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DOI
10.1109/InfoTech55606.2022.9897102

Publication date
2022

Document Version
Final published version

Published in
Proceedings of the 2022 International Conference on Information Technologies (InfoTech)

2022 International Conference on Information Technologies (InfoTech-2022), Proceedings of the IEEE Conference, Rec # 55606
15-16 September 2022, Bulgaria

2022 International Conference on Information Technologies (InfoTech) | 978-1-6654-6870-1/22/$31.00 ©2022 IEEE | DOI: 10.1109/InfoTech55606.2022.9897102

Automated Access Control via License Plate Recognition using Neocognitron Neural Network

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Abstract – **In 1979 Fukushima developed a hierarchical, multilayered neural network called Neocognitron and used it for the automatic recognition of handwritten Japanese symbols. We combined the Neocognitron classifier with a special image and segment processor and applied the system in 2001 for automatic recognition of license plates in laboratory experiments. In this paper we report about a special image acquisition module and a postprocessor. We tested the system in real life conditions in an application of automated access control.**

Keywords – **access controls; characteristics Dutch license plates; image acquisition; license plate recognition; Neocognitron neural network.**

I. Introduction

In 1959 Hubel and Wiesel reported about their work on the visual primary cortex of cats [1]. They described two special cells: simple cells and complex cells. They proposed a cascade network for use in pattern recognition tasks. Kunihiko Fukushima was inspired by the work of Hubel and Wiesel and developed a hierarchical, multilayered artificial neural network based on the proposed cascade model including the S-cells and C-cells [2]. In the first layer S-cells extract local features. In the next layers features are extracted, which are a combination of the simple features in the first layer. Deformation of features and shifts are controlled by the C-cells. The Neocognitron is a first example of convolutional neural network and deep learning algorithm has been used to train the network.

To reduce the training and processing time we developed a parallel version of the original Neocognitron of Fukushima and tested it on a parallel computer N-Cube [3]. In 2001 we developed a license plate recognizer using a special image processing module and Neocognitron as classifier [4]. After applying a special "thinning" image processor on the character on the license plate, the result is similar to handwritten symbols. That is the reason we used the Neocognitron as character recognizer.

In the next section we will discuss much different kind of license plates recognition systems. Automatic license plate recognition has been used in many surveillance, control and violation detection systems. Many cities have their green zones. Old cars producing heavy air pollution are not allowed to enter the inner city. Admission control has been realized by automatic license plate recognition.

The network of highways in the Netherlands is equipped with a system of smart cameras. These cameras are used for traffic control but also for safety control. Cars violating traffic rules can be detected and tracked by the network of smart cameras. Suspicious cars can also be detected and tracked by the camera system. The camera system along the highway is also connected with the system of smart cameras in the cities.

Another application of surveillance by smart cameras is road pricing systems (see fig. 1). Traffic streams show peaks in the morning and the evening (rush hours). To realize peak shaving car drivers have to pay different prices. During peak hours the price is much higher than during other hours. License plates are detected by cameras installed above the highways at the entrance of cities for example. The registration system of license plates includes identity of car owners.

Well known is the application of smart cameras to detect violation of traffic rules. Car drivers passing red traffic lights can be detected on the spot. Also car drivers neglecting speed limits can be detected by smart cameras along the roads or attached to lampposts. A penalty will be send to the violator shortly after the incident.

Car tracking by license plates is also used for assessment of average speed on road segments. The data will be used as input for dynamic routing systems. An important aspect with all developed systems based on license plate detection is the privacy of the car driver. In the Netherlands there are strict rules for assessment and storage of license plates.

In this paper we discuss an application of our developed system for license plate recognition based on the Neocognitron. The original version of the system developed in 2001 has been improved in the course of the years after improvements of Fukushima [10, 11]. We applied the system for admission control of a military area.

