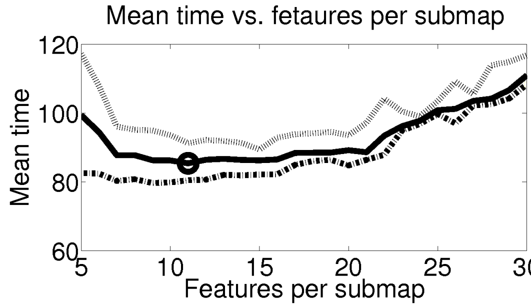

Fig. 7. Computational time required to fulfil the whole mission. The upper curve is the maximum time among all the experiments with a certain number of features per map. The lower curve is the minimum time, and the intermediate is the mean time. The cross shows the lowest time in the mean curve.

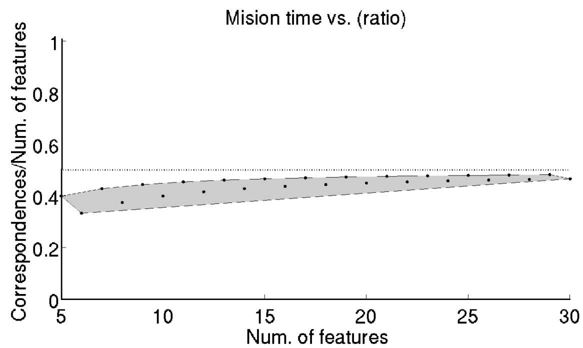

Fig. 8. The lowest mission times occur when the threshold for the number of correspondences is approximately 40% and 50% the number of features per submap. The region in grey corresponds to configurations that produced minimum mission time.

is made on the basis that fusing two maps that share many landmarks will produce a better update than fusing two maps that only share few landmarks. The experiments show a reduction of the effects of the linearisation error and also a more precise reconstruction of the map since the drift suffered in shorter distances is smaller and the data association can be more robustly solved. In addition, different parameters involved with the algorithm have been analysed, driving us to the conclusion that in order to obtain a good compromise between computational cost and map consistency, the best map size should be between ten and fifteen. Furthermore, the best performance was obtained when the threshold used to decide whether to fuse local maps was set near 50% of the total map size.

Future work is intended to integrate this method with vision sensors together with scan matching techniques. The proposed approach will be used as the module to localize the AUV position and to build an accurate 3D map of the seabed.

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