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Rothkrantz, Leon

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Measurement of Air Pollution by Measurement of Traffic Density

Leon Rothkrantz

***Abstract*—The areas of many cities in the Netherlands are covered by a network of stationary sensors, measuring special components of air pollution such as CO2, NO2, PM2.5 and PM10. The pollution with fine dust along roads, surrounding and crossing the city is primarily related to traffic density. To measure traffic density, we used a license plate recognizer based on a special Neural Network Neocognitron, analyzing the video footage of surveillance cameras along the roads. We also studied the onset and offset of traffic density to predict traffic density, using the first recorded sparse traffic data. In cooperation with MIT Senseable City Lab the Technical University of Delft has developed special mobile, low cost sensors to measure air pollution. These mobile sensors are integrated with stationary sensors to a heterogeneous sensor network and enable measurement of air pollution out of the reach of the stationary sensor network.**

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***Index Terms*—Air Quality Monitoring, Distributed Sensor Network, License Plate Recognizer, Traffic Density.**

I. INTRODUCTION

AIr pollution usually doesn't result in sudden death. But exposure to air pollution for a long time may gradually induce heavy damage to lungs and respiration organs. For a healthy smart city, it is important to be aware of pollution in time and place. Currently networks of sensors have been installed in smart cities, sensing the air and compute the degree of pollution. Installing a sensor network is expensive, requires a lot of energy, network resources and has a low spatial resolution. In many cases the pollution cannot be measured directly, but only using interpolation procedures on data measured by neighboring sensors. It proved that pollution data based on predictions or direct measurements may differ significantly.

To complete the stationary sensor stations we propose integration with mobile sensor networks. A typical Dutch solution is to install sensor stations on an electric bike. An electric bike has its own chargeable energy resource and via the smart mobile phone of the user, sensed data will be sending to a central station, if users travel across the city. On the central server the sensed data will be processed and a pollution map will be created, using maps of Street network. To every street segment a vector with the average pollution values of the components will be attached. This annotated street network can be used to compute healthy routes from start to destination.

Currently there are two research groups in the world that have worked extensively in research of monitoring hyper localized air pollution, one at ETH Zurich and the other one at MIT. At MIT a special project is running focused on air pollution, the health of trees and the urban heat island effect. In the framework of this project researchers from TUD developed a mobile sensor RESPIRE [1] to measure air pollution. Similar sensors have developed at TUD and tested by RIVM, the National Institute for Public Health and the Environment. RIVM is the initiator of many global stationary sensor networks to measure air quality.

Most people in Europe think that the air quality is pretty good, but it doesn't even meet the World Health Organization standards. The design and implementation of mobile local networks of air quality measuring stations in the entire city is the focus of this project. It proved that there is a high concentration of fine dust along the main roads surrounding and crossing the city. The global network of stationary sensors measures only the global air quality. The measurements are highly influenced by the weather conditions.

In this paper we discuss the results of air measurements using mobile sensors. But we also discuss some underlying computational models. But the models are complicated by the impact of changing weather conditions. Rain and wind have a heavy impact in the air pollution models. There is still no theoretical model describing the interaction of the many factors in air pollution. In this paper we focus on the factor fine dust PM 2.5, PM 10, having a deep impact on the health of people on the long run.

To summarize, the problems to be discussed in the paper are the following:

-research the possibility to measure smart dust pollution using air traffic density on highways.

-design models to predict air pollution in the course of time.

The outline of this paper is as follows. After the introduction and problem definition in section 1 we present some related works in section 2. Then we discuss the correlation between traffic density and concentration of smart dust along highways in section 3. In section 4 we present forecasting models of air pollution. In section 5 and 6 we discuss the measurement of traffic density on highways, and measurements of air pollution by mobile sensors. In section 7 and 8 we discuss neural network to measure traffic density.

L.J.M.Rothkrantz was with Delft University of Technology, 2628 CD Delft, The Netherlands and Czech Technical University Prague Czech Republic (e-mail:L.J.M.Rothkrantz@tudelft.nl)

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II. RELATED WORKS

The research of the Senseable City Lab [1] is focused on the interface between people, technology and the city. The goal is to create a better livable urban environment. Since 2004 the Lab was involved in more than 35 city projects, together with many partners all over the world. Delft University of Technology was involved in one of the recent projects Treepedia. Digital vision technique based on Google Street View, has been used to study the health of trees along the streets. The development of our eco sensors took place in cooperation with researchers involved in the Treepedia lab.

