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Explicit and Implicit Communication for Automated Vehicles

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1 Abstract

Communication is a key component of everyday vehicle-pedestrian-interaction. As pedestrians feel unsafe when not communicating with a driver, this will become a major challenge for the introduction of automated vehicles. Explicit communication using symbols, signs and colors is not recognized intuitively, which is why a learning process needs to take place. The meaningfulness of explicit cues and the learning process for these can be supported using implicit communication. To identify natural, implicit communication cues, we use model-agnostic methods to interpret a machine learning-based algorithm. This algorithm predicts a driver's intention to stop at zebra crossings. We use various interpretations applying feature permutation to identify five most important features for implicit vehicle cues at crosswalks. These are velocity, x/y-accelerations, steering wheel angle and brake pressure. We then utilize an example-based interpretation, which results in time series for implicit communication at crosswalks. Automated vehicles can apply these implicit cues together with explicit light-based communication to achieve an intuitive interaction with pedestrians or support the learning process of these newly introduced communication forms.

2 Introduction

In today's traffic, communication between traffic participants is necessary to guarantee traffic flow, solve unclear situations and signalize yielding. Pedestrians, being the most vulnerable road users, rely on explicit communication with drivers to make sure they have been seen or assuring the driver's attention. Thus, they seek eye contact or wait for visual cues from the driver before crossing a street. This everyday behavior is expected to be a major challenge for the acceptance of automated vehicles. Previous work shows that intuitive communication is hard to obtain and most explicit signals are not recognized reliably (see chapter 3). Additionally, pedestrians are looking for implicit cues, e.g. vehicle speed, posture, or distance, to get information from vehicle motion and drivers' behaviors. These implicit driver cues could support light-based communication to achieve a most intuitive or learnable interaction with pedestrians.

Figure 1: Pedestrians and vehicle interacting at a zebra crossing [1]

In [2], machine Learning algorithm is used to predict a driver's intention to stop at pedestrian crossing (see chapter 4), which is used as a basis for the implicit communication. The algorithm's model represents the driving behavior of average drivers in proximity to zebra crossings. Thus, finding the most important features to predict the driver's intention and their temporal behavior, these represent typical driving patterns at pedestrian crossings. Assuming, that pedestrians are trained to interpret vehicle motions steered by human drivers, these example-based driving profiles can then be used for automated driving for familiar implicit communication [3]. Finally, both, explicit and implicit communication need to be combined to achieve a most intuitive or learnable communication.

3 Explicit Communication

Explicit communication is defined as an intentional way of communication that is chosen on purpose. In a vehicle context, explicit communication includes lights or sounds that are added to a vehicle to indicate vehicles' intent or driver cues to other road users. Using symbols, dynamics and colored light sources as described below is part of an explicit communication. In contrast to explicit communication, implicit cues are inherited in actions of the vehicle or driver and interpreted by other road users. They are not used to intentionally in first place, however, implicit communication may play an important role, and can include signaling through proxemics and kinesics (see chapter 4) [4, 5].

Figure 2: Explicit Communication Using Symbols in the vehicle's front [1]

In order to enable vehicles to communicate with pedestrians, the most vulnerable road users, in literature there are several approaches to known. One of the most promising and versatile approaches is using signs in the vehicle's front using display like signaling lamps (see Figure 2). Comparable to the approach of Fridman et al., we conducted in a previous online survey nine different symbols in six colors each to evaluate their intuitiveness and meaningfulness. None of the symbols indicating an automated driving mode or detection of a pedestrian (see symbols AD1..3 and D1..3 in Figure 3) was interpreted intuitively correct. Nevertheless, symbols AD3 and D1 were meaningful when matched to giving messages. In contrast symbol C2 indicating crossing to a pedestrian was perceived as an intuitive and meaningful symbol by more than 80 % of the participants. Adding various color to the symbols, including magenta and blue-green, did not raise the symbols' meaningfulness significantly, except for green color indicating crossing [1].

