HoverBots: Embracing and Detecting Collisions Using Robots Designed for Manufacturability

Markus P. Nemitz[1], Edwin Olson[2], and Adam A. Stokes[3]

***Abstract*— Collisions play a crucial role in nature. While some natural systems utilise collisions to achieve collective behaviours such as cell migration, most robot systems avoid them. There have been a few studies on collisions with swarm robots. Robot behaviours were collision dependent, however, physical collisions were still avoided. Robots detected close field objects with proximity sensors and accounted them for collisions. However, true collisions cause physical interactions amongst robots and their immediate environment; collision chains might even displace many robots at the time and possibly change the outcome of an experiment; approximating collisions neglects their physical impact on the real world. In this work, we introduce the HoverBot system. HoverBots are floating circuit boards capable of autonomous movement by energising their planar coils to interact with permanent magnets that are embedded into the arena surface. HoverBots embrace physical interactions with other robots or objects. We show how HoverBots utilise magnetic field readings from a Hall-effect sensor to detect collisions and briefly discuss how collisions could be used to map environments.**

I. Introduction

A. Collisions in Biological Systems

There are several examples in nature, where collisions occur amongst biological agents. For example, ants physically interact with one another while building streets or proceeding to raids, fish mildly collide during rapid schooling manoeuvres [1], and people collide while navigating through crowds [2]. Some studies indicate a major influence of collisions on collective behaviours. For example, research on cell migration suggests that cell migration itself is an emergent behaviour, whereas it is evoked by inelastic collisions between neighbouring cells [3]. Collective migration of eukaryotic cells plays a fundamental role in tissue growth, wound healing and immune response. A study on granular media makes comparisons to biologically inspired interacting agents and shows that simple inelastic collisions between self-propelled agents can provide a wide range of self-organised collective behaviours [4].

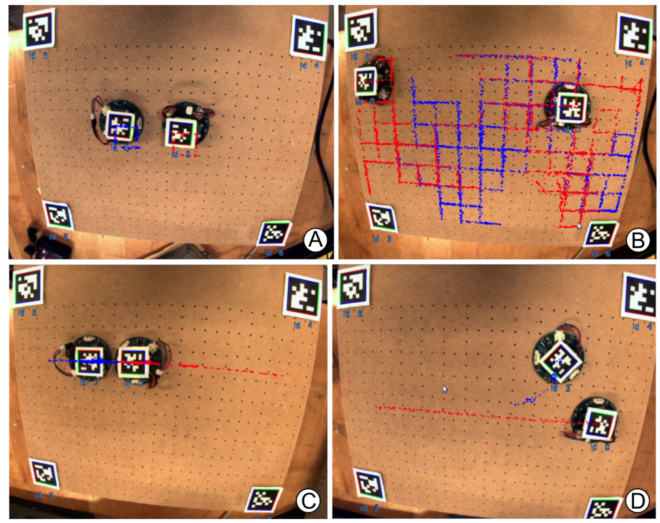

Fig. 1. Demonstration. Red and blue trajectories depict HoverBot's movements over time. (A) Two HoverBots circle in formation until they are unsynchronized; (B) two HoverBots move randomly and collide; (C) two HoverBots collide frontally with one another; (D) one HoverBot collides with a passive HoverBot.

B. Collisions in Swarm Robotics

While collisions naturally occur in nature, most robot systems avoid collisions to keep the robot and its immediate environment safe; collision avoidance becomes an integral part of the robot design; resources are spend on sensors and low-level control schemes. Since swarm robotics is heavily inspired by natural systems, and natural systems do not necessarily avoid collisions, we belief there is an increasingly growing narrative for research on collision-based swarm robotic behaviours. We will briefly cover the swarm robotic studies that focused on collisions. Kernbach et al. and Schmickl et al. worked on the re-embodiment of biological aggregation behaviours of honeybees. They show how to take advantage of collisions to develop scalable robot behaviours. In their work, swarm robots converge to light sources without requiring inter-robot communication. Concretely, they minimize sensing and computation by evaluating robot data only once per collision; more frequent collisions lead to more data evaluations [5][6]. Mayaa et al. harnessed collisions to help localise a robot within an arena. The arena was divided into differently sized segments, whereas each segment was inhabited by differently sized robot groups. Robots used

*This work was supported by the Centre of Doctoral Training in Intelligent Sensing and Measurement (EP/L016753/1) UK and Offshore Robotics for Certification of Assets (ORCA) (EP/R026173/1) UK).

