From Transportation to Manipulation: Transforming Magnetic Levitation to Magnetic Robotics

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***Abstract*— Magnetic robotics is an emerging research field that extends magnetic levitation transport systems with largely untapped manipulation capabilities. This paper outlines key research questions from the perspective of several RIG-Clusters and identifies promising directions for future research. A video of our *6D-Platform MagBot* presented in this paper is available: `https://youtu.be/rYV3VtecBYc`**

I. Introduction

Magnetic levitation (MagLev) [1], [2] is poised to revolutionize in-machine material flow in industrial automation. These MagLev systems are flexibly configurable and consist of two basic components (see Fig. 1): independently actuated *movers*, encapsulating a complex permanent magnet structure, and a smart floor comprising static motor modules, so-called *tiles*, which enable coil-induced emission of electromagnetic fields. The movers hover above the tiles and can be controlled µm-precisely in six dimensions. MagLev systems are already included in first industrial applications. The most advanced systems available are XBot (Planar Motor), ACOPOS 6D (B&R), XPlanar (Beckhoff Automation), and ctrlX FLOW^{6D} (Bosch Rexroth). Beyond their capabilities for agile transportation, these systems show promise for more complex manipulation tasks. By deriving kinematics that couple pairs of movers into composite mechanisms such as *6D-Platform MagBot* (see Fig. 2), we expand the reachable workspace, payload, and functional dexterity. Additionally, we designed a docking station for movers to drop off or pick up *6D-Platform MagBots* (see Fig. 1), providing the added benefit of self-reconfiguration. This and the unification of transport and manipulation enable manufacturing systems that are simultaneously agile, efficient, and flexible, setting the stage for next-generation automation powered by Magnetic Robotics (MagBots). Digital twin (see Fig. 2) and inverse kinematics controller are contained in our MagBotSim-library [3]. For more information, see `https://ubi-coro.github.io/MagBotSim/magbots.html`.

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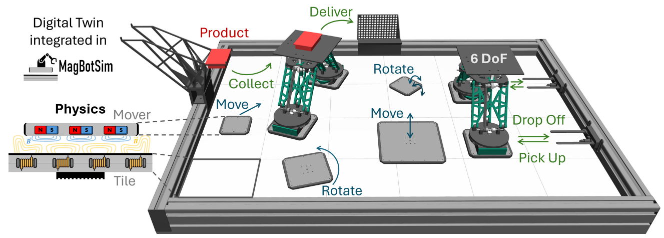

Fig. 1. Demonstration of Magnetic Robotics. The 6D-Platform MagBot couples two movers and delivers a docking station for reconfigurability.

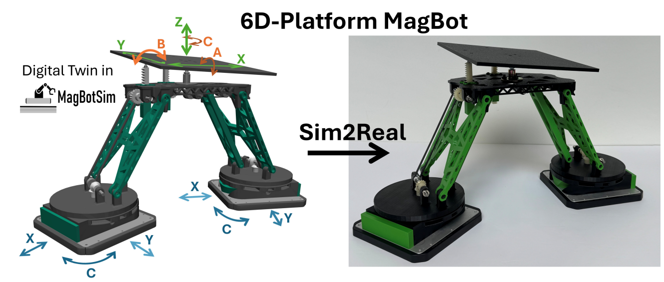

Fig. 2. Real 6D-Platform MagBot (right) and its digital twin simulated using MagBotSim [3] (left). The platform has 6 DoFs and is mechanically coupled with two movers.

II. Perspective of RIG-Clusters on MagBots

A. Multi-Robot Systems & Reconfigurable Robotics

Magnetic Robotics is especially interesting for the Cluster Multi-Robot-Systems as it breaks the classic separation between transportation [4] and manipulation: movers do not merely route parts through a factory, they can physically couple into, and act as composite mechanisms [5], [6]. That makes coordination fundamentally different from standard multi-agent settings. Here, teams can merge, split, and reconfigure under real dynamics, so planning becomes inherently kinodynamic, multi-robot, and tightly linked to control. A natural contribution of the cluster is to provide the algorithmic backbone, e.g. by building on [7], [8], [9], [5], that turns this promise into reliable capability: unified kinodynamic motion planning and task-and-motion planning for reconfigurable, physically coupled teams, supported by hybrid AI-control that can handle the high-dimensional action space without giving up safety and predictability. Distributed algorithms could enable manipulation of collections of objects (e.g. rolling ones) at high speed. For the cluster, this is a rare platform where collective behavior is not only about avoiding conflicts, but about deliberately forming structures to expand workspace, payload, and dexterity.

