5 CONCLUSIONS

In this paper we have presented the **NPen**$^{++}$ system, a neural recogni zer for wri ter
dependent and wri ter i ndependent on-li ne cursi ve handwri ti ng recogni ti on. Thi s
systemcombi nes a robust i nput representati on, whi ch preserves the dyna
i nformati on, wi th a neural network i ntegrati ng recogni ti o
si ngle framework. Thi s archi tecture has been s
temporal sequences as provi ded by

Evaluati on of the systemon
to 20,000 words
i ndep

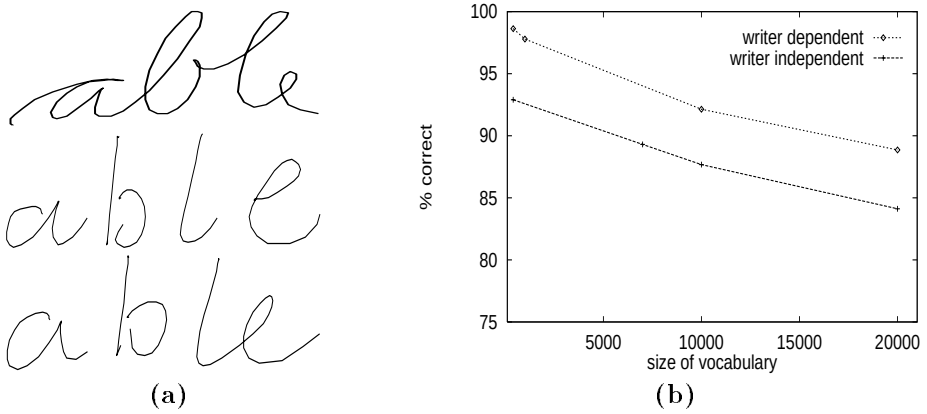

Figure 3: (a) Different writing styles in the database: cursive (top), hand-printed (middle) and a mixture of both (bottom) (b) Recognition results with respec the vocabulary size

For the writer dependent evaluation, the system was trained on a 400 word vocabulary, written by a single writer of patterns from the same writer. In t consisted of 4,000 pattern 60 different wr writ

A

w_i, i.e.

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

Here, the maximumis over all possible sequences of states $q_0^T = q_0 \ldots q_T$
word model, $p(q_t|\boldsymbol{x}_{t-d}^{t+d})$ refers to the output of the states layer
$p(q_t)$ is the prior probability of observing a state

3.3 TRAINING OF THE RECOGNIZER

During training the goal is to determine a
the posterior probability $p(w$
to make that m
syst