Fig. 1. License plate detection of Camera detection of a road pricing system

The outline of the paper is as follows. In section 2 we discuss related research. In the following sections we discuss the components of our developed license plate recognizer based on Neocognitron. In section 3 we discuss characteristics of Dutch license plates. And in section 4 different image processing technologies are presented. In section 5 we discuss Neocognitron and the architecture of our license plate recognizer. In section 6 we discuss the postprocessor of the Neocognitron and in section 7 we discuss a workbench to test the Neocognitron and its components. In section 8 we present some database of recorded Dutch license plates. In section 9 we discuss our main application, the automatic admission control of the military area at Helder. We end the paper with a section discussion and list of references.

II. Related works

In [5] Shashirangana et al. present a survey on methods and techniques of automated license plate recognition. According to the authors the license plate recognizers can be divided in two categories: the multi-stage systems are composed of traditional computer vision technique for feature extraction and deep learning methods for object detection. Our system also belongs to this category. The recently developed single stage license plate recognition used a single deep neural network, which is trained for end-to-end detection, localization and recognition of the license plate in a single forward pass.

Recent developed deep learning systems use large datasets. Collecting an adequate amount of license plate images is challenging and expensive according to the authors. License plates are country specific so transfer of recorded data of one country to the other is complicated. It also proves that many researchers used synthetic data instead of real life recordings. License plates vary with respect to size, color, font and used language, location and style. Next images of license plates may differ with respect to weather conditions, viewpoints, image quality and availability. A general or specific benchmark dataset is still missing.

The authors of the paper discuss several systems belonging to the first category using edge-based detection, color-based detection, texture-bed detection and character based detection. As classifiers statistical methods and deep-learning systems are used. Our system used character recognition and deep learning. In the field of computer vision we can observe that currently deep learning methods and in particular convolutional neural networks are dominant.

In [6] Selmi et al., have presented a localization method using a Convolutional neural network. Their system is composed of two steps. In the first step they applied some preprocessing technique as noise removal and extraction of fine elements or details of the image. In the next stage, possible bounding boxes for the plate region have extracted. A Convolutional neural network classifier is used to select license plates or non-license plates. We used a similar technology in our license localization module. In [7] the authors discuss the strength and weaknesses of the convolutional neural network technology applied to the automatic recognition of license plates.

In [8] the authors solved the problem of localization license plates using the Viola Jones algorithm. We applied Viola Jones algorithm for the localization of faces in the wild. The algorithm start with simple Haar features. To localize license plates automatically we also start with simple Haar features which are very similar to features in the first layer used to train a Neocognitron. It is known that using Viola Jones algorithm requires a huge database to train the network. The authors in [8] used the YOLO framework which is also computational very heavy.

In [2] Fukushima introduced the first version of the Neocognitron neural network. He was inspired by the work of Nobel Prize winners Hubel and Wiesel. They analyzed the brain of cats and found a hierarchical structure in the vision system. Specialized S-cells were involved in the recognition of special features and C-cells for generalization properties. Fukushima used his system for the recognition of Japanese written characters. In the first layer simple combinations of 3 pixels are recognized and in the following layers these simple structures are combined to more complex ones, ending with the selected object in the highest layer. We were inspired by the first version of Fukushima and developed a system for automatic recognition of license plates. After capturing the image of a license plate several image processing technologies were applied. The outcome of the thinning process results in skeletons similar to handwritten characters. For that reason we developed a license plate recognizer based on the Neocognitron neural network.

In the course of the years Fukushima developed more advanced versions of his Neocognitron. Deep convolution neural networks are successfully used in recognition of visual patters. The neocognitron also belongs to the category of deep convolution neural networks [10, 11, 12]. The author presents recognition of partly occluded patterns, the mechanism of selective attention, increasing robustness against background noise, new learning rules as margined winner take all.

In 2001 the research group Knowledge based systems got interested in the Neocognitron neural network. Visiting student from the Czech Technical University in Prague M. Steuer implemented the Neocognitron in C++ [3]. Later he also developed a parallel version of the system on the parallel N-Cube computer supervised by M. Snorek from the Czech Technical University in Prague and Rothkrantz from Delft University of Technology. The system was used and tested by students taking a course in neurocomputing.

