**Session 4**

00:00 → 02:07

**Ralph Etienne-Cummings:** Okay so we might as well get started is 20 past, so we'll you know, we'll take that into consideration. But here we are. So session 4 is kind of a combination of the various sessions that we've heard previously. So we started off with cortical and neuromodulation type applications. Then we moved into prosthetics. This morning we heard about technologies, particularly from the perspective of wearables and computation. And wearables, I guess skin electronics and so on. Now we are moving a little bit into, you know, kind of higher level applications of these devices. So we'll hear a bit about wearables again. We'll hear some analysis from a mathematical perspective or a modeling perspective with Brad, he should be coming at some point. And then we'll hopefully have a robust discussion that will follow, and hopefully we can bring all the pieces that we've heard together today. We had a wonderful talk by Zinan this morning, and this is all kind of intended to integrate well into each other. So with that in mind, this is the lineup that we'll have. So Jennifer Blaine and I will be monitoring this session. The first Speaker will be Shihong Wang from Chicago. Then we'll have Erica Schmidt from Cambria, Llc. Followed by Brad Imoni from Sandia National Labs. And then we'll bring up the panelists composed of Andreas Andreo from Hopkins. Robert Stevens from School of Medicine at Johns Hopkins. We'll have Ampero Gomez Gonzalez from University of Cambridge, and Pamela Abshire, from University of Maryland. So that will be whom we will hopefully be debating some of the ideas that will come forward. So with that in mind, we need to set up the presentation for Jihang.