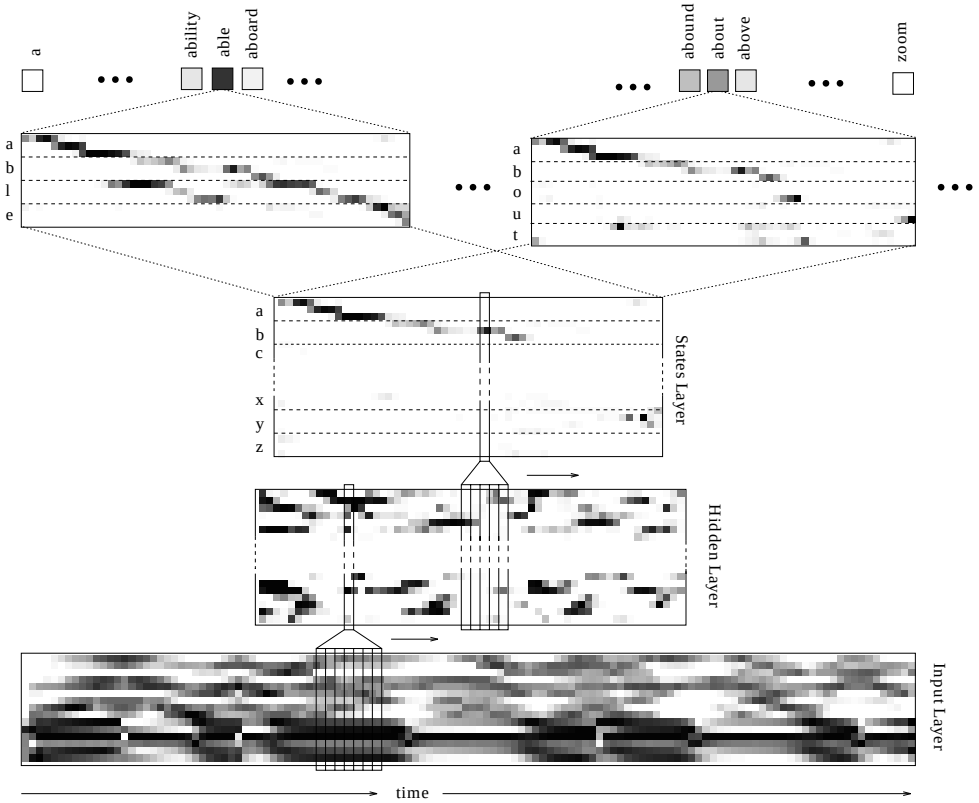

Figure 2: The Multi-State TDNN architecture, consisting of a 3-layer TDNN to
estimate the a posteriori probabilities of the character states combined with wo
units, whose scores are derived from the word models by a Viterbi ap
of the likelihoods $p(\boldsymbol{x}_0^T|w_i)$.

units, 40 units in the hidden layer, and 78 state ou
time delays both in the input and hidde

The softmax normalized output of
the probabilities o
each tim

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 co
bitmaps in addition to the local features, important information
of the trajectory, which are in a limited neighbourho

3 THE NPen^{++} RECOGNIZE

The NPen^{++} recognizer integrates re
a single network architect
TDNN). The MS-TD
recognition

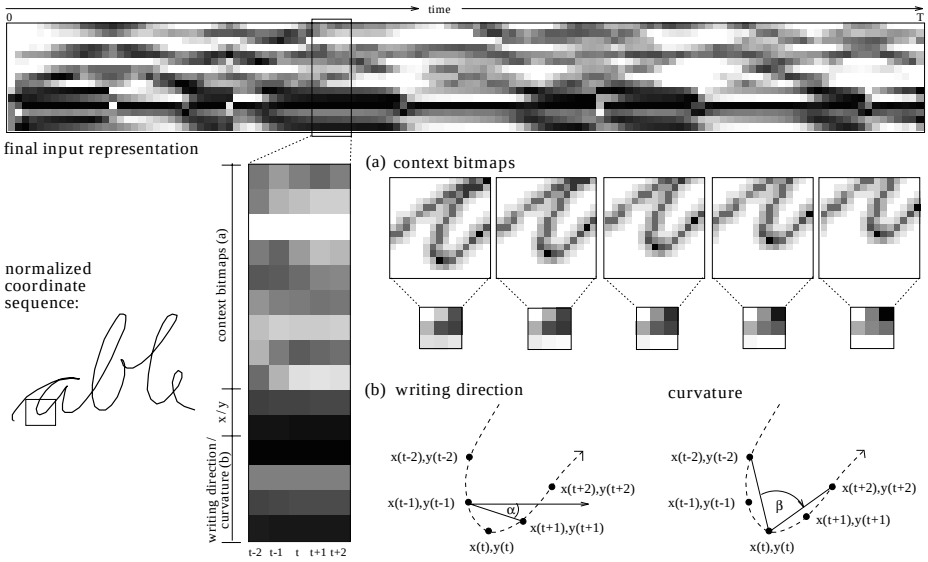

Figure 1: Feature extraction for the normalized word "able". The final input representation is derived by calculating a 15-dimensional feature vector for each point, which consists of a context bitmap (a) and information abo and writing direction (b).

space. This resampled trajectory is smoothed u order to remove sampling noise. In a f a representation of the tra scaling of t a

1 INTRODUCTION

Several preprocessing and recognition approaches for on-line handwriting recog-
nition have been developed during the past years. The main advantage of on-
handwriting recognition in comparison to optical character recogni
temporal information of handwriting, which can be re
tion. In general this dynamic writing info
coordinates) is not availa
paper we pres
writi

G. Tesauro, D. Touretzky, and J. Alspector (Eds.)
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The Use of Dynamic Writing Information in a Connectionist On-Line Cursive Handwriting Recognition System

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Abstract

In this paper we present NPen++, a connectionist systemf
writer independent, large vocabulary on-line cursive
recognition. This systemcombines a robus
which preserves the dynamic wri
network architecture,
Network (MS-T
tation i