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Road signs recognition with two-dimensional hidden Markov models

Abstract. *The automatic road sign recognition system is presented. The system uses two-dimensional hidden Markov models. The system is able to recognize the road signs, which were detected earlier in the image. The system uses wavelet transform for features extraction of road signs. In recognition process system uses two dimensional hidden Markov models. The experimental results demonstrate that the system is able to gain an average recognition rate of 83%.*

Streszczenie. *Zaprezentowano automatyczny system rozpoznawania znaków drogowych. System wykorzystuje dwuwymiarowe uryte modele Markowa. System rozponaje znaki drogowe, które były wcześniej wykryte nas obrazie. Do ekstrakcji cech znaków drogowych system używa transformaty falkowej. W procesie rozpoznawania zastosowano dwuwymiarowe modele Markowa. Wyniki eksperymentu pokazują, że system jest w stanie osiągnąć poziom rozpoznania 83% .* ***(Rozpoznawanie znaków drogowych z dwuwymiarowymi ukrytymi modelami Markowa)***

Keywords: two-dimensional hidden Markov model, road sign recognition, image recognition, image processing
Słowa kluczowe: dwuwymiarowe ukryte modele Markowa, rozpoznawanie znaków drogowych, rozpoznawanie i przetwarzanie obrazów

Introduction

For last years many researches in the field of automatic road sign detection and recognition systems were made. The main object of such systems is to warn a driver of presence of road signs, because he may not notice the presence of sign. The main problem is caused by the variable lighting conditions of a scene in a natural environment, and an automatic system should be able to detect signs in different conditions and positions [1, 2]. Great amount of methods have been developed to locate and identify road signs, which are individual in their colour, shape, and appearance. Most of the existing methods use the combination of these properties to determine the meaning of road sign content [3]. Detection of road sign are based on colour criteria[1] or shape information[4]. As a result, the colour space plays a lead role. The popular RGB colour space is used in [5], but it is sensitive to lighting conditions changes [7]. Colour space that are more independent to such changes is HSV is used in [6]. After detecting of road sign, it should be recognized from a large set of possible patterns using some of classification method. The symbol of detected sign must be suitably represented for a specific classification method that is usually done by extracting some features from the image. Examples of features extracting techniques are histograms [8] and wavelets [9]. Many classification methods have been proposed, neural networks [8, 9, 10], SVM [11] or hidden Markov model [12]. This paper presents an automatic road sign recognition system which uses two dimensional wavelet transform of second level decomposition for features extraction, and the classification module bases on two dimensional hidden Markov models, which work with two dimensional data.

2D problem in HMM

Hidden Markov models (HMM) are used in speech recognition, character recognition, data classification, texture analysis, face recognition, etc. This widely application of HMM is result of its effectiveness. An extension of the HMM to work with two-dimensional data is 2D HMM, which can be regarded as a combination of one state matrix and one observation matrix, where transition between states take place according to a 2D Markovian probability and each observation is generated independently by the corresponding state at the same matrix position. It was noted that the complexity of estimating the parameters of a 2D HMMs or using them

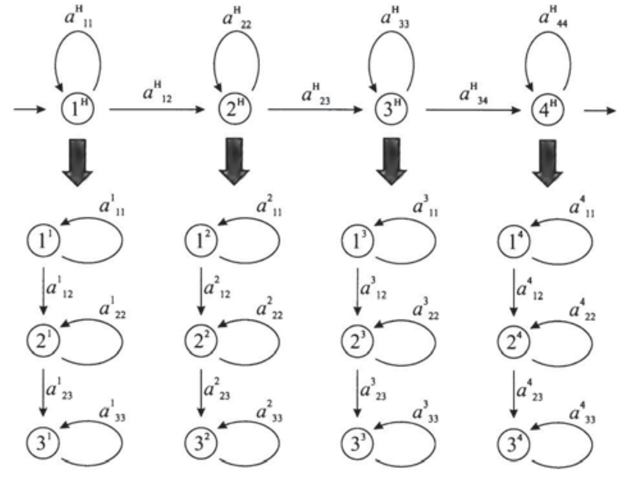

Fig. 1. Pseudo 2D HMM [1].

to perform maximum a posteriori classification is exponential in the size of data. When we process one-dimensional data, we have good tools and solution for this. Unfortunately, this is unpractical in image processing, because the images are two-dimensional. When we convert an image from 2D to 1D , we lose some information. So, if we process two-dimensional data, we should apply two-dimensional HMM, and this 2D HMM should works with 2D data.

One of solutions is pseudo 2D HMM [13, 14]. This model is extension of classic 1D HMM. There are super-states, which mask one-dimensional hidden Markov models (Fig. 1). Linear model is the topology of superstates, where only self transition and transition to the following superstate are possible. Inside the superstates there are linear 1D HMM. The state sequences in the rows are independent of the state sequences of neighboring rows. Additional, input data are divided to vectors. So, we have 1D model with 1D data in practise.