At TUDelft several labs and projects are focused on smart city. The goal of the project "Intelligent cities and social urban data collecting" is to activate people in a city to collect data. Urban data are usual messy, biased and sparse. Our project on collecting data on air pollution, fits in the framework of this project. The City-AI-Lab [2] is the place where data, AI and human behavior come together. The research challenge is to keep cities livable. A main research focus is to tackle pollution in city environments. In our project bicycles equipped with eco-sensors cross the city. The sensed data is collected at a central point close to the City-AI-Lab

RegioLab [3] is founded by TUDelft, companies and local government around Delft. It has been collecting and disseminating traffic data of the region of Delft since 1999. There is a close cooperation with the organization ANWB, the organization responsible for traffic, tourism in the whole of the Netherlands. Most of the data services are available through a web interface. It is also a testbed for many projects on traffic management around Delft. The traffic data are sensed by sensor networks installed around the highways. In our project, we used the data provided by RegioLab and ANWB.

P. van Breugel and G. de Gier are researchers at the Dutch Governmental Organisation Rijkswaterstaat and members of the international CEDr air quality group. They were editors of a report on air quality measures near roads [4]. One of the roads discussed in the report is the A13 the highway connecting Rotterdam and Delft, one of our research topics in this paper. The A13 highway between Delft and Rotterdam runs close to residential areas. Fluid experts have created a model to determine how air pollution spreads from the A13 through the adjacent village Overschie. The DisTUrbe (dispersion in the turbulent urban environment) project tested the effectiveness of measures designed to combat air pollution. One of the research goals was to investigate if Perspex screens along the highway reduce air pollution and the impact of speed reduction on air pollution.

One of the experiments was performed in the water tunnel at TUDelft, to model the spreading of pollution. The model included different wind directions. Another model was focused on the spread of fumes over a large area. The researchers used the DALES model (Dutch Atmospheric Large Eddy Simulation) [5]. In our project we sense pollution data along the A13 highway. The sensed data will be used to validate the developed air pollution and –distribution models.

In the Annual Report 2020 [6] of Amsterdam Institute for advanced metropolitan solutions many eco research studies are reported, with several partners as MIT Senseable lab and TUDelft. Urban challenges are multidisciplinary by nature. Amsterdam Metropolitan Area focused on six urban domains: mobility, energy, circularity, food, climate and responsible digitization. To solve these problems a "Living Lab Approach" has been used. The Institute cooperates with TUDelft, MIT but also Wageningen University & Research for research on ecological topics. Living labs provide a co-innovative setting, in which different stakeholders jointly test, develop and create metropolitan solutions. In the Resposile Sensing Lab, researchers design and implement sensing systems. In the framework of our project researchers from Delft and Amsterdam cooperate via MIT.

The idea to design a mobile sensing network in cities by attaching smart sensors to vehicles has been researched by many people. The project City Scanner [7] collected data from sensors attached to busses, taxis and garbage trucks in the city Cambridge. In the paper different kinds of sensors have been researched. Architecture of mobile smart sensors had been developed and tested. Many research labs in the world participated in the project. The project plays the role of leading prototype of similar projects for many years. Our mobile air pollution sensor network attached to bicycles is based on ideas from the City Scanner project.

In [8] the authors present an air quality sensor network for cities with an existing smart data infrastructure in Canada. The network was used to study the pollution of traffic flow. The authors found that distributed network were able to detect local sources of air pollution. They also studied the coupling of air quality sensors with traffic monitors. We used a similar approach in our study using traffic flow density as an indicator of fine dust pollution.

On the Innovative4Cities conference [9] the researchers Paul and Mora presented some recent developments at the MIT Senseable lab. The mobile air pollution sensor RESPIRE developed in cooperation with TUDelft was also reported. Most research projects are done with cooperating partners all over the world. The research at MIT provides a state of the art of air-measurement sensors. Most research projects provide a proof of concept. To build research sensor network and perform daily measurements takes a lot of funding and efforts.

