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# IDENTIFYING THE URBAN ROAD ENVIRONMENT TYPE FROM TRAFFIC SIGN DATA USING AN ARTIFICIAL NEURAL NETWORK

Zoltán FAZEKAS<sup>1</sup> - Gábor BALÁZS<sup>2</sup> - Péter GÁSPÁR<sup>3</sup>

**Abstract:** Automatic identification of the urban road environment type can be a valuable assistance for drivers. The same applies to the control systems of self-driving cars, as these systems can adjust their parameters to the actual environment to ensure safe driving. In the paper, empirical traffic sign data was used to train a backpropagation artificial neural network (ANN) – via supervised learning – to solve the above classification problem. The data collected for training records the along-the-route sign locations and types. Car-based data collection trips were made to three locations in Hungary. During these trips the actual road environments were also recorded. The input data signals to the ANN were selected to ensure the spatial and categorical relevance. The input data includes statistical features of traffic signs, especially in regards of those that have already proved useful in solving such problems via other methodologies. Results are compared to the ground-truth categorical data in regards of downtown areas, industrial/commercial areas and residential areas.

**Key Words:** road environment detection, traffic sign recognition (TSR) systems, advanced driver assistance systems (ADAS), supervised learning, artificial neural networks

## 1 INTRODUCTION

When entering *built-up areas*, car drivers are legally obliged to change their *driving attitude and behavior*, particularly they need to *reduce the speed of their vehicles* to a certain common limit, which is typically 50 km/h in Europe. This legal regulation is motivated by the more intense traffic in such areas that involve not only motor vehicles, but cyclists and pedestrians as well. Furthermore, drivers need to *locate and understand complex intersections*, watch out for *pedestrian crossings* and avoid driving within *bus lanes*, just to mention a few examples associated with urban settlements and with driving in those.

Nonetheless, *within urban settlements*, there are *various road environment types* that are not, or not always recognised explicitly and are not, or not always controlled separately by traffic regulations, but still require a *distinctive and deliberate driver attitude and behaviour* (e.g. requiring their intense attention). Such road environments often pose characteristic traffic safety risks that need to be tackled by the drivers. For these reasons, an *automatic urban road environment detection* function would be distinctly useful to draw the drivers' attention – in a real-time manner – to the potential hazards in the area. This function can be implemented within the *advanced driver assistance systems* (ADAS) framework, but it is even more important in the case of *self-driving cars*, as these do not have human instincts. So, the control system of the self-driving cars need to adapt to the actual traffic and road conditions – and the changes thereof – by modifying certain control parameters of their own settings. For a survey of the ADAS technologies in general, see [1].

The *road environment detection (RoED) ADAS function* was proposed, realized and tested by Jiménez and his co-authors in [2]. The implemented system uses advanced image and spatial environment perception methodology, vehicle-to-vehicle and vehicle-to-infrastructure communication to analyse and identify road environment types, particularly in rural and intercity settings. An ADAS traffic sign recognition-based (TSR-based) implementation of the function was proposed in Fazekas et al. (2017) [3]. This can be a cost effective solution as a good portion of the high-end production cars today is already equipped with ADAS TSR subsystems.

In their implementation, an enhanced TSR subsystem logs the traffic signs encountered and detected along an urban route. Based on the logs, the subsystem distinguishes between certain urban road environments – along the route – utilizing a minimum description length (MDL) statistical inference

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<sup>1</sup> Dr., Institute for Computer Science and Control (MTA SZTAKI), Budapest, Hungary, e-mail: zoltan.fazekas@sztaki.mta.hu

<sup>2</sup> BSc, MTA SZTAKI, e-mail: gabor.balazs@sztaki.mta.hu

<sup>3</sup> Prof., DSc, MTA SZTAKI, e-mail: peter.gaspar@sztaki.mta.hu



approach. See details of the MDL principle in [4], and the details of the MDL-based change detection in Baikovicus and Gerencsér (1990) [5].

