**Session 2**

1:01 → 01:23

**Ralph Etienne-Cummings:** Okay. If you all don't mind finding a seat, we'll go ahead and get started for our next session. Thanks, everybody. I hope you got something to eat. So as we get going into our next session, we're gonna focus on human machine interfaces and talk a little bit about how neuromorphic principles can impact in this domain.

1:25 → 2:17

**Luke Osborn:** Thank you, Ralph. So just very briefly, I'm Luke Osborne. I'm an assistant professor at Case Western Reserve University, and Francisco is also here. Who's gonna be acting as moderator for this session with myself. So we have. We have 3 speakers lined up. Who? Who kind of talk about their work, and then we'll go into the panel. The panel discussion. So 1st I'd like to introduce Dr. James Cotton. So he's a physician, scientist at Shirley Ryan ability lab. He's also assistant professor at Northwestern University and Department of Physical Medicine and rehab rehabilitation. So his work is at the intersection of artificial intelligence, wearable sensors, computer vision, causal and biomechanical modeling. and novel technologies to more precisely monitor and improve rehabilitation outcomes. So James.

02:47→3:20

**James Cotton:** All right. Thanks for having me here. This is a little bit different from my normal one. So hopefully, it goes. Okay? So, as mentioned, I'm both a physician and researcher. So I was asked to give someone a clinical perspective. So I'm going to talk about some of the gaps with an emphasis on really understanding real world function. And then, where I think AI technology can really help for this as well as some modeling approaches at the end time works out. Mouse advances. There we go. So, as I said, can I talk about these things? Kind of to contextualize and frame this actually want to start with some work that Helen Wong, who's gonna. Recently. Really, looking at prosthetic technologies in the context of technology readiness levels, which are, you know, I think, developed by NASA. They're ways to kind of frame how ready a technology is for the real world. And you know, I have to own my bias like a clinician. I'm particularly interested in things at the top of this list. Right? So things that are ready to go home with end users in the real world and the essential part about that is, we really need to be actually doing studies and trials to demonstrate that those improve real world function for those individuals, and as a rehabilitation physician. This is essentially our kind of our bedrock, of our practice right? We want to improve real world participation and functioning. But then a lot of clinical trials are much more laboratory based, and it's unclear how much, Helen. I was just talking about your work. So it's very unclear. How much some of these lab based evaluations will really generalize the other world. At the same time, you know, while I'm going to focus at the top of this list. I think it's really important to acknowledge. And particularly in the context of what we're discussing here. Sometimes when we're developing more fundamental engineering technology, including a lot of the work that's done at the Center for Bionic Medicine, where I'm at. You really need to make sure those engineering principles are working or at play. And so you're going to be having very different evaluation frameworks. So I think this is a really good way to contextualize things. And then, just as I noted, I'm going to be working at the top. And so here are just two examples of some of the technology readiness tables that were in this paper. One of them was talking about sort of decoding methodology, and I think an important point to take away here is that, for example, on the far left at the top you can see emg pattern recognition. So this is a machine learning based approach to doing a prosthetic control. It's also important to understand. The mathematics for this were essentially developed in the 19 fifties. And so it took a really long time for these, even in today's terminology kind of simple mathematical techniques, to truly get into commercial devices and be part of clinical studies in the real world and demonstrate their efficacy. And then you can see all of the approaches right now going on that are very exciting, using deep reinforcement. Learning and things like that are not really at that stage yet. And then the next table is talking about surgical techniques and their technology readiness levels. So, for example, targeted muscle reinnervation that was kind of partly developed at Shirley rideability lab, then rac is an approach to rewiring the nervous system. To create, making the muscles into a biological amplifier makes it easier to get these signals for control. It's been studied for years. It also has improvements in pain control. And so technologies like that can really make a big benefit in real world function. But it takes a lot of time to get out there. I'm also very bullish on Osseo integration, which I'll come back to when I start talking about some of the clinical needs. And then, of course, there's a lot of exciting technologies coming out like, for example, Rp and I, where they make these little muscle burritos, and they can create more localized amplifiers. But then we have a lot more technological problems in order to get those into the real world because they don't produce signals that are large enough to be recorded on the surface. And so you need to actually now have invasive wires and all the barriers that come with that. And another important point I thought that was emphasized in this paper is that there's just generally not enough home trials, and possibly not enough clinical trials. And so I mentioned earlier. A lot of the studies tend to be in laboratory studies. They're using outcome measures that are hoped to be surrogates of the things we care about in real world function, but that often doesn't hold true. And I'll talk about that again in a moment, and so on. The right, for example, here's 1 sort of exception to this, where it was one of the studies showing pattern recognition really improved arm function. But it takes time to learn these things, right? So we really need these home trials with time for people to adapt to these technologies because most of the time you have this co- learning process between machine learning and the technology and the person in their nervous system. But I also want to highlight a limitation of this, that this is a laboratory-based assessment that was the primary outcome measure. So this was not a study that included, studying real world arm usage at home and demonstrating that this really improves people's ability to do activities of daily living. On the lower left. There's also a really nice study that included. Which one am I talking about here? Yeah. So this was a retrospective analysis that was looking at several 100 transfemoral amputees and the benefits of having a microprocessor to reduce falls. And it was a really powerful predictor. But again, we actually start to need to have causal understanding. Right? So it may well be, while these were a matched population of K. 3 level ambulators. That there could be reasons that clinicians gave some of those individuals microprocessor knees, and other people. Not that could actually be explaining some of this. So we don't necessarily know, based on this, that this gives us the right causal understanding. But still, things like this are really important, and also, like, you know, as a clinician, these are essential when we're justifying insurance. Why, someone need a certain degree of componentry right? Sometimes, for example, we can make a claim that someone who's otherwise a k 2 level. but maybe as a bilateral upper amputee as well, and can't catch themselves as they fall, has an increasing need for a microprocessor knee. So sometimes we read between the pieces of evidence. But we really need that good evidence to be out there to help us. then I think it's also really important to take a step back and say, Hey, if we're trying to get technologies that help people, what are those people telling us will help them right? We can't let the engineers assume that they know that. And I say, this is an engineer by background, right? But, like you also have to work closely with the patients. And I think, you know, this study was really nice. It kind of grouped all the things that participants wanted into a number of things, including that the devices are how it affects their psychology and cognitive barriers, ergonomic factors, and then kind of like another category. And I put arrows, blue arrows by some of the ones that were the most frequently reported in this meta-analysis. And, for example, right up there is good comfort right and right below that is less pain. This absolutely mirrors my experience in the clinic right? When participants come in. They're not asking very frequently about what kind of new software firm updates are out there like how much smarter their prosthesis could get. They're saying, this hurts here. I'm losing weight. My socket doesn't fit properly. I'm having to use so many socks. Everything's sloppy. And or I have skin issues. So I haven't used it for 3 or 4 months. Right? And so these are the problems that we actually end up spending most of our time with with our patients. They also really emphasize kind of the psychosocial aspects of the self-consciousness about their prosthesis when they're falling, actually, embarrassment and shame around that it becomes a really big factor and affects their confidence around movement as well as it actually requires a huge amount of attentional demand for a lot of these individuals to walk so they can't dual task. The way that someone with intact limbs might. And then you can see that actually, the functional performance of walking it ranks pretty highly at 700, but like nowhere near as high as some of these other priorities. And then mobility, and of course, balance and stability. Actually, I'm surprised it's not higher. I thought there was somewhere else. Something about safety was important. But yeah. So safety falls more into the psychological category right? At nearly a thousand. So that's really important. And then, of course, these priorities for individuals vary across time. So, for example, women put a higher priority on balance or time and individual factors. So women prioritize more balance, walking ability, donning and dolphin ease and energy expenditure as people become older and lose some of their independence, actually just being able to do their ads or activities of daily living becomes a higher priority. And so I talked earlier about the importance of real world monitoring. And there's this concept of capacity versus what people actually do in the real world. And it's really essential. And put here some work from Catherine Lang in the upper extremity in individuals with stroke, because I think it says some of the best job of showing a dichotomy where they would actually do various interventions and study how well, as people upper extremity performance was in lab-based