The authors in [10] present a mobile air pollution detection device called EnvioDev. The device has been been installed in public transport vehicles, cars and delivery services. The pollution was displayed on maps of the city. To research how many cars are needed to cover the whole city, a simulation experiment had been used with the traffic simulator SUMO, Simulation of Urban Mobility. The air pollution sensor was constructed with help of the Arduino industrial sensor toolbox. Our sensors are similar but designed for attachment to bicycles and exploration of pollution along highways.

A Survey of Wireless Sensor Network Based Air Pollution Monitoring Systems has been reported in [11]. The authors focus on air quality in urban areas and are focused on microlevel pollution, which is also our interest in this paper. They also report about mobile sensor networks and the design of sensor networks in cities.

In [12] the authors researched the influence of pollution and micro-climatic conditions on the quality of life in Smart Cities. The system was developed in the framework of Smart Healthy Environment, a research project in Italy. The researchers considered a network of stationary and mobile sensors, similar to our project. In the project there was a focus on participation of citizens, to create hybrid sensor data.

In this paper we report about eco-research at TUDelft. In this paper we link air pollution to the density of cars on highways. The group Knowledge based Systems from TUDelft has been involved in many traffic management projects. Expert systems, Artificial Neural Networks and ideas from artificial life as Ant Behaviour have been used to model traffic and to compute shortest paths [13], [14], [15]. We used up-to-date versions of the developed tools in the current project.

III. FINE DUST SENSORS

Fig. 1. Fine dust sensor designed by technicians from MLZ.
Fig. 2. Mobile fine dust sensor designed by DUT-MIT.

The measurement of fine dust is a complicated process. Air with fine dust particles has to pass a filter, driven by a fan. Next the filter has to be weighted and the weight of fine dust particles assessed. Current sensors are able to measure air particles between 0.3 and 1.0 micrometer. The process of filtering the polluted air usually takes 24 hours. After fine calibration of the sensors, it is possible to change the filter every hour, which results in a refinement of the measurement process. Cheap sensors don't weight the dust particles but use optical methods to count the particles. A cheap sensor is displayed in fig. 1. and a mobile sensor in Fig. 2.

The National Institute for Public Health and the Environment Ministry of Health, Welfare and Sport (RIVM) has installed a network of sensors in the Netherlands, measuring the air pollution on a daily basis [16]. We observe some red dots in Fig.3, indication of highest pollution areas. The displayed map provides a global picture of average daily pollution in the Netherlands, but a refinement of the data is needed to research pollution in local areas and regions along highways.

In Fig. 4 the distribution of NO_2 is displayed, measured along highways and cities in the Netherlands. The measurements are performed in June 2019. Preliminary measurements of fine dust on the First Sunday in June, when

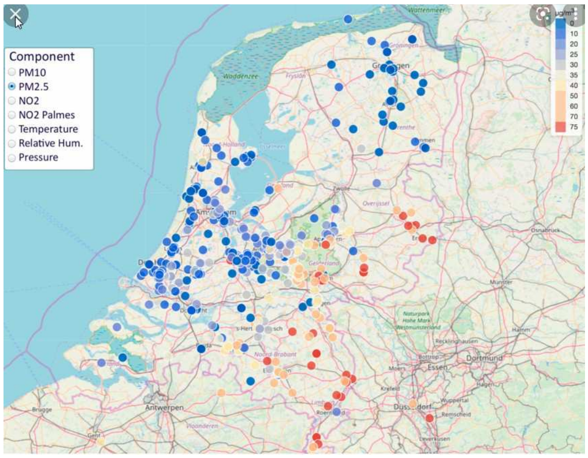

Fig. 3. Map of air pollution in the Netherlands (www.rivm.nl).

there is only traffic pollution, show similar results. The displayed data are compared with the traffic density on that date as measured by the ANWB. The displayed data are comparable with the traffic density on that date and we observed a strong correlation between measured traffic density and air pollution (face validity). More extended measurements on different time of the day under changing weather conditions are needed to compute the correlation. But as stated at the beginning of this section, measurement of fine dust is a laborious, time consuming job.

The city of Zoetermeer is situated along the highway and close to Rotterdam with polluting chemical industry. Usually the wind is coming from the seaside and pollution of Rotterdam, can be measured up to Zoetermeer. But in case the wind slopes down, the pollution of fine dust is mainly caused by traffic. Suspended air particles from the traffic are measured along the highways and through roads using special mobile sensors, designed by technicians from the local group MLZ (measurement group Air Quality Zoetermeer). Solar cells, batteries and communication module enable transmission to a central control room of continuous measurements.

