FAKULTA APLIKOVANÝCH VĚD ZÁPADOČESKÉ UNIVERZITY V PLZNI

STUDENTSKÁ VĚDECKÁ KONFERENCE 2017

Poker Cards Recognition using Neural Networks

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1 Introduction

This problem of designing an artificial intelligence for playing poker consists of several different task. One of the tasks is automatic cards recognition and identification based on image captured by a video camera. In modern tournaments, the cards are usually put on a transparent material face down, where only the can see the actual front side. The purpose of this work was to choose and create methods for automatic segmentation and identification of the cards color and values.

2 Data Recording and Cards Segmentation

The images of the cards were captured by several different devices (camera, mobile phone, etc.) in different conditions and lighting. Two different sets of cards were used for the recordings. To simulate the conditions of the tournament placement, the cards were randomly put on black background without overlapping. This allowed us to use some of the common computer vision techniques to segment the white cards from the black background based on adaptive thresholding and region detection. Th results can be seen in Figure 1. The cards were then rotated and reshaped, and a dataset was created for the purpose of training a neural network. The cards were labeled by manually selecting s template for each type of a card and then using Template Matching to find cards similar to the templates.

3 Convolutional Neural network

The network architecture we constructed for the purpose of this work was based on experience with networks used for ImageNet competition. These networks are specifically designed for the task of classification of images. Since our network only classifies cards and no other images, the architecture is less complex then networks used for ImageNet like Alexnet (Krizhevsky (2012)) or Segnet (Badrinarayanan (2015)). The details of the tested architecture are shown in the results Table 1. The convolutional layers used had kernel size 32×32 with stride one and maxpooling layers had kernel size 2×2 with stride two. The fully connected layer at the end of each network had 52 neurons (same as the number of different cards). The *fc1* in the second network had 4096 neurons.

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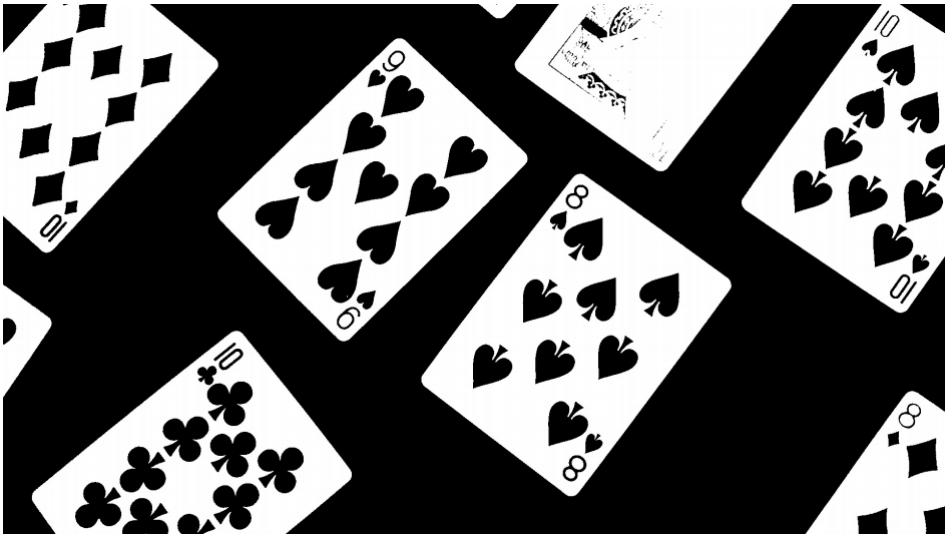

Figure 1: Cards segmentation by thresholding.

4 Results

We developed an automatic method for poker cards segmentation from video file and created several network architectures to classify the cards. The two best architectures are presented here in Table 1. For comparison, the accuracy of the Template Matching method was measured as 81.8 % on the same data. The networks proved to be faster and more accurate than Template matching and thus viable for the development of the next step of automatic poker playing machine.

Table 1: Two developed network architectures with corresponding results.

Network architectures	Classification accuracy
conv1,pool,conv2,pool,conv3,pool,fc1	92.21%
conv1,pool,conv2,pool,fc1,fc2	92.67%

Acknowledgement

This work is supported by grant of the University of West Bohemia, project No. SGS-2016-039. Computational resources were supplied by the Ministry of Education, Youth and Sports of the Czech Republic under the Projects CESNET (Project No. LM2015042) and CERIT-Scientific Cloud (Project No. LM2015085) provided within the program Projects of Large Research, Development and Innovations Infrastructures.

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