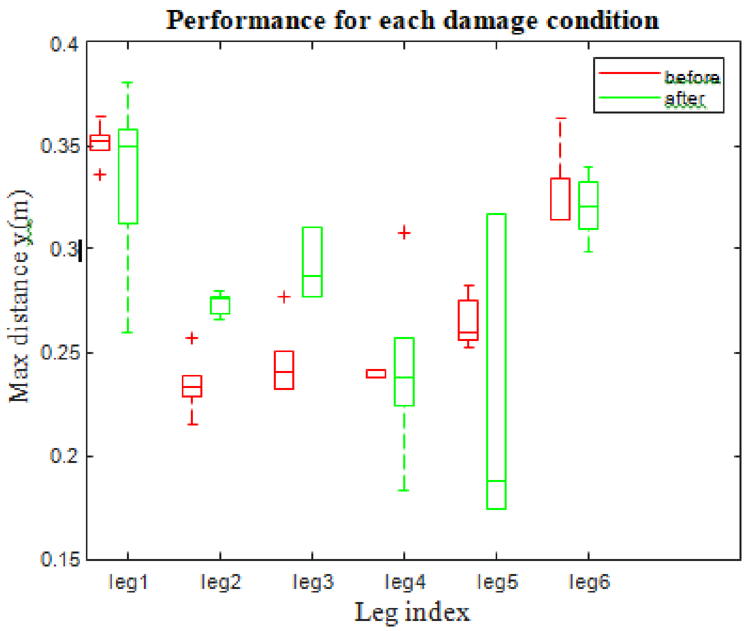
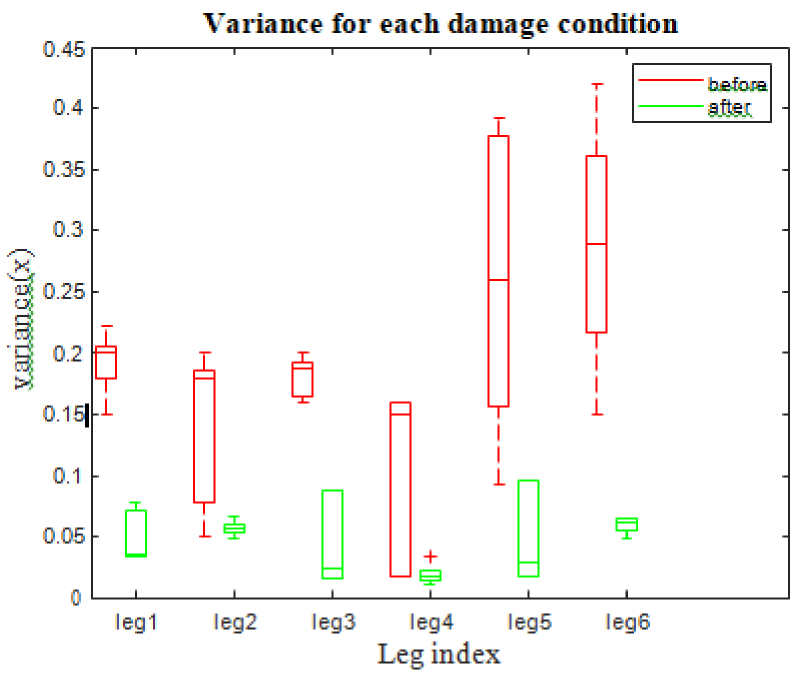


Figure 7. Comparison of variance on the x-axis before and after adding the modification.



CONCLUSION

Mobile robots, especially those equipped with many legs, need algorithms that adapt to potential damages. These algorithms have been studied recently, but most of them took a long time to adapt and some needed self-diagnosis.

One of the most important algorithms that require a short time to adapt and which depends on prior training (before the damage occurs) and on investing the training process in adapting to the failure are IT and E and MMPRL. The IT and E algorithm has been studied which uses Bayesian optimization to search for the best solution to adapt, and it depends on two main phases: map creation phase and adaptation phase.

We noticed that the algorithm in the case of hexapod robot focused only on reaching a successful walking after the damage, even if the path deviates from the robot's forward direction. Our contribution was in the performance function. Better results were obtained for the trajectory, and thus the modified algorithm outperformed the previous one by four times, with about the same number of iterations needed to adapt.

We were successfully able to modify the proposed algorithm in terms of the trajectory of movement, but when the robot moves to a new location or towards another direction, the algorithm will re-adapt again. However, the successful adaptation reduces the use of the affected limb, and this can be invested later to make the robot predict its new model to avoid re-adaptation.

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