In the framework of his master thesis B. Cornet developed a recognition system of car templates using Neocognitron as a classifier [4]. Under supervision of Rothkrantz improved versions of the Neocognitron by Fukushima were also implemented in the new release of the license plate recognizer and used in the testes presented in this paper. A database of captured license plates was developed. Also a first version of the missing module "automated localization and capturing license plates" was developed and tested in a special application about admission control of a military area.

We used our developed license plate recognizer in many applications. In the context of smart cities [13] it was applied for admission control. It was also tested in road pricing systems. Car drivers have to pay a higher tax entering the city during peak hours. Our main application is the admission control and surveillance of the military area at Den Helder [14, 15, 16, 17].

III. CHARACTERISTICS OF DUTCH LICENSE PLATES

License plates may use different colors, fonts, backgrounds, different sizes of characters and syntax. Most developed recognizers of license plates are country specific. Using country specific characteristics of license plates increased the recognition. Applications are also country specific.

Fig. 2. Examples of license plate

The current Dutch license plate system of passenger cars uses black letters on a light-reflecting yellow background. The letters are ordered in three groups of 1, 2 or 3 letters.

Fig. 3. Examples of a Dutch license plate

The license plates have a standard size (52x11 cm) and a fixed font is used. For passenger cars only the consonants G, H, J, K, L, N, P, R, S, T, X and Z are used. Since 2015 the consonants L and T are no longer used. Some combinations of consonants are not used such as GVD, KKK, KVT, LPF, NSB, PKK, PSV, TBS, SS, SD PVV, SGP and VVD because they are acronyms of political parties, companies etc.

Series	Year	Combination	Series	Year	Combination
1	1951	XX-99-99	8	2009	9-XXX-99
2	1965	99-99-XX	9	2006	XX-999-X
3	1973	99-XX-99	10	2008	X-999-XX
4	1978	XX-99-XX	11	2015	XXX-99-X
5	1991	XX-XX-99	12	-	X-99-XXX
6	1999	99-XX-XX	13	2016	9-XX-999
7	2005	99-XXX-9	14	2019	999-XX-9
….	…..	…..	…..	….	….

Fig. 4. Configuration of Dutch license plates and year of emission (X=letter, 9=number)

IV. IMAGE PROCESSING TECHNOLOGIES

Our license plate recognizer is composed of several modules ordered into three groups:

Localization of license plates. Localization of license plates in the wild is a complex problem. License plates can be exposed under different lighting conditions, different posture, orientation, or partial occluded in a static or dynamic environment. A similar problem was the localization of faces in the wild. It has been partly solved by the work of Viola Jones [20]. They designed a special algorithm using special Haar features, AdaBoost algorithm and a huge dataset of faces recorded in the wild.

A great problem is that a huge database of license plates is not yet available in public domain. This is partly caused by privacy aspects. Smart cameras installed along highways for traffic control and speed control made thousands of recordings of license plates every day. Unfortunately the data is not available for research. In this paper we made a start with the creation of our own database of Dutch license plates as discussed in section III.

In section X we present our investigations in the design of a localization algorithm of localization of license plates in the wild. Our approach is similar to Viola Jones. We start with Haar features taken from the first layer of the Neocognitron as defined by Fukushima. More details will be presented in section X.

Image processor In the first release of our license plate recognizer developed in 2003 [4] we used some basic image transforms. After localization the captured image is binarized. The original image is grey scales and some noise reduction filters have been applied. Next a local binarization method has been applied. The segment processor cuts out all segments from the original image.

In the course of the years image processing tools have been improved a lot. Also current cameras enable recordings with a much higher resolution. The modular design of our recognizer implemented using C++, enables replacement of out-dated modules. Especially recordings with a higher resolution enables a much better skeletonized module.

Character recognizer We implemented an adapted version of Neocognitron as designed by Fukushima in 2001. In recent years Fukushima published adapted versions of the Neocognitrons. We adapted our necognitron release from 2003 successively as discussed in section 5.