02:50 → 27:39

**Sihong Wang:** Okay so first of all, I'd like to thank Ralph and all the organizers for putting together such a wonderful workshop, and also for having me here, giving me the opportunity to speak. From yesterday to today, I have been really learning a lot from, you know, this very diverse community, and also really enjoy the exchange of ideas. So I also feel the arrangement of my talk is probably at the perfect place in this program. Transitioning from the material device aspect to the applications because, you know, I come from material science device engineering backgrounds. So, I really view the research that we have been doing between the materials levels and the device level. So, the perspective that I would like to offer here is overall about how to design a new type of bioelectronic interface that can combine high fidelity biosensing with integrated neuromorphic edge computing. So for the materials parts, actually, what you are going to hear from me will be a coincidence with the materials like the Polymer semiconductor, that Professor Bao introduced in the morning, largely because of the postdoc training I had with her a number of years ago. And what I like to do here overall is to first give a broad overview about the current state of the arts in both the commercial space and also the academic research, and then moving to what we have been doing to solve some of the challenges, and then ending with some future perspectives that I have in mind. So the fascinating angle, actually, that has been attractive for us and maybe also for a lot of other people is a future landscape of healthcare and medicine, in, you know, the terminology of precision medicine. So basically, it is having the idea of trying to provide the individualized and the highly precise medication treatment to each patient, which needs to be enabled by the very large scale and the complete monitoring of different aspects of a physiological data. So overall, a key part to achieve precision medicine is AI. Often when talking about AI, we’re talking about what people typically think about is the algorithm developments, which is certainly true. But for myself, coming from a hardware perspective, actually, what I think more about AI is about the other 2 pillars around AI, which is data and computing. So actually, these 2 have also been a big part of the discussion in these 2 days. So for the data, I think what is really needed for realizing, you know, the big data collection from each individual patient needs to come from having the human bio interface sensors that can work to satisfy different types of requirements. And then computing big data analysis will benefit the topic of this workshop, that is neuromorphic computing. So if you know, we take a broader look at what has been out there in the commercial market for both wearables and implantables, we can see there are still several major challenges. The two that I have listed here, one is for most of these devices, they still don't have the access to very many types of very important biomarkers like physiological information. We have already heard about a very wonderful research in the academic lab about how to measure blood pressure, but that just hasn't happened for the commercial product. And then the other challenge comes from the limited lifespan of the implantable devices. For example, if we look at the brain electrodes for brain machine interfaces, they often just have a limited lifetime about one to 2 years. Right? So those are the challenges that are reflecting the limited capability of collecting the data that are needed for this, you know, overall application space.And then, of course, another thing is the incorporation of AI computing, which also hasn't happened adequately for the commercial product. But of course, if we look at the academic research, people have already started to make a lot of efforts in trying to utilize AI to analyze wearable, implantable data. Also, you know, as the work that we have already seen from the presentations in these 2 days. So I also have some examples here. So, for example, like one is, this is a work from Sean Xu's lab in Ucsd that was published last year of developing a wearable ultrasound imager. And then the AI analysis, deep neural network was used to analyze the data collected by the wearable imager, and then to get different kinds of a signal that is correlated with a cardiac condition. For example, the ventricle volume, the stroke volume, so on, so forth. This is one example and then the other example that's also in the variable space is from golf's lab in Caltech that is, designing the variable sensor for multimodel data, sensory data collection. And then further, using an AI algorithm to analyze the data, to assess the stress level. And of course, right beyond these there are also many other types of examples. But if we look at you know really how the AI is happening in these examples, they basically all happen in the way that you know, the raw data is collected on the sensor, on the skin, with, unfortunately, a lot of, you know, unnecessary redundant information noises included. And then the AI analysis just happens simply, separately, right? Either like in computers or in data centers. So basically, you know, those are, you know, all kinds of, you know, cloud computing. And then, from the discussion we had in these 2 days, we are now aware that cloud computing has several challenges, limitations, for example, right? They are slow, especially if you are thinking about closing of functions. They often have latency. And then the second thing is that if you need to, you know, constantly rely on wireless data transmission, you simply just consume more power, right? Making it less energy efficient. And also, if you need to transmit all the raw data you know, containing all the unnecessary redundant information, even noise, then that simply makes the wireless transmission even less efficient. And then the last is the raw data contains a lot of, you know, very private health information, so that it also gives the risk of the, you know, the breach of the information. So then, there is a certain need to incorporate the AI neuromorphic computing in the parts, like on device, right within the wearable, implantable system. And then people certainly have already started to work towards this direction. So not to mention, like the current. The newest version of Apple watch is already starting to include more and more AI functions. But in the research space like in this example, the reservoir computing, and the artificial neural network is designed to incorporate into this a fully integrated, fully integrated silicon based chip to implement the AI directly inside the wearable system in this example is to, you know, provide a function of the detection of a cardiac arrhythmia. But actually, if you look at, you know, the overall form factor of the entire device, the wearable system, including the chip. One thing you can realize is that it is still very bulky and rigid. So then it is not compatible with the skin, with the tissue, not having the desirable form factor that we want for the bio interface data collection. So then, from this brief overview. The grand challenges I like to do, you know. First, there are mainly two aspects. The first aspect is, how can we design the right type of sensor, starting from material level to device level that can enable the collection of high fidelity, multimodel and long-term stable data from the skin and tissue interfaces. This is about the data parts. And then about computing, how can we design such types of neuromorphic devices that can carry out the edge computing function within the wearable, implantable system without sacrificing the desirable form factor, so I will, you know, spend the next part of my talk to over what we are doing towards these two directions. So first, about the sensing function. Overall, for bioelectronic sensing, that's, you know, generally start from taking different kinds of signals from tissue from skin, and then get it onto the sensor and then transduce to electrical readouts. So what we think, is currently the challenge in trying to get higher signal quality, higher signal noise, ratio. The challenge is not necessarily coming from the sensor device per Se, which mainly influenced the second step. But often the big challenge, the bigger challenge, is coming from the first step, that is really influencing how much signal that can be received by the sensor. So this has to happen through having a very good interface that is very conformable with large contact areas and a small distance to minimize the impedance reduction at the impedance induced signal decay at the interface. So then, to remind everyone of the interface that we are really trying to build for the tissue and organ that is like, you know, often highly highly covilinear, and constantly forming the main challenge that is faced by the current rigid device. I think I'm only two aspects. So first is the Nonconformable loose contact, to begin with. And then over like a chronic implantation period for months and years. The second challenge is the immune response in the sense of a foreign body response that will lead to the growth of a very dense layer of fibrotic tissue scar tissue at the interface. So then, to solve this, you know these two challenges together so then, to solve this, you know these two challenges together. What we think is probably there need to be several things. Several new properties to be incorporated so first, you know, achieve a more conformable contact of the device on the cover. Linear tissue surface. We want the device to be soft and stretchable. You have already heard a lot from Professor Bao in the morning. So, and this also has to happen right even, you know, when the teacher is deforming. So of course, stretchability can help in this aspect. But at the same time we also need to have another property. That is the adhesion because the deformation usually is coming from the tissue site, and then it goes to the device. So some bounding force needs to exist at the interface. And then the other thing is about the chronic, immune response. So then, to solve this issue ideally, the material and device need to have what we call immune. Compatible properties to, you know, suppress induce much less foreign body response in the chronic implantation period. So if you look at these 3 properties. first is a kind of a bulk, mechanical property, and then the other two are really the interface property right interface. One is the mechanical aspect, and then the other is a biological aspect. So for the sensor parts, actually, you know, we'll mostly talk about what we have been doing in these 2 interface aspects. And then I will come back to the stretchable property when I go to neuromorphic computing. So for one of the work that my lab has been doing is to think about the adhesion. And then, especially, we are interested in using transistor semiconductor based transistors for the like, a, the bio sensing with even higher sense sensitivity. So then, for this kind of a