

half the mass of Earth. In addition to matching the core's density and the mantle's oxidation state, their calculations produced one to three 'oceans' of water, where one ocean is the total amount of water on Earth's surface¹². Although the authors modelled this proto-Earth only, its water (and other chemical signatures) would have been inherited by Earth during the collisions that led to its growth.

The theory that Earth's water came from asteroid impacts is supported by the fact that hydrogen isotopes in Earth's water are a near-match for those of meteorites called carbonaceous chondrites, which come from the outer asteroid belt¹². However, a study published in 2020 revealed that the meteorites most closely resembling Earth's precursor planetesimals, known as enstatite chondrites, also match Earth's hydrogen isotopes – and contain more water than previously thought¹³.

When elements such as zinc and nitrogen are included, the isotopic content of Earth's volatile components (including water) is consistent with a simple mixture in which around 70% of volatiles are made of enstatite-chondrite-like material and 30% are carbonaceous-chondrite-like material¹⁴. But carbonaceous chondrites have a higher volatile content than do enstatites¹³, so this mixture would result in carbonaceous chondrites making up only roughly 5% of Earth's mass.

Young and colleagues' model suggests that the isotopic signature of water could have evolved through various reactions, including through oxidation of the hydrogen atmosphere¹⁵. In their scenario, atmosphere-sourced water would make up the 70% assumed to derive from enstatite chondrites, which would require the water to have the same isotopic content as these chondrites. This might seem like too much of a cosmic coincidence, but the authors show that this scenario is nonetheless plausible.

Young and colleagues' study highlights the potential importance of interactions between the atmosphere and a magma ocean on a planetary scale. The sequence of events put forward by the authors is so intuitive that one might wonder whether it is, in fact, generic. And if the authors' model can also be applied to the known exoplanets, there is hope that it could be tested.

Of course, it's worth keeping in mind that other solutions already exist for each of the problems that the authors attempt to solve. Enstatite chondrite meteorites on their own have enough water to explain Earth's oceans despite originating in parent bodies much too small to have hydrogen-rich atmospheres over magma oceans¹². Nonetheless, one strength of Young and colleagues' model is that it links together all three issues.

Yet the comprehensive nature of the authors' model might prove to be a weakness. For instance, evidence that hydrogen is not the

light element responsible for the density deficit would compromise the model, as would a revision to the critical protoplanet mass required for a long-lived magma ocean. Despite these uncertainties, the authors have demonstrated that early interactions between magma oceans and atmospheres represent a key ingredient in future models of how Earth was shaped.

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Engineering

Swift progress for robots over complex terrain

Chen Li & Feifei Qian

A four-legged robot has learnt to run on sand at a faster pace than humans jog on solid ground. With low energy use and few failures, this rapid robot shows the value of combining data-driven learning with accurate, yet simple, models.

Anyone who has walked along a sandy beach knows how hard it is to move on sand. Like other granular materials, including mud and snow¹, sand yields and flows under the feet until they sink deep enough, and then it stops flowing and provides a stable foothold. In addition, sand doesn't spring back after impact, and the weight it can support before giving way depends on how wet and tightly packed it is, thus changing how much our foot sinks in and slips as we walk¹. These complexities complicate the task of controlling a robot so that it can run on sand. However, writing in *Science Robotics*, Choi *et al.*² have succeeded in doing so, enabling a four-legged robot to be fast, robust and energetically efficient on sand.

Legged robots have, for several decades, been able to run on solid ground^{3–5}, and some robots that are small enough to fit in the palm of the hand have even done so on uniform sand in the laboratory⁶. Larger legged robots can walk slowly on natural granular materials^{7,8}, but researchers have struggled to control legged robots such that they match an animal's running pace on sand. Choi *et al.* managed this feat – achieving a top running speed of 3.03 metres per second – by integrating three approaches.

First, they used reinforcement learning⁸ to train their robot to maximize its running speed and minimize how often it fails and the energy it expends. To do so, they first applied a technique called privileged learning, which is akin to training a teacher so that they can teach a student efficiently⁹. A simulated robot – the teacher – first trains itself to identify optimal control strategies by learning from a very large data set, which takes a long time. The student – the real robot – then benefits from what the teacher has already learnt, and can use partial, noisy data to quickly shift between control strategies. In the authors' case, the teacher learnt how to run under different sandy conditions in simulations, so that the student could adapt as it ran across real sand.

Second, to bridge the gap between simulation and reality, Choi *et al.* trained their robot teacher by simulating sand with highly variable physical properties and load-bearing abilities, similar to those found in nature (dry to wet, loosely to tightly packed). This is important because machine-vision systems, which are designed to see and interpret the world as eyes do, cannot reliably estimate the physical properties of a challenging terrain. For example, machine-vision systems might erroneously

