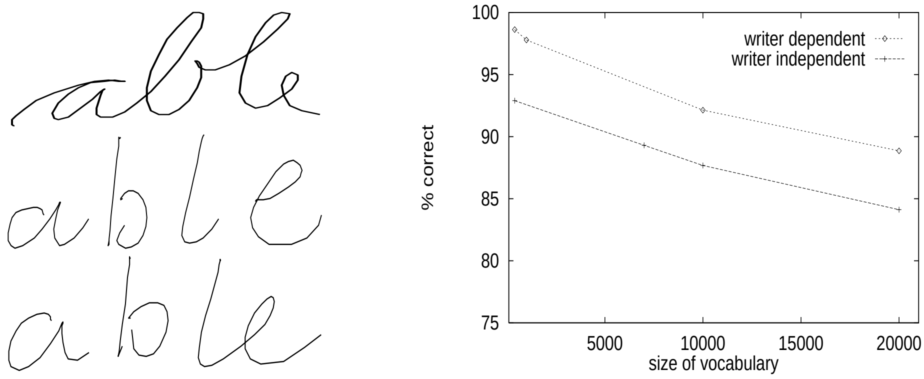
5 CONCLUSIONS

In this paper we have presented the **NPen^{++}** system, a neural recognizer for writer dependent and writer independent on-line cursive handwriting recognition. This system combines a robust input representation, which preserves the dynamic writing information, with a neural network integrating recognition and segmentation in a
ramework. This architecture has been shown to be well suited for handling
provided by this kind of input.

ferent tasks with vocabulary sizes ranging from 400
from 92.9% to 84.1% in the writer
dependent case. These
training



(a) **(b)**

Figure 3: (a) Different writing styles in the database: cursive (top), hand-printed (middle) and a mixture of both (bottom). (b) Recognition results with respect to the vocabulary size

For the writer dependent evaluation, the system was trained on 2,000 patterns from
vocabulary, written by a single writer, and tested on a disjunct set
m writer. In the writer dependent case, the training set
000 word vocabulary, written by approximately
from an independent set of 40

y of Karlsruhe,

w_i, i.e.

$$\log p(\boldsymbol{x}_0^T|w_i) \approx \max_{q_0^T} \sum_{t=1}^{T} \log p(\boldsymbol{x}_{t-d}^{t+d}|q_t, w_i) + \log p(q_t|q_{t-1}, w_i)$$
$$\approx \max_{q_0^T} \sum_{t=1}^{T} \log p(q_t|\boldsymbol{x}_{t-d}^{t+d}) - \log p(q_t) + \log p(q_t|q_{t-1}, w_i). \quad (2)$$

Here, the maximum is over all possible sequences of states $q_0^T = q_0 \ldots q_T$ given a word model, $p(q_t|\boldsymbol{x}_{t-d}^{t+d})$ refers to the output of the states layer as defined in (1) and

bility of observing a state q_t estimated on the training data.

