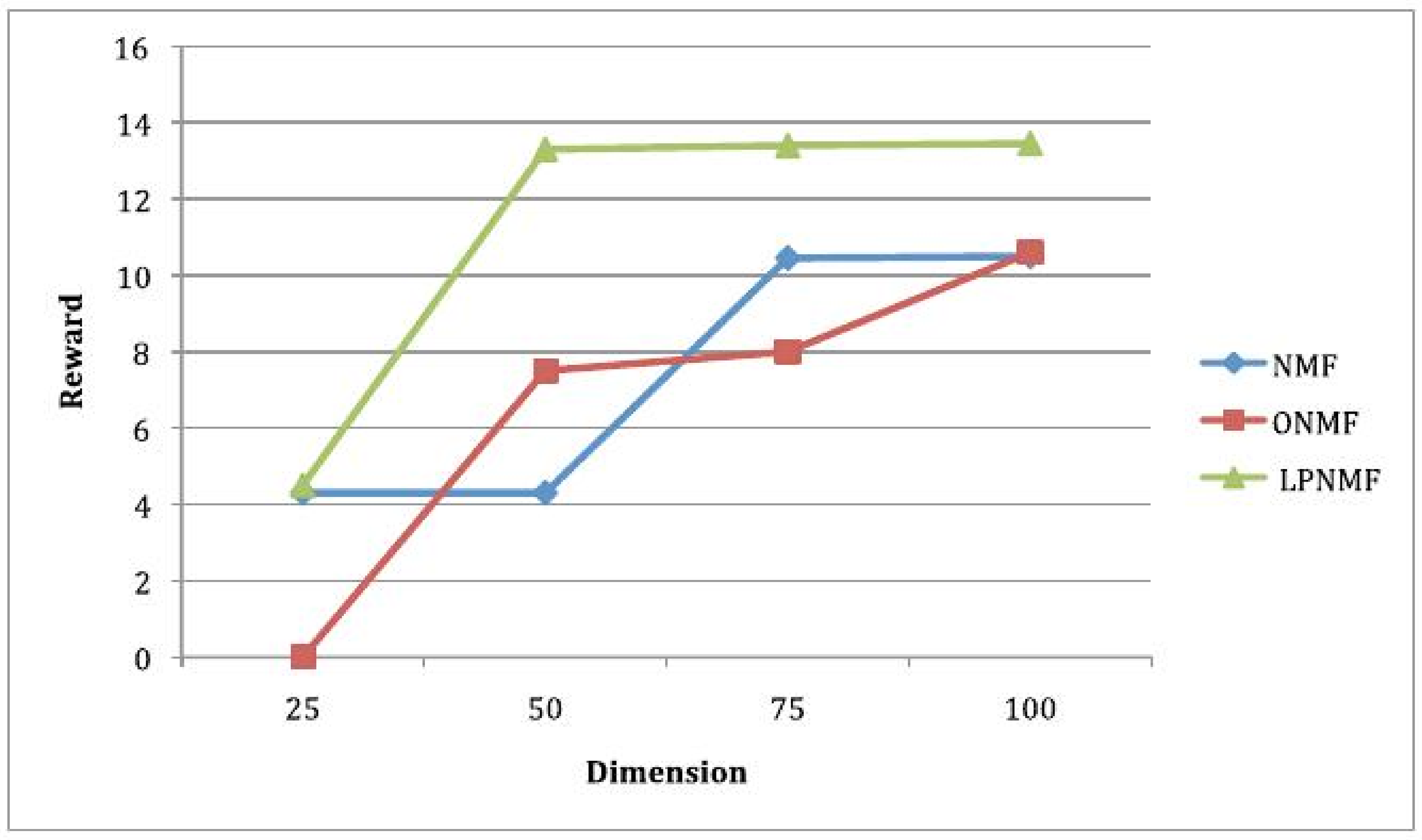

Figure 6: The rock-sample problem has $|S| = 257$, $|A| = 9$ and $|Z| = 2$. The maximum time we ran each algorithm was 50 sec. The graphs show the results for different dimensions and compression algorithms. The LPNMF approach allows for deeper compression than both the NMF and ONMF algorithms.