biosensor, the key of the interface is mainly coming from the polymer semiconductor. That is where the signal is coupled, and then to generate the sense, the sensing response. So there. So, therefore, the best kind of attachment should be directly through the adhesion between the semiconducting layer and the tissue surface.So not like, you know what people have been doing in the conventional methods. Right? That's you know. I will not go through this. They each have some challenges. So therefore, the research that we have started to envision is, can we utilize material design to directly incorporate blood adhesion properties into a high performance? Polymer based semiconductors to serve as a functional tissue interface layer. So that's you know, the whole piece of transistor as a bio sensor can be directly attached to the tissue surface just in a similar way as a tape. So after, you know, being able to achieve this material design eventually, I'm directly jumping to how it's used. So we incorporate it into a fully bioadhesive transistor basis. Sensors like it's also stretchable sensors that can. You know, the 1st advantage is we can attach it onto this beating rat heart surface just by, very simple and very gentle, and the shorts pressing, less than a minute finger pressing, and then it can stay very stable you can. You probably just saw right. There was a pulling applied from a teaser, but it still remained really stable and not influencing the recorded signal quality. So this is a kind of reflection on how the mechanical interfacial adhesion property can help to build such a long-term stable interface. All right. So then, the other thing I just mentioned. That we are also looking at is the immune response, the foreign body response so arguably for almost any type of implantable devices. This probably is the most widely existing and the most difficult challenge. So even for pacemakers, that has been the most widely used, implantable device. About 10 to 15% of patients go through the complication caused by foreign body response during the 1st 5 years of implantation, not to mention other more complicated devices. So then this is a process of having several stages. And then eventually, we're causing several challenges like issues. So then, what's my group has been thinking about is whether we can, you know also on the design of the electronic, semiconducting, conducting polymers to incorporate understanding from immunology into the design in the chemical and the physical aspect into the design principles in the way that it's when it's used as implantable surface, it can suppress the foreign body response. So actually, very luckily, this effort has been supported by the director's new innovator awarded the Dp. 2 mechanism. And now it's managed in Dr. Falcon's portfolio. So one works, you know along this line that we have been doing is about the chemical structure, because the immune response is largely a chemical recognition of a foreign material. So then, for the semiconducting polymer, we have come up with a kind of a synergistic of the two design strategies. One is about the main chain. So for the backbone, that is, to utilize the element of selenium, to replace some of the sulfur which is typically used in the backbone. Selenium is in the same group with sulfur, but has been found to have very nice immune, active properties in anti-oxidation, and also the regulation of inflammation, even treating cancers. So the other strategy is about the end of the site chain to introduce some of the previously identified immunomodulatory groups. So then, with these two designs coupled together, when we synthesize these polymers successfully. The key experiments we carry out is to put these, you know, materials in the mouse models at the back of their on their back underneath the skin, so-called subcutaneous implantation for a period from one week to 12 weeks. So here I'm showing 4 weeks results. So this is after we, after the 4 weeks when we explain the implanted material and the surrounding tissue. And then this is showing the histology analysis. What we are really looking at is this blue part that is showing the collagen layer the fibrotic tissue. And then, if we compare the overall density of the collagen, what we can see is that when we only make the backbone modification from replacing some of the sulfur with selenium, it already reduced foreign body response by 50%. And then, if we fully install the side chain immunomodulatory groups, it will further suppress to totally about 70%. Okay. So this is showing the influence of the chemical aspect. But chemistry is not everything. Mechanical property is also a main driving force. For example, in this previous work people have compared the hydrogels with 2 different modulus levels, one kilopascal and a 50 kilopascal. Both are already very soft, right tissue level, soft, but they have already. They have indeed observed there is a big difference in the immune response even within this very soft modulus level. So then, if we look at you know what is the current state of the material we are having, even stretchable, that is already making the modulus lower compared to the rigid electronics. It's still orders of magnitude higher than the modulus of tissue. So then, that shows us to turn our attention to the material that was studied in that example, hydrogels. So to move into this modulus range. One thing that we did recently is to utilize hydrogen architecture, to realize the semiconducting property, to combine the hydrogen level hydrogen carrots, biocompatible bioactive functions with the semiconducting about interaction properties. So the material that we were able to create using the regular semiconductor. They are not water. Soluble is a, you know, macroscopically giving a hydrogen-like very soft property, with, you know, high water content, and then microscopically forming a very porous network. And then the key thing is the modulus that we realized compared to the pristine semiconductor polymer, it decreased by 2 to 3 orders of magnitude. And then we started to use this material to compare the influence of the modulus on the foreign body response. And then one thing that talks about in the morning is about whether the when we make the material thin enough, it can already suppress foreign body response enough. So we are basically testing this. In that scenario. The semiconducting polymer is used as a thin field supporting a much thicker substrate. So it's in the context of how this will be used in the devices, but once we have observed, it is even with the modulus difference. Right? We only change the so-called cross-linking ratio that leads to the moderate change by about the order of magnitude. We can already see the same subject. The foreign body response is getting very clearly suppressed. Okay, so this is about the Oecd, the transistor base, the sensors. Hopefully, those can be some of the solutions moving us towards the sensing property that we want to have. I will try to be quicker when I move to neuromorphic computing. So what we are thinking in this space is about, you know, incorporating neuromorphic computing onto the edge near the sensors that avoids the clouds. Computing carried restrictions. So then, what's needed, we think, is a stretchable computing device. Right? So the neuromorphic comes into play because the design limitations we have are really limited areas and limited power supply which benefits from the neuromorphic characteristics. So the work that we have done as our 1st step is to, you know, utilize the kind of electrochemical transistor to realize a fully stretchable property that combines a memory function with the computing function on a single device level. And then we have, you know, demonstrated in the 1st work a prototype array. And then using this like the key performance characteristics, we have tested the function of the array in implementing the machine learning algorithm. This is a convolution neural network that carries out the classification of different types of abnormal Ecg signals and shows that even if there is a strain happening stretching the training and the classification accuracy still remain very high. And then, more recently, we move on to make it into a more usable large scale array that can really on the hardware implementing more complicated, useful algorithms. And then one application that we did that probably benefits the incorporation of neuromorphic computing which is coming from a work published by. Gina Adam. I'm not sure if she's still here. In a paper like 2 years ago. Probably that is, you know, about using machine learning to recognize the propagation wavefronts during the ventricular cardiac ventricular fibrillation. So that the precise ablation can be delivered just right at the wavefronts and then one thing I quoted in the paper is, such a system would produce over 60Â MB per second of data which must be processing milliseconds. So this is simply because the propagation is very fast. So therefore it's making us, you know, kind of unrealistic. If you need to rely on outside services like cloud-based AI computing. So then, using our array, the function we realize is to carry out the convolution function that is directly on the hardware to recognize where the propagation front basically pinpoints the location. So that's the precise treatment that can be delivered. So to finish my presentation, you know, I think now it's time to go back to the system level. I think one complicated thing is this is a really, you know, diverse and a large range space. So we are thinking about different functions that can happen either on edge or in the cloud. That will include, for example, so on edge, you really are physically integrated in the system, and then the cloud probably still needs to rely on the wireless data transfer. And then it's a, you know, need to perform for different kinds of functions, including signal conditioning, feature, extraction, encoding, encryption, decoding, and the prediction classification. So then, one question we need to think about is which parts go where? Okay? So my last part of perspective, that's how you know the end. My presentation is the first challenge is, we need to, you know, figure out more. Which part of the machine learning data needs to be physically integrated, like what I just mentioned? Right? And then the second thing is, how can we design the hardware? That's better physically, integrate, even functionally merge the sensing function with neuromorphic computing? And then the 3rd is that there are different kinds of machine learning algorithms. We heard about AI, and we heard about spiking neural networks, which should be the best for all you know, for different parts, different applications of wearable, implantable functions. And then, last, is a. We also need to think about the need for a preferred circuit that supports the neuromorphic function. How should they be incorporated in the tissue skin like properties? Okay? So last, you know, this acknowledgement to my group's founding supporters and the collaborations. Thank you very much.

