Modelling variable communication signal strength for experiments with multi-robot teams

Tsvetan Zhivkov
Dept of Engineering
King's College London, UK
tsvetan.zhivkov@kcl.ac.uk

Elizabeth I Sklar
Lincoln Institute for Agri-food Technology
University of Lincoln, UK
esklar@lincoln.ac.uk

https://doi.org/10.31256/Ld2Re8B

***Abstract*— Reliable communication is a critical factor for ensuring robust performance of multi-robot teams. A selection of results are presented here comparing the impact of poor network quality on team performance under several conditions. Two different processes for emulating degraded network signal strength are compared in a physical environment: modelled signal degradation (*MSD*), approximated according to increasing distance from a connected network node (i.e. robot), versus effective signal degradation (*ESD*). The results of both signal strength processes exhibit similar trends, demonstrating that *ESD* in a physical environment can be modelled relatively well using *MSD*.**

I. INTRODUCTION

Reliable communication is one of the key requirements for successful operation of a multi-robot team—without it, team coordination is difficult. Many works focus on network optimisation and communication-aware motion planning for multi-robot systems [1]–[6]. The aforementioned works use either optimisation-based control or consensus algorithms for centralised or distributed multi-robot communication and resilience against either uncooperative robots or maximising communication performance. The majority of research conducted with physical multi-robot teams takes place in controlled indoor laboratory settings supported by robust network infrastructure. However, many recognise the growing need for reliable wireless communication in multi-robot systems in a wide range of environments and applications.

In earlier work [7], we introduced a behaviour-based, network-aware control algorithm which aims to prevent loss of communication by keeping robots within range of networked nodes (i.e. neighbouring robots), even if the network is severely crippled, e.g. due to reduced signal strength or high percentage of dropped network packets. In order to test this behaviour, we previously modelled two of the most common network problems [7]–[9]: *simulated packet-loss (SPL)*, which drops a pre-defined percentage of messages (0%,25%,50%,75%), and a method of estimating network *signal strength*, which periodically examines the distance between robots and based on a pre-determined threshold warns the robots if they are likely to disconnect. The contribution presented here briefly summarises an extension of our experimental framework, adding *modelled signal degradation (MSD*[1]*)* and *effective signal degradation (ESD)* to allow more comprehensive testing of behaviours that respond to network failure.

[1]In previous works MSD was denoted SSD (simulated signal degradation)

II. APPROACH

In our previous work [8], we performed preliminary analysis of how multi-robot team performance was impacted by *simulated packet-loss (SPL)*. We then extended this work by introducing our novel *Leader-Follower (LF)* behaviour designed to respond to network weaknesses, described in [7] and evaluated using our Multi-Robot Communication testbed (*MRComm*) [9]. Our contributions can be separated into two parts: (1) modelling various aspects of network quality (*MRComm*); and (2) controlling robot behaviour in response to changes in the network quality (*LF*).

The network type is the communication medium that is used to transfer messages between robots. In the experiments demonstrated here we analyse *Ad Hoc (AH)* network type, which is an uncommon network to use in robotics as it has no infrastructure. A robot is used to initialise an *AH* network and the rest of the team connect directly to the that robot. Communication is peer-to-peer, and increasing the proximity of neighbouring robots (i.e. causing signal degradation) negatively impacts communication quality. Moreover, certain assumptions are made about the network type to make our problem more tractable. Firstly, it is assumed that signal-to-noise ratio (SNR) experiences uniform loss and that interference from other devices is negligible. Secondly, the final assumption (limitation) for *AH* is that after 9.0 meters robots can no longer communicate, no matter the experiment configuration. From the tests conducted in our physical environment, a separation greater than 9.0 meters between robots would consistently return a signal strength lower than -60 dBm, which is considered a poor signal.

Here we define two network thresholds that are related to signal strength in order to model different types of communication failure: *MSD* and *ESD*.