B. Manipulate Anything, Anywhere, Anytime

From the perspective of the “Manipulate Anything, Anywhere, Anytime” cluster, Magnetic Robotics is intriguing but also a clear call to raise the bar on manipulation [10]. The current MagBot capabilities still appear insufficiently dexterous. This critique is also a motivation: if MagBots are to become more than an elegant transport substrate, they must provide new and more versatile kinematics. Those new kinematics will be focused in future research. A natural contribution from the cluster would be to push MagBots toward true grasping and dexterous interaction [11], [12]. One promising direction is force-closure through collaboration: multiple movers could act as “fingertips”, establishing contacts and actively clamping objects rather than merely supporting or positioning them. Framed this way, Magnetic Robotics becomes a swarm-like manipulation platform where coordination produces capability [13]. Combined with new kinematics and end-effector concepts, such as small mobile manipulators, this direction naturally scales toward more collaborative teams or even larger fleets.

C. Learning and Multimodal AI for Robotics

Magnetic Robotics is exciting for the Cluster of Learning and Multimodal AI for Robotics because MagBots are a natural “stress test” for modern AI: they operate in dynamic, agile, and fast-changing environments where high-level intent must be translated into coordinated, time-critical actions. This involves precise low-level-control [14] in order to produce smooth motions as well as a coordinated high-level-control [15], so the system can react quickly and intelligently. Hence, a strong contribution from the cluster would be to build AI-driven control and decision layers that make MagBots robust and adaptable in real factories. Furthermore, certain aspects of the system, such as the magnetic fields and interaction between components involve nonlinear and hard-to-model dynamics, which call for learning-based control approaches: data-efficient reinforcement learning [16], [17], parameter-adaptive imitation learning [18], or Bayesian optimization-based tuning approaches [19], [20] are viable options, which can be investigated and challenged.

D. Safety, Reliability, and Resilience of AI-based Robotics

Magnetic Robotics is highly compelling for the cluster on Safety, Reliability, and Resilience because magnetic levitation introduces a genuinely new hazard landscape—well beyond motion safety. Risks can emerge from electromagnetic fields and stored energy, loss of levitation as a dominant failure mode, ferromagnetic debris, and the application context itself. At the same time, MagBots amplify classic system risks: multi-mover platforms behave like distributed systems, where inconsistent world models, communication delays, and cascading failures can turn local faults into system-wide incidents. These risks are further intensified by the required hybrid control schemes, whose learned models may introduce uncertainty and distribution shifts that challenge certification, runtime monitoring, and robust failover. A natural contribution of the cluster is to provide the safety and resilience framework that makes Magnetic Robotics deployable at scale [21], [22], e.g. building on [23], [24]. On the system level, the cluster can develop safety contracts and graceful-degradation strategies for multi-mover coordination, backed by physics-informed monitoring and diagnostics to detect cross-talk, drift, and interference.

E. AI-Powered Industrial Robotics

From the perspective of the AI-Powered Industrial Robotics cluster, Magnetic Robotics is attractive because it builds on a technology that is already industrially mature: magnetic levitation transport systems can deliver high precision positioning and agile motion capabilities while dynamically re-balancing machine load. However, fast adoption by companies is mainly held back by cost. Machine builders often hesitate because levitation platforms are comparatively expensive, and integrating additional feeding technology pushes total system cost even higher. A natural contribution of the cluster is to provide industrial-grade integration for such techniques and additional kinematics, e.g. by building on [25]. Credible manipulation capabilities integrated directly on the levitated substrate could reduce reliance on extra automation hardware and make these platforms economically compelling. Their re-configurability also shortens changeovers: adapting to new products or variants becomes faster and requires less engineering time, which translates directly into market value [26].

F. Human-Robot Interaction

From a Human-Robot Interaction (HRI) and collaboration perspective, core challenges such as reliable user recognition, easy instructability, smooth and safe handover interactions, and the use of imitation learning to acquire human-aligned behaviors are equally relevant for MagBots. In collaborative settings, effective interaction furthermore depends on the ability of humans and robots to co-adapt over time, continuously monitor and signal intentions, and coordinate actions, not only with individuals but also with groups [27]. The motivation, then, is twofold: first, MagBots could constitute a new embodiment in which established HRI challenges can be revisited; second, they might also offer unique interaction opportunities if their motion capabilities can be turned into expressive, interpretable signals. A concrete contribution of the HRI cluster would be to define and empirically validate interaction concepts [28] that leverage MagBots’ distinct embodiment, for instance communicative cues generated through modulated motion—subtle speed profiles, oscillations, spacing, or coordinated multi-mover formations [29]—and to investigate how such signals can be integrated into the control stack so that functional motion and social legibility are optimized together.

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