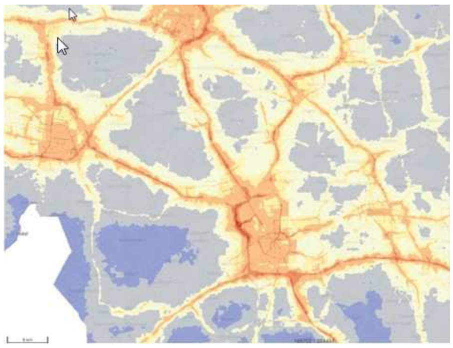

Fig. 4. Map of measurement of fine dust in cities and along roads in the central part of the Netherlands (picture weblog Bernard Gerard).

The mobile sensor RESPIRE has been designed by engineers from Delft University of Technology (DUT), in cooperation with Senseable Lab of MIT. The sensor can be attached to an electrical bike, and then it uses the energy supply from the battery of the bike. The research group Knowledge Based Systems from DUT, uses Zaurus handheld for many years in crisis environment experiment (see fig. 5). The handheld can be used for wireless ad-hoc communication but also used as sensor in a central communication system. The Zaurus has been embedded as communication module in RESPIRE. In [15] we described how daily measurement of traffic information can be stored in a historical database. Now the same technology was used for the design of a pollution database.

Fig. 5. The Sharp SL-C860 Zaurus Handheld used by first responders during a field experiment of a disaster.

IV. Measurement of Fine Dust

Fig. 6. Map of network of Highways surrounding Delft and traffic density maps, green circles no jams, red circles heavy traffic jams (photo RegioLab-Delft).

The cities of Delft and Zoetermeer are close to big polluters The Hague and Rotterdam. Especially the petrochemical industry in the harbor of Rotterdam, between the North Sea and Rotterdam is a great source of pollution. Depending on weather condition as rain and wind, a lot of the polluted air settles in the city of Delft and Zoetermeer. Moreover a network of highways with polluting traffic surrounds and crosses the cities. The daily pollution around Delft is computed and displayed by RegioLab-Delft (see Fig. 6).

In principle, it is possible to design a fine grained network of sensors covering the cities and its surroundings. But the implementation of sensor networks takes a lot of time and money. Instead of measuring fine dust caused by traffic on the highway, another option is to measure the density of traffic on the highways. A network of sensors in the surface of highways and cameras along the highways has already been installed to measure traffic density (see Fig. 8, 9), traffic incidents and accidents and violation of traffic rules. The measurement of traffic density, combined with weather forecast of rain and wind direction, proved to be a useful first indicator of pollution with fine dust and air pollution. A simple network of sensors and mobile sensors may complete the sensor network.

Fig. 7. Perspex screen and houses along the highway A13 close to Delft. (photo M.M.Minderhoud)

The major highway A13 is passing the city of Delft. For many years, citizens living close to this highway worry about suspended air particles. Every day they observe a layer of fine dust on the windows of their houses. To reduce the influence of fine dust, screens of Perspex have been erected along parts of the highway (see fig. 7). There is a cycle track parallel to the highway and many students from DUT use this cycle track on their daily visit to the University.

In first experiment students, cycle along the highway using electric bikes equipped with air pollution sensors. The sensed data was sent to a central office at DUT. It proves that the following factors have their impact on the sensed air pollution data: time of the day, data, day of the week, weather, special events, holidays, accidents and incidents.

The fine dust pollution along the highway was mainly caused by the traffic. We detected a strong correlation between the concentration of fine dust and the traffic density and average traffic speed. The traffic speed itself has a stochastic character because of different speed of cars and distances between cars. The suspended air particles are smoothed and for that reason the average speed is a good measure of air pollution. We observed three dips in the traffic speed corresponding with the morning rush, lunchtime and afternoon/evening traffic congestion. We observed corresponding peaks in air pollution and the dips in average traffic speed, based on the first preliminary recordings with the mobile sensor. It will take a lot of time and effort to measure air pollution during the whole year and over the

Fig. 8. Traffic recordings by the surveillance camera A13 (photo RegioLab-Delft).

whole year. The current Corona pandemic delayed the measuring process of measuring pollutions by students using their bikes.