Herein, we demonstrate that *distinguishing between urban road environments* can be realistically and viably achieved based solely on *traffic sign data* recording the traffic sign *types* and the *along-the-route locations* of the signs. Assuming that similar traffic sign data together with the corresponding *urban environment types* had been recorded, after processing, they can be used for training the *artificial neural network* (ANN) that is presented and set to work for environment detection here. For information on the origin and roots of ANN, see McCulloch et al. (1943) [6], for a more recent overview about its theory, development and applications, see [7].

Over the last two decades, artificial neural networks have been employed widely to solve rather complex tasks in a so-called ‘soft’ and *heuristic manner*, through studying examples and using little to no expert knowledge. These tasks are often problems that are comprehensible, and sometimes easily solvable by the human brain, yet it is hard or even impossible to explicitly define a solution algorithm for them. In general, among others, they include pattern recognition, computer vision and data classification, and, to name a few ADAS-related tasks, fast traffic sign recognition, see [8], or driving style analysis systems, such as driving style distinction and driver drowsiness detection, see [9].

Artificial neural networks are constituted by elementary computational units called (artificial) *neurons*, much like their biological equivalents. Neurons have connections between each other, called *synapses*, which transmit data values, while multiplying them by *weights*. Each neuron calculates the sum of the weighted values coming in through its input synapses, and based on this sum determines its output value using an *activation function*. The output value is passed to the next neuron(s) through the output synapse(s), and the same process repeats until the data reaches the output neurons. Neurons are typically ordered in *layers*, the first one being the *input layer*, and the last one the *output layer*. All the other layers that lie between these two are called *hidden layers*. The network input is loaded in through the input neurons, processed throughout the hidden layers, and the result is finally given by the output neurons.

In order for the ANN to operate properly, it has to find the connection between the input and desired output data, i.e. to *adjust its weights*. This can be achieved through the process of network *training*, which, in practice, usually involves teaching the network examples of corresponding input and ground-truth output data. A well-trained network can duly predict the outputs pertaining to yet unseen inputs.

## 2 VARIOUS URBAN ENVIRONMENTS

The research effort communicated herein is closely related to the work by Fazekas et al. (2017) [3]. The same urban environment categories are defined and used as in their work. The categorization is based on what the particular area is fundamentally used for. *Downtown areas* are the cultural, touristic and business centres of a town, *industrial/commercial areas* accommodate factories, workshops and shopping centres, and *residential areas* are the home to families. As to their appearance, downtown areas feature typically multi-storey buildings built very close to each other, with narrow pavement in front of them; industrial areas feature factory buildings, stores with rather spacious yards, as well as supermarkets with parking lots; while residential areas feature green spaces and one- and two-storey buildings with somewhat more space between neighbouring buildings.

As mentioned before, the environments involve *different things to look out for*. To mention some of these, in downtown areas one should be aware of e.g. pedestrians wandering onto the streets, or occasionally crossing even at red light, cyclists roaming among cars, and other cars suddenly stopping to reverse into a parking spot. In industrial/commercial areas one should be more prepared to see and tolerate a relatively slow and steady flow of heavy vehicles that sometimes also block the road while executing Y-turn manoeuvres. Residential areas are likely to have children playing in the street or dogs running around, but a lower rate of traffic is to be expected there.

Throughout the paper, there is a uniform colour-code used to easily set the environments apart visually: industrial/commercial areas are designated with dark grey, downtown areas with middle grey, and residential areas with light grey.

### 3 DATA COLLECTION FROM URBAN ENVIRONMENTS

#### 3.1 Methodology

In order to explore the relationship between urban road environments and traffic signs, data collection trips had been made in three urban settlements within Hungary. These towns were Csepel (a district of Budapest), Vác and Százhalombatta.