assessments, which they consider a rat or capacity, and sometimes that would improve. But when you actually look at how people are using their arms in the real world as assessed with accelerometry that wouldn't necessarily change. And there's different subgroups of participants. But again, this speaks to the fact that changing our laboratory measures may not be the actual, true, surrogate endpoint that we want. and then lower limb prosthesis users fall a lot, and I'm talking about half of them will fall in a given year. There's a lot we don't know about their falls, a lot of context that we don't have the quality of our clinical predictors, for this isn't great. I mean, the best thing that will tell you if someone's going to fall is, ask them if they've fallen right. But if you want to identify the person who's going to have their new fall, if you, for example, look at the performance on these different functional tests. They actually really don't do all that. Well. and having that context of falls is essential. Right? I remember Francisco actually at the Nsf Dare meeting. We were talking about the number of steps people take. Typically, it's very few before they go down. And additionally, there's kind of these paradoxical patterns, you'll see where transfemoral amputees might actually fall less than you would expect. Given that they have relatively low performance on a functional test. But when you go and actually measure how much they're walking, it turns out they're barely walking right? So if you control, if they're per step in incidents, you get a much different picture of what these different outcome measures mean. So it's really important to contextualize people that way. And so now I'm going to talk a little bit about some of the work in my lab. And really, what my lab focuses on doing is making high quality movement analysis more accessible in clinical settings and then trying to make sense of that data, to improve outcomes. And that's just based on my clinical experience. How someone moves and walks in my clinic tells me so much about their health status. And that's just information we leave on the floor right now. But that's because we don't have the technology to measure it. So on the left is kind of a picture of one of our acquisition systems that runs off a nice little dashboard and on the right. You're seeing a bunch of cameras integrate into a hallway. So we can actually do gate analysis of participants going through inpatient rehabilitation. And if we survey our therapists. They really are desirous of ready access to gate movement analysis, right? They think it would help them track people quantitatively as they treat them, make sure they're responding in the ways they expect, and that it would allow them to better justify to insurance that people are making progress if they maybe plateau on some of our cruder measures which typically require only a stopwatch just for time. I'm not going to belabor the way we do some reconstruction. But there's some kind of fun math we've been developing to account for some of the challenges with AI and computer vision based approaches. But the end result is something like this. So here we actually took our system, like our portable system, to a prosthetics conference, we were able to get a bunch of people 17 prosthesis users in 2 days as they did a number of tests. Here, you see someone walking regularly. You can see that biomechanical reconstruction looks quite nice. We can. Oh, the color bars didn't show up on this. Oh, well, so yeah. You can see there's differences in the joint angles that you can pick up just from walking. You might wonder how we actually divide the gate cycles, but we, you know, a couple of years ago developed an algorithm for doing gait analysis from a smartphone and breaking down the per gate cycles, which, if you look at when those feet change color and they hit the ground. It tracks quite nicely. There's some interesting things we could discuss about AI fairness for people with disabilities and generalization of algorithms for different clinical populations. But I won't right now and then. Of course, we can get people doing different activities. So here's someone doing a L test on the right and timed up and a test on the left. Again, These are tests that are typically used for predicting fall risk, but purely based on kinematics. Here's another individual in the lab setting on the right. You're seeing the 4 square test. Another test that's often used for predicting falls. But what's great about this is now, when we do all of these tests with minimal setup time, right, we just bring someone and we click, go. We can get this much, much richer understanding of how they're moving, which we hope will help predict particular types of falls. Oh, and and then just kind of we can, you know, to make this more accessible, right? Because we can't always bring people to where we have tens of cameras. We also have approaches now that are working really well and can track from an individual smartphone within 5 degrees. We can, you know, track within a couple of centimeters. I'm not going to talk too much about upper extremity function. But here we actually have approaches that can track every individual joint in the hand. So we can really understand what people are doing in the real world. Actually, just kind of as a shout out to some discussions earlier, we're starting to use some of these in a collaboration with monitoring neurophysiology, with Dbs in apartments. And so I'm very excited about these methods. But going back to the real world outcomes, which is essential. Right? So we hope that these methods in the laboratory setting will be more sensitive. That's a scientific question. But we need to actually measure what people are doing in the real world. So here's a wearable sensor system. We designed that kind of record, everything on the SD card. Every single step the person takes uploads that to the cloud. I'm sure battery life would be a big usability issue. But then we can see kind of just different examples of things we might capture, including a very clean stable gate in the middle, an example of someone that actually has a bit of a stumble, but manages to recover. So you get this quick reversal of their foot, but then they swing through it, and then another example of a stumble in a fall, which is what we don't want to occur. But if it does occur, we really want to capture that, and then we'll have the context of how someone's walking as well before that, to really tell us, did this person have a long bout of walking and a couple of stumbles, and one of those stumbles turned into an unrecovered falls as opposed to another person, and perhaps that person will have a low minimum toe clearance in a laboratory assessment. Another individual might have very unstable performance on a timed up and go and tend to fall after just a couple of steps with more of a lateral pattern. So we think we can really answer those questions. But what do we do with all that data? Right? And I think it's really essential to think a lot about this, because I started doing all this movement analysis because people were saying, Hey, we really should do this. And then I got all that data. And I'm a clinician. I'm like, Okay, how do we make anyone better? And as far as I could tell, no one really had a framework or a formalism for how to address that problem. And so the way we're thinking about this. And actually, there were some comments earlier about causal using digital twins and causality. And so I think this is kind of a relevant touch point. But we need ease and part. It's computational that changes their walking. So we don't have to run every single Rct out there, because that's just impractical, and my field absolutely suffers from a lack of Rcts. And we also have a huge amount of variability in our people, which means that most of the studies that are out there have such narrow inclusion criteria, and they're completely irrelevant for me in clinical practice. Right? So we need different approaches. So we really take seriously the idea that we can model and rehabilitate plasticity. I love the causal frameworks and causality and recommend that book highly. But taking this to the point, oh, that got butchered, didn't it? So, taking, there were words on that when it was on a mac but so jeez give me a second. So essentially, this is meant to represent a causal diagram that we're going to fit to the data right? So there's the brain. And it's sending all these signals back and forth to what's intact with the nervous system and the musculoskeletal system. There's a prosthesis on there. A brief shout out to the myosuite group who has their Myo challenge on prosthetic control. This year. We are on the right. These are meant to be laboratory measures of stability and real world measures of stability. We also have a bunch of surveys you can ask about. Like, you know, balance, confidence and mood and cognition, which is hugely important, too. A lot of people have comorbidities that affect cognition, cognitive demands on walking, those that interact, we got our age and comorbidities which are meant to go down to the K level, which is then meant to go down and cause all of these things. It's almost impossible to draw a sufficient causal model because there's so many interactions, right? But we can start to build explicit hypotheses of these and then fit them to our data And our data is going to be longitudinal right? It's going to have a rich amount of understanding of people, medical biomarkers, imaging biomarkers. It's going to know about the interventions we did. And then, finally, we can take these digital twins and learn. And what's called the optimal dynamic treatment regime which says, If you phenotype a patient this way, this is a data driven prediction of the intervention that will then maximize their long term function, which is the thing I always care about. Yeah. And even just like we started developing this framework around using Emg biofeedback and the need to have short-term surrogates for how we optimize the biofeedback protocols to maximize long-term arm function. Right again, I think that has touch points to what we were talking about earlier about like, how do you figure out what are the bio signals in the brain that you want to adjust to get long-term seizure control? And just because we were talking about devices earlier, I'm just giving a brief shout out to another collaboration with some of my colleagues on this next generation, brain machine interface chip. This thing has 65,000 channels. It's fully wireless. Slip it under the brain we were talking about like the telemetry being a bandwidth limiter here. This device is powered at 60 milliwatts, but we can get 100 megabits per second through the skull. There's a hype like, you know, a relay system that can do the real time computation. So I'm excited about this technology as well to be able to touch on some of the things we were actually discussing earlier. And there we go, oops overshot. Thanks to everyone that supported this. And I think I finished on time

