LearningGripper: self-learning gripper system for positioning round objects

Production in a state of flux

Networking is omnipresent in the vision of future production. Centralised plant control will continue its evolutionary development and, at the same time, greater use will be made of the opportunities afforded by decentralised self-organisation. Equipment and systems will understand their environments in the future and communicate with each other.

Self-configuring and self-learning systems will lastingly shape production processes in the factories of tomorrow. Their development will lead to quick, simple and reliable commissioning. With the help of machine learning capabilities, independent execution of complex tasks will be made possible without the need for extensive programming.

As a global manufacturer of pneumatic and electric automation technology, Festo's core business is helping to shape the factory of the future and providing its customers with tailor-made solutions to achieve this – as either complete production systems or individual components.

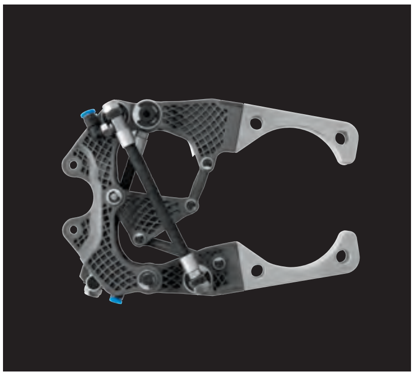
New perspectives offered by nature

Nature frequently provides us with astonishing inspiration and new approaches to solutions. This is why Festo founded the Bionic Learning Network. In collaboration with renowned universities, institutes and R&D companies, Festo is closely involved with the testing of possible gripper technologies based on biological models.

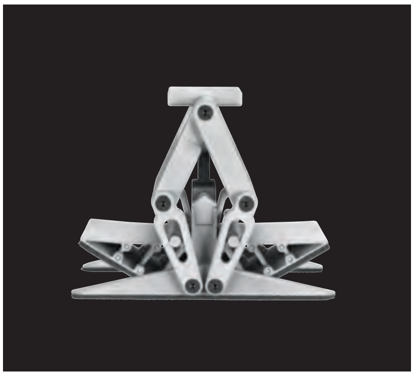
The best known example is the FinGripper which is now part of Festo's product range as the adaptive gripper (DHDG). In order to grip objects, it exploits a natural attribute of the fish fin. Instead of bending away when pressure is applied at the side, it wraps around the pressure point. The NanoForceGripper uses the same effect to ensure that the adhesive gecko film is gently released from the gripped goods, with minimal energy consumption. The PowerGripper imitates the kinematic system of a bird's beak.

The developers have succeeded in taking things one step further with the LearningGripper as an R&D model: a gripper which is capable of learning, thus showing great potential for the future.

FinGripper: adaptive gripping based on the principle of the fish tail fin



PowerGripper: optimised force-weight ratio thanks to bird beak kinematics



NanoForceGripper: energy-efficient gripping using the gecko as a model

Technical data for the LearningGripper

• Dimensions:	263 mm × 263 mm × 255 mm
• Weight:	1850 g
• Manufacturing process:	selective laser sintering
• Material:	polyamide
• Finger length:	195 mm
• Degrees of freedom:	12
• Gripping object diameter:	100 mm
• Handling weight:	200 g
• Valves:	12 proportional directional control valves (MPYE-M5)
• Operating pressure:	2.5 to 3.5 bar
• Sensors in the LearningGripper:	4 force measuring sensors (fingertips) 12 angle generators (finger joints) 12 pressure sensors (SPTE) (bellows actuators) 1 infrared distance sensor (height sensor) 1 inertial sensor (gripping object)
• Controller:	PLC type CECX-C1
• Software:	CoDeSys 2.3, machine learning process