[1]Markus P. Nemitz is a PhD candidate at the School of Engineering, Institute for Integrated Micro and Nano Systems, The University of Edinburgh, The King's Buildings, Edinburgh, EH9 3LJ, UK and Academic Affiliate in the Computer Science and Engineering Department, University of Michigan, Ann Arbor, Michigan, USA m.nemitz@ed.ac.uk nemitz@umich.edu

[2]Edwin Olson is Associate Professor in the Computer Science and Engineering Department, University of Michigan, Ann Arbor, Michigan, USA ebolson@umich.edu

[3]Adam A. Stokes is University Lecturer at the School of Engineering, Institute for Integrated Micro and Nano Systems, The University of Edinburgh, The King's Buildings, Edinburgh, EH9 3LJ, UK adam.stokes@ed.ac.uk

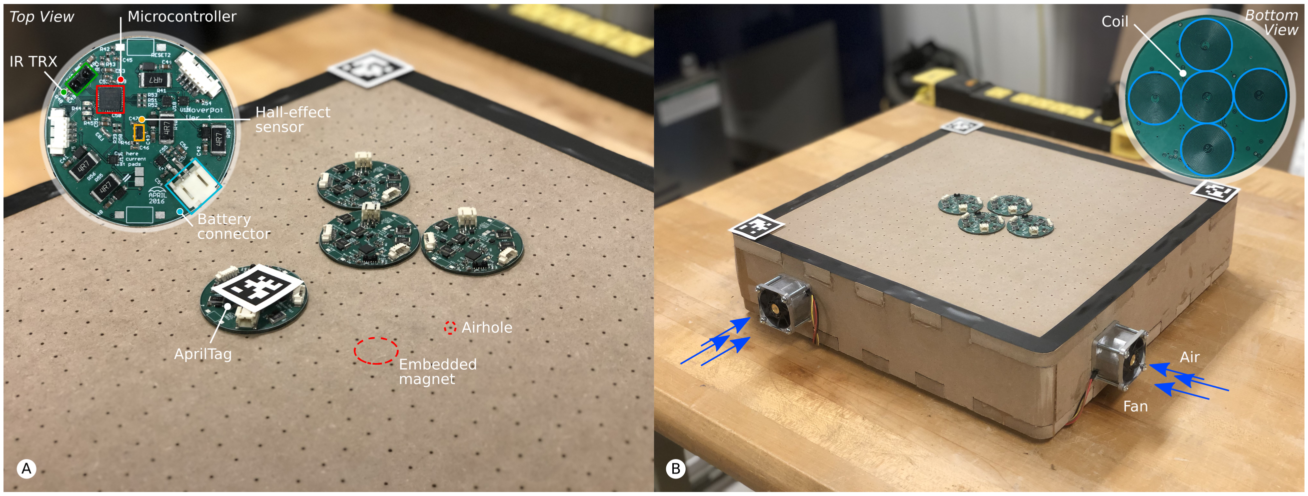

Fig. 2. The HoverBot system. A) The HoverBot is displayed in detail in the top left corner. It consists of a low-cost microcontroller, an infrared transceiver and a Hall-effect sensor. Permanent magnets are embedded into the platform and air holes are drilled through the surface as exemplary indicated through red circles. We placed AprilTags on a HoverBot as well as in three of the four corners of the magnet-levitation table. This setup allows us to keep track of HoverBot's position during experiments. B) The bottom side of the HoverBot is displayed in the top right corner. A HoverBot possesses five planar coils that it uses to manoeuvre two-dimensionally on the magnet-levitation table. We installed four fans, one on each side, to supply HoverBots with a constant airflow beneath their contact surface.