ZER

at will maximize

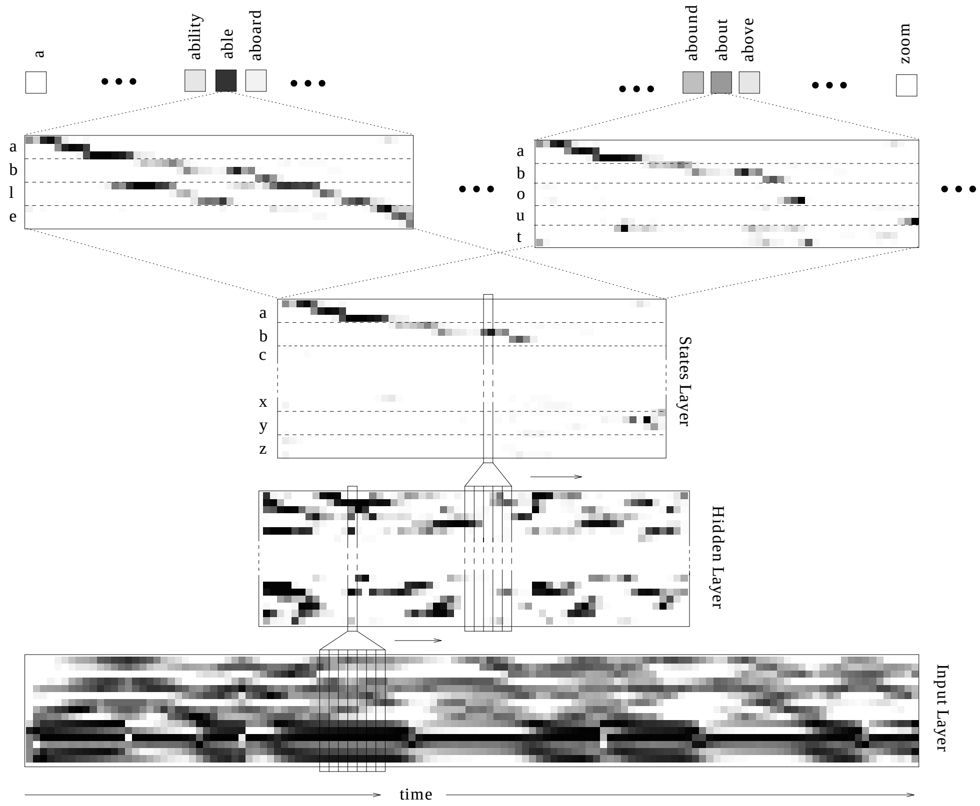


Figure 2: The Multi-State TDNN architecture, consisting of a 3-layer TDNN to
estimate the a posteriori probabilities of the character states combined with word
the word models by a Viterbi approximation

in space but global in time. That means, each point of the trajectory is visible from
each other point of the trajectory in a small neighbourhood. By using these context
ures, important information about other parts
oded

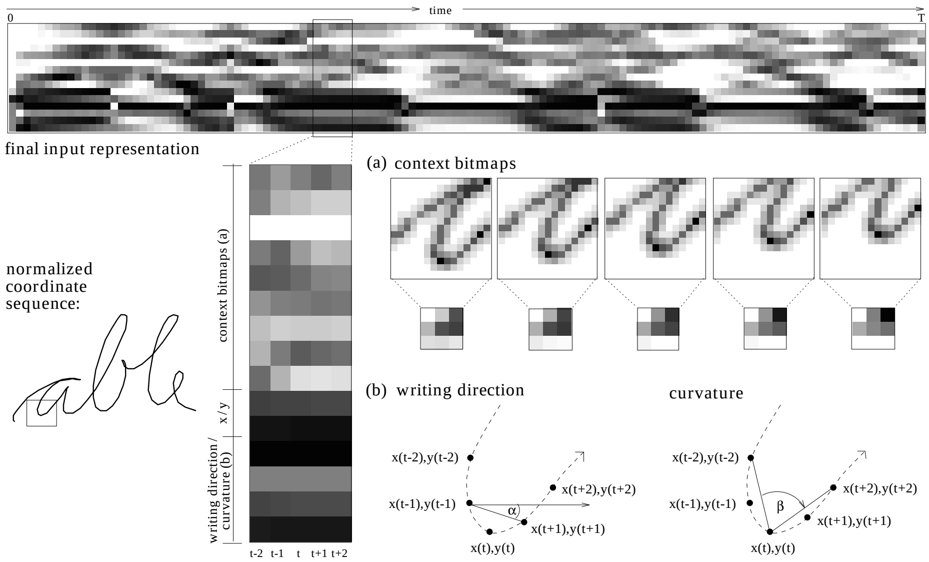


Figure 1: Feature extraction for the normalized word "able". The final input representation is derived by calculating a 15-dimensional feature vector for each data trap (a) and information about the curvature

1 INTRODUCTION

Several preprocessing and recognition approaches for on-line handwriting recognition have been developed during the past years. The main advantage of on-line optical character recognition (OCR) is the

G. Tesauro, D. Touretzky, and J. Alspector (Eds.)
Advances in Neural Information Processing Systems 7
MIT Press, Cambridge MA

The Use of Dynamic Writing Information in a Connectionist On-Line Cursive Handwriting Recognition System

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