Project participants

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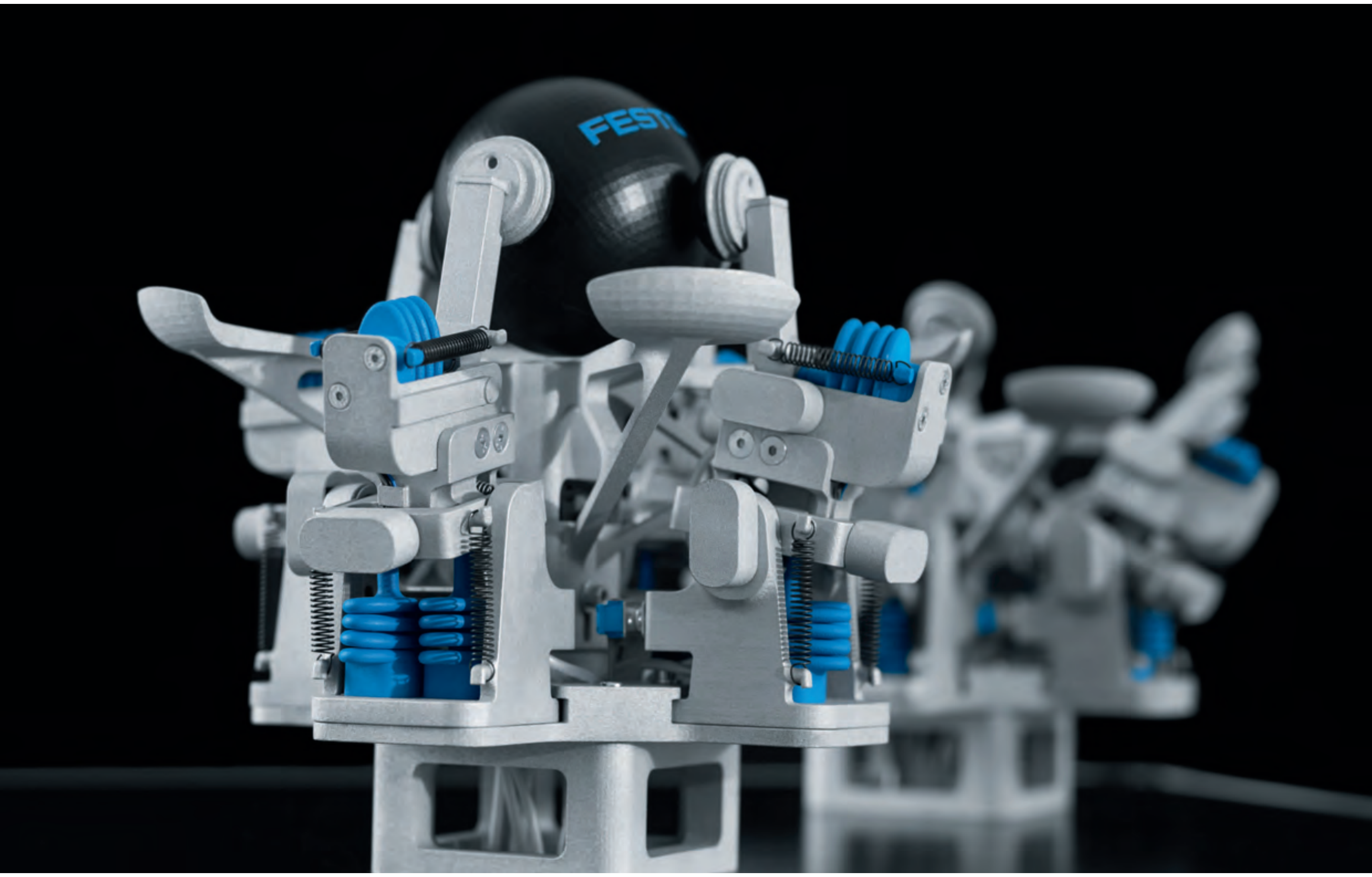
LearningGripper



Machine
learning

Gripping and positioning through independent learning

The LearningGripper from Festo looks like an abstract form of the human hand. The four fingers of the gripper are driven by 12 pneumatic bellows actuators with low-level pressurisation. Thanks to the process of machine learning, it is able to teach itself to carry out complex actions such as, for example, gripping and positioning an object.