The trips were completed with a car and involved two people: a car driver and a data entry assistant. Furthermore, a tablet application specifically developed for the purpose was put to use. The application was capable of recording traffic signs in a log file, after the manual input of the data-entry assistant. The traffic sign records also included the geographical location of each sign, as well as the current road environment. The former originated from the built-in GPS sensor of the tablet, while the latter was determined after the subjective judgment of the data collecting personnel, based on the visual appearance of the urban scenery. Besides being able to record traffic signs, the tablet application automatically recorded the geolocation periodically, without any human interaction, so that later on the route could be backtracked, and distances could be measured more accurately.

The resulting log file consisted of a sequence of recorded observations along a route, each of them featuring the actual geolocation and road environment, and the traffic sign observed or the absence of signs. Statistical data have been extracted from the logs, and are detailed in the next section.

#### 3.2 Data collection results

Downtown, industrial/commercial and residential areas showed different numbers of traffic sign occurrences per unit distance travelled on the routes driven in the given environment. The *empirical average distance between traffic signs* in each environment is shown in Figure 1. This piece of statistics is also the reciprocal of the probability of the occurrence of any traffic sign along a given stretch of road within the environments. It clearly shows that sign observations in downtown areas are more than twice as frequent as in the other two urban areas, which have nearly the same frequencies.

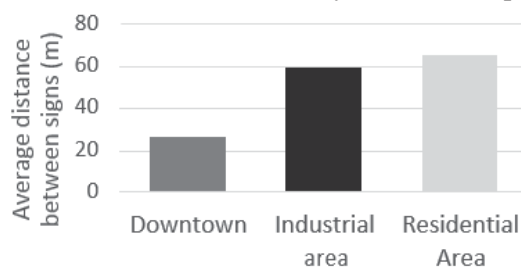


Figure 1 Average distances between neighbouring traffic signs within urban environments.

From the recorded logs the number of occurrences of each traffic sign type has been separately counted within each urban road environment, and the conditional probabilities of the traffic sign types have been calculated for each environment. Thereafter, the signs typical of each urban area have been identified, based on these conditional probabilities. Those signs have been declared *typical* of a given urban area that displayed a significantly higher empirical conditional probability of occurrence in that area than in the others. This means that perceiving a typical traffic sign implies driving in the urban area it is typical of with a significantly higher probability than driving in any of the others.

In Figure 2, the three diagrams show the appropriately chosen typical traffic signs of each urban environment, and the inference of their occurrence to the environments. The rings represent the specific traffic signs that point onto them, and the arc lengths of the ring sections represent the proportion of the conditional probabilities of the signs within the environments.

It is worth noting that the occurrence of the mentioned typical signs only infer the probabilities shown in Figure 2 under the assumption that the urban environments are represented equally within the urban settlement. If, for example, it is known that a particular town does not contain industrial areas, then in the case of, say, a 'Speed limit 50 km/h' sign, the inferred probability of an industrial area should be zero.

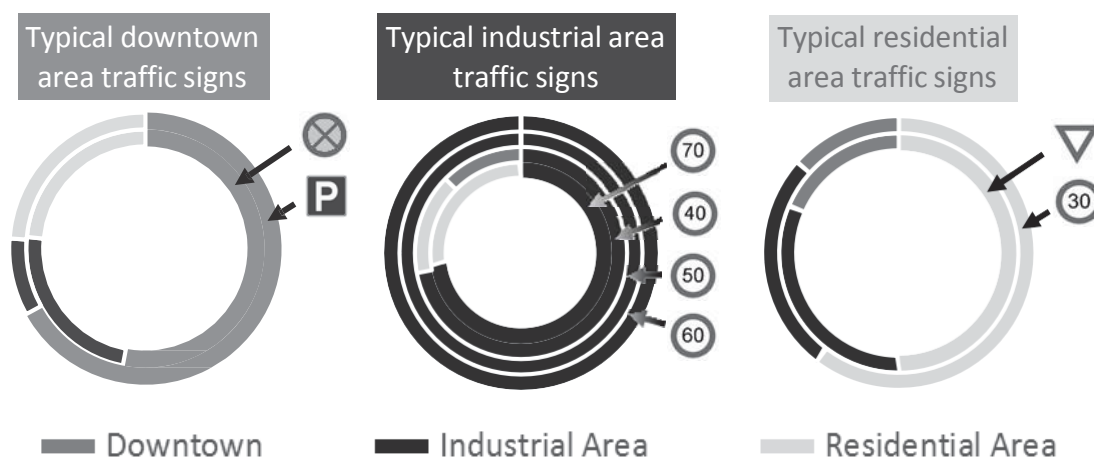


Figure 2 Prevalence of typical traffic signs in urban environments.