Signature algorithm

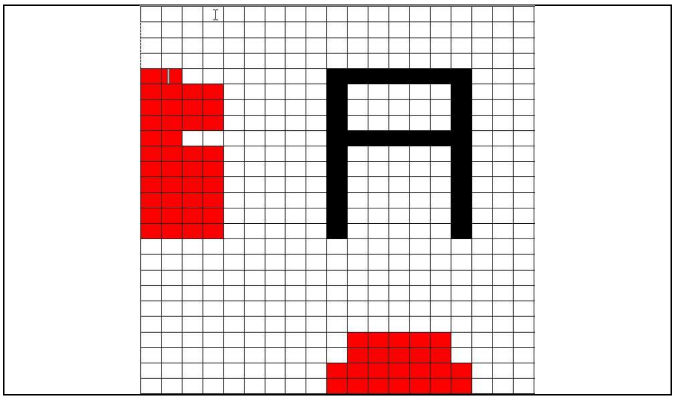

Fig. 5. Signatures of characters on x,y axis

Dutch license plates have a fixed format. The signature algorithm will be used to localize characters on the plates using variation in greyness. Let us consider an array of pixels e_{ij} with values of greyness. In Fig. 5 we consider only black and white pixels. Let us consider the greyness of adjacent pixels e_{ij} and $e_{(i+1)j}$ in the j-th column. If the difference in greyness of the two adjacent pixels passed a defined threshold T_0 then then the signature at the bottom of column j will be raised by 1. The same procedures hold for two adjacent pixels e_{ij} and e_{ij+1} in row i. For the regions with homogeneous greyness the threshold will not be passed and the signatures remain low. In the region of the characters the threshold will be passed and we may expect high varying values of the signature.

Inspecting the signatures along the x, y axis enables localization of the characters and the empty spaces in between. Using the possible configurations of Dutch license plates as displayed in fig. 4, the final arrangement of letters and empty spaces can be assessed.

V. NEOCOGNITRON

In 2001 we developed our first prototype of a license plate recognizer [4]. We were inspired by the Neocognitron, designed by Fukushima used for the recognition of handwritten alphanumeric characters in Japanese language [2]. The Neocognitron is a hierarchical neural network composed as a cascade of connected layers. Every layer is composed of one or more planes. Every plane is an array of three types of cells: S-cells, C-cells, and V-cells.

The S-cells are the feature extracting cells. An S-cell is excited if a specific input pattern is presented as learned during the training process. The V-cells are inhibitory cells; they prevent S-cells to excite on random input features. In the second layer specific combinations of basic features are defined used for training. The C-cells make the network tolerant for small distortions, deformation and translation of patterns. Each cell takes input from several cells of planes in a previous layer. The source neurons are grouped within a square area, referred as a connectable area (see fig. 6, 7).

