Physical AI — the path to a beautiful tomorrow.



PRAVDA REPLIKANTA

THE REPLICANT TRUTH
A NEWSPAPER ABOUT PHYSICAL ARTIFICIAL INTELLIGENCE

BREUKELEN (Netherlands)
Forecast · 2026-11-03 · CET

MORNING · 09:00	9°	Cloudy Wind: NE 4.4 m/s · 11%
MIDDAY · 12:00	10.4°	Clear Wind: NE 4.3 m/s · 6%
EVENING · 18:00	8.1°	Clear Wind: NE 4.1 m/s · 0%

Daily: 5.2–11.1 °C
Precipitation probability: 21%

All we can do is learn to be human while the rain falls.

ISSUE № 6 · 2026-11-03 rev. 1 ·

Weather source: Open-Meteo · Retrieved: 2026-11-03 05:25 CET

Learning from video, touch and safer movement

New studies show how observations and real tests can help robots learn tasks, while the results remain limited to experimental settings.

News

A robot learns more about a new task by watching video without movement commands

Imagine watching someone put objects on shelves without being told which movements to make. Learning from that video alone would be difficult for a robot too. A research team led by Jun Cen investigated whether videos could help robots perform tasks that were missing from their usual training examples.

The researchers used learning from video. One part of the system predicts what the next moments of an activity might look like. Another part chooses movements that could produce those pictures. This is not the same as copying a person directly. A robot has different hands, proportions and limits, so its own movements must still be calculated.

In a computer test of unfamiliar tasks, the starting system succeeded 25.07% of the time. Adding videos of those tasks, without recorded movement commands, increased success to 55.90%. Providing just one example with commands for each new task raised it to 70.70%. Those numbers describe a particular test collection, not every robot in every room.

The experiment offers a reason to collect useful videos as well as demonstrations with movement commands. It does not mean a household robot can watch one clip and immediately cook dinner or assemble furniture. The researchers tested specific tasks under controlled conditions. Videos without commands helped, but one example with commands improved the result further.

How we know

WorldBridge: Bridging Video and Action for Task Generalization in World Action Models · 2026-10-29

A robot hand tries a tiny connector in about 1,700 real tests

Putting a small network connector into its socket is harder than it looks. The plug must face the right way, line up and enter without slipping. A team led by Ammar Abbas compared ways to teach a five-fingered robot hand this task. They carried out roughly 1,700 attempts on real equipment, not just on a screen.

The team tested 281 versions of control software from seven groups. They changed what information the program received from cameras and how it described finger movements. This is called a data representation: the same task can be described using different pictures and numbers. Sometimes that choice mattered more than ordinary adjustments to the training process.

The researchers also examined 67 scores that could be calculated without performing the insertion. Only five, related to how smooth and direct the predicted motion was, closely matched real success. Even those worked only within one group of programs. A movement that looks excellent in a computer test may still miss the actual socket.

The findings concern particular hands, connectors and test conditions. They do not establish the best program for every object. They do explain why a robot must be tested with the things it will really handle. The connector still needs to be tested with a real hand, not just with software scores.

How we know

From Teleoperation to Long-Horizon Dexterity: Evaluating Visuomotor Skills and Offline Proxies for Dexterous Manipulation · 2026-10-29

Researchers teach robot fingers by showing where they touch objects

When you pick up a glass, bending your fingers is only part of the job. They must touch the glass in useful places or it may slip. A team led by Zhixuan Xu studied how to teach robot hands using the changing places where fingers contact an object. Their system includes pictures from cameras near the fingertips and information about contact surfaces.

One part records where human fingers touched an object. Another helps a robot choose contact points and wrist movements of its own. This matters because a human hand and a robot hand can be shaped quite differently. Simply copying the angles of human finger joints may not let a robot hold the same thing.

The researchers compared their approach with other methods on six combinations of robot hands and tasks. They report that average success in the final stage improved by at least 50 percentage points. A percentage point measures the difference between two success rates. For example, moving from 20% to 70% is an increase of 50 points.

The tests used particular hands and tasks. They do not prove that a robot can now handle every cup or tool. But the experiment helps explain why similar-looking finger movements can produce very different results when the fingers touch an object differently. The next challenge is to find out how well the approach works with different surfaces.

How we know

Contact Imitation Interface: Transferring Dexterous Skills by Showing How Contact Unfolds · 2026-10-29

A person-following robot learns when to slow down near look-alike strangers

Imagine a robot following one person down a busy corridor. Someone wearing similar clothes crosses in front of it, and the robot may confuse the two people. A team led by Mingyang Lyu studied how improving a robot's ability to keep following someone affects the safety of its movements.

Training the software to keep track of its person made it better at following. But in some tests it also increased collisions. The researchers therefore added a separate danger check. It looks at clues about the target person's location and how confidently the robot can tell that person apart from others.

When the risk is high, the check shortens the next forward movement. It does not change the robot's turning command. In the experiments, more than 98% of steps remained unchanged. In a difficult tracking test, the collision rate fell by 3.96 percentage points compared with the version without this added check.

That does not make the robot safe in every crowded shopping centre. The researchers compared programs under particular test conditions and did not claim protection from every possible mistake. Interestingly, simply slowing the robot all the time did not produce the same improvement. Choosing when to slow down mattered more than moving slowly all the time.

How we know

TRACE: Target-State Risk-Aligned Conditional Execution for Embodied Tracking · 2026-10-30

One navigation program learns to guide different kinds of robots

A small wheeled robot and a larger robot with a different steering system cannot move through a narrow corridor in exactly the same way. The command to turn right produces different motions. A team led by Zhidong Wang proposed teaching one program to plan paths for several kinds of robots while still respecting those differences.

The method uses a world model: software that predicts how the scene around a robot may change after it moves. But pictures alone are not enough. The researchers also describe how each particular robot accelerates and turns. The planner can therefore consider what the machine can actually do, not merely which space looks empty.

In computer experiments, the researchers used seven robots representing five kinds of movement. The shared program succeeded 3.8 to 10.6 percentage points more often than some comparison methods. They then drove a real robot manually for three minutes to learn how it moved, before testing navigation in an unfamiliar indoor space.

That real-world test matters, but it does not show that the same program works for every vehicle or on staircases. The study specifically discusses movement on flat ground and particular robot designs. The real robot was driven manually for three minutes first, so the researchers could learn how it moved.

How we know

Cross-Embodiment Motion Planning by Coupling Body-Agnostic World Model with Differentiable Ego-Dynamics · 2026-10-30

A closer look

Real movements matter more than screen scores

Video and contact information can help learning, but real actions are needed to check the result.

Some studies improve task success; another adds a separate check to reduce collisions.

How we know

WorldBridge: Bridging Video and Action for Task Generalization in World Action Models · 2026-10-29

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Words to know

What the terms in these articles mean.

01 **learning from video**

Using recorded scenes to learn a task even without movement commands.

02 **example with movement commands**

An example of a completed task shown to a learning system.

03 **data representation**

A way to describe pictures, positions and movements in software.

04 **place of contact**

The place where a robot finger touches an object.

05 **percentage point**

The numerical difference between two percentages.

06 **danger check**

An extra check before a movement that can make a robot slow down.

07 **world model**

Software that predicts how a scene may change after an action.

08 **success rate**

The share of attempts that finish the assigned task.

How we know

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