## 4 ARTIFICIAL NEURAL NETWORKS FOR ROAD ENVIRONMENT DETECTION

### 4.1 Structure and interconnection of the ANN

Artificial neural networks have been applied in recent years to solve problems that the human brain is innately capable of solving, but are impossible or very difficult to work out analytically. Herein, a classification issue is to be solved, namely to determine the best fitting urban environment type at a sample position along a route. The neural network can only perform this decision after it has been trained for the task. Training the ANN only takes showing it examples of input data sets with the desired results, i.e. teaching it to empirically infer the function between the input data and the result, where the connection is *time-invariant*. This type of machine learning is called *supervised learning with teacher*. The ground-truth environment information of every observation in the log had also been recorded, so the training set of the network could be composed.

Besides the training dataset, ANN's usually use another set of data, called *validation* dataset. The network is inclined to adjust its weights specifically to the training data, so the inferred connection will apply exclusively to the particular training examples, thus the network becomes overtrained, as detailed in [10]. To resolve this, the validation set is used, which consists of some yet unused corresponding input and output data, about a tenth of the size of the training set. Using validation, the inferred function of the ANN will be more general, thus more capable of predicting the environment from yet unseen traffic sign data.

Setting up the neural network also requires choosing the input features in a practical manner, so that they *represent the actual environment adequately*, and it is fairly easy to tell environment types apart based on the input feature values; as well as training and validating the network with sufficiently many sets of data. The chosen input features are discussed in Section 4.2.

The input layer of the implemented network consisted of as many input neurons as many input features there were, one for each. According to [11], one hidden layer is enough for most applications, therefore in most test cases only one was used, however, some experimental cases with two hidden layers were also studied. The network output, namely the inferred urban road environment, was found to be best implemented with three neurons, one for each environment type, since the types cannot be quantified. This way, the output environment can be specified by the output neuron representing the true/inferred environment having a high value, while the other two having low values.

The implemented ANN is fully interconnected, that is, all neurons in one layer are connected to all neurons in the next one, see the sample network in Figure 3. This allows for using the *backpropagation method*, which is commonly used to solve supervised learning problems, see [12-13]. The method first assigns random weights to the neurons, calculates the network output for one training row, and compares it to the ground-truth output. The error is then worked out, backpropagated through all the hidden layers to the input layer, and – while looping through all training rows and re-adjusting the weights – gradually reduced using an *optimization algorithm*, e.g. *gradient descent*.

The construction of the ANN and the backpropagation have been carried out using a software called SimBrain [14], that has pre-defined network types including backpropagation network, which can

easily be created and trained with the help of the program. Figure 3 is also a screenshot taken from this software.