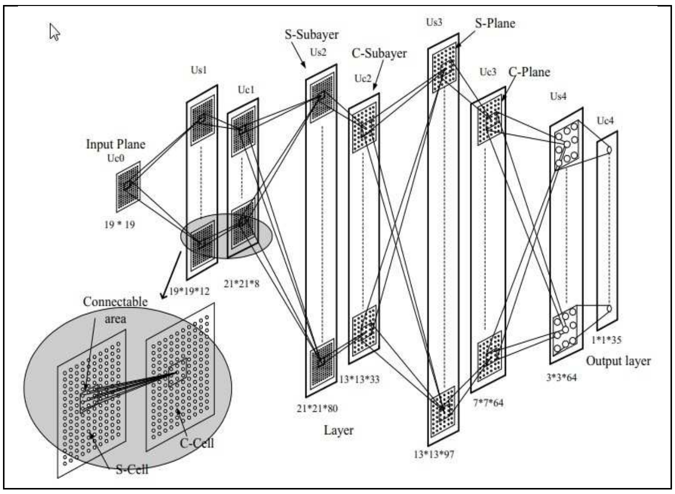

Fig. 6. Hierarchical structure of the Neocognitron

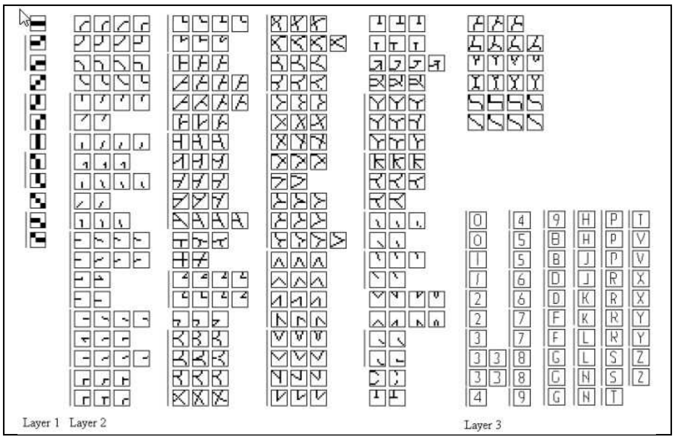

Fig. 7. Training set of patterns used in our license plate recognizer

In [10, 11] Fukushima published recent advances in the deep CNN Neocognitron. We implemented most of them in our License plate recognizer based on Neocognitron. The focus of our innovations is on improvement of the post processor and localization of license plates. We will list two examples. A new learning rule AiS (Add-if-Silent) was introduced to train intermediate layers. A new cell is generated and added to the network if all postsynaptic cells are silent in spite of non-silent presynaptic cells. The generated cells learn the activity of the presynaptic cells in one-shot. In the deepest layer, a method called IntVec (Interpolating vector) is used for classifying input patterns based on the features extracted by intermediate layers. For the recognition by IntVec, we search in the multi-dimensional feature space, the nearest plane (or line) that is made of a trio (or pair) of reference vectors. Computer simulation shows that the recognition error can be made much smaller by the IntVec than by WTA (Winner-Take-All or even by the SVM (support vector Machine).

VI. POST-PROCESSOR USING A-PRIORI KNOWLEDGE

In principle a license plate recognizer based on Neocognitron can be developed for universal license plates. But a huge amount of data is needed to train the system. In this paper we restrict ourselves to the development of a recognition system for Dutch license plates. We have enough data to train our system. To improve the results we use characteristics of Dutch license plates.

Used characters. On Dutch license plates a limited set of characters of the alphabet are used. These characters have a special font. These characteristics are used during training of the system.

Image segmentation. From fig. 4 can be concluded that the architecture of license plates is limited. Special boxes with 1, 2 or 3 characters can be used. The special boxes are localized using the signature algorithm as defined in section IV. In the application of this algorithm we used that Dutch license plates have fixed sizes and possible locations of characters.

Used grammar and syntax. Limited set of combinations of characters is possible. After recognition of characters the most probable combination will be used.

Confusion matrix. It proved that the pair of character 0/D, 2/Z, 5, S and 8/B are confused regular. We trained special recognizers to process these pairs of characters.

VII. WORKBENCH TO TEST THE DEVELOPED NEOCOGNITRON AND ITS COMPONENTS

Our Neocognitron system has been implemented in C++ and has a modular design (see fig. 8). The different components can be connected in different ways using a special user interface as displayed in fig. 9. A car license plate is fed into the system and converted as a bitmap. Next different image processing modules can be activated and finally the Neocognitron character recognizer will be activated. The system has been tested. But during runtime it may happen that that the recognition results are too bad or errors are reported.