Depending on weather conditions as rain and wind, air pollution usually climbs up in the air and a cloud of polluted air may cover a city as a cloud. This pollution is sensed by the stationary sensors and is rather stable in time. In this paper we study pollution close to the highway on a distance of less than 300 meters. It is not recommended to live and stay in such areas, but in the older part of many cities, new roads were built recently. On a short distance of the highway we found a strong correlation, between average traffic density and air pollution.

V. MEASUREMENT OF TRAFFIC DENSITY ON HIGHWAYS

Fig. 9. Wires in the surface of roads and cameras along highway (photo Regiolab-Delft).

The highways in the Netherlands are equipped with wires in the surface of the road on regular places (see Fig. 9). Using these sensor loupes, it is possible to detect the speed of cars. Processing the speed measurements, the average density on road segments can be computed. The data processing is performed by the company Tenuki [17]. Unfortunately the recorded and processed data is not free of charge, so we decided to build our own system.

Measurement of traffic speed is currently also done by camera systems along the highways. The system will also be used in future road pricing systems. But again because of privacy reasons the data is not public available. The first experiment with a road pricing system was successfully. But the available infrastructure related to the wires system is still in use.

Many route planning system as TomTom and Google use smart phones to display shortest route. Users are requested for permission to track them during their trips. By tracking many users real time traffic information becomes available but only for the route planner companies.

VI. DATABASE MEASUREMENT OF FINE DUST

At this moment, there is no large database of local fine dust measurements available. Only data of global measurements over a long period of time are available from the network of stationary sensors. Because there is a strong correlation between the average traffic speed and fine dust pollution, we focused on traffic data measured along the highway A13 close to Delft.

In the Netherlands the company ANWB is focused on mobility. They provide a website with information on traffic congestion and travel time between big cities on a daily basis. The data is provided by the Company Tenuki [17]. They compute traffic speed using measurements of wires in the surface of roads. Via the ANWB website it is possible to get real time traffic information. But access to the whole database is not free of charge. For that reason, we were polling the ANWB website for a year and created our own database of traffic information [15].

VII. FORECASTING AIR POLLUTION USING ANN

Fig. 10. Traffic speeds and flows viewer from Regiolab-Delft (scale measure in KM.).

We found a strong correlation between traffic density on the highways and air pollution in the surrounding ideas. Instead of sparse measurements of air pollution via mobile sensors we used the well-equipped traffic sensor network. Given a specific location x, we can predict the traffic speed/density by the average over all days of the year. But the actual data show a lot of variation. The question, we research in this section is the prediction of traffic speed/density on a given time and location and then some time and distance ahead, $x+\Delta x$, $t+\Delta t$. This is important in case if the first measurements are known before the morning rush or accident. In this section we researched the possibility to predict the traffic speed and related traffic density on a given place x and time t. In general the prediction of traffic speed/density is complicated because many parameters as weather forecast, incidents and accidents have their impact. We expect better results, if we predict traffic speed/density some time ahead or some location ahead.

We used Neural Networks trained on a recorded dataset, using Feedforward architecture and the Back-Propagation algorithm. As testbed we used the highway A12 from The Hague to Utrecht. The traffic speed is measured at many successive sensor locations, every 15 minutes. The data is recorded by the company Tenuki [17] using the wires in the road network (Fig. 9) and stored by Regiolab Delft [3] as displayed in Fig. 10.

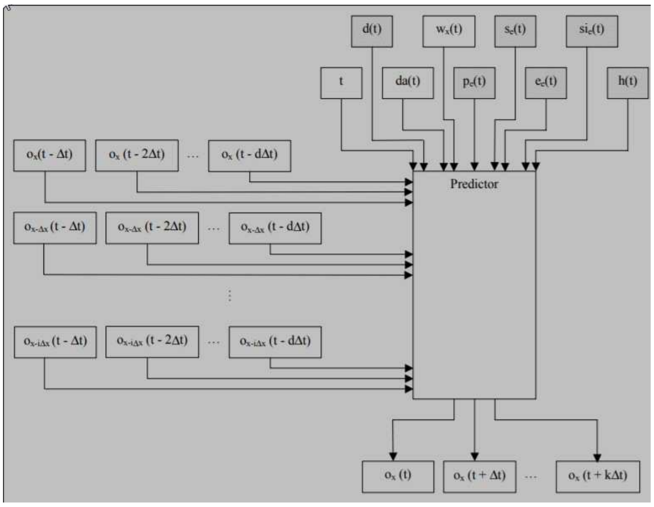

Fig. 11. Average speed prediction using artificial neural networks.