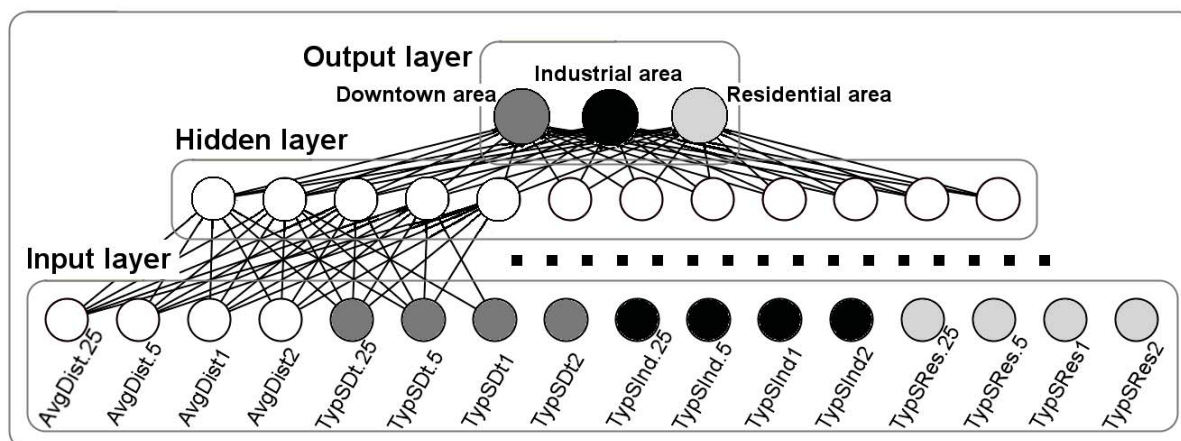


Figure 3 The ANN with one hidden layer used in the experiment. Screenshot with the actual SimBrain model that has been slightly simplified for typographical reasons.

#### 4.2 Input features

The inputs to the ANN have been constructed solely from the traffic sign logs recorded earlier. Since only traffic sign types and locations had been recorded, the input fields could only be originated from these two features. Moreover, the input signals had to carry more information than the momentary feature values at a single time instant, therefore the utilization *statistical indicators* over the preceding stretch of road was necessary. The length of the stretch had to be determined too.

The possibility of feeding the logged observations *as a time-series* into the network instead of reducing the data to statistical indicators was also considered, as it has been studied and implemented in [15-16]. The idea consisted of the following steps: divide the log of observations into road sections with equal length, and label these sections with the traffic sign(s) they include, or nothing in the case there was no occurrence of a sign in the given section. After this, give the labelled, equally long sections to the network as input, compare the succession of the sections with pre-defined patterns, and quantify the agreement. The patterns are essentially strings of sections exhibiting various traffic signs or the lack of signs in a sequence that is characteristic to an urban environment. If a sample taken from the traffic sign logs shows sizeable agreement with patterns vastly pertaining to one environment, it suggests that the sample was recorded in that particular urban environment.

However, this concept assumes that there is significance in the order of traffic signs occurring after one another, but the empirical evidence of the observation logs suggests otherwise. According to the recorded logs, it is only the frequency of occurrence of traffic signs, and the presence of certain types of signs that matters in deciding the actual urban road environment. Besides, this approach would call for quantifying traffic signs, so that a number on a continuous scale can be linked to them to provide an applicable input for the neural network. In addition, quantification would also be needed to compare the signs of the sample road stretch with the signs of the patterns. For the above reasons, this approach has not been implemented, but nevertheless, a similar idea can still be viable that operates with traffic sign categories instead of individual signs.

The final concept in the study involved using statistical indicators to represent the individual features, which still reflects the temporal – or in this case spatial – characteristics of the traffic sign data. Several features have been tried as input to the neural network, represented by simple statistical indicators – averages and sums – over the preceding stretch of road.

The notion behind selecting input features was to find the ones that show the greatest diversity in the three environments. In order to achieve this, the empirical data detailed in Section 3.2 were analysed.

The first input feature investigated was the *distance between neighbouring signs*. An average of the distances between each neighbouring pair of traffic signs was evaluated, counting two signs at the same location as being 0 distance apart. The average was considered over the last 0.25, 0.5, 1 and 2 kilometres. Using various path-lengths as separate inputs is aimed to retain some of the information that

gets lost as a result of the averaging. The shorter path-length evaluations can *indicate a recent change* in the environment, while longer ones help *cancel out the effect of local irregularities* in sign occurrences. The shortest path-length was chosen to still include at least 3-4 traffic signs regardless of the environment, while the longest was chosen to still fit multiple times inside the average length of trajectories driven continuously within one urban area. Choosing an evaluation over too long a stretch of road in an urban context would most likely *reach through several different urban areas*, thereby creating an input the network had not been trained for, and probably causing a faulty output.

