

Fig. 10. Collision Classifier accuracy and errors.

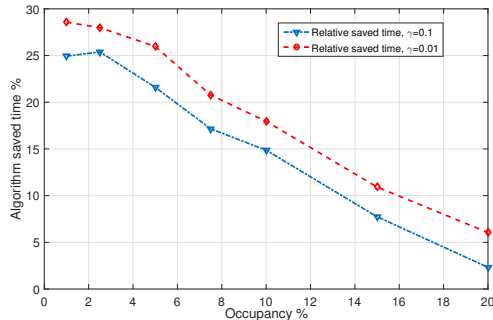


Fig. 11. Time saving relative to two variables solution, SNR=0 dB.

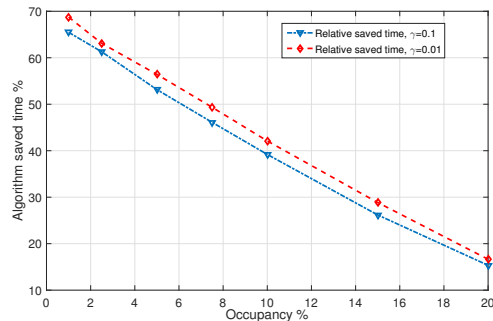


Fig. 12. Time saving relative to three variables solution, SNR=0 dB.

Hence, we evaluate time saving relative to a fixed variable resolver. Two cases are considered for comparison. In the first case, the solution of fixed $v_\ell = 2$ variables is compared to the reconstruction algorithm in which v_ℓ is set to 2 when a collision is detected, and $v_\ell = 1$ otherwise. Fig. 11 shows the time saved by implementing the algorithm. Similarly, Fig. 12 shows the relative saved time by implementing the reconstruction algorithm for $v_\ell = 3$. Obviously, the time saved for the second case is much higher due to the fact that for $v_\ell = 3$ and $D = 10$, 120 combinations of three variables, compared to 45 combinations of two variables for $v_\ell = 2$ and $D = 10$, are solved for each sub-Nyquist bin. The saved time is the result of solving for only 10 one variable combinations instead, whenever no collision occurs. In both cases, the saved time is inversely proportional to the occupancy level because of a lower number of collisions at low occupancy levels. Furthermore, the saved time is higher for lower threshold because more bins are taken into consideration. While a trade-off between saved time and detection accuracy exists, Table I shows that the change in P_D and P_{FA} values as a result

TABLE I
EFFECT OF COLLISION DETECTOR ON P_D AND P_{FA} , SNR=0dB

		$v_\ell = 2,$ $\gamma = 0.1$	$v_\ell = 2,$ $\gamma = 0.01$	$v_\ell = 3,$ $\gamma = 0.1$	$v_\ell = 3,$ $\gamma = 0.01$
P_D decrease	Max	0.0178	0.0134	0.0249	0.0227
	Mean	0.0112	0.0069	0.0168	0.0160
P_{FA} decrease	Max	0.0465	0.0537	0.1182	0.1285
	Mean	0.0333	0.0399	0.0794	0.0931

of using the collision detector is insignificant. The first and second columns show the maximum and the mean of decrease in P_D and P_{FA} values for Fig. 11. The third and fourth columns show the same values for Fig. 12.

V. CONCLUDING REMARKS

In this paper, we studied a sparse spectrum reconstruction method in which a delay-based multicore system is employed to reconstruct a sub-sampled signal. While many other sub-Nyquist systems exist, this system is preferred for practical implementation due to its simplicity and relatively fast signal reconstruction time. We defined the general reconstruction model and derived the multi-combination least square approach. In general, solving for a higher order of variables even when there are less active tones in a sub-Nyquist bin produces more accurate estimates. However, higher order solutions require more time in addition to more branches.

In order to reduce the time needed to reconstruct the signal, we proposed a classifier to classify the aliased sub-Nyquist bins. While the total accuracy of the classifier decreases as SNR decreases, the reduction in the accuracy has minimum effect on the overall detection performance. However, more time is gained for more accurate classification. The saved time for the algorithm resolving a maximum of three variables is more than double that of algorithm resolving up to two variables. This is crucial since detection performance of the three-variable resolver is much higher than that of the two-variable resolver, provided that there are enough branches to solve for three variables.

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