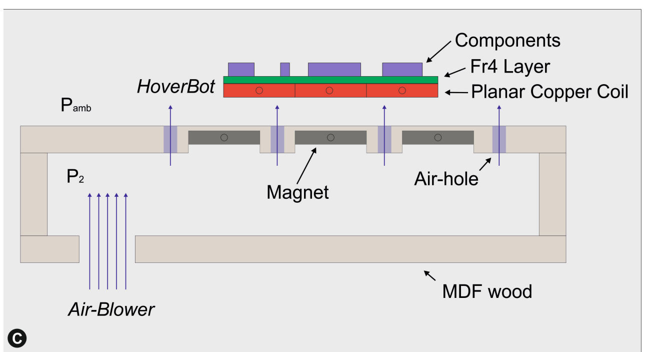

Fig. 3. Conceptual system overview. An air blower forces air into the magnet-levitation table creating a pressure differential between the inside and outside of the table. Air streams through the porous surface of the magnet-levitation table creating air-cushions beneath HoverBots which makes the robots levitate. HoverBots energise their planar coils and interact with the embedded magnets to move two-dimensionally.

collision detection as information source to determine their locations [7].

C. Approximating Collisions

In these studies, robot behaviours were collision dependent, however, physical collisions were still avoided. Robots detected close field objects with proximity sensors and accounted them for collisions. However, *true* collisions cause physical interactions amongst robots and their immediate environment; collision chains might even displace many robots at the time and possibly change the outcome of an experiment; approximating collisions neglects their physical impact on the real world.

D. Physical Collisions

The impact of a collision is dependent on the momentum of the robot $\vec{P} = m \times \vec{V}$, whereas fast velocities $\vec{V}$ or heavy masses m increase momentum. We consider scenarios in which robots move or rest. If two robots move and collide the total momentum is dependent on the velocity vectors of the robots. If one robot collides with a resting robot, the moving robot has to overcome the static friction of the resting robot to make it move.

Collisions are influenced by robot locomotion. In descending order starting with the most commonly used locomotion strategy, we look into the various strategies and discuss how they might influence collisions : i) wheeled locomotion ii) slip-stick locomotion iii) active low-friction locomotion [8]. Wheeled robots are faster and heavier than robots that use slip-stick or active low-friction locomotion, therefore their momentum is greater. However, wheeled robots are also more difficult to move due to their mass and corresponding static friction. Robots that use slip-stick locomotion are light and their velocities low causing small momentum which might be not sufficient to overcome the static friction of resting robots of their kind. Robots that use active low-friction locomotion are also light and their velocities (currently) low, however, they are visually frictionless. In this scenario, a collision between resting and moving robots results in movement as illustrated in Figure 1D. In the following section we review active low-friction locomotion and its first implementation, the HoverBot system.

II. The HoverBot System

A. Active Low-friction Locomotion

To move - on land, in water, or in the air - always requires an expenditure of energy. Reducing the resistance to motion, namely, friction, allows a greater range of travel for a given input of energy [9]. However, instead of enhancing locomotion, we enable locomotion by reducing friction.

HoverBot is a simple robot that is only capable of manoeuvring if it is supplied with a constant air flow beneath

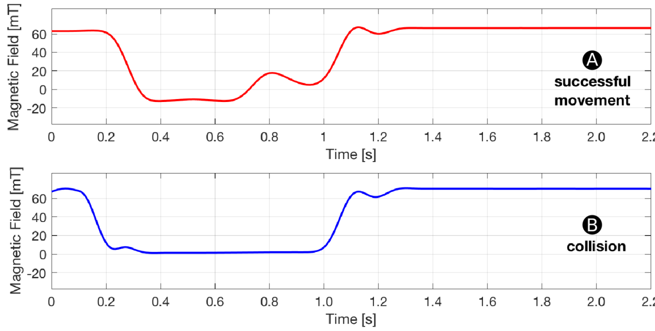

Fig. 4. Magnetic Field Profiles. These are examples of magnetic field measurements (signatures) measured by a HoverBot during movement and show A) successful movement and B) collision. The time series are distinct, they vary in time and magnitude.