Another set of input features used along with the previously mentioned one is the *number of occurrences of the most typical traffic signs* of each environment over the last 0.25, 0.5, 1 and 2 kilometres. The typical signs have been determined from the data collection results, discussed in Section

3.2. These signs – in accordance with Figure 2 – are ‘Parking place’ and ‘No stopping’ in downtown, ‘Maximum speed’ signs from 40 to 70 km/h in industrial areas, and ‘Maximum speed 30’ and ‘Give way’ in residential areas. This set of features technically contains 3×4 input signals, i.e. the sum of the occurrences of any of the typical signs of an urban environment for each of the environments, calculated over each of the aforementioned path-lengths. Figure 3 shows a network setup with these input features and the average sign distance. The input layer is activated with the signal values of a single set of input data at a time, containing the sign distances (marked with ‘AvgDist’ on the labels of Figure 3), and the typical sign occurrences (marked with ‘TypS’) for each environment (Dt, Ind, Res), over the labelled path-lengths in kilometres.

In a real-life application, the input features would be formed based on the traffic sign recognition system output and distance measurement, and *re-calculated every 50 metres*. An artificial neural network would then process each new set of input features. This network needs to be trained previously using an *excessive database* containing matching traffic sign and urban environment data, collected from a *wide range of regions and countries*.

## 5 URBAN ROAD ENVIRONMENT IDENTIFICATION RESULTS

For network training, fairly long (ca. 2-3 kilometres) road stretches located exclusively in one single urban environment all along were extracted from the data collection trips from all the visited cities. All the sections pertaining to a particular environment were *seamed together* one after the other. The aforementioned input features were then calculated from the so generated environment blocks, producing a *new set of input values every 50 metres*. Special care was taken to use the same number of training instances - and thereby the same training path-lengths - from all the environments, so that the network isn't biased toward or better trained to one of them.

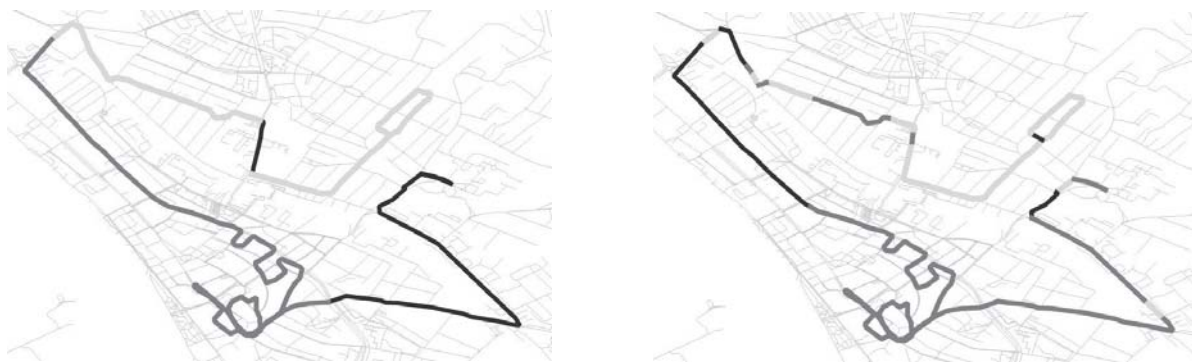


Figure 4 Trajectory of the data collection trip in Vác. In the left panel, the ground-truth urban environments are marked with the colour code detailed in Section 2, while in the right panel, the environments according to the ANN output are displayed similarly.

To test the trained ANN, the same collected data was used, but without sectioning or modification of the sequence. From the *raw data sequences* of the visited cities, the same input features were *calculated every 50 metres*. These input feature sets were then fed to the network, and the network output was analysed and compared to the ground truth. Figure 4 shows a comparison between the ground-truth distribution of road environments regarding the data collection trip in Vác, and the distribution of environments inferred by the neural network. The *agreement* between them, i.e. the *accuracy of the identification* is 70.2%.

