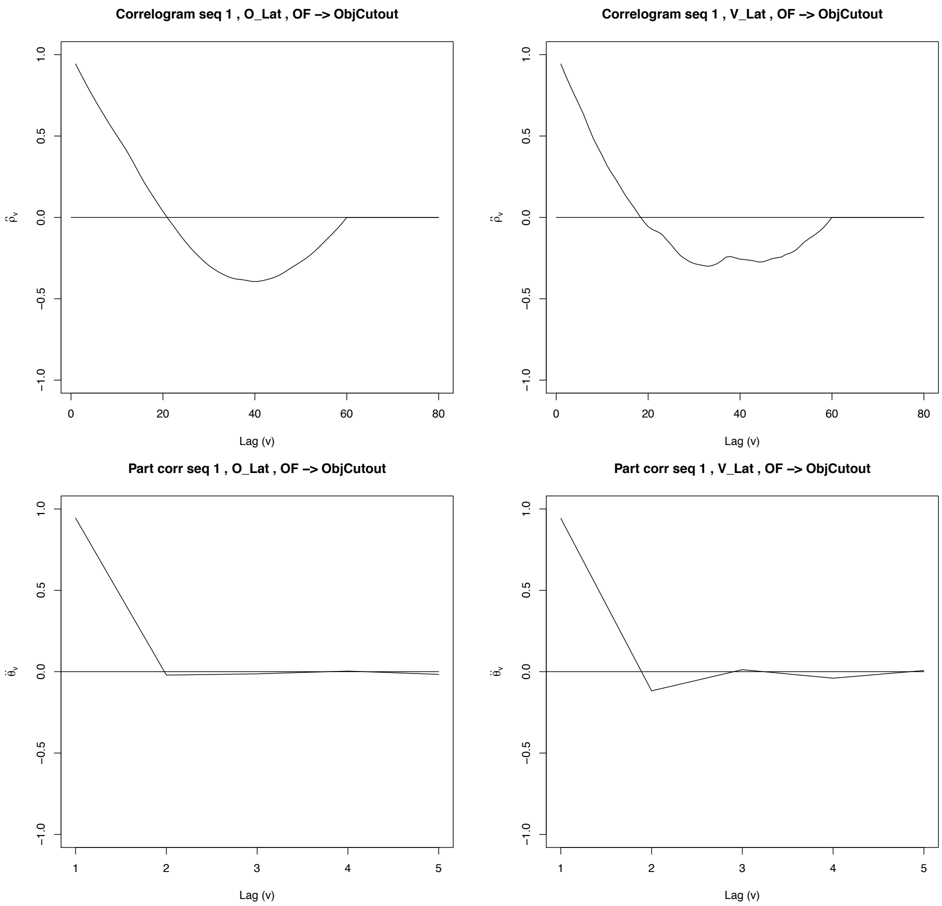

Figure 9: Correlograms and partial correlograms for Lateral velocity and offset.

for both variables, the correologrąms take some time to decay to zero, while the partial correlograms are large for lag one and then small of all other lags. This indicates that the correlation between non consecutive samples is due to the common relationship of these samples and the samples in between [5].

Figure 10 shows the temporal for all hypotheses. The final event is then determined by the combination of these hypotheses and the position of the OBJ with respect to the EGO car.

Additionally, we believe that even earlier prediction of manoeuvre intentions could be achieved before any development of the trend for lateral evidence LE has been observed. A first indication of possible lane change intention can be observed through the relative dynamics between one vehicle (host or object) and the vehicles in front of it on the same lane. Once again, the goal is to further increase the prediction horizon for manoeuvre recognition (up to 5 seconds), and this approach will be further explored in future stages of the project.

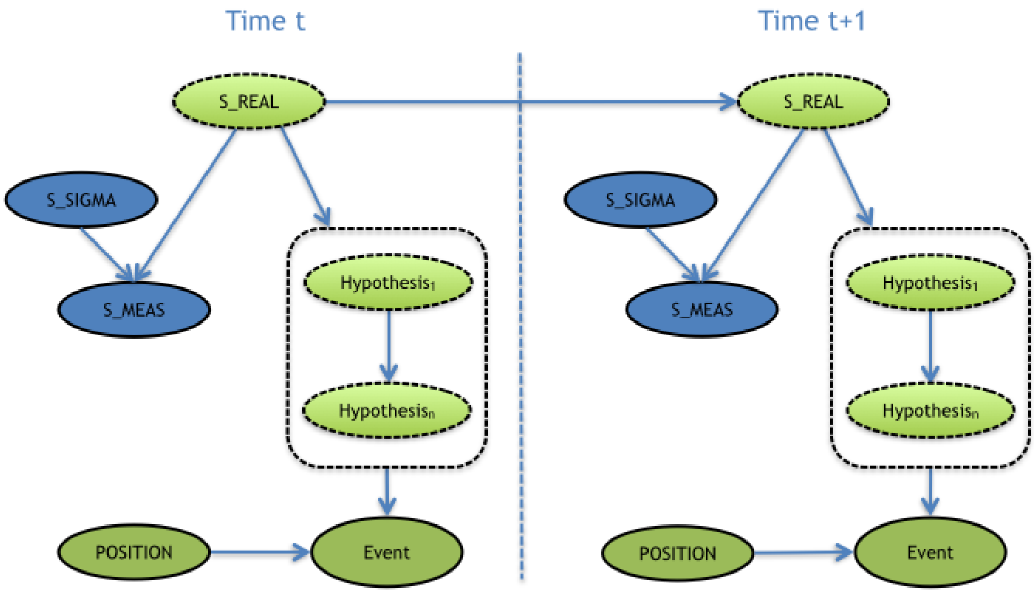

Figure 10: Daimler Temporal model with several hypothesis.

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