27:40 → 27:46

**Ralph Etienne Cummings:** Thank you so much, Sihong. Very nice. But we won't have time for questions, we'll wait till the panel. Erica, please.

28:07 → 44:13

**Erika Schmitt:** While he's pulling that up I can give a quick introduction. My name is Erica. I'm with Cambria. We are a startup working on auditory, blind source separation. My background is a little bit different than most of yours. My expertise has been in industry bringing complex systems to market. So new technologies change management across organizations. What do we really think about an end to end new solution looks like in terms of delivering? And I think we've talked a lot about this over the last couple of days. This is really more than a technical challenge. It is changing behaviors and getting buy-in across the ecosystem so that we can bring neuromorphics to life. So today, I'm gonna talk about key features and structures within our network, what we're building, what we see as addressable use cases, and then some of the challenges and outlook for next steps. So we are working primarily in auditory blind source separation. Like I said, we're currently working with mono channel audio. So we don't have any of the spatial or temporal cues that you would rely on for beam forming techniques. And that's really so that we can isolate algorithmic performance directly the task is challenging, because it requires building a rapid contextual awareness of not only the signal but of what's important within that signal and being able to dissect signals when you don't know the number of inputs or the type of inputs that you may be encountering. So to do this. We've developed a novel neuromorphically compatible algorithm that we talk about as a synchrony loop propagation model. That means that a signal is exchanged continuously bidirectionally across graded spikes in the network. Every region in the network has neurons that are equipped with distinct behaviors. This means that we can have learning at multiple time scales with different properties. So the beginning of the network is a series of oscillators that are each attuned to a specific set of frequencies. These are connected tonotopically to a pitch detection region that within about 5Â ms of activation begins to consolidate signal across those oscillators to recognize a consistent harmonic signature, to start pulling information out of the environment within about 20Â ms, the signal is consolidated into a consistent harmonic signature. So that's recognition of a voice or an instrument that builds an active working memory that's actually physically represented in the network itself. So we watch the network behavior with a kind of persister to see where those pathways are forming. And the network actually then starts to develop longer term memory of that signal, to build fractally deep representations in a fully plastic, long term learning region. That region then begins to exert expectation back down the network, almost like predictive coding, to be able to say, I expect this sound source to continue to be present in practice. As the memories form, this looks a lot like the auditory system, so our network architecture is inspired pretty directly by, but does not mimic. So again, that kind of idea of form versus function, the auditory system which we know features tonotopic organization. Early in the network with increasingly complex cognitive function along the way, sorting into semantic reasoning and auditory reasoning. And so that's exactly what's happening within our system. We use multiple types of signal that are continuously exchanged. We have 2 types of feed forward signal exploratory that can be thought of as calcium that is sort of propagated freely across the network until thresholds are reached, using ion gating principles to allow for activation signal that actually takes action to change the state of neurons throughout the network. Again, because neurons in the network can have unique behaviors, those gating principles at different regions and in different structures across the network can be unique.They can also respond differently to different types of sound. So we can have the network recognize speech versus instruments and the decay on the expectation of the consistent harmonic frequency, the complexity of the harmonic frequency to try to recompile those sounds is actually different, depending on how the channel recognizes what source is being played in the environment. After that forms, we have that prediction signal that is exerted back down the network, as well as a number of different regulatory signals that allow for local management of excitation and inhibition. There is no global loss, for there's no global loss function within the network and no sort of external control. This is all emergent behavior based on those collective behaviors in the differentiated structures. And this signal propagation is multiplexed at every neuron in the region. So that is how we extract multiple types of signal across channels simultaneously. So the other interesting thing about the network is that all behavior is completely transparent because we don't have any concept of a differentiation and network behavior between a training and a testing phase. We can use simulated neuromodulators to sort of ramp up attention. If we want the network to pay extra attention to a stimulus. For example, you say you wanted to learn a new voice, but the behaviors within the network don't change between training and testing. So on the left, you can see information of gating principles at a neuron level. We have region level monitoring. Those are really just persisters. Again, behavior that reports out of the network and overall system level responses, scoring accuracy in response to phonetic stimuli in a test set. So this is all well and good. But I want to transfer a little bit to what this means and how we see this working in practice. So this network is designed to be able to dynamically learn and extract multiple sound sources in a crowded auditory environment like this one responsible. And what is happening within the network is that it's starting to pay attention to the sound of the instrument, the sound of the voice, the sound of the water within that crowded sample. And so if we play back just the output of the channel with the instrument, this is what the network produces. That occurs in a network that had 0 prior training data. This is a newly instantiated network, and that is all emergent behavior based on the recognition and expectation of those continuous feedback loops within the network. If you listen really closely within about the first half second, you'll hear a little bit of fuzziness. That's the training time of the network. And this occurs with a network of only 12,000 parameters. We trained a Dnn. On the same task. Our test set included 5 instruments in our training set, and an additional 5 kinds of adjacent instruments in our test. The Dnn. Did perform us qualitatively, outperform us quantitatively. But what the training requirements and parameter size show is that Dnns are fundamentally unsuited to doing this kind of live learning and separation at the edge. You can never infer how many different combinations and what type of information you're going to encounter in the real world. So what we really view are being held responsible. So we did also benchmark this against Nmf and Ica to other unsupervised line store separation. We outperformed both approaches in all of our levels of difficulty except for level one. Ica did outperform us, and we also were able to demonstrate that that half second learning period was replicated across our entire training set. So what does this really mean? We know globally that over 1.5 million people suffer from some form of hearing loss. The majority of those people suffer from mild to moderate hearing loss. And that's typically classified as having a hard time hearing in a crowded conversation and hearing loss has significant comorbidities, social isolation, depression, anxiety falls, lack of autonomy, and educational employment. And this has real economic impact and is a growing problem. We all abuse our ears constantly, and the projections of those who are going to be impacted by hearing loss is a massive health problem. But despite that, most people have mild to moderate hearing loss. Don't use hearing assistive devices, and because the truth of the matter is, it's because they don't work very well in those crowded auditory scenes where you really need them most. We've also seen other deterrents like high cost, low battery, life, discomfort, stigma. We haven't started to see it yet, but I do think the Otc. Deregulating apples coming out as wearables, will help to reverse those trends. As I mentioned, we don't have any data on that yet. That is my speculation. But you still need the ability to replicate an organic experience. So that is the ability to select and amplify a single voice, and that's exactly what we set out to do. Can I go to dinner? And, sitting across from my friend or partner, have only their voice projected back to me, and not the person sitting at that close city table right there, or the person right behind me, and then again pop your device into learning mode and say, I know I'm going to be speaking to this waiter all night. I want to learn their voice as well. That's really what we're seeking to do. This is also important, because privacy with this model is inherent, because of your property, because the learning is happening directly on the device. None of this information is being sent back to the cloud. None of it is being recorded. It's just the name of the person as a neural pathway in your local network. And it's an extreme. It can be implemented with an extreme low power for all day use long term. We think that this approach is actually extensible to multimodal learning. So being able to incorporate vision, touch action, there's nothing fundamental about this note about the learning approach that isn't extensible to other senses other than resources. But think about being able to pair gaze with that sound source automation, so that I'm able to say, when I see that person's face and that person's lip moving. I can also understand that I expect to hear that voice we use naturally. That's really where we see the long term potential of this technology, and where you would need to definitely be on neuromorphic hardware to get there. But we are a small company, and so practicality prevails. We are looking to go to market in traditional hardware. We would love to deploy this as a flexible SDK, where the waveform is a complex waveform. We have our sound model that processes with that 1Â ms latency, because the input layer is a series of oscillators. We don't have any windowization through fft. So it's continuous processing in a neuromorphic device that would be true temporal, continuous processing where the output is sound sources that can be labeled by each user directly. This means that you can utilize existing on-device hearing microphone arrays and incorporate directly into the DSP with that SDK layer being flexible at any stage, and the user experience designed to meet the needs of elderly patients, younger patients. And the ability then to say, I want to mix how your output channels are being played back to you. So I may have a preference to say I want to change my secondary audio channel to 0. Some people find that to be really stifling, but giving people the ability to have that control is really important. So as I mentioned, we plan to go to market in existing hardware, but long term we would love to be on a neuromorphic device. So we've spoken with groups like Spinnaker and Atera. And while there's absolutely customization that would be required to implement this in neuromorphic hardware, there aren't any fundamental limitations. The multiple signals of graded spikes will require some customization. But we have good ideas about how to get there. But it's a tough road. So long term. That would basically mean you have your neuromorphic processor doing all of your sensory processing. But all of the digital could live in the CPU of. And that's consistent with the design of current neuromorphic chips. Now, I will be really candid. We've stopped telling potential investors and partners that the core of this algorithm is neuromorphic. And I think that's an interesting idea for this group, because it makes it feel risky. There's not a lot of neuromorphic devices that are implemented in consumer hardware right now. And so we just need to show that it works. But we also need to be able to work within that ecosystem. And there is the entire. How do consumers understand how this algorithm should work and how they should interact with its component, and that we don't expect computers to work with us in this manner. And so we really are trying to kind of put together the industry R&D hardware partnerships. Now, we do have algorithmic improvements that we need to make to be completely device ready. But it's really thinking long term across that ecosystem of How do you create an appetite for what we think neuromorphics could provide in a near term interactive solution. So this is where funding has gone by. Sectors over time. Thank you, Pamela, for this slide. And we heard earlier in commercial spaces. You need a 3 to 5 year return on your investment. We could probably get to market in a hearing aid in 3 to 5 years with the right funding. But what we really see and what we want to be able to do concurrently is develop the core of this as neuromorphic. To say, this is a win for this field. We want to be able to see if this is a helpful mathematical model that could be useful for all of the incredible use cases that we've seen today. This is a very simple problem compared to what we've heard in skin sensors in prosthetics. But it's important, and we see it as a potential opportunity to win in space. So I'll conclude and try to go quickly. I know we're a little bit behind. Broadly, we see neuromorphic promise for applications that perform more naturally that and the function matters, and is in our case enabled by the form. But we also see the form inspired by the required function. In this case the form needs to perform, like our ears do when they stop performing well, and it's sort of that give, take model of how do we kind of naturally engage in that co-design? So we would love to figure out how to engage more broadly across the community and really merge the objectives of research and industry, because I think they are incredibly aligned. But funding models don't always agree with that. So thank you. Guys so much for the time and look forward to questions.