Smart and intuitive – the LearningGripper principle
In concrete terms, the gripper assigns itself the task of turning a ball so that a particular point of the ball points upwards. Based on the trial-and-error principle, the intelligent system thus acquires the motion sequences required to achieve this. The more time it spends learning, the more reliably it completes its task.

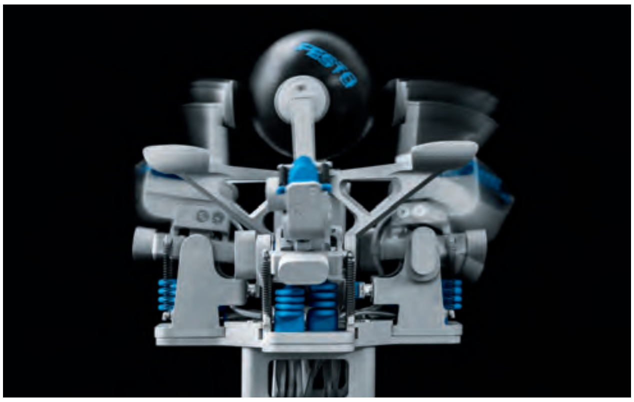
Reduced programming effort
With its LearningGripper, Festo demonstrates how, in the future, systems will be able to execute complex tasks independently without time-consuming programming. When the conventional procedure is used, the developer has to assign a separate action to each possible status of the fingers and the ball.

Only the elementary actions and possible positions of the LearningGripper's fingers, as well as the function for feedback from the environment, are defined in advance. The gripper is only told what to do, but not how to do it. The complex motion strategy required for this is developed independently by the gripper's learning algorithms – without any further programming.

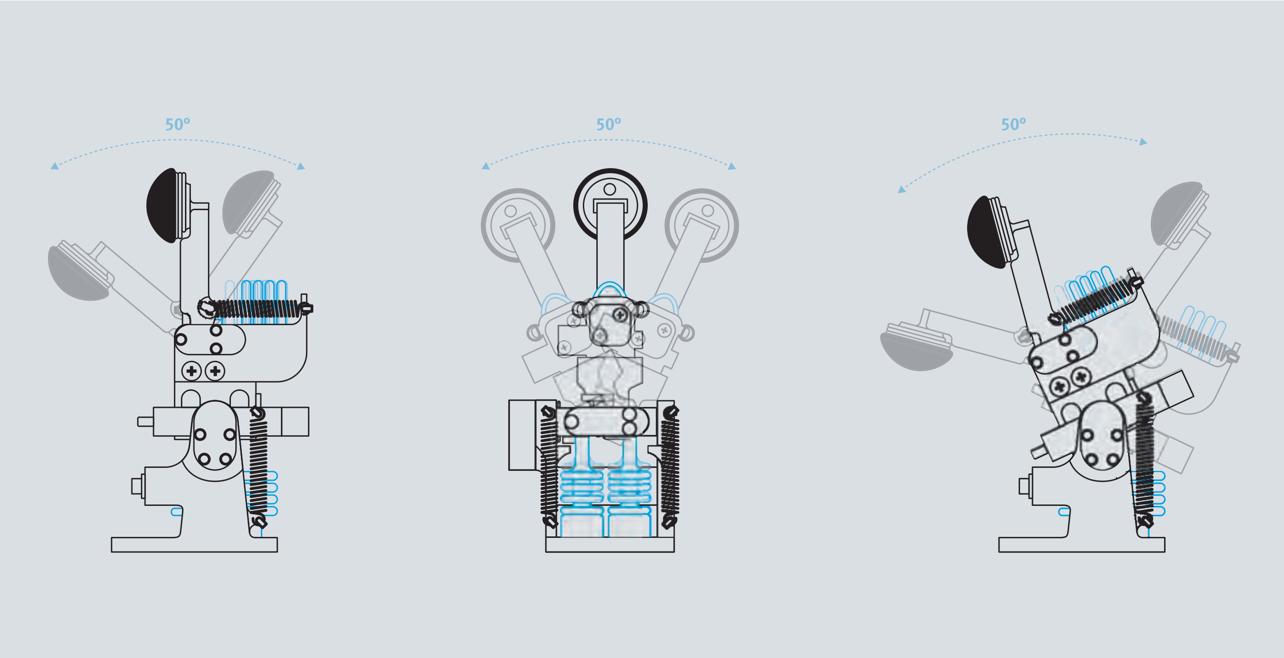
Knowledge transfer to other grippers
By transferring the strategy from one gripper to another, the second gripper is provided with the first gripper's previous knowledge which it can use to develop its own strategy more efficiently. The more similar the hardware is for the two grippers, the more productive the transfer is. The more previous knowledge is available, the more quickly the system becomes fully functional.

