

Participant	Per-document averages		Tables found (total=156)		
	Recall	Precision	F ₁ -meas.	Complete	Pure
<i>FineReader</i>	0.9971	0.9729	0.9848	142	148
<i>OmniPage</i>	0.9644	0.9569	0.9606	141	130
Silva	0.9831	0.9292	0.9554	149	137
<i>Nitro</i>	0.9323	0.9397	0.9360	124	144
Nurminen	0.9077	0.9210	0.9143	114	151
<i>Acrobat</i>	0.8738	0.9365	0.9040	110	141
Yildiz	0.8530	0.6399	0.7313	100	94
Stoffel	0.6991	0.7536	0.7253	79	66
Liu et al. 2	0.3355	0.8836	0.4864	0	29
Hsu et al.	0.4601	0.3666	0.4080	39	95
Fang et al.	0.2697	0.7496	0.3967	28	41
Liu et al. 1	0.2207	0.8885	0.3536	0	25

TABLE II
RESULTS FOR THE TABLE LOCATION (LOC) SUB-COMPETITION

Participant	Per-document averages		F ₁ -measure
	Recall	Precision	
Nurminen	0.9409	0.9512	0.9460
Silva	0.6401	0.6144	0.6270
Hsu et al.	0.4811	0.5704	0.5220

TABLE III
RESULTS FOR THE TABLE STRUCTURE RECOGNITION (STR)
SUB-COMPETITION (BASED ON CORRECT REGION INFORMATION)

Participant	Per-document averages		F ₁ -measure
	Recall	Precision	
<i>FineReader</i>	0.8835	0.8710	0.8772
<i>OmniPage</i>	0.8380	0.8460	0.8420
Nurminen	0.8078	0.8693	0.8374
<i>Acrobat</i>	0.7262	0.8159	0.7685
<i>Nitro</i>	0.6793	0.8459	0.7535
Silva	0.7052	0.6874	0.6962
Yildiz	0.5951	0.5752	0.5850

TABLE IV
TABLE STRUCTURE RECOGNITION RESULTS FOR THE COMPLETE PROCESS
(COM) - BASED ON THE SYSTEM'S TABLE LOCATION RESULT

Our evaluation metrics were found to be a fair representation of the actual quality of the output from the various systems. The combination of completeness and purity with precision and recall on the character level gives a good overall picture of the region detection quality. Similarly, we have found that using cell adjacency relations to evaluate table structure detection enables us to obtain precision and recall measures which are repeatable and accurately reflect the quality of the result.

By calculating the results for each document first, we were able to reduce the bias of “data-heavy” tables on the overall result. A further improvement for the future would be to evaluate regions by calculating the area (in square points) of region overlap instead of counting characters, after “normalizing” each region first by shrinking it to the smallest region encompassing all characters within its bounds. This would avoid regions containing overprinted or non-printing characters skewing the result.

The structure results for the complete process (see Table IV) should also be treated with some caution. A number of systems

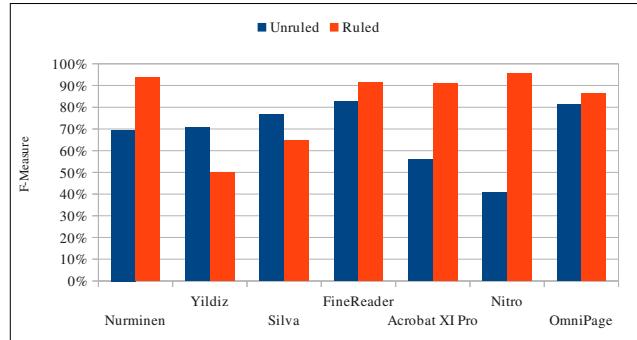


Fig. 1. Comparison of results with ruled versus unruled tables for the complete process sub-competition

returned large false positive regions, whose table structure consisted of only one cell. In many cases, this huge cell only neighboured one or two other cells, and therefore did not raise the overall false positive count significantly.

A further issue with our structure recognition metric is in the comparison of adjacency relations by their textual content. Although our normalization routine stripped or replaced most special characters, there were still some remaining encoding issues when evaluating certain approaches. This is a double-edged sword, as removing all non-alphanumeric characters would make it no longer possible to distinguish between cells that do not contain at least one letter or number, of which there were many in our dataset. In the future, we will therefore consider requiring further information about the cell, such as a bounding box, to enable its unique identification.

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