CRAIG: ([00:00](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=0.03))

Hi, I'm Craig Smith and this is Eye on AI.

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[STOLEN GIN](https://www.facebook.com/stolengin/) - [SECOND TO THE SUN](https://www.youtube.com/watch?v=eflzJOM7_sg)

CRAIG: ([00:13](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=13.16))

A lot of listeners are AI practitioners, students or researchers or engineers engaged in the field, but many of our listeners are interested and informed but are not experts. I want to propose to those listeners and to those who have friends or family who want to understand AI a quick way to get up to speed. The people at the application design and development company, [Infinite Red](https://infinite.red/) who are supporters of this podcast are offering a free mini course, [AI Demystified](https://academy.infinite.red/courses/). That's a great place to start for anyone intrigued by AI. At the end of five days, anyone will be able to speak intelligently about supervised, unsupervised and reinforcement learning and about practical business applications for AI. If you're a business leader, you need to know this stuff. In fact, I think everyone who wants to participate in the global conversation about our future should know this stuff.

CRAIG: ([01:15](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=75.41))

I've taken the course myself and I'm recommending it to all those people in my life whose eyes glaze over when I start talking about AI. Check it out at [learn.infinite.red](https://academy.infinite.red/courses/).

CRAIG: ([01:29](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=89.06))

Now listeners to the podcast know that one of the subjects that fascinates me is the blending of machine learning and robotics. While much of the world thinks they are the same thing, most robots are preprogrammed with classical control theory using complex and precise equations. Thinking robots, the kind that inhabit the popular imagination, are still the stuff of research institutes. They generally move slowly. Their researcher overlords focused on how the control algorithms are learning rather than on swift or dexterous movement. But my guest this week, [Aude Billard](http://lasa.epfl.ch/people/member.php?SCIPER=115671) from the [Learning Algorithms and Systems Laboratory](http://lasa.epfl.ch/) at Switzerland's, [École Polytechnique Fédérale de Lausanne](https://en.wikipedia.org/wiki/%C3%89cole_Polytechnique_F%C3%A9d%C3%A9rale_de_Lausanne) , blends [control theory](https://en.wikipedia.org/wiki/Control_theory) with machine learning to build robotic systems that are both swift and precise, but can handle some of the unpredictability of the real world. Her lab famously [taught a robotic arm to catch a tennis racket](https://www.youtube.com/watch?v=24TCUZISIdU) looping through the air. We talked about how she and her colleagues accomplished that feat and her work on evermore precise robots that can even do the work of Switzerland's famous watchmakers. I hope you find the conversation is fascinating as I did

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Can you tell me about your work, what your background is, where you're from, how you got involved in this particular aspect of machine learning?

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Oh wow. It's a broad question. So, my background is in physics and I actually studied particle physics at a time when AI was, you know, starting off and we were using knowledge works in particle physics to predict the statistics of the particles and I got interested. So, I went on to do a PhD in what was called artificial intelligence and that's how I got started in AI and robotics because the two of them were already quite tight at the time. And then continued doing that as a faculty member.

CRAIG: ([03:39](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=219.87))

And robotics, then did you do your PhD in?

AUDE: ([03:43](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=223.99))

It was in AI, but robotics was part of the general curriculum and I really loved to actually program robots, so to develop algorithms AI algorithms and then put them in a robot because this way you actually see the algorithm doing something for real. So, I love that aspect, especially as a physicist where when you work in particle physics, you are only one among long list of names and you know you're studying the data but you're not actually constructing machines and doing the experiments. And in robotics, you do everything, you construct the robots, you program the robot and then you do experiments. So, I love that. And of course, I loved the algorithmic part, which is applied mathematics, which is very close to physics.

CRAIG: ([04:24](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=264.17))

In the public imagination. Robots are AI, you know, every article you see has a robot illustration and marrying the two brings us closer to what the public imagines AI will be at some point. And what struck me about your work, I've been to the Berkeley AI research laboratory and watched the robots there and the grasping and the movements are extremely primitive and extremely slow. And I had never seen this kind of dexterity and speed in an AI driven robot. So, I wanted to hear more about that research, how it came about, some of the technical aspects, I mean, is this all supervised learning? Is that reinforcement learning? And then we'll talk a little bit about the videos which were spectacular.