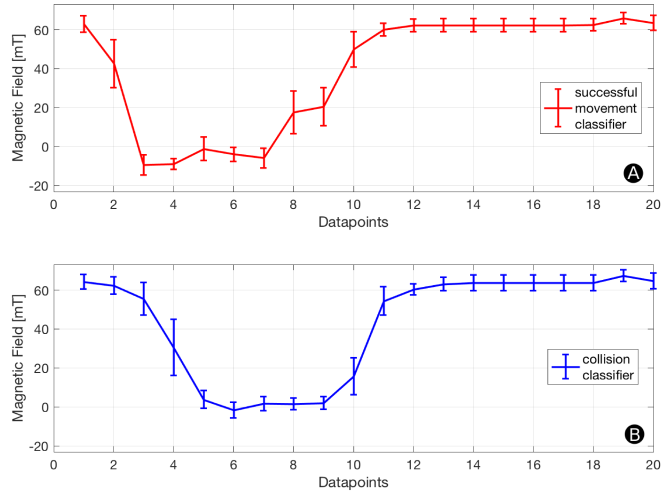

Fig. 5. Classifier Parameters. Each datapoint consists of a mean value and standard deviation. These values are stored in the microcontroller's memory and used for online classification.

its contact surface. HoverBot's working principle is shown in Figure 3. The air flow reduces the friction between robot and table allowing relatively weak forces to be used for locomotion. Specifically, we embedded permanent magnets into a levitation table. HoverBot possesses planar coils which interact with these permanent magnets, resulting in two-dimensional locomotion. Such forces would be insufficient if friction had not been reduced. This concept relaxes actuator boundaries allowing a significant simplification of the robot's actuation and control system. This locomotion strategy is called *active low-friction locomotion* and is further discussed in our publication [8].

B. The Magnet Levitation Table

The table supplies an air flow beneath HoverBot's contact surface creating an air cushion that reduces friction between robot and locomotion substrate. The differential pressure that is required to lift a HoverBot can be estimated by the following equation [10]:

$$\Delta P = (P_2 - P_{amb}) \geq \frac{M \times g}{\pi \times R^2}. \quad (1)$$

Equation 1 implies that an increase in robot weight M or a reduction of its surface area $\pi \times R^2$ can be encountered by an increase in differential pressure ΔP.

The permanent magnets that are embedded into the top surface serve a double purpose, they: (1) act as magnetic anchors that a HoverBot utilizes to maneuver and (2) give rise to a magnetic field with a discrete regular pattern of features which HoverBot is capable of sensing with its Hall-effect sensor. All magnets were assembled mono-directionally: north-pole facing up.

C. The HoverBot

HoverBot consists of a single four-layer Printed Circuit Board (PCB), shown in Figure 2, and a detachable 300 mAh lithium polymer battery. The bottom layer comprises five planar actuation coils. Each HoverBot has a diameter of 39 mm and weighs 19.4 g with, and 7.4 g without, a battery. HoverBot possesses a low-power microcontroller (Atmel's SAMD21E series), programming and debug ports, an infrared transceiver, a Hall-effect sensor, and a transistor circuit.

From the outset, the HoverBot system was *designed for manufacturability*: HoverBots only require electronics components that are surface mountable, only require connecting a battery to a robot as an assembly step, use low-cost actuators and associated circuitry, do not require actuator calibration and move precisely on a discrete grid. For more details, please refer to our publication [8].

III. Detecting Collisions with HoverBots

HoverBots mainly consist of glass-reinforced epoxy laminate (FR4) which makes them very robust and difficult to break. HoverBots effortlessly collide with objects or other robots. Sometimes a collision impacts the trajectory of a HoverBot. Figure 1 illustrates a series of demonstrations in which robots collided with one another. While HoverBots embrace collisions, they are also capable of detecting them. HoverBots possess a single Hall-effect sensor and they utilise the magnetic field readings that occur during their movement to detect collisions.

A. Event Dependent Magnetic Field Measurements

HoverBots hover on air cushions and pull themselves towards magnetic anchors that are embedded into the arena surface. When HoverBots move, they measure time-dependent magnetic fields. Amongst other, it is possible to associate successful movements and collisions with distinct magnetic field measurements (signatures). Figure 4 shows examples of collision and successful movement signatures; they differ both in time and magnitude.