In Fig. 11 we show the general architecture of the used ANN to predict the speed $o_x(t)$ on time $t=t_0,\ldots.t_k$. As input we used speed predictions on d preceding time steps and locations. We also used as input the following parameters: time of the day, date, day of the week (d(t)), weather forecast (w_xt)), place of event ($p_e(t)$), start time of events ($s_e(t)$), end time of event ($e_e(t)$), size of event ($si_e(t)$) and holidays h(t).

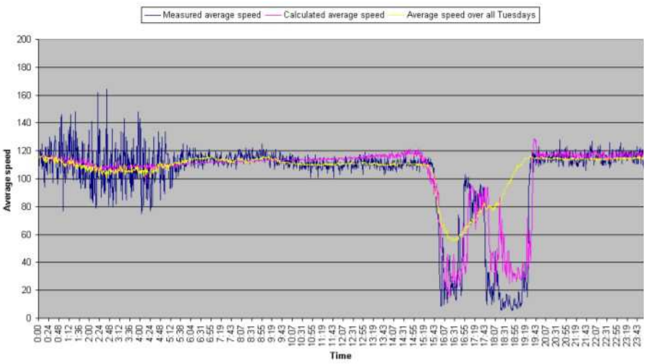

Fig. 12. Predicted average speed near Zoetermeer using 5-8-4 topology on10 minutes ahead.

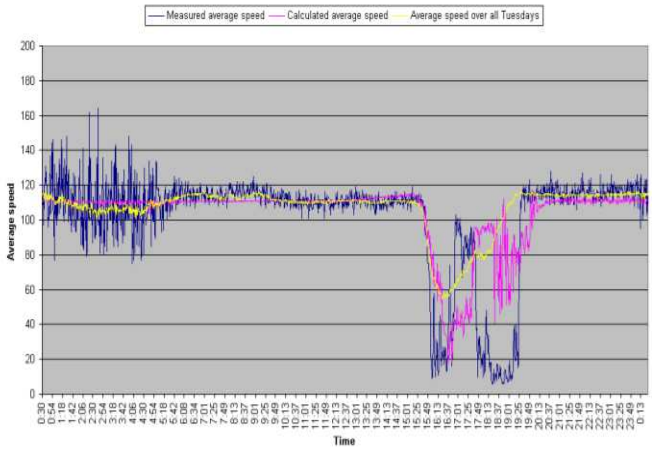

Fig. 13. Predicted average speed near Zoetermeer with the 5-8-4 topology 40 minutes ahead.

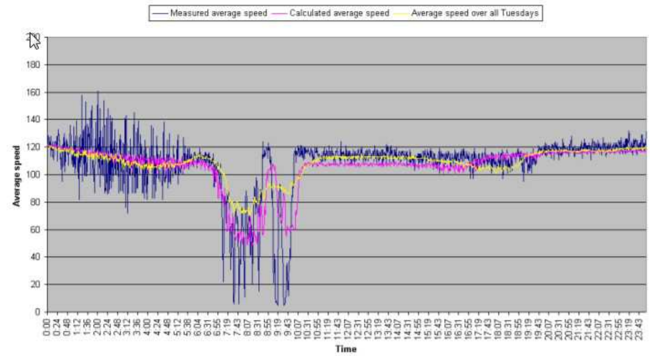

Fig. 14. Predicted average speed near Gouda with the 5-8-4 topology 10 minutes ahead.

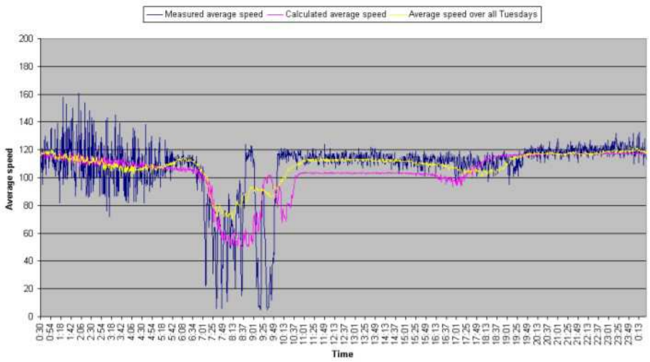

Fig. 15. Predicted average speed near Gouda with the 5-8-4 topology 40 minutes ahead.