44:16 → 44:22

**Ralph Etienne Cummings:** Thank you. Thank you for the industrial perspective. I think that's very important and that's missing for us. Wonderful, Brad.

44:35 → 45:13

**Audience:** I just wanted to say that what's really interesting about that is that the thing about using earbuds is that there are all sorts of other sensing modalities you can put into earbuds. I know Gert Kambergs, who was talking earlier. He's working with people on seeing what kind of brain computer interface you can do, what kind of EEG you can do through the ear like whether there are any signals that would be useful for any kinds of tasks. So it's just an interesting platform, I think. Hearing aids for other kinds of sensor modalities.

47:03 → 47:07

**Ralph Etienne-Cummings:** We're ready to go to the next Speaker, who is Bradley Aimone, San Diego National Labs.

47:08 → 01:04:32

**Bradley Aimone:** Alright. Well, thanks, thanks, Ralph, and thanks everybody for your patience and getting set up, and I think I'm the last official speaker on the agenda. So I know the lead up kind of encouraged me to be a little bit provocative, and that's a challenge you may not want to give me. So I'm going to talk a little bit about neuromorphic computing algorithms as a whole and kind of where I think this can be used to help us understand neuroscience better. My role at Sandia for the last 10 or so years has been to look at these emerging neuromorphic systems that are being developed broadly in industry and in, you know, the broader academic world. And we don't really build hardware ourselves. We build test beds for these systems. My background is actually a neuroscientist. I came from a computational neuroscience world. I'm going to start with a little bit of a personal history there, and why I was attracted to neuromorphic computing originally. I think part of the reason that's interesting is given the context of the last couple days. This is a very interesting time for neuromorphic computing, to turn back to neuroscience and see what neuromorphic computing can offer neuroscience. So I'm intentionally trying to throw some questions at you and to think about going forward. So my background before I got into neuromorphic computing was, as I mentioned, theoretical neuroscience. I worked at the Salk Institute during my Phd. And for a short postdoc looking at adult neurogenesis. And if you're not familiar with adult neurogenesis, this is a process by which our brains, everyone in this room, are adding a small number of new neurons. As we're sitting here, the rates are quite low. I mean, we're probably talking about on the order of a few 100 or thousands that are born on any given day. It's not entirely clear. It's very hard to study in humans, of course. And of course, many of you, if you're my age or older, were taught while in school there are no new neurons in your brain. Once you pass the age of like 10 turns out, this dogma was false and has been reliably seen in most mammalian species, and certainly non-mammalian species, couple of exceptions. Now, since then, and especially when this was an emerging field about 20 years ago, there was kind of a flurry of research. This is a new system. This is a new dynamic in the brain that we can characterize. And it's kind of nice because its development occurs in an adult system. So there's quite a bit of work that was done to characterize these new cells in the context of broader hippocampal computation. It was. It was convenient that this is occurring in the dentate gyrus, which is actually a very well studied area. So I'm not going to go through big details of the modeling I did at the time other than to say that we found out, by looking at the sort of biophysics of these new cells the slice physiologist at the time characterized that. Basically, these young neurons are extremely excitable. You know the mature cells they sit around. They don't do much. They're quiet. They, you know, like this old guy here. They only respond to one or 2 things, but the young cells respond to everything. And this is actually a pretty interesting thing from a computational point of view, because you end up seeing this kind of complex mixed coding that comes out of it where you have a lot of sort of grandmother cell- like responses in the dentate gyrus. And this is always forever has been the theories in the dentate gyrus that this sort of sparse coding, because cells are very, very selective to what they respond to. And you have this, like a small population of young neurons just firing everything and the combination of them yields an interesting dynamic. So we had a number of models over the years. And it's not just me. There was a kind of a growing little cottage industry of computational modeling. And everything kind of settled on this point, which was that new neurons help something we would call pattern separation, which has long been thought to be the function of the dentate gyrus. Now, pattern separation. If you're not out of that world, you can think of it as decoration. Take 2 things that are relatively similar, and the coding coming out of the output is quite distinct. Now, I won't go into full details here. But this is a little bit unsatisfying because it's like, you have this amazingly complex, interesting new thing happening neurogenesis in the adult, and the function of it is to do what the region was already believed to do. And so that was. And it was kind of circular. And with all this data that said that this might be important in aging and depression and mental health and stress and all sorts of things. And yet we can't really connect it to anything clinical. So that was kind of the sort of reason I was kind of like. I wait a second. I'm not sure if we're doing the right thing. Chasing theoretical neuroscience in this way led me to neuromorphic eventually. So kind of to be a little bit provocative. Here, we saw this slide here from the Stevenson group, with a kind of recording originally. Where we were looking at the rate at which we're improving our tools, the ability for us to record from the brain, whether it's bottom up. Looking at spikes, recordings, we're now tens of thousands. The optical tools that were mentioned. But you did this morning. Where are far more than that? Different resolutions, of course, and it happens top down as well with Fmri. You know, we're starting to get higher and higher spatial resolutions and temporal resolutions. These are our computational tools, our frameworks, keeping up with this. And I think it's very interesting to look at the Nobel Prize that was just awarded, which I mean I love the Hopfield paper that I cite here right. It's like an exercise. For you know, basic understanding of what neurons can do. Everyone should read this paper. It's 1 of the most beautiful papers I know of like 5 pages. It's worth your time. But the idea, as elegant as it is, and as simple as it is, still dominates a lot of the thinking of computational neuroscience today. And it's not that it's wrong. And there's a reason it dominates. You can see this very nice paper by Iulafiat and the group. And you can see how there's these attractor landscapes and manifolds. Kind of, you know, that's kind of the words of systems neuroscience. Now, the problem is that I believe. And this is Brad's opinion here that we have a lot of frameworks that are physics based or basic computing based control based whatever that has been thought. You know what? We can sit there and look at a thousand neurons and think to ourselves, what can a thousand neurons do well? I can form some tractors, and I can look at these dynamics and visualize it right? We need to put things on Powerpoint. So we need to be able to compress it o 3 dimensions, of course, or maybe 2 ideally. But when we do this, I feel like we're at the risk of doing something like this, which is, I get my little 1,000 or on brick, and I stack up 2 million of them, and I can get a you know very beautiful thing. But ultimately, just like in this case of a present, it's just layer upon layer upon layer of exactly the same thing that doesn't really, you know, just does more of what the small system does. Right? I can build a pyramid out of a thousand Legos, and it's gonna look the same as the pyramid out of 2 million. It's just going to be a lot smaller, right? I don't think this is right. You know, if you go to something like I was in Spain earlier this year. I was at the Mosquita in Cordova, one of the most beautiful places I'd ever been. And if you've never been there, what it is is, it's a mosque. It's about a thousand years old that the Moors had built. And then, when the reconquista happened, instead of tearing down the mosque, which is what they did in most places in Spain, Cathedral inside. And so you end up having this like evolution over centuries of architectures and complexity that is shocking. And you look at the brain. You see, you know, I'm not going to say it's the same thing. But there's this sort of richness and this complexity. Every little part of the brain is different from every other part of the brain. And it's not at all obvious that there's 1 framework that just applies to everything equally. And so I think that we do very well, maybe trying to model and understand the brain using a limited