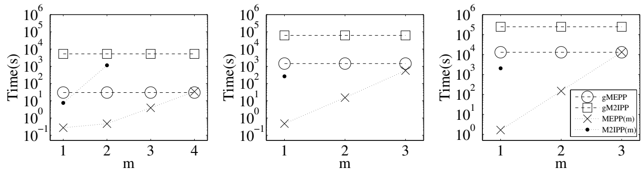

(a) 1 robot. (b) 2 robots. (c) 3 robots.

Figure 5: Graphs of incurred time by different active sensing algorithms vs. m for plankton density field with varying number of robots.

the transect is high (i.e., field d) instead, it can be exploited by MEPP(m) and M^{2}IPP(m) to improve active sensing performance and consequently allow m to be reduced to small values of 1 or 2: MEPP(m) can perform better or, if not, at least as well as gMEPP and gM^{2}IPP in the prediction error and entropy metrics while incurring 1 to 4 orders of magnitude less time. M^{2}IPP(m) can perform likewise in the mutual information metric while incurring less time (in particular, 2 orders of magnitude less time than gM^{2}IPP).

6. CONCLUSION

This paper describes two principled information-theoretic path planning algorithms based on entropy and mutual information criteria (respectively, MEPP(m) and M^{2}IPP(m)) for active sensing of GP-based anisotropic fields. Two important practical implications result from the theoretical guarantees on the active sensing performance of our algorithms (Theorems 2 and 4): Increasing m trades off computational efficiency (Theorems 1 and 3) for better active sensing performance, and our algorithms can exploit a low spatial correlation along the transect to improve time efficiency (i.e., only needing a small m) while preserving near-optimal active sensing performance. This motivates the use of prior knowledge, if available, on a direction of low spatial correlation in order to align it with the horizontal axis of the transect. Empirical evaluation of real-world anisotropic temperature and plankton density field data reveals that our algorithms can perform better or at least as well as gMEPP and gM^{2}IPP while often incurring a few orders of magnitude less time. In particular, it can be observed that anisotropic fields with low spatial correlation along the transect or high correlation perpendicular to the transect allow our algorithms to perform well using small values of m, thus yielding significant computational gain over gMEPP and gM^{2}IPP. To perform well in a field with high correlation along the transect and low correlation perpendicular to the transect (i.e., less favorable conditions), our algorithms have to increase the value of m or the number of robots but can still achieve comparable or better time efficiency than gMEPP and gM^{2}IPP.

7. REFERENCES

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