This previous survey confirms, as many others found in literature, that symbols are not intuitively understandable. Only some previously learned symbols and colors can ensure an intuitive communication. Thus, Othersen, Cramer et al. [6], Krieft, Thoma, et al. [7], and others clearly state, that new signal lights are not intuitive or self-explanatory. Therefore, many symbols, colors and other explicit communication cues must be learned by road users, especially pedestrians.

Figure 3: Symbols and colors from a previous survey [1]

Even though explicit communication can be learned [8] it remains in many cases non-intuitive. Making the learning process quicker and to start the learning phase at higher recognition rates, a combination of explicit and implicit communication is necessary.

4 Implicit Communication

Non-intentional, implicit communication can help interpreting a driver's intention and support explicit communication [6]. Therefore, we developed five temporal behaviors for vehicles' velocities, brake pressures, steering wheel angles, x- and y-accelerations. These temporal behaviors can be used for automated vehicles to implicitly communicate at pedestrian crossings.

This contribution relies on the interpretation of an algorithm for a driver intention prediction at zebra crossings to define implicit communication cues. The underlying assumption is that this algorithm's machine learning model represents typical behaviors of human drivers. Therefore, interpreting and understanding the algorithm's model means to some extend interpreting average human behaviors. These once more lay the foundation for a natural, implicit communication.

Algorithm for a Driver Intention Prediction

Basis for this contribution is the algorithm introduced in [2]. The algorithm consists of three stages (see Figure 4), with stages 1 and 2 being the most important ones being interpreted in this contribution. In Stage 1, a deep neural network predicts, with 22 input sequences of 3.5 s length each, five time series. These are velocities, brake pressures, steering wheel angles, x- and y-accelerations. In Stage 2, a random forest interprets the predicted time series and outputs the driver's willingness to stop. Following a simple rule set, stage 3 gives the actual prediction whether the vehicles will stop in the next 2 s.

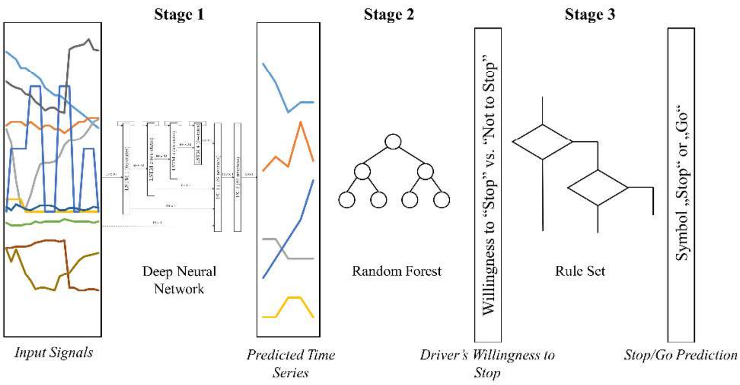

Figure 4: Architecture of the algorithm for a driver intention prediction [2]

The algorithm, and especially a personalized version of it, is predicting the driver's intention reliably and therefore, represents average drivers' behavior at pedestrian crossings quite well [9].

Technical Background

In contrast to decision trees, linear regression, and rule-based programming (e.g. stage 3), neural networks and random forests, amongst others, are considered not to be directly interpretable [10]. These models are sometimes referred to as blackbox-models and need to be interpreted to understand what their basis for decision making is.

Permutation feature importance (PFI) is a model-agnostic interpretation method and thus, capable of interpreting different sorts of machine learning models. The importance of a features increases the model's prediction error after permuting this feature's values, as the correlation between input and output is broken. Therefore, we can measure the feature importance by permuting the features' values one by one and calculate the increase in the prediction error. The permutations' error functions are normalized by the original metric's value. Thus, important features will lead to significant changes in the relative error changes and unimportant ones will result in constant prediction errors, because in this case the model ignored the feature for the prediction [11]. In this contribution, PFI is used to assess the most important features.

