

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

Task	Vocabulary		Training	Test	Recognition Rate	
	Size	Size	Patterns	Patterns	Local Features	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%
m_400_b	400	- " -		- " -	93.2%	96.7%
1000	1000	- " -		2000 (writer ms m)	90.5%	94.8%
10000	10000	- " -		- " -	82.1%	86.6%
20000	- " -	- " -		- " -	79.9%	83.0%
100	3000 (15 writers)	2500 (10 writers)		-	85.0%	

Adult subjects had to write a set of isolated characters from the vocabulary, covering at least one set of isolated characters, and digits. The tasks are described in sections 3 and 2. For different writer independent character recognition tasks, comparing with the new context

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Figure 2: Calculation of context bitmaps

These features are still local in space but no longer in time. Each point of the trajectory is visible to each other point of the trajectory in a small neighborhood. Therefore, we call the local bitmaps L_t maps. Another way of interpreting these features is to view them as low resolution, range and spatial short range trajectories. Compared to those in [3, 2], they consist 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 parts in a connected sequence (see figure 1 for examples).

These problems arise due to the fact that the features are local, which means that they are local both in time and in space. This is inadequate for modeling long range contextual dependencies and sequences of patterns. In this paper we use now is a Delayed Neural Network. After the sequence of points $\{b(i, j)\}$, where $b(i, j)$ are points (x_t, y_t) falling

in the local character recognition, the amount of information, we use of the points. The features are in the following way: for each pixel (i, j) , we use a B centered grey scale value. That is, the value of the point (i, j) is

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

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Abstract

*dependent, large vocabulary on-line hand-
writing require robust input rep-
resentation*