language of tools. It's not that these are wrong. We still need bricks, of course, but we also may need more, and I don't think there's enough of that going on. So with that sort of context in mind, I guess the question is what you know, what is the solution? Right? It's easy for me to throw bricks at glass right? So one of the things that we've thought about is that many of the methods that we have are kind of baked into our mindset by having a sequential processing of states. That's how we program things. That's how we think about math when we're taught from algebra and up. And that's when we look at the brain, we look at a raster plot of spikes coming off of electrodes. And we say, how do we chop this up into time bins and see how these States change over time? It can be dynamic. We can have manifolds, all sorts of things, but it's still very sequential when it all comes down to it. So I have a postdoc, Brett Thielman. He came from the birdsong community. And he basically asked, Well, why does it have to be chopped up in space? Why not divide things in spatial, temporal sort of threats. And people, of course, have been thinking about causal chains through spiking networks forever. And it's been. It's like, let's revisit this because now we're seeing we have the connectomes. Right? So it's not just looking at the raster and finding some causal chains. But we can actually take structural relationships that constrain those causality measures and take rules that are similar to spike timing to minute plasticity. And we can pull out some activity threats. And now we can think about what algorithms look like. Where you might have these sort of weird little trajectories, these sort of we call them Nats that are tied together. This becomes your sort of computational kernel, and they can happen in parallel right? They don't have to like, say one or the other. You can have many of these going on, and they can weave in and out of each other. So that brings us to neuromorphic right? So as I mentioned at Sandia. We gather neuromorphic chips. We've been gathering them kind of as you know, kind of a bad hobby of a collection. Right? If we see a new one, we have to have it. And we have actually the world's largest loi, 2 systems over a billion neurons. Right now. We have. We're going to be having one of the largest spinnaker systems coming up. We have a lot of analog systems and so forth. I'm not going to show the whole list. What you have to kind of appreciate is that this is a time. Step along a longer trajectory, right? The future is going to be something analog. It's gonna have a lot more complexity, maybe Memristers, maybe other materials. Who knows? And we can scale up even bigger. But right now, this is what we have. And what can we do with it? What these chips are is basically lots and lots of neurons where I can program a graph of neurons to do whatever I want. I can build whatever connectome I care about, whether it looks like the hippocampus looks like a cortex. Looks like a cloud stream. Whatever that circuit looks like. I can do what I want. This is very different from say. What we do on a GPU or CPU, where I'm programming a sequence of operations. Even if that sequence might be a parallel operation like a vector matrix, multiply that all happens at once. It's still a sequence of layers. Again, we're back to this very sequential way of thinking about computation that the brain has no reason to believe to be constrained to. Furthermore, the neuromorphic systems can embrace heterogeneity. I don't need everything to be the same. I can actually have everything be a little bit different. So in the last couple of minutes. I'm going to throw out 2 things that we have found that neuromorphic systems are really good at. If 5 years ago, if you'd asked, are neuromorphic systems going to be good? At this, they would have said, no way. And I think this is important, because what this tells us is that, you know, if you really want to get philosophical here. The brain is going to be good at things that the brain is good at, and there's no reason for it to be really good at other things. Neuromorphic systems which in principle have copied the brain's kind of components and architectures. If we find things that the neuromorphic systems are really good at, it might be a clue to understand some computing primitives, motifs, if you will. That might actually be something to look for in the brain. So the two things that we have found are sampling problems, things like Monte Carlo and I'll show briefly an example of what I mean by that. And things like actually physically mapping the sort of physical interactions over space. Finite element type approaches. Actually, the first example of looking at Monte Carlo Random walks. We had a paper a couple of years ago that shows that you can actually wire up a population of neurons. I usually lay things out. It's not a brain inspired circuit. It's just a system of neurons that's kind of structured to map to the state space over which I want to do a random walk. So think about a stock price randomly moving up or down, according to you know. The vagaries of the stock market, and I want to model that stock one million times in parallel. Well, today I loop through, you know, trial, one trial, 2, trial, 3. And I run through the code a million times, and I average over everything. What the neuromorphic system does is actually runs everything simultaneously. The random walks or a spike traversing over this complex network of neurons. I don't think the brain does this right. But if you start looking into the literature going back years about where sampling shows up in places like hippocampal replay. For instance, it actually is not a bad idea that the brain is actually doing Monte Carlo sampling in advance of decision making. And so there's some interesting directions to pull on. And I actually think the circuits that work well, here may be things we could look for as motifs as we start looking at these more complex connectomes. The other one is a newer result. This is something that in my postdoc Brad Thielman has developed, which is an idea that we can actually take these sort of physics- based models like finite elements where you're actually trying to solve a partial differential equation. A victor yesterday had a great example of you know. They wanted to put this under a morphic. They didn't really know how. Well, I think this is how actually. And so you can take the idea that combining some of the sampling stuff we did, and the fact that we can wire neurons together as a kind of population that talk to each other according to the physics interactions that might be modeled in a system. If you're coming from a more neuroscience kind of systems, neuroscience view, this, this sort of framework where I have this sort of mesh of neurons where each little vertex is a small cluster of neurons that are tightly coupled. But broadly or kind of globally, sparsely connected. That's like a cortex model. Right. You can think of this almost like a cortical column sort of thing. That's not what we did. We looked at the sort of math finite element simulations projected into neural hardware. But all of a sudden we see something that looks similar to these sort of abstracted cortical model things that people have, turns out, this works really well, like almost, kind of freakishly. Well, if I covered up which one was the ground truth, which one was the spiking network you wouldn't be able to tell. And I think part of the reason is that each of these, these, not even that many neurons, but each of those vertices of like a dozen neurons or so have a bunch of little independent estimators that when they combine you end up getting this sort of settling control thing. So we've talked a lot about control. In effect, this is a distributed control circuit distributed over 20,000 mesh points of something. So you can almost think of something like a particle filter sort of approach right? And so, as you can see from the dynamics, this is what you'd expect if you stuck electrodes into the brain and started observing things. This is the behavior of scientific computing, numerical methods, solving partial differential equations on neuromorphic hardware. It looks like nothing. It's not at all based on what the brain does. But yet it's giving us dynamics and behaviors and functions that are kind of brain-like. So, I'm not going to say that the brain is solving partial differential equations. I don't think it's solving stochastic differential equations necessarily in the ways that we do mathematically. But I do think that these sort of approaches are things that neuromorphic hardware, if you look at an architectural level, is intrinsically well suited to do because of what makes neuromorphic hardware special and what makes neuromorphic hardware special are the things that make brains special and because brains are special in these ways that embrace heterogeneity and parallel sampling and spatial temporal processing. I think it's something we also probably need to think a little more seriously about when we think about theoretical frameworks for understanding how the brain is working. So with that, thank you very much. Please, if you're interested in this, come to Nice in Germany next March. Thank you.