The research on the architecture of neural networks and tests showed that a feed forward neural network with one hidden layer, from which the number of hidden neurons is determined by the formula of Fletcher and Goss (between 2Ni+1 and 2√(Ni) +No, is capable of predicting the average speed using only the time, month, day of the week and the average speed of 60 minutes before. At least 76% of the predictions have a difference smaller or equal to 10% if the prediction is made 60 minutes ahead. From these results it can be concluded that Artificial Neural Networks are capable of making good approximations for problems like predicting the average speed.

The data in fig. 12 to fig.15, are recorded on a Tuesday 11-12-2021. The yellow line in the figures indicates the average of all speed measurements over all Tuesdays in that year. The magenta lines in the figures are the speed predictions computed using ANN. It is clear that predictions using ANN perform significantly better than the average speed computed over the year. From displayed figures can be concluded that using other ANN architectures may bring small improvements.

VIII. MEASUREMENT OF TRAFFIC DENSITY USING ANN

The highways in the Netherlands are equipped with a network of cameras for surveillance and traffic management. The video recordings are freely available via Internet (see fig. 9). Via a camera at the start of A13, it is possible to identify cars by their license plate during a time interval. The sampled cars can be tracked, using the network of cameras along the road. Knowing the distance between the cameras and time elapse of recordings it is possible to compute the average traffic speed and traffic density for the sampled cars at the location of the cameras. In the recorded video of the sampled cars by the first camera, we have to detect license plates out of the whole cohort of license plates. At the next camera positions we have to verify if a limited set of license plates are present, so recognition out of a small cohort.

We used a special hierarchical, multilayer, self-organizing neural network NEOCOGNITRON, developed by Fukushima [19] and was used for recognition of handwritten characters. Our first system was developed in 2003 [18]. In the later versions we used “deep learning” to train the system as developed in [20]. The recognizer is inspired by visual systems of animals. We developed a similar system and applied it to the recognition of license plate characters. These characters are composed of the letters A,…. Z and the numbers 0,…9 of a well-defined format. The recognizer should recognize the characters of different size, position and variation of illumination. In some cases, cars carry license plate from abroad or the license plate is occluded by other objects, or to small or badly illuminated by the lightings of the car. In all these cases we expect the recognition process will fail.

The system starts with localization of license plates in the video footage. Plates in the Netherlands have a typical yellow color. Next, cars are supposed to drive in the middle of the lanes unless they take over. The yellow blobs of the car templates could be localized using image processing technology as color filtering. Our system has been tested during daytime under good light conditions. Exceptional cases of yellow cars and other yellow objects on the road induced sparse errors.

The character recognizer is composed of several layers (see fig.16). In the first layer 4 line segments composed of 3 pixels are depicted and the system tries to detect these line segments in a picture of the car template. In the next layer combinations of the basic line segments are displayed and the system tries to recognize these combinations.

Before the character recognizer can be applied some preprocessing image processing steps are needed (see fig. 17). The image processor starts with biniarising the image, next a thinning operation will be applied on the isolated segment. The binary image is sent to the character recognizer module as displayed in fig 17.