Other approach to image processing uses two-dimensional data presented in works [15] and [16]. The solutions base on Markov Random Fields (MRF) and give good results for classification and segmentation, but not in pattern recognition. Interesting results showed in paper [17]. This article presents analytic solution and proof of correctness two-dimensional HMM. But this 2D HMM is similar to MRF, works with one-

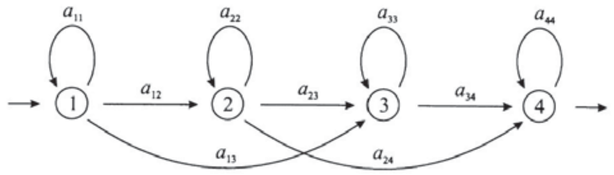

Fig. 2. One-dimensional HMM.

dimensional data and can be apply only for left-right type of HMM. This article presents real solution for 2D problem in HMM. There is show true 2D HMM which processes 2D data.

Classic 1D HMM

HMM is a double stochastic process with underlying stochastic process that is not observable (hidden), but can be observed through another set of stochastic processes that produce a sequence of observation [18]. Let $O = \{O_1, .., O_T\}$ be the sequence of observation of feature vectors, where T is the total number of feature vectors in the sequence. The statistical parameters of the model may be defined as follows [19]:

- The number of states of the model, N
- The number of symbols M
- The transition probabilities of the underlying Markov chain, $A = \{a_{ij}\}, 1 \leq i, j \leq N$, where a_{ij} is the probability of transition from state i to state j
- The observation probabilities, $B = \{b_{jm})\} \quad 1 \leq j \leq N, 1 \leq m \leq M$ which represents the probability of gnerate the m_{th} symbol in the j_{th} state.
- The initial probability vector, $\Pi = \{\pi_i\} \quad 1 \leq i \leq N$.

HMM requires three probability measures to be defined,A, B, Π and the notation $\lambda = (A, B, \Pi)$ is often used to indicate the set of parameters of the model. The parameters of the model are generated at random at the beginning. Then they are estimated with Baum-Welch algorithm, which is based on the forward-backward algorithm. The forward algorithm calculates the coefficient $\alpha_{t(i)}$ (probability of observing the partial sequence $(o_1, \ldots, o_t)$ such that state q_t is i). The backward algorithm calculates the coefficient $\beta_{t(i)}$ (probability of observing the partial sequence $(o_{t+1}, \ldots, o_T)$ such that state q_t is i). The parameters of new model λ, based on λ_0 and observation O, are estimated from equation of Baum-Welch algorithm [18], and then are recorded to the database.

There are three fundamental problems of interest that must be solved for HMM to be useful in some applications, namely: (1) probability of generating observation, (2) optimal state sequence and (3) parameters estimation. To create a road signs recognition system is necessary to solve the problem 1 and 3. To solve the problem 1 you can use well know forward-backward algorithm, and to solve the problem 3 - Baum-Welch algorithm [20].

2D HMM

Yujian in [17] proposed definitions and proofs of 2D HMM. He has presented several analytic formulae for solving the three basic problems of 2-D HMM. Solution to Problem 2 is usefull., and Viterbi algorithm can be easily adopted to image recognition with two dimensional input data. Unfortunetly, solution to problem 1 and 3 may be use only with one dimensional data -observation vector. Besides presented solutions are for Markov model type "left-right", and not ergodic. So, we present solution to problems 1 and 3 for two dimensional data, which is sufficient to build a image recognition system. The statistical parameters of the 2D model (Fig. 3):

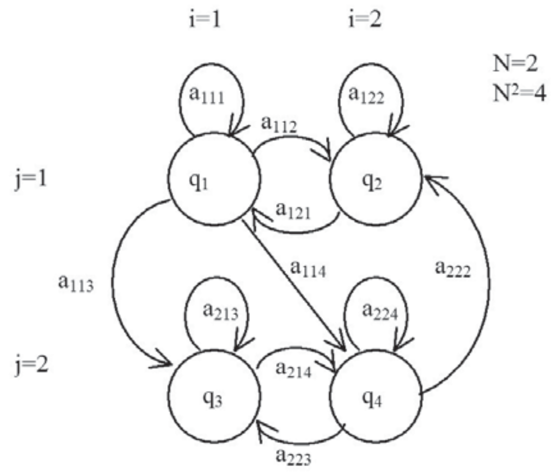

Fig. 3. Two-dimensional ergodic HMM.