AUDE: ([05:18](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=318.21))

So, well thanks a lot for your comment on the video. So, we've been working on this for several years now and I mean maybe we're not broadcasting ourselves often enough, but certainly, I mean dexterity has been core to all the research that we're doing. And fine dexterity, and by that I mean also controlling all the fingers of the robot and we're lucky enough to have a robot that has many of those. It's not AI driven and I really want to emphasize this because in robotics traditionally we use control, control theory, and it has to stay there. AI is not going to replace this. It's going to supplement control theory and we should not ignore it. All the actual robots, they're driven by law of control and [inaudible] now for decades and they are very useful but they have all limits. And one of the limits is really to be able to embed very complex function and to embed also a notion of this uncertainty, which is key to a world and most importantly is the ability to be able to retrieve fast solution which control can find.

AUDE: ([06:12](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=372.11))

So, control can find a solution to all these problems. Like you said, the grasping that we can see maybe the grasping that you've seen is primitive and we have more developed grasping ability or developed things in pure control. But it takes time because we have to solve for very complex equations and it requires, you know, a lot of information about the world, which we may not be able to write down in mathematics explicitly. We will, it will be fairly complicated. So, they cannot be ported for robots to act in the real world extremely rapidly as we want them to do when they work in our world. Let's not forget that robots have been out there in the industry now for two decades and they, and they are doing very impressive manipulation. Actually. It's a world completely designed for robots, a world designed for control theory. And now if we want to move a little bit into the real world, which is a little bit more uncertain than we need to leverage the strengths of machine learning, but I insist they have to work together, we cannot suddenly say, well, everything has been done in control should be forgotten because that was the old-fashioned way of doing things.

AUDE: ([07:09](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=429.35))

No, this is absurd. It will be like physics saying, well, you know, Newton, it was interesting, but now let's move on. You know, or revisit physics with machine learning. It's ridiculous. No, we need to, science builds upon things and we should remember that. So, the reason why we manage these things is because we were lucky enough to find a way to combine some of the strengths of control theory and some of the strengths of machine learning is a little bit of a coincidence. I just got exposed to both fields and, and I could put things together and, and I'm not the only one. In fact, in robotics there are many people working like I do, which are combining those fields.

CRAIG: ([07:41](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=461.05))

Yeah, I'm certainly aware that all of the robots, 99% of the robots, industrial robots are pre-programmed and everything, all the equations have to be perfect for precise applications. If they are precise applications. Let's take the video of the tennis racket, which I thought was incredible. So, a tennis racket, the trajectory or the path it takes towards the robot is not linear. It's looping. And as you explained this, the center of gravity is not in the racket part. It's in the handle. I guess the first question, how is the robot tracking that? And the second question is how has it learned that its goal is to grasp the handle?

AUDE: ([08:27](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=507.13))

Oh, I see. So how does it track the racket? We're using external cameras that are sampling at very high frequency, so they're something like 250 Hertz, but the total duration of the flight is less than half a second. So, 250 Hertz, half a second, means that you have about 120 frames. If you're lucky and you lose some frames. And so, you cannot say, well it's easy because you have lots of frame. Because in reality, if you start moving when a racket is about to hit you, it's too late.

CRAIG: ([08:57](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=537.69))

How does it know that it has to grab the handle that was given to the robot that was part of making the task complicated? In fact, why did we choose these tasks to showcase that we could control in close form extremely rapidly. So, we had to find something that was super-fast and picking up the handle made it interesting because the handle is looping. If we had chosen to pick the racket in the middle of the center of mass, it will have been easier in that sense. So, on propose we chose something that we could grab that was large enough for the hand of the robot, which is actually quite big. So, we needed a big object and that can spin that we could throw easily. So basically, the handle is given by default, you could imagine to train the robot to know that this is the only place that it can grab from. We actually also did work on that, but that wasn't the purpose of that particular video.

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INTERLUDE

CRAIG: ([09:52](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=592.78))

so, you've got the camera that's tracking. The trajectory that is being tracked is being collected as data that then is being analyzed through machine learning.