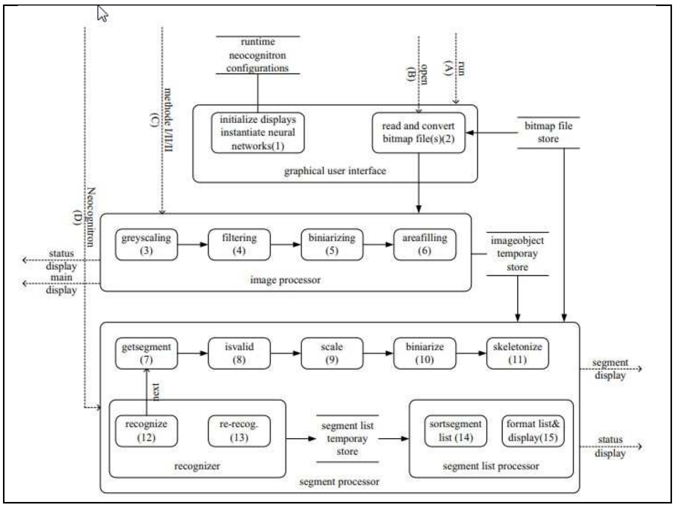

Fig. 8. Workbench with image preprocessing tools and Neocognitron

To test the developed Neocognitron and its components we developed a special workbench composed of several components ordered in the following groups auto-preprocessing, pre-processing, segmentation and recognizer (see fig. 9). The Neocognitron is one of the topics in the course deep convolutional neural networks at Delft University of Technology. Students are supposed to perform some assignments using the workbench.

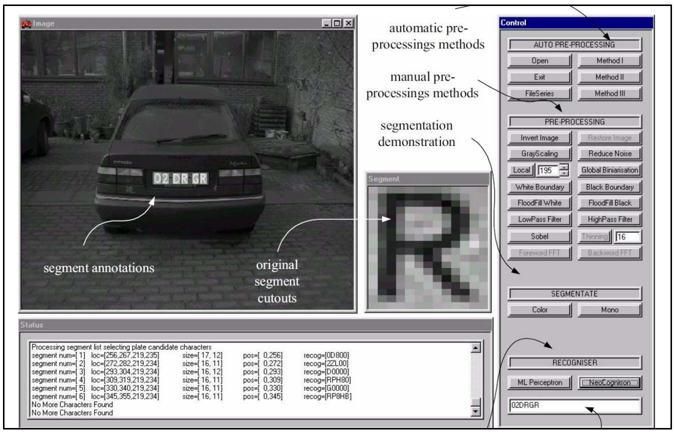

Fig. 9. Workbench with image preprocessing tools and Neocognitron

To test the included Neocognitron module we may select one of the auto-preprocessing modules and then select Neocognitron. After pushing the button the module starts running. An interesting option is to compare the Neocognitron module with a ML-perceptron module. In general Neocognitron outperformed ML-perceptron.

Error analysis can be performed by selecting and comparing the results of different modules. In the preprocessing group different modules are included.

TABLE 1. RECOGNITION OF LICENSE PLATES BY THE NEOCOGNITRON LICENSE PLATE RECOGNIZER

Recognition rate (correctly classified license plates)	93.2%
Error rate (misclassified plates)	2.3%
Rejection rate (unclassified plates)	4.5%

VIII. DATABASE OF LICENSE PLATES

A Neocognitron is neural network. A neural network has to be trained before it will be able to recognize license plates. Training a neural network requires a database of license plates. Recordings of license plates may differ a lot depending on lighting condition, direction, occlusion but also depending of country specific characteristics of the license plates. To train a general recognizer a huge database with examples of license plates in all possible situations. As a starting point we developed specific databases. A problem creating databases is the privacy aspect. In general it is not permitted to process data recorded on public streets. Recorded data may only be used for private purposes and cannot be published.

Inner city of Delft. We mounted a dashboard camera on a private car and made daily recordings. It took a lot of work to select suitable frames from the video recordings. Recordings from cars on parking lots and park houses provide a lot of data in a convenient way. Our database is composed of 300 single frames with license plates and 50 short video fragments of driving cars.

Fig. 10. Localization of cars in the city of Delft on a road and parking lot

Recordings at the entrance of the military defense academy

The military defense academy is one of our test environments to be discussed in the next section. To enter the military area visitors have to communicate with the safety guard via the booth control or need a special admission card. In either case cars stop for some time allowing us to make high quality recordings of the license plates. When cars are leaving the military area the barrier is opening automatically. So there is no need to stop at the booth for identity control.

