Table 1: Results for different writer dependent/writer independent handwriting recognition tasks

Task	Vocabulary Size	Training Patterns	Test Patterns	Recognition Rate Local Features	Recognition Rate Context Bitmaps
0_9	10	1600	200 (20 writers)	97.9%	99.5%
A_Z	26	2000	520 (20 writers)	92.5%	95.9%
a_z	26	2000	520 (20 writers)	89.9%	93.7%
m_400_a	400	2000 (writer *ms m*)	800 (writer *ms m*)	94.7%	98.1%
n_400_b	400	– " –	– " –	93.2%	96.7%
000	1000	– " –	2000 (writer *ms m*)	90.5%	94.8%
0	10000	– " –	– " –	82.1%	86.6%
	20000	– " –	– " –	79.9%	83.0%
	00	3000 (15 writers)	2500 (10 writers)	-	85.0%

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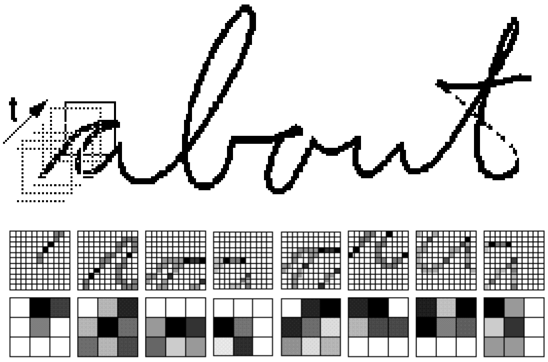

Figure 2: Calculation of context bitmaps

Figure 1: Hard to detect differences between cursive characters

First we started with a set of strictly local features similar to those in [3, 2]. Each time frame consisted of information on the pen position (x, y coordinates), directional features ($\delta x, \delta y$), curvature, speed and pen-up/pen-down indicator. But an inspection of the confusion matrices of networks trained on these features revealed significant problems in discriminating between cursive letters like "a" and "u" or "g" and "y" which look very similar and differ only in small ...of the characters (see figure 1 for examples). ...blems arise due to the fact that the features ...y local, which means that they are local both ...ce and time. Therefore they are inadequate for ...ing long range context dependencies ...trajectory.

...set of features we use now is ...of the digitizer input. After ...map the sequence of points ...p $B = \{b(i, j)\}$, where ...f points (x_t, y_t) falling ...

...al character recognition, ...rce of information, we ...f the points. The ...s in the follow- ...p pixel (i, j). ...B centered ...grey scale ... That ...on

...se features are still local in space but no longer ...in time. Each point of the trajectory is visible from each other point of the trajectory in a small ...hood. Therefore, we call the local bitmaps L_t ...maps. Another way of interpreting these ... is to view at them as low resolution ... They seem to be appropriate for ...ange and spatial short range ...trajectories. Compared ...res we achieved a 50% ...ature set.

...os in a connec-

...scribed in this paper ...ognizer [1], which is ...al sequences of pat- ...e input representa- ... Time Delay Neu- ...a scheme ...network.

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Combining Bitmaps with Dynamic Writing Information for On-Line Handwriting Recognition

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Abstract

independent, large vocabulary on-line handwriting recognition systems require robust input representations, which make optimal use of the dynamic writing information, i.e. the t sampled