Potential for the factory of the future
With this principle, self-learning systems like the LearningGripper could be built into future production lines and autonomously optimise their own performance. This is why Festo is already closely involved with machine learning capabilities.

Self-learning: The LearningGripper's four pneumatic fingers …



… position the ball until the correct side is at the top.



Flexible: Three degrees of freedom provide each finger with the basic functions of the human index finger.

Pneumatic bellows-kinematic system
The LearningGripper reduces the human hand to four abstract fingers, each of which possesses three degrees of freedom and the basic functions of the human index finger. Each degree of freedom has an angle range of ± 25°. The gripper's kinematic system is operated with low pressure between 2.5 and 3.5 bar.

Highly complex coordination
Retracting, advancing or maintaining its current position – by using proportional valves (MPYE) and the pressure transmitter (SPTE) from Festo, the 12 pneumatic bellows structures can be moved to any required intermediate or end position. Each finger can thus be moved in three directions. Just in its initial state, the hand has a total of 3^{12} actions to choose from in order to reposition the ball.

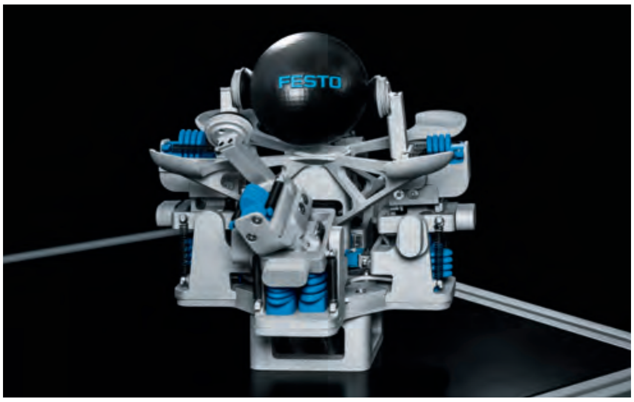
Thanks to intelligent coordination of the fingers and the flexible polyamide bellows structure, the kinematic system is pliable and can move freely. It can reliably grip, lift and rotate even the most sensitive objects – just like its example in nature.

The human hand is a highly versatile tool. It can be very powerful, as well as extremely delicate and sensitive. Many of the characteristics exhibited by objects are best appreciated with the hands – for example, shape, size and texture, as well as temperature and weight.