With further tests, the intention was to analyse the network performance in different cities, and to study how well the network can identify the different environments. Therefore the test sequences were extracted from the trajectories of data collection trips in different cities, making sure that each urban area is represented. In Figure 5, two test sequences are shown, for which the environment inferred by the ANN is compared with the ground truth, one from Csepel, and the other from Százhalombatta. The environment agreements are 76.1% and 74.2%, respectively.

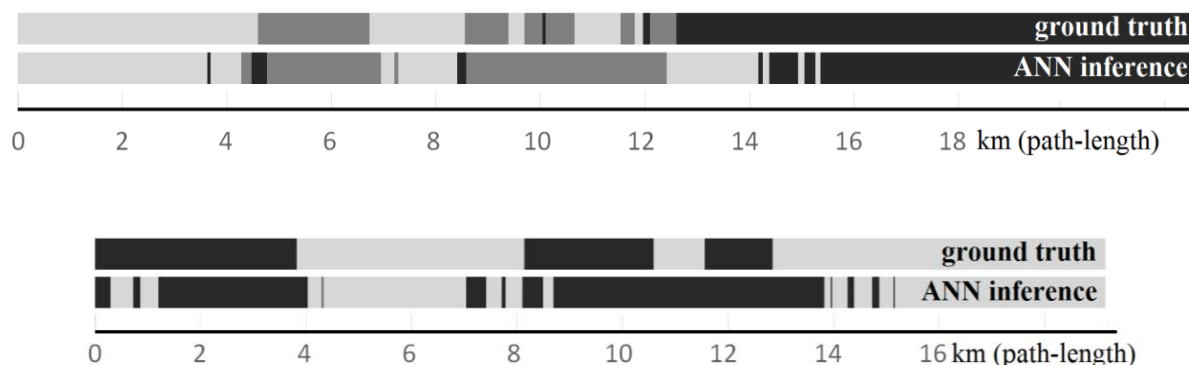


Figure 5 Comparison of the ground-truth road environment and that inferred by the trained ANN. The actual urban area – either known or inferred – is indicated by the colour code used in Section 2. The upper image depicts the environment distribution of a road stretch recorded in Csepel, while the lower one is regarding a road section in Százhalombatta.

## 6 CONCLUSION

The aim of the small scale study presented herein was to *automatically identify the actual urban road environment based on traffic sign data*. Three urban road environments – or more precisely environment types – namely downtown, industrial/commercial and residential urban environments, were considered in this work.

The road environment detection (RoED) is a *relatively new ADAS function*, which – in the proposed implementation – heavily *relies on the TSR ADAS function*, which is now available in many smart production cars. It should be noted that the road environment type detection is also vital in the context of self-driving vehicles.

A *heuristic approach* for RoED using *artificial neural networks* (ANNs) was presented in the paper. Traffic sign data was logged in three urban settlements within Hungary, namely Csepel, Százhalombatta and Vác. These logs served as a knowledge base for our experiments with ANNs aiming at environment type identification. A set of suitably chosen simple statistical features – derived from the traffic sign logs – were employed to distinguish between the mentioned environments.

Despite the *small-scale nature* of the data collection and of the experiment, the presented ANN – *trained with statistical features* derived from the aggregated traffic sign data – produced credible and promising results in respect of the road environments. The marked routes and route-layouts presented in Figure 4 and 5, respectively, exhibit a good agreement between the ANN output and the ground truth. To reduce the number of inputs, only a few traffic sign types were chosen for the experiment. By introducing groups of traffic signs – consisting of signs sharing some common trait – more of the gathered information could be utilized. For the training of the network, homogeneous route segments were used in terms of urban areas, however, as a potential improvement to the approach, inhomogeneous route segments could also be used for the purpose. Each of these would then incorporate a road environment change, e.g. at about half-distance. To improve the accuracy of the detection, the ANN should be trained with a larger database of traffic sign and environment data coming from a more diverse variety of countries and regions.

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