20:42 → 20:50

**Grace Hwang:** 3 second question very quickly. Pardon my, go to the user survey earlier in this presentation. And there was a category called embodiment and I was wondering, does that mean wearable in the context of the user survey?

20:52 → 21:49

**James Cotton:** No, typically. So actually, Helen's paper talks about how it's not a terribly, consistently defined concept. So I'm hesitant to speak too much about it. But It often refers to how much someone feels like they're in control of their limb, or how much they identify it as a part of themselves. Self. It is often like people with osteointegration or bone anchored limbs, because they have osteoperception. They feel like they own that limb more, they feel more in control of it. I think there's some hope that some of the modalities that can give sensory feedback can also increase embodiment. And we know we can do it like, there's that one famous neuroscience experiment where you have with, like their real arms over here, and there's that kind of fake rubber arm here, and they can't see it, and you do the paired stimulation for a while, and they slam a knife into the rubber hand, and they freak out right because they've embodied that. So that's what we want all the time. But the moment it acts out like people disembody it.

21:53 → 22:15

**Audience:** Sure, it's great. Yeah. I will make it quick. Thank you for the presentation. Very clear for the causal approach that was a slide in Klingon that you were sorry about that. What are the causal models you have to have and what will you use phenomenologically, mechanistically because it's such a complex system. So what do you envision?

22:16 → 22:58

**James Cotton:** Yeah. So I suspect that the solution will be kind of hybrid. But I also think we're going to have to explore multiple approaches. Right? So like, there's 1 approach where you can just almost work with abstract, latent, variable models and try and, like maximize, the data fit. There's a lot of exciting work going on right now in the field of causal representation, learning and causal discovery. like Bernard Chopkoff, and Tubing is like really pushing on that. And so there, you can kind of like, look at a lot of data. Let's say images and try and have it. Understand the causal structure, such as cups that give rise to things. So I'm kind of hopeful we'll be able to do that one day for deep, big rehabilitation data, because, even like all our outcome measures, we don't fully understand the construct validity, and where they fit within the Icf. In terms of impairment activities, disability, like we think we do. But sometimes we're wrong. And then I think there's gonna be a lot of places for the way you were talking about like really normative theories, right? So I like to build more and more depth. Then that's why I put a neuromuscular model in the spinal cord. So my hope is that we build these more neuro realistic models. But at the right level of distraction for the phenomena we're trying to explain.

22:59 → 23:00

**Luke Osborn:** Thank you, James. That was great.

00:23:01 → 00:23:09

**Grace Hwang:** Our next speaker is Dr. Elisa Donati. She's a research scientist and group leader at the Institute of Neuroinformatics at the University of Zurich and Eth Zurich. Her research focuses on designing neuromorphic circuits that are suited for interfacing with the human nervous system.