- The number of states of the model N^2
- The number of data streams k_1 x $k_2 = K$
- The number of symbols M
- The transition probabilities of the underlying Markov chain, $A = \{a_{ijl}\}, 1 \leq i, j \leq N, 1 \leq l \leq N^2$, where a_{ij} is the probability of transition from state ij to state l
- The observation probabilities, $B = \{b_{ijm})\}, 1 \leq i, j \leq N, 1 \leq m \leq M$ which represents the probability of gnerate the m_{th} symbol in the ij_{th} state.
- The initial probability, $\Pi = \{\pi_{ijk}\}, 1 \leq i, j \leq N, 1 \leq k \leq K$.
- Oservation sequance $O = \{o_t\}, 1 \leq t \leq T, o_t$ is square matrix simply observation with size k_1 x $k_2 = K$

Solution problem 1 for 2D

Forward Algorithm

- Define forward variable $\alpha_t(i, j, k)$ as:

(1) $$\alpha_t(i, j, k) = P(o_1, o_2, \ldots, o_t, q_t = ij|\lambda)$$

- $\alpha_t(i, j, k)$ is the probability of observing the partial sequence $(o_1, o_2, \ldots, o_t)$ such that the the state q_t is i, j for each k_{th} strem of data
- Induction
  1. Initialization:

     (2) $$\alpha_1(i, j, k) = \pi_{ijk} b_{ij}(o_1)$$

  2. Induction:

     (3) $$\alpha_{t+1}(i, j, k) = \left[\sum_{l=1}^{N} \alpha_t(i, j, k) a_{ijl}\right] b_{ij}(o_{t+1})$$

  3. Termination:

     (4) $$P(O|\lambda) = \sum_{t=1}^{T} \sum_{k=1}^{K} \alpha_T(i, j, k)$$

Solution problem 3 for 2D

Parameters reestimation Algorithm:

- Define $\xi(i, j, l)$ as the probability of being in state ij at time t and in state l at time $t + 1$ for each k_{th} strem of data

(5)
$$\xi_t(i, j, l) = \frac{\alpha_t(i, j, k) a_{ijl} b_{ij}(o_{t+1}) \beta_{t+1}(i, j, k)}{P(O|\lambda)} =$$

$$\frac{\alpha_t(i,j,k)a_{ij}b_{ij}(o_{t+1})\beta_{t+1}(i,j,k)}{\sum_{k=1}^{K}\sum_{l=1}^{N^2}\alpha_t(i,j,k)a_{ijl}b_{ij}(o_{t+1})\beta_{t+1}(i,j,k)}$$

- Define $\gamma(i,j)$ as the probability of being in state i,j at time t, given observation sequence.

$$\gamma_t(i,j)=\sum_{l=1}^{N^2}\xi_t(i,j,l) \tag{6}$$

- $\sum_{t=1}^{T}\gamma_t(i,j)$ is the expected number of times state ij is visited
- $\sum_{t=1}^{T-1}\xi_t(i,j,l)$ is the expected number of transition from state ij to l

Update rules:

- $\bar{\pi_i j}k =$ expected frequency in state i,j at time $(t=1)$ $=\gamma_1(i,j)$
- $\bar{a}_{ij}=$ (expected number of transition from state i,j to state l)/(expected number of transitions from state i,j:

$$\bar{a}_{ijl}=\frac{\sum_t\xi_t(i,j,l)}{\sum_t\gamma_t(i,j)} \tag{7}$$

- $\bar{b_{ij}}(k)=$ (expected number of times in state j and oserving symbol k)/(expected number of times in state j:

$$\bar{b}_{ij}(k)=\frac{\sum_{t,o_t=k}\gamma_t(i,j)}{\sum_t\gamma_t(i,j)} \tag{8}$$

Experiment

There was used the road signs image database German Traffic Sign Benchmark [24] in the experiment. The database contains over 1700 images of road signs. The images show the signs in variable condition, lighting, rotation and size. The images contain margin (at least 5 pixels) around the traffic sign to allow for the usage of edge detectors and are not necessarily square. Fig. 4 shows the example of traffic sign [23].

Fig. 4. Random representatives of the traffic sign in the GTSRB dataset [24].

We chose the 50 objects in order to verify the method, and for each object chose three images for learning and five for testing. The 2D HMM implemented with parameters $N=4, N^2=16, K=16, M=25$. Wavelet transform was chosen as features extraction technigue, and db10 as wavelet function. Table 1 presents The results of experiments.

Table 1. Comparison of recognition rate

Method	Recognition rate [%]
ESOM [25]	84
HMM [12]	49
1D HMM[our]	81
2D HMM[our]	83

Conclusion

In this paper, the new conception of road sign recognition with two-dimensional hidden Markov models is presented. Presented method allows for faster signs processing and recognition because they do not have to change the two-dimensional input data in the image form into a one-dimensional data. We show solutions of principle problems for ergodic 2D HMM, which may be applied for 2D data. Furthermore, we do not lose the information. The obtained results are satisfactory in comparison to other method and proposed method may be the alternative solution to the others. Recognition rate of the method is 83%, which is better than 1D HMM.

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