MSD is modelled in the same environment that the multi-robot team experiments are conducted in (i.e. indoor office building). Furthermore, it is modelled using two separately trained Support Vector Regression (SVR) models with Radial Basis Function kernels (RBF), for both direct and obstructed line-of-sight signal strength. The data for the models was obtained by dividing and performing two levels of granularity tests (i.e. at a rate of 0.1 m and 1 m steps) on signal strength

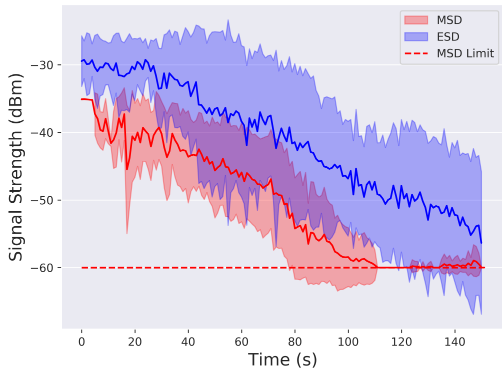
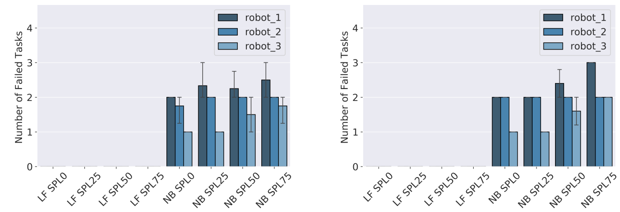


Fig. 1. Signal strength of *ESD* and *MSD* samples, measured over time



(a) MSD (b) ESD

Fig. 2. Comparison of the average number of failed tasks for *MSD* vs *ESD*, using *AH* and $\{SPL0, SPL25, SPL50, SPL75\}$, for both *LF* (on the left of each sub-plot) and *NB* (on the right of each sub-plot) behaviours. The *LF* behaviour recovers from all perturbations so there are no failed tasks. *NB* reveals the effects of *MSD* versus *ESD*.

with increasing distance[2]. The fine granularity test was to get more accurate data and the coarse granularity test was to allow for acceptable estimation of signal strength with increasing distance.

ESD is a new process implemented in *MRComm* that queries all network devices connected to the *AH* network at a frequency of 2 Hz, obtaining the signal strength from each device. Executing this process in parallel with our package provided three main benefits. Firstly, if a robot experiences hardware malfunction and loses some/all sensor functionality, assuming the network device is still functional, it would continue pulsing a signal. Secondly, if a robot experiences a software crash caused by an internal or external issue of *MRComm*, it would continue pulsing a signal. Finally, this functionality of *MRComm* would allow almost any type of device to run this process and send out a signal, therefore increasing its utility.

Figure 1 shows the mean *MSD* and *ESD* signal strength over a range of time t, measured in seconds from when experiments start at $t_0 = 0$ up until $t = 150$ s (i.e. the first 150 seconds of each experiment). To improve comparability between *MSD* and *ESD* the results were obtained from experiments using the same configuration. It was expected that *MSD* and *ESD* would yield near identical signal strength results. However, as observed in Figure 1 the distributions are different, but the trends are similar and the standard deviations overlap in many cases. The difference between *MSD* and *ESD* is to be expected, since *MSD*'s accuracy is limited to the SVR models used. The SVR models are based on a small sample size of the physical environment and to improve the predicted signal strength either the sample size needs to be expanded to include a data point at every possible location of the physical environment or a more accurate model needs to be introduced. However, the most simple approach can be to apply an offset to the current SVR models to artificially boost the predicted signal strength and thereby improve *MSD*.

MRComm provides a response to the network parameters in the form of one of two robot behaviours, which are the baseline *Non-responsive Behaviour (NB)* and the novel *Leader-Follower (LF)*. The *NB* behaviour does not react to any network parameters and simply enables robots to attempt to complete tasks assigned to them, even if the network drops out. In contrast, *LF* responds to different network perturbations and thresholds. It uses a high-level grouping technique to alert and force robots to move together in the event that signal strength is too weak (degraded).