23:18 → 45:26

**Elisa Donati:** Okay, thank you. So can you hear me? I guess. So thank you for inviting me here. So what I want to do in this presentation is something that comes right after this beautiful presentation about what we can do nowadays with upper limb prosthetic devices. And I want to give you an idea of how we can have neuromorphic inside these prosthetic devices. So okay, this is maybe redundant. But just to give you an idea about what this human machine interfaces with. So what we have, we have many devices, even very popular and very successful, like pacemakers. We saw a pacemaker before. So we can have a cochlear implant visual implant. We have deep brain stimulation, vagus nerve stimulation. So what I wanted to show you with this slide is basically even if you have different applications, all of them, they have something in common. So the idea is that you want to communicate with the nervous system. So you want to decode something from the nervous system, and you want to give something back. You want to modulate something, and this needs to be done in a continuous closed loop. So you want to read, react, and then continuously check to be able to continue to react. And if you look at these. Okay, it's not working anymore. I think it's just low. I have the correct slide here. But go here. Oh, okay, no sorry. So if you think of these devices, both, they are implantable, implantable, or wearable, they have something in common. So if you want to process this data continuously in real time. You need to process a lot of neural data. And this requires a very high power consumption. That is something that we say today, we said many times at the same time. if you want to monitor with many electrodes, you need to have these letters implanted somewhere. So it means that you have. You need it. You have cables and these cables. They have to come out, for example, of your brain. And if you don't want to have this actual cable you can. You can trust me. This information, for example, by using Bluetooth, and this requires a lot of bandwidth, especially if you have high frequency. If you have many letters. and this is going to be a problem because you can slow your data transfer. If you have multiple of these electorates at the same time, most of the devices. So we saw each other this morning. So they're not adaptable. So what they can have is predefined functions. So the doctor defines some functions, and the subject needs to stick with them. So they're not really adaptable with the needs of the subject, and they're very poor in spatial temporary solutions. So the reason why, then, I started to work in neuromorphic is because I believe the neuromorphic can solve most of this problem. Because, as we said already, so neuromorphic works by definition in a low power regime. And one of the reasons is because they work with events meaning that they don't process the entire signal. So they process just the event. And the event is something that happens once you have something to process. Okay? So you have some information. You want to process, you generate an event, and then you process the events and what you can do. You can even stream the events outside, so you can, rather than streaming your entire signal, you can only stream the events. So, making the low power the bandwidth a better bandwidth, and then you can even other. You can even do local processing. That is something that we mentioned before. So rather than sending to some cloud the information and then processing outside, you can do local processing, and you can stream outside the results. And then you can have a system that they can. They are able to react in real time. They can adapt, and they can learn, and they by definition. They are very good at special temporary resolutions. So before I want to mention what is neuromorphic for me. So I'm using this term today. But maybe we are not all of us on the same page. So before we mentioned some big chips like spinnaker brainscale. So what I'm doing is something that is slightly different. So what I'm using are mixed signals, devices that I want to build, because I want to solve a very specific task. So I want to do something at the edge. And in particular, the devices I'm using so similarly, by the way, to all the others. So the principle is that we have multiple instances, all of them. They have similar behavior, making them very fault tolerant, because if something doesn't work you can replace them. You can even take all those instances and make parallel processing. So you can have something working on different tasks at the same time and they don't have to be active all at the same time. So you can have a very sparse activation. But what makes this system different from classical microprocessors is the idea that you don't have a memory. So you have something that is, the memory is collocalized between the units. So in the ways that you have among these units. They're also similar to the brain in time, because here we don't have simulation. Here we have emulation. So the idea is that we have circuits solving our equations. So we send signals into the chip, and we actually read the output of the chip in real time, and everything is completely synchronous. So anytime I have an event. So I read something, and then I can process it and we can have dynamics that can actually match the one of the environment. So we can build secrets with exactly the same dynamic of the one I want to interact with. And in particular, as I was saying, I work with this mixed signal neuromorphic architecture. So the idea is to use this transistor working in these analog subthreshold secrets. I'm not going to go on in detail, but the idea is that if we combine many of them together, we can build neurons and synapses. You can think of them like Lego. So you can think of. You can make the model that you want. You can have particular features that you want, you can add secrets, remove secrets. So they're really like Lego, and you can combine many of them to build this analog core. But one of the ways to communicate with the analog core is to use a digital periphery. So the idea is that you want to communicate similarly to the brain using spikes. So you want to send these spikes in the chip so you can send. And you can read spikes. And you can use this digital peripheral to actually change the network set parameters so you can use them to configure the net that you want and the system that you want. And so then, in the end you can have the chip. So these are the chip I'm building. So the idea is to make my own chip designed for this particular application. Okay, so something small, something very dedicated to a particular task. So and now I want to make an example. So unfortunately, we are not at the level of the presentation we saw before, and they are very advanced, so very powerful. So it's very early stage, as you can imagine. So the idea. But the idea is similar, right? So you want to control the prosthetic devices. So you want to generate some motor commands from some residual activation. And then you also want to give something back to the subject. So you want that the subject is engaged in the movement is engaged in the grasping. So this is not only improve the performances of the prosthetic devices. but also increase the acceptance of the of the subject. and this makes a huge difference. But then, if you actually go and look at all the steps. So there are multiple steps. If you want to build these prosthetic devices. So you need to decode motor intention. So we can actually have different ways for decoding this motor interaction. I'm currently working on classic superficial emg, that's something I'm going to show you later. But I'm also working on something from intraneural. So some recording directly into the fascicles. We can even use motor neurons, or we can even use the motor cortex. So we can have different access to this muscle information or motor information. Then, once we move. So then we want to have a device that is a. There are sensors, right? Basically touch sensors that can give you information about the grasping and ideally, even information about proprioception. So something about how the hand is moving. And then, once you have this information. you need to encode it. Okay. But unfortunately, once you have this information, the current stimulator, they have really few number of active points. So you have maybe 1,000 of these sensors. But then you have 1, 2, 8. So the number of channels where you can actually stimulate. So the idea is that you need to compress this information and possibly keep the temporal and spatial information. And then, once you stimulate, you want to have a stimulation that is biomimetics because there is evidence that a biomimetic stimulation increases the perception of the subject, and once you stimulate, especially when you stimulate with invasive stimulation. Then you want to understand how the subject reacts to the stimulation, because we will see later that sometimes we have some side effects that we actually want to avoid. and everything needs to be done in real time in a continuous closed loop, and possibly in a very low power regime. That's why I'm working with neuromarket. Oh, sorry this one. So, starting from how we can control prosthetic devices, using some traditional superficial emg. So if you can think of how we move our hands, and if you look at me, I move my hands a lot, so you can see that you can. Actually, the movement is continuous, right? And if you look at what prosthetic devices that they can do nowadays, they just do really classic, you know, predefined gestures, so just just gesture recognition. This is the state of the art. However, it's not how the hands actually work so ideally. We would like to have this continuous momentum. So rather than having just a recognition, we would like to have regression. We would like to be able to map the motor intention in something that is continuous, like the finger movements. And if you're able to do that, we can have something that can give you some smooth movements. you can actually control multiple joint degrees of freedom at the same time. So your fingers, the wrist, all of them together at the same time, and you can have a very smooth transition between movements. So here you can see that it is like regression. So the mapping from the activity of the muscles and one and 2 fingers. So the idea is to really map this continuous behavior and spiking neural networks and the chip we are using. They actually do that. So you can send something inside, and you can continuously read the streaming output. So here is the emg. So what? As I was saying, we can map this information to the finger movements