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There are two parts. One during the training part we just threw the racket out without the robot catching it because it doesn't know how to catch it, so it would be as if you're watching animals passing by and then you learn the dynamics of a jaguar jumping around so you observe the racket flying. We're tracking specifically the handle and so we put markers on that and we are tracking the displacement which gives us information solely about the position over time. From that we can compute the velocity and the acceleration and then we can learn a model of the translational acceleration, rotational acceleration as a function of the position of velocity. Basically, we are identifying the unknown term in the Newton equation. They are unknown because it's difficult to explicitly write what is the model that applies to the racket because we will have to go and measure the mass of the racket.

AUDE: ([10:57](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=657.4))

It's mass distribution. We'll have to have a good model of the friction coefficient to estimate the air drag, which will of course completely change as a function of how the racket is flying. If it's flying facing, you know the wind or if it's flying, flying a little bit on sideways, it will be completely different. It will be difficult to write this down and it will be very difficult also to choose at runtime as soon as you launched a racket. Which of those different models applies to this particular trajectory? So, we thought that was a good avenue to show that machine learning can actually simply leverage the fact that we know from Newton that acceleration will be related to some extent to velocity and position. It's a, it's a law of physics, but we don't exactly know how and what the terms are in machine learning can identify that from a few examples of throwing the racket.

AUDE: ([11:46](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=706.06))

It was the same for the bottle half filled with water. Same thing. It would be difficult to give a complete model of a bottle half filled with water, but then we can identify the nonlinear dynamics from the data themselves. Once we have this, then at runtime when we want a robot to catch the object, then it's using the learned machine learning. It's no longer learning. It's actually retrieving and predicting and using this in a feed forward manner. So, feed forward manner means that the algorithm's picking up the current position of the racket, it's current velocity, querying the model to see what is going to be the acceleration at the next step, compute the acceleration and then integrate twice to compute the position at the next time step. Use this prediction again, inside itself to say, well what will be the acceleration in the next time step and so forth.

AUDE: ([12:33](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=753.61))

So, it's really a feed forward mechanism and this is the reason why sometimes our prediction is a little wrong because we're predicting forward but we are verifying along the way but much slower, our verification is slower than actually the prediction of the model. So, the model is going to predict, you know at 1000 Hertz, extremely rapidly the motion, but we are sampling at 200 Hertz, so one fifth of that. And we verify every five times. If you want, are we correct in our prediction? And if you're not, then we correct. We give the current position that is measured and we get the algorithm to predict again forward. But the algorithm predicts forward really fast. It predicts forward the entire trajectory until it gets into the workspace of the robot. And that's needed for the robot to decide if it goes, if it's going to run on the right-hand side or run left-hand on side.

Speaker 6: ([13:18](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=798.57))

Then the robots, once it's made this calculation, it knows the position that it has to reach to. How far in advance does it know?

AUDE: ([13:28](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=808.11))

Oh, it computes the trajectory until it gets out of the workspace of the robot. So basically, it computes forward a trajectory flight and verifies if the trajectory will actually cross its workspace. That's something I didn't mention, but if you estimate the trajectory is going to be outside the workspace of the robot, the robot doesn't even try. It doesn't go there. But if it sees that it's going to go through the workspace, then it will determine which point is the most likely that it should, you know, be capable of catching it and it will start moving towards that point. But that as it moves, it keeps track of the object a little slower than its prediction. Keeps updating this model and keeps adapting its motion to eventually meet the object. And since both of these adaptations, the adaptation of a prediction system, the adaptation of the control are happening very rapidly, then that's how we can meet, in fact, the object on time.

Speaker 6: ([14:18](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=858.55))

And then the grasp is that traditional control theory or is there also machine learning in how tight it has to grasp, the configuration of the grasp?

AUDE: ([14:29](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=869.92))

That's a very good question. When we close our fingers on things, it's completely coupled to the motion of the arm. And so, the faster we go, the faster we're going to close the fingers usually. So, the fingers have to be, to close extremely rapidly. And for that we leverage the fact that we can have a dynamical system for controlling the closure of the finger and a dynamical system for moving the arm. And we can couple them with traditional coupling in dynamical system theory. So that is control. Yes, the coupling, there are many different ways in which we do the coupling. We could learn it. We've done this in other works, not in that one, so it will be possible to learn the coupling. In this case we don't do that. So basically, these two things are there. This is control for you.