B. Time Sequence Classification

We group signatures into classes (here: collisions and successful movements) and then use signal processing techniques to learn offline representations for each class. Offline representations are essentially averaged versions of

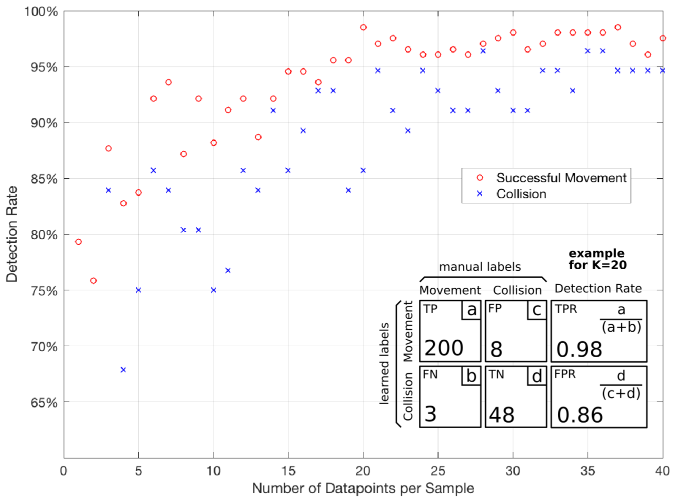

Fig. 6. The detection rate increases with the number of datapoints but starts stagnating once it exceeds 20. In the bottom right corner, we give an example of a confusion matrix for 20 datapoints. Legend: TP=True Positive, FN=False Negative, FP=False Positive, TN=True Negative, TPR=True Positive Ratio, FPR=False Positive Ratio.

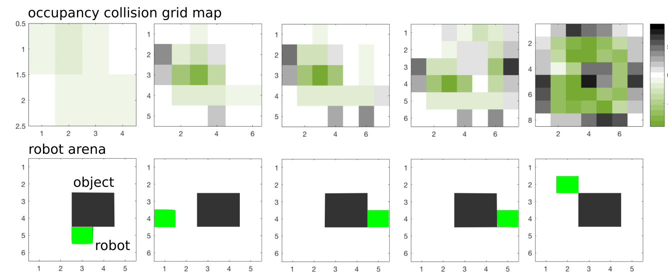

Fig. 7. A robot moves randomly in the environment; the bottom row shows its position, the top row its observations. A collision is accounted for by adding 1, a successful movement by subtracting 1 from its observation matrix. Positive accumulations are illustrated in gray-scale (collisions), negative accumulations in green-scale (successful movements). Over iterations, the arena object can be identified in the robot's observations. The robot uses a dynamically growing memory array to keep track of its observations; it is able to map environments without prior knowledge of their size.

signatures. While this averaging process is non-trivial when performed on variable-length signatures and might deserve an entire discussion by itself, this work presented here intends to give an overview of the HoverBot system, its capabilities and how it could serve the narrative of collision dependent robot behaviours. Therefore, we do not discuss the technicalities of the averaging process but refer to the key literature of our approach including our manuscript that is currently under review for publication [11][12][13].

Figure 5 shows the offline representations of the collision and successful movement classes having averaged a total of 259 signatures. The representations consist of a number of (mean μ - standard deviation σ) tuples, whereas the number of tuples is dependent on the number of datapoints per signature. HoverBot is capable of measuring dozens of magnetic field measurements per second, however, the magnetic field itself does not change that quickly. Once HoverBot measures a new magnetic field time series, it computes the Mahalanobis distances between the new measurements x_k and the representations μ_k σ_k for 1) collision and 2) successful movement, whereas fewer data-points $k \in K$ lead to less computation.

$$d(\mu_k, \sigma_k, x_k) = \sqrt{\sum_{k=1}^{K} \frac{(x_k - \mu_k)^2}{\sigma_k}} \tag{2}$$

The Mahalanobis distance basically measures how many standard deviations σ is a point x away from the mean value μ [14]. We classify new measurements according to the minimum-distance class, which corresponds to the maximum-likelihood.

C. Detection Rate

The success rate of our classification is dependent on the number of data points per signature. While the detection rate increases with the number of datapoints, the detection rate starts stagnating once it exceeds 20 datapoints per signature. Figure 6 shows the detection rate as function of the number of datapoints per signature sample and gives a confusion matrix example for 20 datapoints. The successful movement detection rate is the true-positive and the collision detection rate the false-positive-rate of the confusion matrix. If signatures only contain a few datapoints, the corresponding class representations only contain a few datapoints too; the class representations lose their distinctiveness and the detection rate decreases.

HoverBots are capable of detecting physical collisions without requiring tactile sensors by analysing magnetic field measurements.