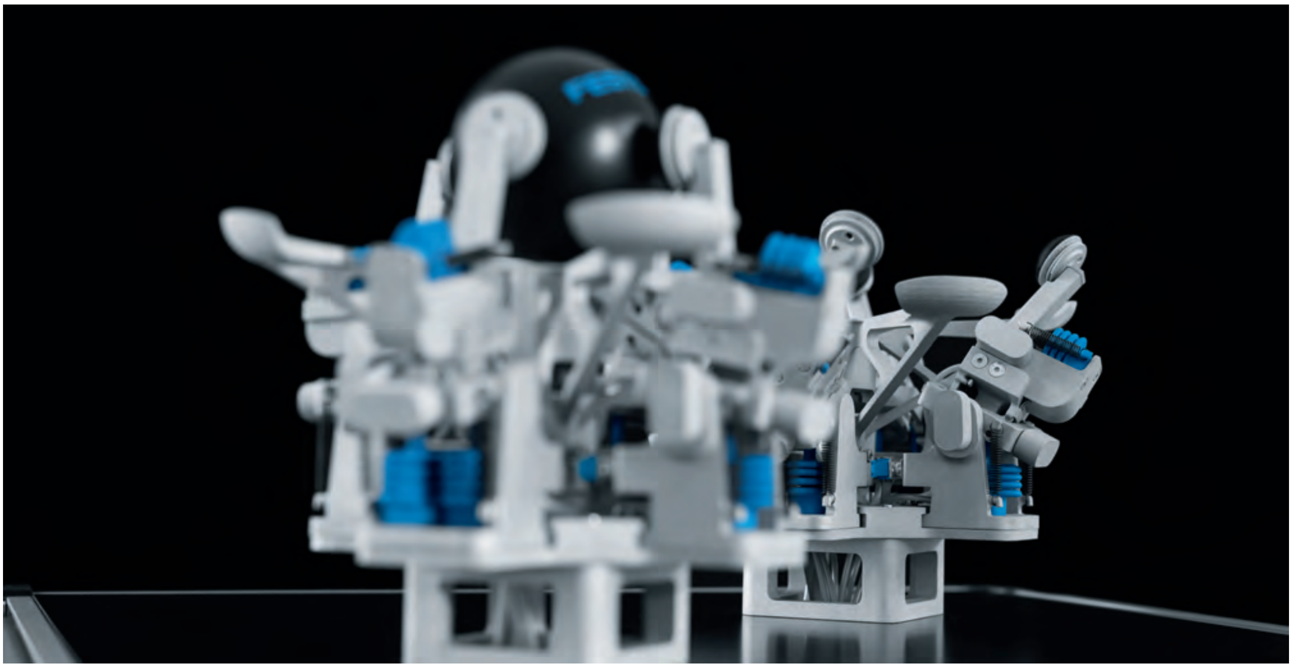
Gripping and learning – intelligent interaction
There are theories stating that human beings are only as intelligent as they are because the hand can carry out so many complex tasks. Babies start gripping objects very early – for example, their mothers' fingers. As soon we learn to correctly grasp an object, we can turn it and look at it from all sides. Only this enables the human mind to reconstruct a three-dimensional object. The hand is thus a learning tool for the human being as well.

And, people learn in two different ways: explicitly and implicitly. In the case of explicit learning, an exact pattern is provided which has to be imitated or learned. Implicit learning is understood as the unconscious or playful acquisition of skills and knowledge while an activity is being carried out.

Imitation: As is also the case with its example in nature ...



... the hand helps the LearningGripper to learn.



Simple: knowledge transfer from one gripper to another

Machine learning
Machine learning methods are comparable to those of human beings. Their practical implementation within this subdivision of artificial intelligence is the work of algorithms which develop performance or motion strategies on the basis of feedback received on its behaviour. Just like people, machines also need feedback on their actions – positive as well as negative – in order to classify them and continue learning.

Trial and error – learning through reinforcement
The LearningGripper makes use of the method of reinforcement learning. The gripper optimises its capabilities exclusively on the basis of feedback that it receives concerning its previous actions. The system is not provided with specific actions which it has to imitate, as would be the case with supervised learning. The learning system alternates its actions with the key objective of maximising feedback over the long term. Consequently, this increases the probability that a successful action will be executed and that a less successful action will therefore not be repeated again.

The reward principle
At first, the LearningGripper attempts to randomly rotate the ball so that its label is on the top. It receives feedback from a position sensor inside the ball indicating how far the label is from the palm of the gripper's hand – the greater the distance, the more positive the feedback.

In time, the learning algorithms develop a motion strategy on the basis of this feedback. The gripper learns which action needs to be executed for each given status. It knows how to modify its motion so that it receives as much positive feedback as possible, and finally executes its task reliably.

The LearningGripper display for trade fairs demonstrates a gripper which takes less than an hour to learn a mechanical motion strategy – from its first attempt to the reliable execution of the required task. A second gripper demonstrates a process it had learned previously within the desired target scenario: it lifts the ball and positions it so that the embossed lettering can finally be seen at the top.

Smart: The learning algorithms replace complex programming ...

... and allow for quick commissioning of the system.