and one of the ways we started to look at doing something like that. So the 1st thing we started to do was to use a neuromorphic chip as I was mentioning before. So we need to generate events because we want to process events. So actually, what we can do, we can use our feature distraction as a way to convert the signal into spikes. Okay, so rather than having a classic ADC, take the signal and convert it into digital events and send it to your microprocessor. You can actually look at the features of your signal, and you can convert the features of your signal into spikes and let them be processed by the morphe processor. So here is what we use. So before we heard a lot about the feature. That is the power. So actually here, we did exactly the same. So we're actually looking at the power of the signal. So in particular what we did, we took a channel, so we sent the channel in the bank of the filter, so to divide in different filters, or the different frequency information of the signal. And then we send these outputs to some stage of the amplifier and everything to like an integrator. So the Integrator was actually integrating the information and giving you the energy or the power of the signal. So and this one is something that actually, we even have a chip that is doing that. So you can actually send your input and then you can have the filters that you want. We were even using logarithmic distribution of filters, because we know that in the low frequency we have most of the signal in biomedical signal processing. So here, in this particular case, we had 16 channels of superficial eng, so we were sending these 60 channels to 4 banks of filters. And then so for a total of 64 inputs to the network. And remember, these were the features. So the features of the energy of the signal. Then we were multiplying them by another neuron that was basically a kernel like an exponential kernel. And then we applied a very simple linear regressor. So nothing super complicated, like, you know, CNN, and whatever. So really something simple, a linear regressor to map the emg to the finger movements. And these are the results we got. So we calculated the difference. So the difference between the actual movement and what we calculate with our system. And we found an error of 8.8 4. Okay? So then, that is, if you look at the state of the art, it was a 6.8 9, so it's only 2 degrees, but with a system that is much lighter. It can run everywhere, and it's able to work in real time. So and then sometimes when I present this slide, people are saying, okay, maybe the task is easy. Maybe it's too easy, the task. So you can actually solve it with a linear regressor. Then I did so then I did my benchmark. So then, I look, okay, let's see what deep learning and how deep learning would solve the same problem. So then I look at the state of the art. So this is the state of the art. So I was analyzing a transformer, a temporal convolutional network, a specific Tcn that is, a temperament, and also the neural Od. And then I use all these methods to solve exactly the same problem. And what you can see, you can see the error. after various levels of optimization of parameters, it was slightly better, something like 3 degrees better. But, the number of parameters is 3 times higher and if you look at the clinical evidence of these results, they are not significant, because the subject is the people with amputation, they cannot perceive an error that is lower than 10 degrees. So even if these methods are able to have 3 degrees better results, the subject doesn't even perceive that so this is not the element we should actually solve. So we should actually focus on other metrics to optimize rather than accuracy. So then, just briefly to give you an idea of when we close the loop. So we can actually use the similar network, not only for the direct control, but also for the classification. So the idea of once I have multiple sensors to compress them for the simulation. So this is something that we were using this method. So this is something that comes from the Mit. So there were. These are resistors. So a matrix of 32 by 32 elements, resistive elements. And we collected the data set just for grasping 17 gestures. And so you can see the output here is like an image. Okay? So you can actually see which different part of the hand was active once while the person was performing the grasping and so this is something you can think of as really an image in time. Because if you can think when you grasp something, you can see that this information about tactile information increases, and when you release it decreases. So you can really have really something changing in time. So the way they actually processed it was using a classic CNN, so they just did a pure classification of objects, and it was performing well. So what we try to do, we try then, to actually do use the spiking neural networks, and you on Chip for doing the same exact rectification. So here what we did, rather than extracting the energy of the signal, we were extracting the information about the changes in time. So if it was something like grasping something, we had an increase of the signal. So we were actually looking at the differences and also during the releasing we were looking at. So the decreasing elements. So basically at the derivative of this information, and that we were using this information as an input for one layer networks. Again, something super simple. And what we managed to have was to have some very high results. So using this network, there is basically one neuron per input so 32 by 32 around 1,000 inputs and then 17 outputs. So in total, less than 1,100 neurons, we were able to match exactly the same accuracy as CNN. So something around 90% for 17 objects. And finally, I want to give you an example, another example. And I picked this one something where the neuromorphic is really powerful compared to classical approaches. So here, what we can have is that anytime that you stimulate, especially when you're stimulating invasively. So you can actually elicit some sensation to the subject. However, after a few minutes, sometimes even after a few seconds, depending on the location of the simulation. So if it's something in the cortex is in the order of seconds, if it's in the peripheral, is the order of minutes. So the subject stops perceiving the sensation, so you elicit something, and then the subject stops perceiving it so. And you can see here there are recordings from the actual brain. So during stimulation, so stimulation in s 1 so, and they were injecting continuous stimulation. And you can see that the subject, after a few seconds, stopped feeling the sensation. And this is something that the onset of the adaptation comes earlier if you increase the stimulation. Okay, so what we did, we wanted to find a way to understand this mechanism, to actually trick the brain and to modulate the stimulation to avoid that and something. So what we started to do. So we started to look at the cortex. So the cortex is very complex. 6 layers. So this was a model. It was too complicated. So we started to look at, for example. which layer is involved in this adaptation, and we know that layer 4 is the one that receives the stimulation from the intracortical, and is also the one that receives the information from the peripheral. So receiving the input from the thalamus. So here we wanted to reproduce the behavior of layer 4. So we focus on this layer. And we try to implement what we call a neuromorphic twin. So to be able to match experimental data by using our chip. And remember. So we have a chip, we send input and we just read the output. So we don't have any simulation. So it's something completely in real time. So we have equation solving. So we have secrets solving the equation. So something complete in real time. So here you can see some names. They are not important. So they are just names, because what we wanted to have we wanted to have some dynamics. The reason why you can see names is because we had to start somewhere to set the parameters, because otherwise the variability is too large. So then we looked at some literature, and we found a lot of literature for rats, and we tried to match the behavior of this population with the one in literature, and so we match one to one. So the chip was able to reproduce the behavior of this population. So then, we connect them together to see what happened on the level of the network. And what happened is. And then we stimulated, using exactly the stimulation I showed you before. So this increase in failure rate. And as you can see here, we can actually have a network that is responsive to this input so the 1st thing we did, we actually just created some spontaneous activity. That is something also there, because of the noise of the chip where we actually send the kick to create some basic activity. And then we started to stimulate the network with constant stimulation, and, as you can see, when the stimulation was very low, there was no adaptation. So the 3rd column then increases the stimulation. So you can see that there was adaptation. And the adaptation is when the subject, when there is a decrease of the activity of 40%. So and you can see that if you look at the graph, so you can see that our neuromorph between something super small, less than 200 neurons working in real time was able to match the data that we were recording into the brain of humans and then to validate that, we even try to implement the bursting behavior, because in this stimulation, so they saw that if you want to increase this feeling in the subject, you can rather than stimulate it with a continuous stimulation. You can send bursts of stimulation. So these are recordings from humans, and you can see that you can double the perception in the subject before the rotation appears. And so we did the same with our chip, and we actually managed to have the same results except for the last one, because apparently when we stimulated for a burst of 500Â ms, it was exactly the recovery time of the network. So the network basically started to oscillate. But it is something that you can solve by making your network a little bit larger. So to conclude, I want to show you that we are also working on some other projects. So not only in upper limb, prosthetic control, we are also working on an adaptive pacemaker based on central generators. We work on long-term monitoring in particular for patients with dementia, we are focusing on multi-days and multi-subject adaptability, and also in normal detection for Ecg and Eeg. And also. Now we have started working on post-stroke rehabilitation. So now I want to thank you. And I'm waiting for the panel.