The recorded data may only be used to test our admission control system via license plates. We recorded 150 single frames of license plates and 100 short video recordings of entering and leaving cars.

Fig. 11. Entrance barrier at the Netherlands Defence academy at Den Helder

Recordings traffic on the highway. Close to Delft University of Technology passes a highway A13 with high traffic density. We placed for several days a video camera on one the bridges crossing the highway. We recorded 225 short video fragments of passing cars.

Fig. 12. Highways in the Netherlands with electrical wires in the surface of the road to assess traffic density

We recorded license plates on 5 locations and stored them in a database. A summary of the numbers is presented in table 2.

TABLE 2. DATABASE OF RECORDED LICENSE PLATES

Location of recordings	Single pictures	Videos
Inner city of Delft	300	50
Recordings at the entrance of Military Defence Academy	150	100
Recordings traffic on the highway	-	225

IX. ADMISSION CONTROL OF THE MILITARY AREA AT DEN HELDER

The military area is surrounded by water or gates. On two places there are removable barriers. During the rush hours members of the security guard control admission. A special admission pass is needed. During the silent hours car drivers have to push a button and communicate via a microphone array. During that time with help of a camera installed at an opposing lamppost it is possible to make pictures of surrounded areas including the license plates. These pictures are processed in license plate recognizer connected to a database with data of unwanted or cars from suspicious persons.

Fig. 13. Entrance barrier at the Netherlands Defence academy at Den Helder

The position of the car stopping in front of the barrier is known in advance and also the position, distance and view angle of the camera. The recorded area including the license plate is scanned by a small window corresponding to the fixed sizes of the Dutch license plates. On every position the scan window is analyzed by signature technology if the window includes a license plate (see section IV).

X. LOCALIZATION LICENSE PLATES

Our research challenge is to localize license plates in the wild. In current applications recordings are restricted to enable localizations. In our application on access control we used still pictures recorded from cars stopping in front of a barrier. When cars are leaving the area there is no security check and we made video recordings of leaving cars. We processed the movies manual and selected frames showing license plates on different locations in the visual field. From the 100 video recordings we extracted 1500 single frames, annotate the license plates and stored them in the database of positive examples. Next we selected 1500 frames without license plates and stored them in the database of negative examples.

We need a classifier, train the classifier on a part of the recorded examples and test the classification result on test the trained classifier on a test set. We realize that the recordings are limited in the wild, but it is a first test to generalize for recordings. Localization of license plates in the wild has some similarity with localization of faces in the wild which has successfully solved using Viola Jones algorithm. We first report part of this research.

TABLE 3. DATASET USED TO LEARN THE HAAR-LIKE FEATURES

Dataset parameters	Values and description
Database	Viola Jones
Sample size	24x24 pixels
Number of classes	2
Class 0	Non-faces
Class 1	Faces
Number of samples (0/1)	1500/1500

In 2014 we researched the localization of faces in the wild [18]. In order to classify a face, some characteristic features need to be extracted. For this purpose, we used Haar-like features. We found that using intensity values directly as input for the RVM classifier does not work adequate. Therefore, features need to be extracted from the images of the dataset. The features that are extracted are Haar-like features. These features have a rectangular shape and are fairly simple. Compared with other filters, these features are somewhat primitive. For example, it is hard to use them for boundary analysis or texture analysis. They are also sensitive to the presence of edges, bars, and other simple image structures. But on the other hand due to its simple construction, they have only horizontal and vertical orientation. It is computationally very efficient. This is the compensation they offer for their limited flexibility. As a result these features can be computed very fast. In our face detection algorithm, five types of rectangular features are used (see fig. 14). Type 1, 2 and 5 are calculated as the sum of all pixels in the dark area minus the sum of all pixels in the light area. Type 3 and 4 are calculated as half the sum of all pixels in both dark areas minus the sum of all the pixels in the light area in the middle.