[2]Each data point reading was repeated 30 times to get an average result.

III. Experimental Results

A series of experiments were run using the *MRComm* framework [7]–[9] and an *AH* network, which is initially established and then maintained by the robot team using the Robot Operating System (*ROS*) framework and the multi-master package (*FKIE* [10]). The experiments were run in in an office building and each experiment was performed 5 times. Experiments were run with 3 Turtlebot2 robots performing 7 independent (i.e., not constrained by any other task), single-robot observation tasks, starting in a clustered formation. A network perturbation and threshold are applied to each experiment: an SPL (with packet loss varying from 0% to 75%), followed by either *MSD* or *ESD*).

Figure 2 shows a sample of experiment configurations and the number of tasks that failed to be communicated per robot in the team. The results for this performance metric showed that *no* robot using *NB* successfully communicated *all* their task status messages. However, Figure 2 shows that robots using the *LF* behaviour managed to always communicate *all* their task status messages.

IV. Summary

The results presented in this paper show that communication of shared messages was successfully carried out on a physical multi-robot team using the novel *LF* behaviour. Furthermore, we observe that the *MSD* parameter has a similar signal strength trend to the *ESD* parameter. Our objective of having a behaviour capable of reacting and mitigating common network issues has been achieved. In future work we will focus on optimising and expanding the capability of the behaviour to deal with more challenging tasks and environments.

REFERENCES

[1] J. Le Ny, A. Ribeiro, and G. J. Pappas, "Adaptive communication-constrained deployment of unmanned vehicle systems," *IEEE Journal on Selected Areas in Communications*, vol. 30, no. 5, pp. 923–934, June 2012.

[2] M. Lindhé and K. H. Johansson, "Adaptive exploitation of multipath fading for mobile sensors," in *2010 IEEE International Conference on Robotics and Automation*, May 2010, pp. 1934–1939.

[3] A. Ghaffarkhah and Y. Mostofi, "Communication-aware motion planning in mobile networks," *IEEE Transactions on Automatic Control*, vol. 56, no. 10, pp. 2478–2485, Oct 2011.

[4] L. Sabattini, C. Secchi, N. Chopra, and A. Gasparri, "Distributed control of multirobot systems with global connectivity maintenance," *IEEE Transactions on Robotics*, vol. 29, no. 5, pp. 1326–1332, Oct 2013.

[5] K. Saulnier, D. Saldaña, A. Prorok, G. J. Pappas, and V. Kumar, "Resilient flocking for mobile robot teams," *IEEE Robotics and Automation Letters*, vol. 2, no. 2, pp. 1039–1046, April 2017.

[6] A. Mannucci, L. Pallottino, and F. Pecora, "Provably safe multi-robot coordination with unreliable communication," *IEEE Robotics and Automation Letters*, vol. 4, no. 4, pp. 3232–3239, Oct 2019.

[7] T. Zhivkov, E. Schneider, and E. I. Sklar, "Establishing continuous communication through dynamic team behaviour switching," in *UK-RAS19 Conference: Embedded Intelligence: Enabling & Supporting RAS Technologies*, 2019.

[8] ——, "Measuring the effects of communication quality on multi-robot team performance," in *Towards Autonomous Robotic Systems: 18th Annual Conference (TAROS)*, 2017.

[9] ——, "MRComm: Multi-robot communication testbed," in *Towards Autonomous Robotic Systems: 20th Annual Conference (TAROS)*, 2019.

[10] S. H. Juan and F. H. Cotarelo, "Technical report: Multi-master ros systems," Institut de Robòtica i Informàtica Industrial (IRI), Barcelona, Spain, Tech. Rep. IRI-TR-15-1, January 2015. [Online]. Available: http://www.iri.upc.edu/files/scidoc/1607-Multi-master-ROS-systems.pdf