AUDE: ([15:10](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=910.88))

The tightness of the grasp is a good question also. We go as tight as possible because of the speed at which it flies and especially because in the video I've shown here in that particular grasp we were stopping and that was a real problem. That's why we had 40%, well maybe a little less, of unsuccessful grasps because it will hit so hard the hands, the elastic shock will be so strong that it may break the hand from time to time or the rocket may fly back just because of the elastic shock and there is nothing you can do because it, we tried to measure the force at impact and try to change the impedance which is also control but in fact there is really no time for doing that. Practically speaking for that type of application. If it was slower then we could do it. If you're interested, I can show you also another video, but this is not machine learning.

AUDE: ([15:58](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=958.28))

We found out that humans are very good at catching and the reason why they do that is that they put themselves a little bit in orbit with the object. When you have a board coming in, you get there and then you move with the ball for a little while and then you close and that allows you to also leverage an uncertainty. So, but that, yeah, that's, that's a different way of addressing the problem of controlling, not so much for the force but for the uncertainty at impact. So, in that case, for that particular work, there was no learning for the grasp,

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The adjusting in the way that a human hand does for the trajectory to in effect, slow down the object. If you're moving with the object, right, then you're slowing could be learned as well.

AUDE: ([16:37](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=997.2))

It could be learned as well. Yes. The way I approach machine learning is to use it when I need it and to not use it when I don't need it. And similarly, for control to use it as much as I can and when it fails me then to find, you know, an alternative as machine learning. But if you already have a good solution such as coupling then there is no point to, to redevelop.

MUSIC: ([16:57](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1017.781))

INTERLUDE

CRAIG: ([17:05](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1025.82))

And the other problems of force, knowing as the weight of the object changes when you were filling a glass or tugging on an object, knowing how much pressure to maintain the grasp, is that also learning or is that traditional control?

AUDE: ([17:21](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1041.99))

It's a bit of both. So there learning is needed because it's another example where you need to react extremely rapidly. When the glass starts slipping off your finger it's not as if you have the time to run a complete system to determine or where should I put my finger to restabilize that. I mean, you know, you as a human also do it as sort of reflex manner. So, we learned, but we learned that from - part of it was learned from demonstration. So, we will have somebody moving the finger of the robot and as move to the fingers of the robot are compliant, they can be moved as they hold the glass and as you move them then the robots recalls the displacement of the finger as well as the change of the force felt along the finger. And this is very important because basically it's implicitly learning to some extent how should I displace my finger to compensate for the change in the loads that I'm perceiving? And it's the relative change of the load. It doesn't matter if it's fairly heavy or fairly light, it's more like suddenly I feel that there is more load on the righthand side it's probably, I feel that there is a tension force going down so it's probably slipping, so I should tighten my grip. And it doesn't matter if you feel that it's a hundred gram slipping from your finger or 200 gram or 300 grams.

AUDE: ([18:35](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1115.88))

So machine learning is very useful because it can learn a very high dimensional math which basically it learns correlation between position of your finger and particular tactile information and so at runtime afterwards when you feel that there is a change in tactile information, you can create a system and say, well usually when you feel this type of tactile information, let's say all the load on left hand side, how should your finger be? And it's going to say, well my fingers should be compensating for that. They should be on the other side and it will immediately retrieve the most likely posture for the finger to compensate for this weight. And you don't have to solve explicit equations, you just have this in fact in the system, it's in closed form so you can just query the system at runtime.

CRAIG: ([19:18](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1158.38))

I'm just curious, what kind of sensors are you using in the finger?

AUDE: ([19:21](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1161.35))

So, we're using the BioTac sensor, which was created as a spinoff from University of Southern California and they are very interesting sensors because they can perceive tangential force in addition to normal force.

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Because in Berkeley they're using, I think they're called gel tips. It has a camera mounted in the gel. Is that what this is?