45:37 → 47:13

**Luke Osborn:** Alright our panelists are up next, let us know if there is any feedback or a question that you might want to ask. session 2 panelists please come up and we'll get started with that. We ran for a few minutes. Yeah okay, yeah. So we will. What we'll do is we'll lead over into the post recession. Break for maybe 1015Â min or so. If that's okay. So let me. We have a few folks joining, and also the speakers, too. Please come back up. So yeah. so I'm gonna so she and Vikash, if y'all are online, if you don't mind turn your cameras on. But while I get their video feeds pulled up, maybe we could just go down the line and do some quick introductions from all our panelists here to hear their thoughts. Not only, I guess, on the work that they're doing, but also their perspective of the needs and impact and kind of some of the big opportunities that we see using normorphic principles in the research domains here in human machine interfaces. So maybe Ching Qin, if you want to start.

47:15 → 47:47

**Xing Chen:** Hi, my name is Xing Chen. I'm at the University of Pittsburgh, where I'm an assistant professor. I'm also the co-founder of a neurotech startup called phosphoenix, that aims to get tiny little probes into very deep brain structures with the high density of electrodes. So my background is mostly on stimulating the visual cortex in monkeys. I tend to implant Utah arrays with about a thousand electrodes per animal. I do stimulation and recording for visual prostheses, and I work closely with collaborators in Spain. It also has Utah arrays in blind human patients.

47:49 → 48:09

**Francisco Valero Cuevas:** I'm Francisco Valero Cuevas at the University of Southern California, in biomedical engineering in engineering, and also in kinesiology and physical therapy. And I work on neuromechanics essentially trying to understand how brains interact with bodies. And I also have a startup on medical devices.

48:11 → 48:18

**Nitish Thakor:** I'm Nitish Thakor professor at Johns Hopkins and I'm delighted to be here learning a lot. Thank you.

48:20 → 48:42

**Helen Huang:** I'm Helen Huang. I'm from biomedical engineering at Nc. State and Unc. Chapel Hill. So my research focuses on your machine interface for prosthetic arm and the leg basically trying to decoding what a person wanted to do with the control device and also close loop getting a sensation of coming back and then helping overall the motor mobility of people has a limb loss.

48:45 → 48:50

**Luke Osborn:** Thank you. Yeah. Since we've already heard from the speakers Akash, would you mind unmuting? Give us a short interim.

48:51 → 49:27

**Vikash Gilja:** My name is Vikash Gilcha. I'm an associate professor at Uc. San Diego. I'm also a chief scientific officer at paradromics. My research is focused on intracortical implants primarily in the motor strip for restoring computer use computer mouse control as well as vocal synthesis and keyboard control. This is an area that the field is moving forward with. There have been academic trials, and there's a small cohort of companies that are pushing in this direction. In the medical device domain.

49:29 → 49:30

**Luke Osborn:** Thank you. Shichi.

49:31 → 50:08

**Shih-Chii Liu:** Yeah. Hi, my name is Shichi Liu. I'm at the Institute of Neuroinformatics at University of Zurich and Eth Zurich, and have been working in the neuromorphy engineering field for quite a while, and did most of the work in silicon cochleas. But in the last few years I've been coordinating this project called Neuroviper, where Zing Chen was involved at the very beginning. And the idea was to build a cortical visual neuroprosthesis and actually, I would say, the event camera also has been used as the input to one of the systems.

50:11 → 50:50

**Luke Osborn:** Wonderful. Thank you. So I think. You know the 1st question that's on my mind, which maybe Shinga might direct towards you, and then the rest of the panelists can answer if they're interested is, you know, what do you think about? You know how neuromorphic principles could be used in this context? Or what impact would they have in conveying highly complex information back into humans through user user interface? Right? We've heard a lot about sensory feedback, but also decoding information. Kind of what your take on as we scale to these larger, more complete pieces of sensory information that we're trying to communicate to humans. How might you see some of these principles being valuable or playing a role?

50:53 → 51:47

**Xing Chen:** Well, to put it briefly, I'll think about it in terms of efficacy, feasibility, and safety. So in terms of, if you want to impart actual, useful perception to blind people, you need to have a device that's capable of stimulating such that it's going to be useful, and people are able to recognize objects. You have to make sure that you're able to calibrate your system during a clinical trial, where it doesn't take months and months of very onerous manual reporting of where the phosphines are located, or figuring out current thresholds. You need to be able to do that relatively quickly for it to be usable and we have known that you can generate epileptic seizures if you stimulate the visual cortex, and that's still something that I think people haven't really been talking that much about openly in visual prostheses. So in terms of safety. How do you prevent these ways of activity from propagating?

51:50 → 53:04

**Francisco Valero-Cuevas:** Thank you. One of the things that I think is wonderful about biological systems is that they're essentially flooded by sensory information, right? But we are essentially not paying attention to most of it. If you were actually there there are, you know, psychiatric conditions where you cannot filter. And that's a problem. So what I liked a lot about the work that was being presented Lisa Randu, etc is that there's this concept of a percept. So in a sense, as engineers, we like to talk about signals. We like to talk about the state variables, etc. But I think that the biological system at the end of the day just needs to be able to form a percept by whatever means, and we adapt to creating percepts, depending on the clothes we're wearing, whether we're swimming or walking or whatnot. So I think if we stop being engineers for a little bit. We should also ask the question, is not to replicate the signals themselves, but to enable the biological system, essentially the human, to extract percepts by whatever means.

53:07 → 54:33

**Nitish Thakor:** So I'll take a queue from the work that's already presented. Right? So one part is decoding like Luke has done some work on, and Zenon will talk about it right? You have sensors and produce spiking activity. You got to decode it. The other part is encoding, which means at the periphery. And what Alyssa presented all the way to come to the brain! How is it being encoded. or do you perceive it well taken? And then, finally, it's control which Sri and Ranu presented. Right? You do want to close the loop and each one is a science question, right like, How do you model receptors at the periphery of it? How are these nerves and fascicles you saw encoding in precision, sort of way. And then despite what Alissa said, right. It's, she said, 6 layers. But we didn't even cover various nuclear devices in between, right? So modeling that system and then Anu presented that closing the loop is empirical, and there is a control theory, but at a coarser level. So I think 3 of them should get together and write a grant, and I'll be happy to be the pi, you know. So that's why we are here. Right? Let's close the loop.

54:36 → 54:53

**Luke Osborn:** Maybe. Maybe she might if you're okay jumping in and also answering your question about you know this, the scalability, as we think about these highly complex systems. And you know, if we are to model all these, say, peripheral inputs or neurons. Right? Given your expertise with a dynamic vision sensor, right? How is this? What do you think about all this?