Example-based explanation is a model-agnostic method too, which selects particular instances of the dataset to explain the behavior of machine learning models. Using example-based explanations, we neither need to modify the input features nor the model itself, which makes it a straightforward procedure [11, 12]. In this contribution, example-based explanation is used for developing temporal behavior of most the most important features to communicate implicitly with pedestrians.

Method

To identify the most important features, we applied PFI on stage 1, stage 2 as well as combined stages 1 and 2. We ran a randomized PFI 100 times for each feature in order to prevent noise by scattering measurement values. Using a PFI, it is important to permutate correlated signals together so that the inherited statistics apply properly. Metric for stage 1 was a mean squared error, while for stage 2 and the combination of stages 1 and 2 true-positive rates (correctly predicted as stop) and false-positive rates (wrongly predicted as stop) are used. Applying example-based explanation to get temporal behaviors of important features, we were relying on stage 2. Only time series, which led to a prediction probability of more than 90 % to be classified as true (true-positive) were considered. We aligned all these time series relatively to the point in time (t = 0 s) when the vehicle was located just before the zebra crossing. Using this cloud of different time series, we could calculate their mean and standard deviation starting 8.2 s before the zebra crossing to 2.0 s after the zebra crossing. We chose this time span according to [2] and [13].

All following results are based on the validation dataset described in [2]. The validation data is not used for training the model directly and is therefore well suited for the following evaluations. It consists of 42,570 samples, each with 22 features times 35 (3.5 s input length) and a prediction horizon of 2 s [2].

Results

Interpreting the algorithm's stage 1 with a PFI, we found that velocity is by far the most important feature regarding the overall mean squared error (see Table 1). The second important features are y-acceleration and steering wheel angle –permutated together, as they correlate– which are 4.25 times less important than velocity. Following in their importance are x-acceleration and gas pedal as well as brake pressure and brake pedal. Each feature contributes most to its own feature importance and their importance decreases at least exponentially over time within the prediction horizon.

Table 1: Feature importance in stage 1 [3]

input signal	**feature importance**
velocity	19.18
y-acceleration + steering wheel angle	4.51
x-acceleration + gas pedal	2.65
brake pressure + brake pedal	1.53

Feature importance for stage 2 and stages 1 and 2 combined show similar results. Medians for the feature importance in stage 2 (importance true-positive rates / importance false-positive rates) show that the vehicle's velocity (0.26 / 4.0) is the most relevant feature, followed by brake pressure (0.96 / 1.7), x-acceleration(0.96 / 1.3) and steering wheel angle together with y-acceleration (1.00 / 1.1). The importance is heavily influenced by the labeling and generation of the random forest in stage 2. Similarly, PFI's medians in stages 1 and 2 combined (importance true-positive rates / importance false-positive rates) show that the vehicle's velocity (0.66 / 4.3) is the most relevant feature. It is followed by x-acceleration together with gas pedal state (0.86 / 1.3), braking pressure together with braking pedal state (0.88 / 1.2) and y-acceleration with steering wheel angle (1.0 / 1.2).

Summarizing the PFI's results, velocity is clearly the most relevant feature. We can explain this due the labeling and generation of the random forest in stage 2. Nevertheless, also in stage 1, velocity shows a significant higher importance to the overall error function than other input signals. We also want to highlight, that y-acceleration and steering wheel angle are clearly more relevant than other variables in stage 1's analysis but does not show significant feature importance when evaluating stage 2 or stages 1 and 2 together. We expect this also being due to the labeling and generation of the random forest.

Finally, knowing the features' importance for the driver intention prediction, we can extract suggested temporal behaviors from the model. Figure 5 shows the velocity's typical behavior. The mean velocity starts 8.2 s before the zebra crossing at an approximate speed of 30 km/h and steadily decreases to 1 km/h. This confirms results of [14] and [13] that often no stillstand is reached at zebra crossings. In addition, braking progressively leads to a “nodding” of the vehicle and therefore emphasizes the intention even more.