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No, it's, it's a gel but it's not a camera. it's [inaudible] is based on [inaudible]

CRAIG: ([19:44](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1184.08))

And so, the algorithms that you're using to do this at very high speed, to learn this I should say what kind of learning is involved is this

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INTERLUDE

AUDE: ([20:00](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1200.91))

We use various different techniques, but for the one that we just discussed where we learn a mapping between the tactile information in the fingertip and the position of the fingers, we were using Gaussian mixture model, which is a mixture of Gaussian function. It's a Bayesian approach.

CRAIG: ([20:16](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1216.23))

And for the catching in the air

AUDE: ([20:18](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1218.77))

Catching in the air, we don't use off the shelf algorithms. We actually develop new algorithms, which are a combination of, in one case it was Gaussian mixture model plus stability constraints. So, it's a new, we call this a SEDS, that's the name of the algorithm. We're doing multiple catchings or multiple position catching. This was an augmented SVM if you want. This is a new algorithm, which we developed. So, in both cases are new machine learning algorithms,

CRAIG: ([20:42](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1242.32))

The grasping that you were working with, grasping in different configurations, the fingers, not just the traditional pincer movement. Is that also a learned behavior or is had a control problem?

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So, this was, it was first control. So, what we often do is that we run control. It's slower. So, we do that offline. So, we generate feasible posture for the finger that will ensure stability constraints. So, we will balance the weights that we will make sure that we have large enough friction and things like that that are feasible, that the fingers do not intersect. So basically, we solve an optimization problem under constraints, which is traditional control. It's slow and it's slow in a sense it may take a few minutes to solve. We sample all feasible solutions. So, we sample the space of feasible solutions and then we use machine learning to learn this piece of feasible solutions as well as the space of unfeasible solutions. And so, then we have the close observation. So, this is really the approach that we always do; that we use control for generating things that we know how to solve, but which will not be solvable at runtime. And then we use machine learning to get a generic sort of model that can be queried at runtime.

CRAIG: ([21:54](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1314.29))

You also had some demonstrations, some videos of, for example, of peeling a zucchini, right? And that's imitation learning, right? Because you have a human demonstrating. Is that pure imitation learning or is there, once it's learned, the basic for fine tuning, do you go through some reinforcement learning or something?

AUDE: ([22:15](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1335.72))

No, we did not do that and we did not need to do that. But one could certainly do that. We've done that also in the past. The reinforcement learning is, you have to guide a little bit your reinforcement learning algorithms. So, if you start off with demonstration, human demonstration, then you can use them as a way of guiding and saying, well, you should be looking for things that are around the demonstration. We did not need that for this particular task, but one could of course do it.

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INTERLUDE

CRAIG: ([22:50](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1370.49))

So where are you going now with this research? I presumably you're continuing with this.

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Yes, actually currently we're working on two sub type of problems. We're working on one type, which is to understand how we can do very, very fine manipulation such as, since I'm in Switzerland, we're working on watchmaking and trying to understand how we can actually do this insertion or do this very, very tiny polishing. But what interests us most specifically is the fact that humans can do that because it's almost beyond human capability in term of precision of control. So, we're trying to understand how humans managed to go beyond our capabilities so that we can put the same control algorithm in robots because robots will go beyond their own sensing capability. So how can they do that? So that's, that's what we're working on is extremely dexterous precision for insertion and different insertions without breaking. So, it's also learning how to shape the compliance.

AUDE: ([23:45](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1425.05))

There is a huge amount of learning there. So, we're interested now in designing in new algorithm that allows to learn what is the optimal posture of the finger because humans also learn to pose the finger in a way that ensure, maximize their ability to do the task and they probably learn to sense things that they couldn't sense before. And this tiny change in force. So, we're trying to design, this would be probably a variant a little bit on reinforcement nine because there is a bit of learning from demonstration, but it's mostly a reinforcement learning. And because what happens in watchmaking is that people try over and over again, when they are students. They do that for two years in a row, they break things, they lose things. They, and some of these elements, by the way, are semi deformable such as one element in the watch is called a spring.