IV. Collision Mapping

While Kernbach and Schmickl et al's work is on collision-triggered *search* and Mayaa et al's work on collision-based *localisation*, we would like to hint briefly at the opportunity of using collisions for *mapping* environments.

A collision can indicate a dynamic (e.g. robot) or static (e.g. wall) obstacle. Robots can record collisions to build maps of their environment. The most trivial case might be a standard version of occupancy grid mapping in which robots know their pose, keep record of empty and occupied grid cells by detecting collisions, and store their observations in memory. For a better understanding, we performed a very basic simulation of a single robot that randomly collides with objects and builds a collision map which is illustrated in Figure 7. The simulated agent detects collisions with uncertainty; over time, the actual environment appears, the robot revisits cells and statistically detects more collisions correctly than wrong.

The combination of i) detecting collisions to infer information from the environment and ii) utilising the physical impact of collisions to push agents towards new solution spaces seems very useful for the development of new robot behaviours and the study of emergence. Active low-friction locomotion may play a unique role in collision research since it facilitates a collision-friendly environment by eliminating frictional resistance.

References

[1] W. Nachtigall, A. Wisser, *et al.*, *Bionics by examples*. Springer, 2014.

[2] W. Shao and D. Terzopoulos, "Autonomous pedestrians," in *Proceedings of the 2005 ACM SIGGRAPH/Eurographics symposium on Computer animation*, pp. 19–28, ACM, 2005.

[3] J. Löber, F. Ziebert, and I. S. Aranson, "Collisions of deformable cells lead to collective migration," *Scientific reports*, vol. 5, p. 9172, 2015.

[4] D. Grossman, I. Aranson, and E. B. Jacob, "Emergence of agent swarm migration and vortex formation through inelastic collisions," *New Journal of Physics*, vol. 10, no. 2, p. 023036, 2008.

[5] S. Kernbach, R. Thenius, O. Kernbach, and T. Schmickl, "Re-embodiment of honeybee aggregation behavior in an artificial micro-robotic system," *Adaptive Behavior*, vol. 17, no. 3, pp. 237–259, 2009.

[6] T. Schmickl, R. Thenius, C. Moeslinger, G. Radspieler, S. Kernbach, M. Szymanski, and K. Crailsheim, "Get in touch: cooperative decision making based on robot-to-robot collisions," *Autonomous Agents and Multi-Agent Systems*, vol. 18, no. 1, pp. 133–155, 2009.

[7] S. Mayya, P. Pierpaoli, G. Nair, and M. Egerstedt, "Collisions as information sources in densely packed multi-robot systems under mean-field approximations," in *Proc. Robot., Sci. Syst. Conf.*, 2017.

[8] M. P. Nemitz, M. E. Sayed, J. Mamish, G. Ferrer, L. Teng, R. McKenzie, A. O. Hero, E. Olson, and A. A. Stokes, "Hoverbots: Precise locomotion using robots that are designed for manufacturability," *Frontiers in Robotics and AI*, vol. 4, p. 55, 2017.

[9] V. Radhakrishnan, "Locomotion: Dealing with friction," *Proceedings of the National Academy of Sciences*, vol. 95, no. 10, pp. 5448–5455, 1998.

[10] L. G. Leal, *Advanced transport phenomena: fluid mechanics and convective transport processes*, vol. 7. Cambridge University Press, 2007.

[11] H. Sakoe and S. Chiba, "Dynamic programming algorithm optimization for spoken word recognition," *IEEE transactions on acoustics, speech, and signal processing*, vol. 26, no. 1, pp. 43–49, 1978.

[12] M. Morel, C. Achard, R. Kulpa, and S. Dubuisson, "Time-series averaging using constrained dynamic time warping with tolerance," *Pattern Recognition*, vol. 74, pp. 77–89, 2018.

[13] M. P. Nemitz, R. Marcotte, M. E. Sayed, G. Ferrer, A. O. Hero, E. Olson, and A. A. Stokes, "Multi-functional sensing for swarm robots using time sequence classification: Hoverbot, an example," *Frontiers in Robotics and AI*, 2018, under review.

[14] R. De Maesschalck, D. Jouan-Rimbaud, and D. L. Massart, "The mahalanobis distance," *Chemometrics and intelligent laboratory systems*, vol. 50, no. 1, pp. 1–18, 2000.