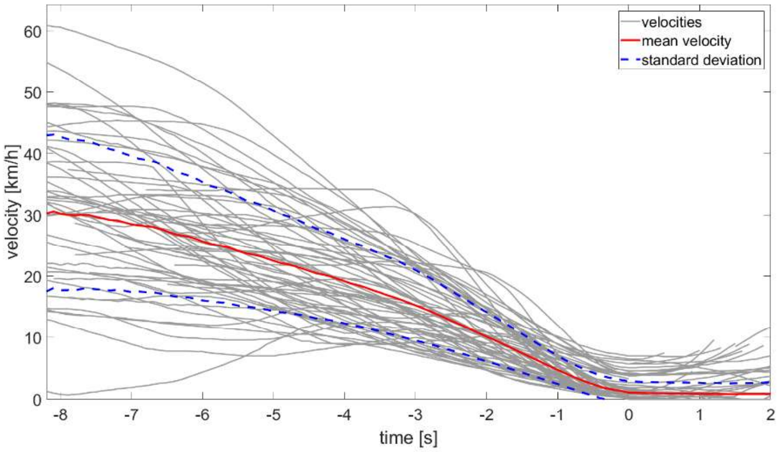

Figure 5: Suggested temporal behavior for velocities at zebra crossings; according to [3]

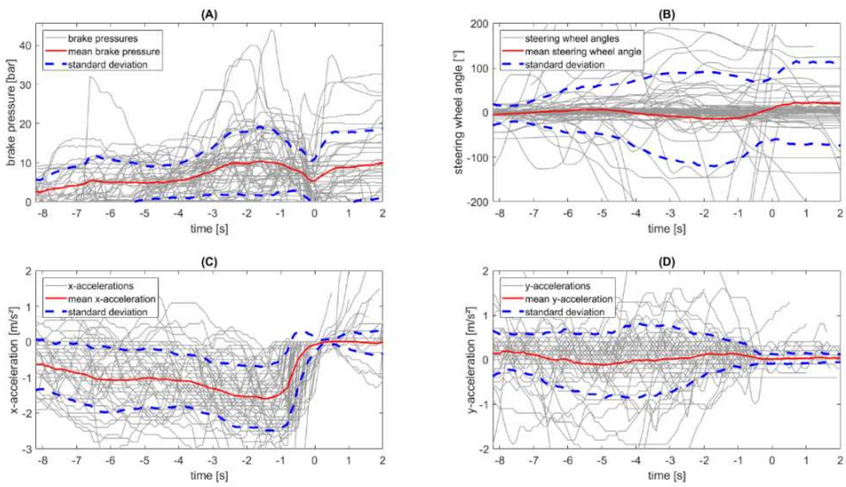

Figure 6: Suggested temporal behavior at zebra crossings for brake pressure (A), steering wheel angle (B), x-acceleration (C), y-acceleration (D); according to [3]

Figure 6 shows the temporal behaviors of brake pressure, steering wheel angle and x/y-accelerations. The mean values of brake pressure and x-acceleration inherently correlate quite well to the velocity shown in Figure 5 and each other. Likewise, steering wheel angle and y-acceleration match each other and show a tendency to steer to the right before coming to a halt at the pedestrian crossing. This might indicate to pedestrians that the driver is willing to stop, although, this trend is not significant.

5 Summary and Outlook

In this contribution we give insights how to communicate explicitly and implicitly. Previous surveys could confirm that explicit communication using light signals need to be learned, while only few symbols and colors are understood intuitively. We therefore propose temporal behaviors of certain vehicle signals to communicate implicitly with pedestrians. This is used to support explicit communication and thus, make interaction with user road users more natural and understandable. For future work, we must evaluate the advantages of combining implicit and explicit communication for automated vehicles in order to assure a highly meaningful and thus safe interaction with other road users.

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