54:54 → 57:16

**Shih-Chii Liu:** Yeah. So I think these new probes are coming out. They're high density probes that Zing Chen can probably talk more about. It is actually, really, really exciting, because, you know, we're going to go from, say, 100 electrodes or so from the Utah Ray to maybe a thousand or 10,000 in the future right? And these electrodes are both stimulation and recording. So you can actually do simultaneous recording and stimulation which really sets it up for a closed loop scenario right? And so currently, what we can do is take the input from a camera or say, the dynamic vision sensor and then pass it through some algorithm that creates information enough to stimulate a person so they can get some perception right. And this perception is useful, because then they can, for example, move around the apartment one day right? But, of course, what people are doing now is putting a bottle in front of them, and then the person sort of reaches for the bottle right and so the person moves the head so that they can see the edges of the bottle, and the one thing I want to say is because there's so few electrodes at the moment. It's like a research question that you need to understand what is the information that you need to pass to the lecturers, and it could be also that this information that you pass to lecturers depends on the responses that you get at the place that you're stimulating. Right? Because maybe the area that you're stimulating is receiving information from other brain areas. So you cannot blindly just stimulate from. You know, the sensor to the electrodes. And I think the nice neuromorphic thing which plays out again and again is that we're always looking for information, for ways to extract sparse information so that you can run the whole system in real time at low latency in this feedback system because it's a feedback system. So you need to be fast enough so you can react to what's happening at the place that you're stimulating and so I think when, when the selectors scale up to 10,000 or so. then we might be able to even stimulate different layers of the cortex. And who knows? You know what sort of information we can pass to the blind person, so they can even do more than just switch for a bottle. One day.

57:17 → 57:45

**Luke Osborn:** Right? I wanna take a second. And your point about you ultimately what goes to the user. So, Helen, I'm curious. Your thoughts on the system that adapts right over time to the user? Is it from a rehabilitation perspective? Is there? What kind of value do you see, or what kind of role would that have? And the impact it would play in? Not only this, the research and science, but also with the user.

57:57 → 59:58

**Helen Huang:** Okay, so I spend a lot of time working on this personalization of this medical device. I work mainly with the patient population. I see a variety, you know. The intersubject variation is large. So having this device, just one fits all. It's very, very challenging. So I think about the adaptation. So I think this morning people will talk about changes or observations of Dbs effects right away versus like 3 months later. So actually, I think the human adaptation needed to be like at a different time, frame work of time frame as well. So in this case, in terms of software and hardware. I think hardware. We are getting there in terms of cloud computing, agile computing, those Internet of things that have a different layer of different locations. The hardware could do a different type, different timeframe adaptations. I think that that's already kind of a solution for the medical device in terms of a software. So we use a lot of reinforcement learning. So especially if you have learned a certain policy that could continue adapting, I think that would be the way to go. I don't know if you know, in the field of the DBS people have to look at the reinforcement learning kind of approach to actually updating this device across a different timeframe. The other one is, talk about this neuromorphic approach. I also think that this analog approach is really attractive to me because it will. Actually, there's not much of a delay. So analog is very straightforward, especially if these analog circuits could directly interfacing with the human nervous system. Then everything's supposed to be straightforward as long as the hardware can be available. But that's just my thoughts.

59:59 → 01:00:04

**Luke Osborn:** Anyone else care to comment, James, you have a perspective, maybe from bringing.

01:00:05 → 01:01:04

**James Cotton:** Yeah, mostly, I love her work. B, yeah. I think when we're thinking about this adaptation optimization, right? We really have to be driving towards long term functional outcomes and then I think that the limitations, particularly in the prosthesis space, is that restoring normative behaviors may not always be currently the best way to maximize function. Right? So it's 1 thing to go and look at like able-bodied kinematics and then be like, well, you know ideally, the prosthesis would work so perfectly that they would walk exactly like that. But really, you know, and this is more well known, I think, in the stroke field, certain degrees of asymmetry are sort of like local optima given the constraints of the neuromuscular system. And so this is why we need to really kind of be able to build in these kinds of normative causal models and fit them to our data and understand them. Given all these comorbidities and all these limitations on the control loops this is kind of the best way to optimize this particular individual. Then, probably using her techniques, you know.

01:01:07 → 01:01:41

**Vikash Gilja:** The 1 point made. Ranu made a point to her patient just adopted it very quickly and was fantastic at it, and so on. But we could have some subjects who are congenital and may not have the prior cortical maps or understanding. So I think this personalization and perception is overlooked by engineers. Right? Because we want to build and code according to control algorithms, chips and electrodes. So there is that subjective element that I'm glad it's coming out and individualization.

01:01:43 → 01:03:44

**Ranu Jung:** So I think, as I'm listening to all of you. I think one of the issues we will have from person to person is actually sparsity of data even though we may say we can put so many electrodes and get all that information. You don't know how much of that information is useful, so to speak, right or and and it is more likely to be that you'll have sparse information from which you need to make decisions and then it is not clear how much you really need to give, how much stimulation you need to give back, because the way I like to think of it is when we read a sentence. We do not read every letter. We do not even read every word. You know, we just can read the whole sentence right? And it is we have the person in the loop, and our brain in the loop is able to fill in the gap and do things. So in in that same sense, I think of, how do we give just the minimum amount of information back and let us take advantage of the biological system to fill the gaps but we need to make the decisions based on very little pieces of information or sparse pieces of information and that's where, even though I have no expertise in this. But when I keep hearing about all this, AI based big learning models and all. I get worried that somebody is going to say that all of that should be applicable to all of this stuff that you're doing with neural interfaces where you have got loads and loads of data that is all collected with the same things. And here we have very different individual people and in some cases data like especially percept data. Right? We really don't know what that person is feeling, what that person is, how we make sense of what we are decoding, at least on the motor side. I feel like, okay, we can see. Oh, yeah, the muscle is contracting, you know. But how do we do that? So I think that those would be questions to think about.

01:03:45 → 01:04:55

**Elisa Donati:** I'm sorry if I cannot. Something. It's not only valid across subjects. But even within the same subject, because one of the problems with these prosthetic devices in general, when you record any kind of data is that if you record the data one day, and then you go. A week later the signal is completely different. So there is a lot of variability that is due, for example, to turnover of cells, or it can be because the electrics shift a little bit and unfortunately, so if you want to solve this problem like the AI based methods. You need to have a huge data set. And unfortunately, as someone mentioned also before data, when you work with this kind of sub. This kind of application is a huge drawback. So we don't have data. So we cannot, you know, train across multiple days across multiple subjects. So we need to find other ways to solve this variability. And if we look at what the brain does, actually, we can find some trick from the brain. So, for example, we can go in some low latent space in some low dimensional space, and you know, to be able to adjust across, you know, days and even across subjects, because there are many things in common across days.