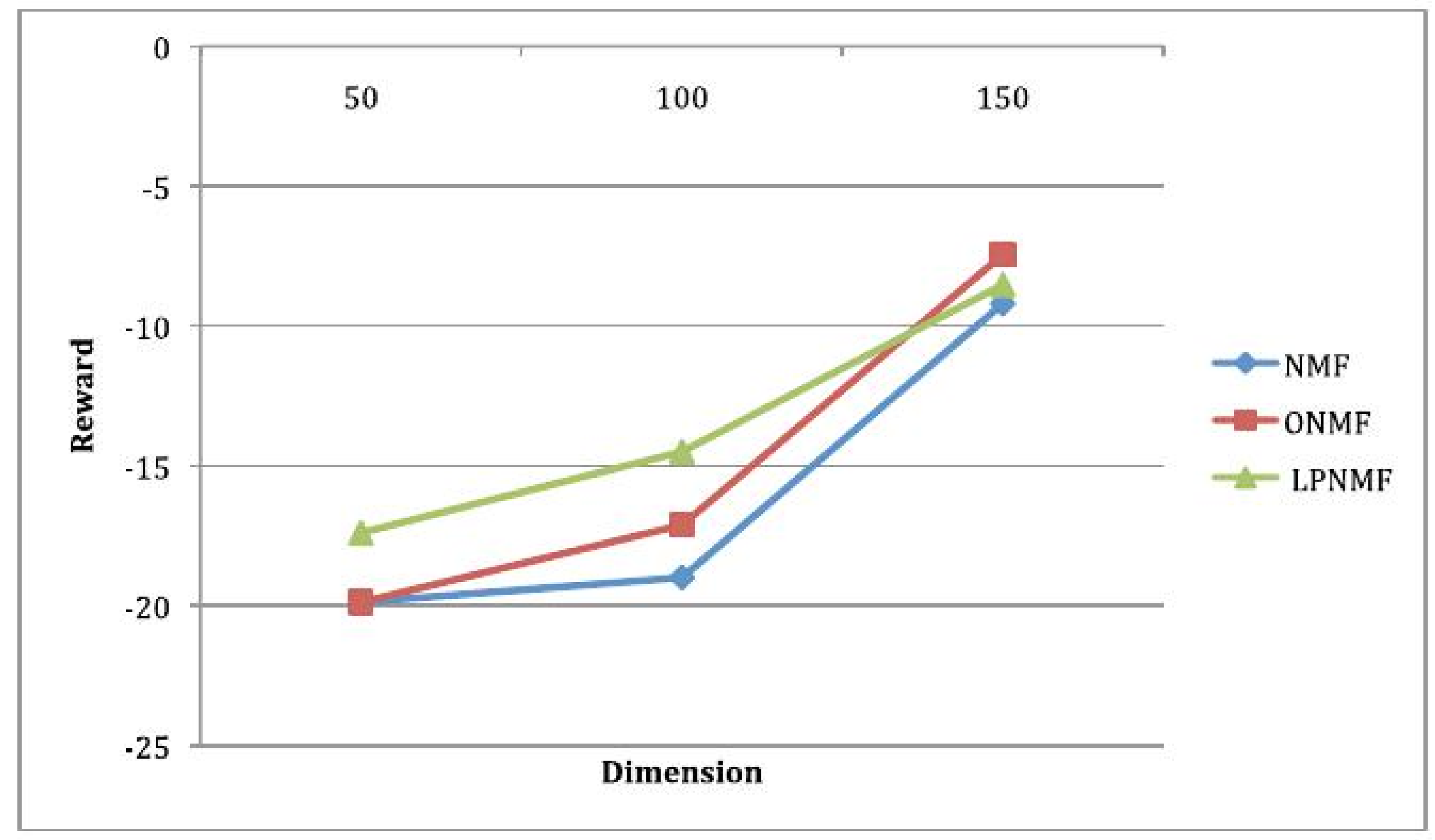

Figure 7: The tag-avoid problem has $|S| = 870$, $|A| = 5$ and $|17| = 2$. The maximum time we ran each algorithm was 2200 sec. The graphs show the results for different dimensions and compression algorithms. The LPNMF approach allows for deeper compression than both the NMF and LP-NMF algorithms.

Table 2: PBVI versus LPNMF.

	Time (sec)	$\frac{\sum_t r_t}{N}$
tag-avoid $|S| = 870, |A| = 5, |Z| = 17$		
Perseus-PBVI	2300	-6.5
	500	-13.0
LPNMF ($|\tilde{S}| = 150$)	500	-9.0

dimensionality reduction methods need to be investigated as well.

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