presented a formal metric called expressive entropy that can be used to determine the point in the parameter space with maximum expressivity. We propose that swarm systems should operate at, or near, the point of maximum expressive entropy to provide the maximum flexibility in possible collective behaviors. However, maximizing the expressive entropy of a swarm also means that the estimation problem is harder because the prior probabilities of being in any given collective state are maximally uninformative.

We presented a novel framework for classifying the collective behavior of a bio-inspired robot swarm using locally-based approximations of global features of the emergent collective behaviors. Using a bio-inspired model of swarming proposed by Kerman et al. [6], we showed that even if agents are not capable of determining their location or heading, we can accurately classify the group behavior of the swarm using local samples from individual agents. This accuracy remains high even if limited bandwidth restricts the number of observable agents. We investigated behavior recognition for swarms undergoing transient dynamics and provided evidence that our method of detecting collective behavior from limited samples scales to larger swarm sizes.

We also demonstrated that our methodology for behavior recognition generalizes to Couzin's swarm model [3]. Kerman's model has collective behaviors that are very distinct and afford high accuracy behavior recognition with very low bandwidth. Couzin's model, on the other hand, has emergent behaviors that are not as distinct which resulted in lower accuracies and higher bandwidth requirements to sample more agents. Thus, while we hypothesize that our approach is applicable to many other multi-agent systems, depending on the distinctness of the collective behaviors, obtaining high recognition accuracy with limited bandwidth may require sampling agent positions and headings and using more complex models such as Hidden Markov Models or Conditional Random Fields [20].

Future work should investigate how well the methods we described scale to larger swarm sizes and also investigate how human or environmental influences affect behavior recognition accuracy. Other future work includes applying our collective behavior recognition framework to more complex swarm behaviors, to models with many emergent behaviors, and to actual robot swarms.

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