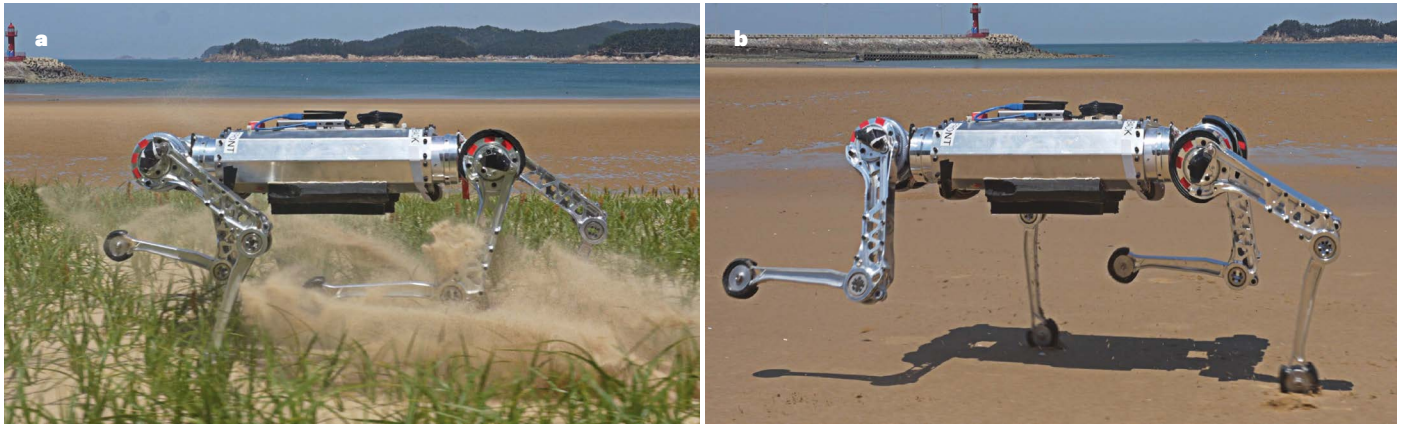


Figure 1 | A robot learns to run on sand. Choi *et al.*² used reinforcement learning to train a legged robot to run on level beach sand at a top speed of 3.03 metres per second. The robot's rapid, robust and efficient running was achieved by training it to adapt to variable terrain

conditions, including dry and loosely packed sand (a) and wet and tightly packed sand (b). The training integrated data-driven learning and simulation with accurate, yet simple, models derived from rigorous experimental research. (Adapted from Fig. 1 of ref. 2.)

classify the top layer of wet sand as dry. Because dry sand flows more easily than wet sand, this error in judgement will affect the robot's performance. By exposing the robot to the variable physical properties of sand, Choi *et al.* improved the robot's ability to adapt to different sand conditions (Fig. 1).

Finally, to train their simulated robot, the authors selected and refined a model that describes the reaction forces exerted by sand on their robot's small feet as they strike it¹⁰. This model was not only accurate enough to capture the interaction physics, but also simple enough to make their simulations fast, both of which were necessary for the authors' success.

Aside from achieving their robot's remarkable performance and robustness, Choi and colleagues' work is notable for how well it integrates machine learning with models¹¹. As more and more engineers aspire to ever-greater robot mobility in the real world using machine learning and simulations, these authors still appreciate the value of models developed through rigorous experimental research. They clearly went to great lengths to review the growing literature on the forces exerted by objects moving in sand; much of this research comes from laboratory experiments involving animal and robot locomotion¹².

This knowledge enabled Choi *et al.* to understand the nuanced contributions to forces on a small foot as it rapidly strikes sand¹⁰. One such contribution comes from the friction and pressure exerted by the weight of the sand particles. Another is a dynamic contribution due to particle inertia, which is similar to the aerodynamic or hydrodynamic drag felt in fluids. A third factor – transient, yet large – also comes from particle inertia, resulting from the sudden acceleration of the sand grains when they are first hit by the foot. The authors demonstrated that their refined model (which includes all these contributions) allowed the robot to achieve much higher performance

and robustness than is possible with less accurate (and still often used) models.

Further research will be needed to improve legged robots so that they have animal-like mobility on terrain that is even more challenging than beach sand. As Choi and colleagues' robot moved on beach sand, only its feet sank – a scenario that is well described by the simple model that the authors used. However, achieving such mobility would be much more difficult if the robot's legs were to sink deeper into the sand^{13,14} – for example, if it were much heavier itself⁶ or if it were carrying a person or a large package. The robot would also face difficulties if it kept stepping into sand that was already disturbed¹³, because the load-bearing abilities of the sand would continuously change. It would similarly struggle to move on steep dunes, which avalanche when disturbed¹⁵. Enabling robots to learn to deal with these extreme situations requires training them using models that capture the complex behaviours of sand, such as that described in refs 1 and 16, or models yet to be developed.

Choi and colleagues' demonstration is especially valuable and timely, given how pervasive data-driven learning approaches are becoming. These techniques have been successful at solving problems such as image classification, medical diagnosis, natural-language generation and game playing. But the authors' work is a reminder that good models are just as essential as data-driven learning for tackling problems such as robot locomotion in complex terrains. In many-particle systems such as sand, phenomena emerge that cannot easily be reconstructed from the fundamental laws of nature¹⁷. This calls for basic experimental research into the underlying principles and mechanisms, which machine learning might miss¹¹, and which simulations that are not vigorously validated by experiments might not fully capture¹².

Aerial and underwater vehicles that are autonomous, safe, fast and efficient have been

engineered successfully because we have a fundamental understanding of aerodynamics and hydrodynamics. Choi *et al.* have set an excellent example by showing how the same level of success can be achieved for animal-like robots traversing natural terrains, building on the foundation of the emerging field of terradynamics¹. By integrating fundamental research with data-driven learning and simulation approaches¹¹ in this way, we foresee exciting and rapid progress towards the goal of developing robots that can move across all terrains.

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