01:04:33 → 01:05:51

**Ralph Etienne Cummings:** Wonderful Brad. So please the speakers. Panelists, please come up. Okay? So maybe what we'll do is let us know. Yes, why don't you stand up and tell us who you are and give us your position statement.

01:05:53 → 01:09:38

**Andreas Andreou:** My name is Andreas Andreou. I'm at Johns Hopkins University. So Ralph asked us to make a Powerpoint and give a position statement. And my position statement seems simple. There's basically 2 dimensions in which to think about spire inspired and neuro and biomedical and neuroengineering technology is really forming much. I've heard that this is kind of unusual. But I worked in a meeting, and everybody talked about form and function. I don't. I started with it. And let me start with a function. Function is really from an algorithmic perspective. And what we need is really algorithmic constructs that exploit, temporary processing and explicitly using time in algorithms, for example, machine learning that uses learnable delays event based algorithms. I don't know. It seems interesting, etc. So that's really the needs, the impact. By doing this, we can actually go on and design and achieve robust design methodologies for mixed signal circuits. Because now analog dimension is a time, it's not a value which really allows us to do processing with robust challenges investment. We need research and design methodologies, such as co-design algorithms with a synchronous circuit design by the definition event based and challenges design automation cut tools are not at the level of readiness to fully support a complete automated flow for design from algorithm to chip design portal. Well form, I associate form with hardware design. And here I'm gonna throw a term. I don't know if you talk about that, too. Neural chiplets. If you don't know what about what is no triplets it's a way of actually using reusable, cheap Lego, like design to make complete system most AI chips today the ones that are gonna survive are really based on chiplets or the ones that are they're emerging. It's a modular, scalable and reusable hardware design that can be mixed and matched. Using heterogeneous devices with a structural complexity that involves different materials and structures, challenges develop standards, libraries, and a chip led ecosystem to ensure scalability, impact, rapid prototyping or minimally viable solutions, which is really what we want to do if we want to take products to robotic designs to market research. Investment. And I think our colleagues from Nih probably should pay attention to this research and design methodologies to ensure usability and certification standards of neural triplets that perhaps involve knees. There is actually a no, no harm that was released a few days ago. Through the Chips act, which is napmp, which is really the National Advanced packaging manufacturing program. October 18.th There is a note of funding opportunities to do that. And that's it. That's my pitch.