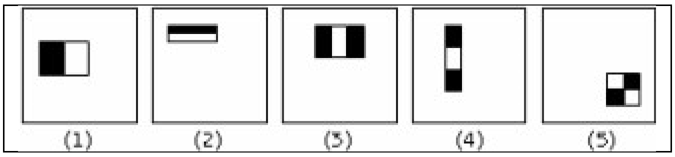

Fig. 14. The five basic types of Haar-like features used in our approach

Each of the five basic features is scanned on every possible scale and every possible position within a training sample. Given that the sample's dimension is 24x24, the complete set of features that can be constructed is quite large, namely 162336. From this set of features, we want the most relevant ones that best characterize the face. The best features are chosen using the AdaBoost learning algorithm.

The AdaBoost algorithm is proven to boost the performance of the classifier. It is also proven that the training error of the strong classifier approaches zero exponentially in the number of rounds and the generalization performance is also very high. The AdaBoost algorithm can be interpreted as a greedy feature selection process. Consider a general boosting case where a large set of classification functions are combined using weights. The challenge is to associate a large weight with each good classification and a smaller weight with poor functions. AdaBoost [19,20] is used to select a low number of good classification functions, so called 'weak classifiers', to form a stronger classifier. The classifier is called weak because we do not expect even the best classification function to classify the training data well. The final strong classifier is actually a linear combination of the weak classifiers.

In our approach, the latter is slightly different. Instead of using a threshold, the chosen weak classifier is the Relevance Vector Machine – RVM for discriminating between the positive and negative examples. This means that for each feature, the weak RVM classifier determines the optimal classification function such that a minimum number of examples are misclassified [21].

To localize license plates we used the same procedure as we did localizing faces. We used the Haarlike features from fig. 14. And also applied AdaBoost. After 3 hours of training on our recorded databases we got a recognition of 94% on a test set. We realized that the recorded license plates are limited in the wild. As stated in the beginning of this section we sampled data from the video recordings at the access gate of the military area. There was little variation in weather conditions and context of recordings

TABLE 4. 2-FOLD CROSS VALIDATION ON CLASSIFIERS FOR LICENSE PLATE DETECTION BASED ON HAAR-LIKE FEATURES.

Kernel			
	Feature 1	Feature 2	Feature 3
Gauss 2.0	26.30%	35.45%	38.60%
Gauss 5.0	25.35%	32.40%	36.55%
Laplace 0.5	35.20%	26.70%	42.70%
Laplace 2.0	29.25%	32.00%	41.60%
Laplace 5.0	26.20%	25.90%	37.45%

To improve the results we planned to use the Haar-like features in the first layer of the neocognitron (fig. 7). This is ongoing research. We will train this system on extended databases of recorded license plates. We are aware of the fact that real time license plate recognizers are currently available, but not for recognition of Dutch license plates. As stated before because of privacy problem huge databases of license plates still not available. From our research on the localization of faces in the wild we know that huge databases, high computer power and long training time is needed. But step by step we want to develop our own recognizer for Dutch license plates recorded in the wild.

XI. CONCLUSION

Systems for automated license plate detection have the interest of many researchers. Current systems are applied in traffic control, admission control, crime detection and many smart city applications. We developed a first release of a system for automated license plate recognition in 1993, inspired by the neocognitron neural network developed by Fukushima. Over the year we implemented many improvements of the first release as discussed in the paper.

The neocognitron neural network is one of the first deep convolutional neural networks, successfully applied in the recognition of visual patterns. The architecture of the neocognitron was based on neurophysiological findings on the visual systems of mammals.

One of the unsolved problems is the localization of license plates in the wild. That is to say independent of lighting conditions, weather conditions, occlusion, position and movement. To train systems such general systems huge databases are required. One of the problems in creating public domain databases are the privacy aspects of car owners.

We developed a system for automated admission control of a military area based on license plate recognition. We also developed our own limited database of license plates and applied it in the training of systems for localization of license plates.

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