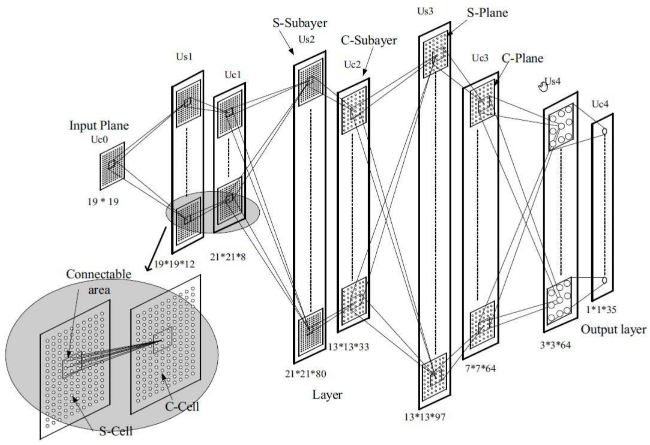

Fig. 16. Hierarchical network structure of Neocognitron model

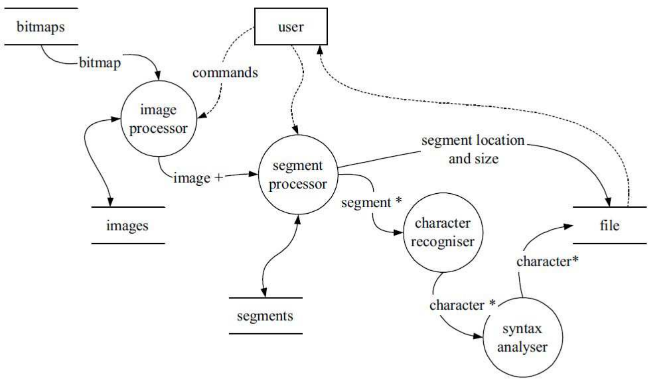

Fig. 17. Dataflow diagram of license plate recognizer

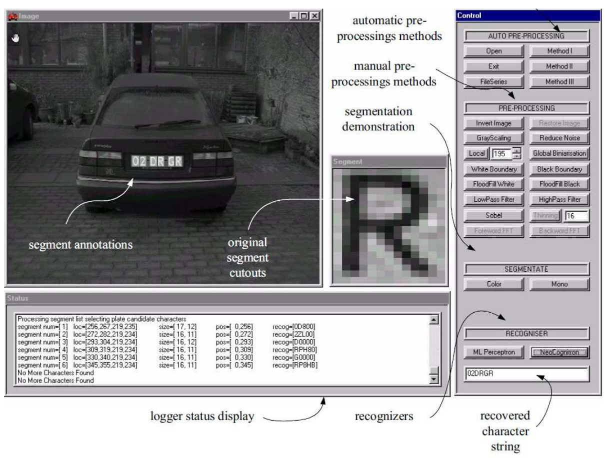

Fig. 18. User-interface of license plate recognition system

The performance of the license plate recognizer can be analyzed using the toolbox. The different components of the recognition system can be selected using the user interface as displayed in fig. 18. As stated before the video footage of the traffic cameras are real time available via Internet and can be downloaded for further analysis by our license plate tracker. The video footage was fed into the system via user-interface displayed in Fig. 18. The recognition rate of license plates in the recorded video stream of the first camera at the beginning of A13 was 86%. The recognition rate is sufficient to assess traffic density.

The initial set of recorded license plates was tracked by the other cameras along the road to assess traffic speed. Some cars may leave the highway or take a stop at some of the petrol stations. A sufficient number of license plates have to be verified in the downloaded video footage of the following cameras, given some fault tolerance.

Recognition license plates from a limited set of prerecorded plates, resulted in a higher recognition rate of 98 %. From the recognized license plates, the speed of the cars, the average, speed and traffic density was computed from the sample set of recognized license plates. We are aware of the fact that some systems used by the road police have a higher recognition rate. But as stated before, we wanted to use homemade technology to save costs of licenses.

TABLE I
RECOGNITION LICENSE PLATES

Recognition rate	(correctly classified license plates)	86.2%
Error rate	(misclassified plates)	5.1%
Rejection rate	(unclassified plates)	8.7%

IX. CONCLUSION

It proved that in many cities, there is a great discrepancy between computed air pollution using models and measurements on the spot. We discussed several recently developed air pollution sensors developed in the research framework with MIT Senseable City Lab and the Technical University of Delft. But to develop a network of these sensors covering the city, takes a lot of money and cost. We discovered a strong relationship between pollution by smart dust and traffic density on the main roads surrounding and crossing the city. An infrastructure of smart sensors to measure traffic density has already been installed. Regional traffic center collect and process these data in the Netherlands.

Unfortunately traffic data is not free available. For that reason we developed and used technology as license plate recognition using smart surveillance camera installed along the highway in round the cities. The recorded video footage was processed to compute traffic density. The recorded video streams were also used to predict traffic density over time and place based on early measurements.

The next step is to measure air pollution on a large scale along the highway with a focus on fine dust. Measurement of fine dust is time consuming and rather complicated. A professional global sensor network has already been installed by RIVM. This global network should be integrated with locale, mobile sensor networks.

In this paper we report the first findings of sensor measurement using traffic density, for the city of Delft as a proof of concept. Validation of the idea to use traffic data to compute pollution should be done by experiments in other smart cities in the Netherlands and abroad.

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