AUDE: ([24:30](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1470.2))

It's absolutely key. You need to put it in place, but it's so tiny and if you don't put it well it springs out. It's terrible because you have to look for it. It's very tedious. These watches are super expensive. You've break them and you have, you know, it's a problem. So how do humans learn to manage this very, very fine control mechanism? This is what we are studying and its modeling [inaudible]. That's one. The other is that we've started also working with different university hospitals on surgery. Because it's typically a direct application for modeling how to do soldering and changing the, to model the change in the impedance of the tissue as you're actually cutting the tissue because there is liquid coming out, which is very similar to what we've seen with the model.

CRAIG: ([25:10](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1510.52))

Yeah. I mean you had the demonstration of scooping a melon. Is that recent also?

AUDE: ([25:15](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1515.23))

That's uh, that was published in 2018.

CRAIG: ([25:18](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1518.03))

Yeah, because it was interesting you were saying that even during the act of scooping the resistance and texture changes through the motions and then you were talking at the end about going beyond in cooking for example, where the materials that are being manipulated change their state. I found that fascinating. And that would require multiple sensors. I mean not only vision and touch? Well I guess there's only vision and touch for that.

AUDE: ([25:47](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1547.7))

Probably or maybe some other vision than human vision. Yes, yes. Actually, you know for surgery people are interested in OCT, optical coherence tomography, because that allows you to see under the tissue and to see the deformation inside tissue and I'm just bringing it up because it could be that we develop new sensors for robots that may also go beyond human senses and help out for these types of things. But yes, I think it's absolutely fascinating the fact that we when we do a task of this type we manipulate objects, which at the beginning are two very separate objects with very different consistency. We mix them and then they become yet something entirely different and obviously we must have learned that through observation via observation as well as sensing the texture and sensing the weight, the change in weight. This is an open area.

AUDE: ([26:34](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1594.17))

I don't have answers I have more questions. How do we manage that? How we will learn this, how will we allow robots to, to learn those things because this is really needed. And computer vision struggles to recognize static objects that are all the same, you know, and are very, very rigid. But when you manipulate these objects, there are multiple objects on the melon scooped is like once it's scooped, it's a series of little pieces that are orange and how do you determine that this is a melon and it's not just a piece of carrot or a piece of potato because you have the context because you understand that this is a result of what you've done. This is a result of scooping. And so, what would we be your reward function if you were to learn from that? The amount that you've scooped? The roundness of what you've scooped? What is it?

AUDE: ([27:17](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1637.7))

The taste when it comes to it. But that's the future. That's what we want robots to be able to do, right? To do all those tasks. And so, we need to be able to learn how to manipulate things. That's just as an effect of me touching them, they change and that's an open question. But it's a lot about prediction, prediction of what your actions have on the world and a model of deformation which may require a very complex model of computer vision. Certainly, leveraging machine learning, sensor fusion. I don't know. It's an open question.

CRAIG: ([27:48](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1668.82))

One question I had about the catching, have you measured that against human benchmarks?

AUDE: ([27:55](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1675.43))

No, but you know it's simple. You can try in your kitchen if it's safe to catch an object like that, you'll see you fail if we are not trained. Of course, trained people are very good at that. You go to a circus, you're going to see people playing around that and they're going to be very good. But it's because they're extremely well trained and also because usually - I have seen a clown who could actually throw six rackets and he was passing them, he was juggling with six different racquets but he was launching the racket and then catching it. I am ready to bet that it's much easier than if somebody was throwing a racket at him and especially somebody who doesn't know, that he's not trained to work with. Those people who throw at each other or knives for instance. They are trained people that you know, it's a trained team. How do they train? Probably with a fake knife, I imagine in the beginning. It's hard to compare because the question would be what do you compare with? We're good at catching balls because probably the symmetry. But catching things where we have to align with at least one axis, like catching just a bottle.

CRAIG: ([28:54](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1734.53))

I'm laughing because we should be good at catching balls. I could never catch a ball. What about the error rate? I mean once this robot is trained and you're throwing a tennis rackets at it, is it catching 80% of the time? 30% of the time? I mean very hard to tell obviously in a, in a video.

