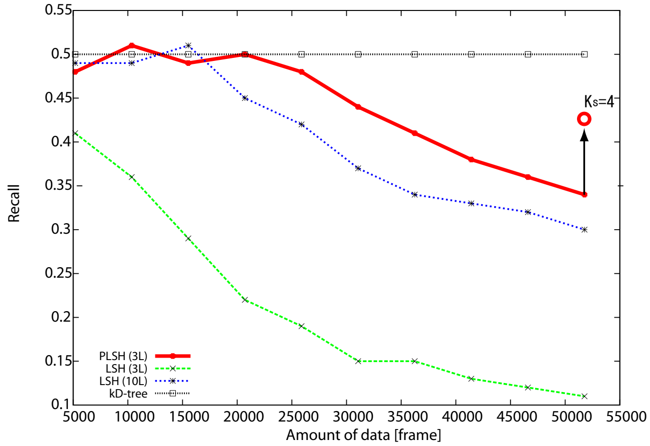

Fig. 7. Evaluation of recall ratio v.s. amount of data.

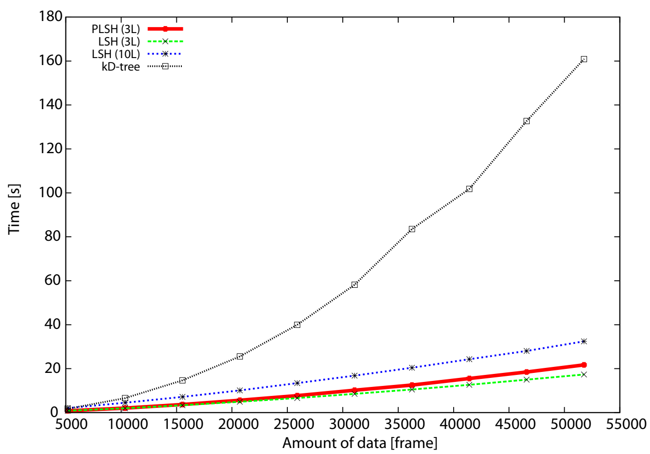

Fig. 8. Evaluation of computational time v.s. amount of data.

2) Different amount of data: In the second experiment. the 3 methods were evaluated against different amount of data. 10 datasets of different length were generated by simply concatenating the dataset in TABLE IV with Gaussian noise added.

Fig. 7 shows the Recall ratio obtained from the different methods. As the amount of data increases, recall ratio decreases. This is because the number of data points in a hash bucket increases as well. The result of kD-tree is the best. PLSH is far better than LSH with the same parameters. We also tested the case where $C_{\text{search}} = 10L$ for LSH to increase the number of buckets and to decrease the number of data points in a bucket, but PLSH is still better.

If we increase K_s, the number of locality sensitive hash functions, recall ratio is dramatically improved with a slight increase of computational time. If we set $K_s = 4$, the computational time is increased by 10 %, while recall ratio of the 10-th dataset becomes 0.43 as shown in Fig. 7.

Precision ratio achieves almost always 1.00 for all the methods, thus we omitted the evaluation of precision ratio.

Fig. 8 shows the computational time obtained from the different methods. The time of kD-tree increases quadratically, while the time of LSH and PLSH increases almost linearly. This is the strong advantage of the proposed method when dealing with a huge amount of observations.

VII. Conclusions

This paper presents a method that detects consistent repeated patterns from multiple observations in $O(N^{1+1/\alpha})$ time where N is the total amount of data.

Partly Locality Sensitive Hashing (PLSH) is proposed to find candidate repeated patterns efficiently by sparsely sampling nearby patterns in subquadratic computational time.

The proposed method was evaluated by detecting repeated interactions between objects in everyday manipulation tasks. The proposed method outperformed the method based on kD-tree and LSH in terms of accuracy or computational time.

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