01:04:57 → 01:05:58

**James Cotton:** Subject just to keep piggybacking on that last point, though I think this is where the interaction intersection of like correctly used AI approaches and big data can synergize at the individual level, right? So like in Bci decoding, for example, Lee Miller, has some great work showing that you can align the latent manifold between different individuals, even between monkeys and humans, and allow much more rapid calibration of the system. But that requires a big data to understand the shape of that manifold. And I think, similarly, as we start collecting like large rehabilitation data sets, we'll start to be able to like these kind of calls and models I was describing, and infer the relevant latent variables for an individual that tell us how to personalize things so, and and I guess where I'm kind of bullish on. This is, 1st of all, we've seen in rehabilitation at least the history of trying to approach things to a series of Rcts hasn't pushed the field forward very quickly, or at least not quickly enough and we now have the technologies to start to collect these data sets at scale, right, like 12Â TB of of Eeg data and then in the future with new technologies. So I think hopefully, it'll be a hybrid approach that will push the field forward.

01:05:59 → 01:06:00

**Vikash Gilja:** Good.

01:06:01 → 01:06:02

**Luke Osborn:** Oh, sorry! Go for it! Perfect!

01:06:03 → 01:08:21

**Vikash Gilja:** Perfect timing. So yeah, I was gonna draw analogy to a lot of the comments that were made just now to the work that's happening in restoration of speech. So this is work happening. At Stanford, with Jamie Henderson and late Krishna, Schnoy, Frank Willett, and then over at Uc. Davis, with Sergey Sovinsky and David Brandman, and the approach that they're taking is to bring in foundational models that you know. Now, trillion dollar industries have pushed money into around speech and language and to connect those models to neural decoders. And that's been a very impactful approach. And we can see in the basic science work that they're doing that. What's enabling that decoding is that these foundational models have a relationship to speech articulation. The areas of the brain that they're decoding from have information about articulation and underlying phonemes. And so they can connect these large scale models that have been trained on healthy individuals to neural decoders that are much smaller scale architectures. They don't require a ton of data. They require a lot from an individual user, but it's tractable. And so they're able to connect the dots there. I think one of the challenges for much of the technology that's been described in this session is that there may not be an equivalent foundational model. And maybe that is a strategy to start exploring how to start building those models how to bring them in, how to also generate them in a way that is impactful for the participants to. To actually run so much of the work that's happening with these large scale models requires large scale compute that compute would limit at present day, the users, because well, you're not going to be carrying around a large scale workstation. You can't guarantee that you're going to have a high bandwidth connection to a data center. So you know, how do we drive forward? How do we build an equivalent foundational models? And how do we run them? In a way that is compatible with the usage case for the patients that we're trying to help.

01:08:24 → 01:10:18

**Francisco Valero-Cuevas:** Yes, I'd like to follow up on these ideas. And I think one area where neuromorphic or physiomorphic computing has promised is in the area of what's called embedded logic. So the biggest favor our parents did for us is to give us a body that was easy to learn to use within our lifespan, in fact, within our childhood. So this is a counter example to big data. This is a counter example to optimization. All right, it's actually little data and suboptimal solutions that in the context of a substrate that we inherited, that somehow was ready to learn, however imperfectly. That we're able to do what we do. So I think I would, you know, just caution the field from saying what robotics has used to say in the eighties right? If only my computer were faster, my robot would serve me breakfast right. We have fast computers that if only my robot had more experience. Well, you can simulate that simulate years of experience right? But some of the work that I do is in learning with limited experience in the context. When data are expensive in our lifetimes, we don't experiment too much because we waste time. We waste effort. We risk injury. There's the opportunity cost. So somehow, there's a way in which we can learn from the substrate with which learning is happening and performance is happening and I think that's where neuromorphic and physiomorphic computing has a potential advantage. This is anathema to a lot of the a lot of what's going on in engineering these days and neuroengineering. But biology does it just fine.

01:10:19 → 01:10:30

**James Cotton:** I just want to add that can also be framed as Meta learning through evolution of the biological system for the learning algorithms. Right? So it's not yeah, it's not oppositional to using data and like machine learning approaches. Right?

01:10:34 → 01:10:57

**Luke Osborn:** So maybe for the sake of time, we'll kind of pose one last question as we wrap up. I'm curious, you know. Do you have thoughts? Are there hardware limitations? Are there software limitations? Are we just not creative enough? Have we not come up with the right solutions? But we have all the resources available to us. To implement some of these great things that we're talking about. So if you have, you know, 30 seconds or less to say your parting words, and then we'll.

01:10:58→ 01:12:00

**Nitesh Thakor:** I'll give a quick stab at the negativity of this. So the neuromorphic community, including Telluride Conference, that Ralph goes to every year, and several people in this have been around for a while it hasn't grown. I think there is a significant challenge to convey this concept to the more established neuroscience. The community whose attitudes are based on more classical experimentally driven, mechanistic reductionist neuroscience and this construct the neomorphic construct is it's preaching to the choir. And I think there's a big challenge to crossing over and as a case in point, it's the same thing with cameras, right? That Avis and Davis cameras are a small piece of the entire camera ecosystem. So I think we need to bridge the gap to neuroscience. I think that's how Grace will shake the Nih money tree because or or start a new path.

01:12:01 → 01:12:02

**Luke Osborn:** New path funders panel later this afternoon.

01:12:02 → 01:12:25

So can I also say that we needed to show the benefit of this neuromorphic approach. I mean, no matter. It's hardware. And the software, essentially, especially like, you know, a couple of us is from the clinic aspect that this would show the benefit to the patients. Probably that will really speed up the growth of the field.

01:12:26 → 01:13:16

**Xing Chen:** I think we're seeing some pretty let's say, preliminary payoffs and visual prosthetics, where, by carrying out recordings from the brain simultaneously during stimulation, you know, we're able to leverage extensive knowledge of the functional anatomy of the visual cortex and apply, you know, dimensionality reduction methods like map, and actually predict the locations at which phosphines are going to appear instead of having patients just constantly, manually report where they're located. There might be ways to semi automatically do current thresholding, or maybe even potentially detect spreads of after discharge activity or epilepsy like activity. So I think there's quite a few reasons to be optimistic, despite the challenges

01:13:17 → 01:14:10

**Elisa Donati:** So effective just to say that. So I like to say that it's like a call for action, because there are limitations in neuromorphic too. But we also need to involve neuroscientists to really fill the gap. But also I think that if you really want to have this technology at the very, at the mature level, we also need to involve even material scientists, because, you know, materials is the new challenge. So we need to have something that is going to interface with the nervous system. So we need to build something that is able to speak with the nervous system. So we need new materials, compatible materials, organic materials. I don't know. It's not my feet, but I mean, we don't only need advanced advancement in neuromorphy per se, but also in materials and neuroscience. And you know, it's really cool for the mole team.

01:14:10 → 01:14:18

**Luke Osborn:** Thank you for that. So I'd like to thank all of our speakers and panelists one more time, and then you have a break and posters outside feel free to come up and continue the discussions.