AUDE: ([29:11](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1751.78))

Yeah, so no, no. We did compute that for, for the paper, I don't remember for the racket but in general it was between 60% and 80% of the time. And so, we analyzed the failure and that's what brought us to go to this next step of the research which was published a couple of years afterwards, which was to give the robot more time. The major reason for failure was usually that it wouldn't have the time to close the fingers on the racket. The elastic shock was too strong. Stopping at the target was a mistake. It was smarter to continue so that brought us to the next stage. So, for that reason, but I like the fact that it was making mistakes or failure because it allowed us to address these failures, try to understand what could, what could we design? Clearly, we could have tried a faster robot.

AUDE: ([29:56](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1796.02))

It could have been an answer, but we were not interested in that. We were interested in finding ways to go around problems with sensing and precision and robustness and the physics system of the system. We also had failures simply because it's very difficult to predict extremely accurately the trajectory of the object, so we will sometimes be wrong and we could train more. Of course, we could throw more rackets, but again, that's not really the point. To me, the very fact that already you know, more than 60% of the time it will catch it, I was very satisfied because it showcased that you know, it's [inaudible] and we can solve the problem. If I was to produce a robot that should do that, this would become engineering. I would make sure that I train the system well enough so it's 100% successful.

CRAIG: ([30:40](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1840.02))

Well, that's actually one of my questions is how many other people or institutes or teams are working on this high-speed reaction as well as the very fine dexterous operations that you're working on is, is that, I haven't come across anyone doing that before.

AUDE: ([30:58](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1858.83))

I will say very, very few people, you may not have seen them because the one that I know or are not in US so in Japan and that has been absolutely fantastic work. Also, on flipping a cellphone, catching it and there, they've been, the university of Tokyo. But their focus was to develop cameras, extremely high speed and to also develop models for modeling complex dynamics from a camera, really observing the flying dynamics of the objects. So, this is something that we don't do. It Is computer vision but plus, plus using very, very precise sensors. So, there is both hardware and also the software. In Germany, in the university of Munich, they also have a paper published recently. Very interesting where they also have another strategy to catch objects in flight, which is also using now more control actually and using a model of the physics and estimating the weight of the object as it's flying, which is something interesting especially to, you know, avoid breaking the hand as we did. So, I love this type of approach. It's not machine learning, it's, it's more control. But I'll say adaptive control. So, if you want, adaptive control is a little bit of the early days of machine learning.

CRAIG: ([32:04](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1924.48))

That's right. And then in industrial applications, is any of this moving into products?

AUDE: ([32:11](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1931.29))

Of course, not forgetting I'm a researcher. I don't know if I need to [inaudible] at this stage, but yeah, but definitely, the fact is that all the algorithms that we've developed, we have a startup from the lab, which is now transmitting some of this to the industry, but we have a lot of partnership also with industry, both in Europe but also in Asia.

CRAIG: ([32:29](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1949.98))

And are you collaborating a lot with researchers? You mentioned Japan and Germany. Are you collaborating with, with these different teams that are working on similar things?

AUDE: ([32:39](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1959.8))

Oh, no. It's not that we're competing, but we're not collaborating either.

CRAIG: ([32:42](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1962.62))

That's interesting, but this is open source.

AUDE: ([32:46](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1966.43))

Yes, everything is open source. I think it's just science progressing. We're aware of each other. We cite each other, we like each other work, but we have not been collaborating.

CRAIG: ([32:54](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1974.86))

Yeah, well I found it absolutely fascinating and I'll be watching the work going forward. It was some of the most advanced work in robotics and machine learning that I've seen. So, congratulations on that.

AUDE: ([33:09](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1989.14))

It's very kind of you.

CRAIG: ([33:14](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=1994.28))

That's it for this week's podcast. I want to thank Aude for her time. For those of you who want to see some of Aude's robots in action, you can find videos of her experiments on our website. eye-on.ai. You'll also find a link to a transcript of this episode. I encourage you to spread the word about AI, and I recommend Infinite Red's mini course at learn.infinite.red to anyone interested in AI, but confused about where to start.

CRAIG: ([33:53](https://www.temi.com/editor/t/NcmioqduyN0sXOM0lk9nj5A6csYRwCn_RnXmmFD_abhL0b8HpytA1aqTgisMDA4KaiPhbv5NrSRGtiGAPZ58l2TGUG8?loadFrom=PastedDeeplink&ts=2033.88))

The singularity may not be near, but AI is about to change your world, so. pay attention.