01:09:47 → 01:09:49

**Ralph Etienne Cummings:** Okay, so let's go to Robert.

01:09:50 → 01:12:05

**Robert Stevens:** So my name is Robert Stevens, and I’m from Johns Hopkins University, like, I guess. And I am a position and also a position scientist with sort of straddling the school of medicine, the school of engineering. So my primary focus of my research has been in the use of computational models to gain further insights on mechanisms of acute brain injury, primarily traumatic brain injury and to develop novel approaches to classification as well as prediction both of outcomes and treatment response. So traumatic brain injury is a leading cause of death and disability globally and we have over the past 30, 40 years, implemented a large number of different therapeutic paradigms in preclinical models and in randomized trials. And those have been, you know, inconclusive for 95% of them. So there's really no treatment for this disorder. And the question is, can we do better if we leverage rich data sets? So, for example, imaging as well as continuous physiologic time series biomarkers. Multi omics use these as inputs in sophisticated simulations or models to better understand both the acute injury, the recovery potential, the response to treatments. So we're working right now on multiple different types of data. We're building these multimodal fusion models. And in many ways what we're doing resembles a kind of digital twin for brain trauma and so we're exploring this paradigm as a potentially powerful method to evaluate and test hypotheses regarding brain injury and its treatment. Thank you.

01:12:07 → 01:17:21

**Pam Abshire:** So Ralph did ask us to be somewhat controversial. So I'll just start. I'll just lob one out there. I think that, you know, we're all a little bit in awe of where things have gone with large language models and the capabilities of large modern AI systems that we see today. We're also pretty impressed with the power consumption of those systems. I think that like to me when I look at that, though I say I'm looking at it a slightly different way, saying, Wow, what I'm learning by looking at this is that a lot of what I previously conceived of in my life and in the world, just in terms of understanding the world as cognitive is actually a much simpler task. Right? It's actually correlation. It's actually just mapping. It's a lookup table, right? All modern artificial intelligence systems, no matter how many, how many parameters, or how big or how complicated, are fundamentally just fancy lookup tables. Right? And so what this is really teaching us is about the nature of the problems more than about anything that we would learn or know about intelligence. And so I would argue that right, really, what we're learning is just that a lot of what we previously thought of as cognitive, or something requiring us to be involved is maybe not quite as intensive and operational at some level. And so we're learning that language is a lookup table, or at least a lot of parts of language or a lookup table. So that's the first one. The second thing that I wanted to kind of lob in is, we've had a lot of discussion about the value of neuromorphics in different kinds of domains. I thought it was really cool that we had the talk this morning. That was like an angle I hadn't thought of before, like, fundamentally, there's this mismatch that there's you know that the gorillas, the 800 pound gorilla sitting in the corner over there is the real advantage of most of the neuromorphic stuff that everybody's talking about is for really ultra extreme edge, low power computing. Right? That's what the benefit of that's what the benefit is. And the mismatch for this meeting, which I'll just put my finger on, is for most medical applications. You don't need that right, because if you're doing it for prosthetics or for some sort of disability services. The power that you're spending in the motors or in the emergency room, or within the car, or whatever like that. That power completely by orders and orders of magnitude, dwarfs what you could achieve with the neuromorphics. Tony disagrees. Tony disagrees. Okay, okay, I'm looking forward to the conversation. So I think that like the power there's just this mismatch and so that leads me to thinking that the niches where it would be relevant would be where you have data, rich information, poor problems, where you want to use some sort of initial early, you know. So what are these kinds of things good at? They're good at correlation. They're good at filtering. They're good at simple estimation and prediction. And so when you need that estimation prediction, and you don't want to have access, you know you. And you want to apply that to a very data rich information. Poor problem where you want to pull out some of those nuggets early on or if you haven't, if you have a system where you have maybe a deep, implantable. You've got a remote agent, and that remote agent needs some ability to operate autonomously, or you've got a system where you need fast feedback, like, you know, that's why do we always have the pole balancing problem? We could really do the pole balancing problem with neuromorphics, right? Because it's fast. So those are the kinds of applications that I think neuromorphics still would offer some distinct benefit for. And then I'm gonna finish with my last kind of plug, which is that? I am very fortunate to have a couple of research projects I've on neuronal computation. And so I've been thinking, is Timmer still here? Timur was here earlier. Yeah, he's 1 of my colleagues in both of these projects. And so we have. You know, based on a technology convergence that we've seen in the last 10 or 15 years we have. And we've seen several really good examples in the talks. Our ability to interface with neuronal systems spatially and temporally has kind of exploded both in terms of high density. Electrode arrays in terms of optogenetics and optical interfaces. So we have a lot more ability to observe and control. And we're trying to use that to learn how to kind of engage with neurons as a computing system. There was a speaker yesterday who put up the ball of organoid cells and said, Wow, that looks like computation. And I look at that and say. I don't even know where to start with inputs and outputs. And I do with inputs and outputs. So I think that that's a really important thing to do. And we're beginning to try to take baby steps to do it, like, even. How do you conceive of what neurons can do in terms of computation? I don't think we have the answers.

01:17:28 → 01:22:01

**Amparo Guemes Gonzalez:** Yes. Well, first, thank you very much for inviting me and for allowing me to connect remotely. So I'm a real academic research fellow at the Bioelectronics lab at the University of Cambridge. And here I work on developing algorithms and algorithms and bioelectronic interfaces to improve metabolic control through neuromodulation. So my current work is centered on understanding this link between electrophysiology and metabolic changes. And how can we use neuromodulation to interface with the 2 systems? And I use these conformable neural interfaces that we can fabricate in the lab. This lab is led by Professor Josh Madaras, and these interfaces kind of align with what's been discussed.So they are very flexible. They can be stretchable, conformable so, and they are based on conductive polymers. So they work very nicely. But we are facing problems that I think neuromorphic systems will or integration with neuromorphic systems will work. So, for example, we also do a lot of organic electrochemical transistors in the lab aspects and for various applications. And recently I read a paper from Simone Fabiano that they were developing what they call organic electrochemical neurons based on these Oecds. And they basically demonstrated that this integration boost. So not only had the advantages of Oecds in terms of biocompatibility in terms of ability to to operate in different scenarios. But also gather all the benefits of being fast and low power. All the advantages of neuromorph engineering that we've been discussing. So this is just an example, but on a different thing, that they work a lot which is data analysis and signal analysis, we are recording signals and like very high frequencies. So over 10 kilohertz sampling frequencies, many channels. And this is something that has been pointed out throughout the workshop. There's a lot of information that we don't need, but still we are recording it. And then not only was it like the need of sending all that information, but also analyzing, storing it. My files are tens, hundreds of gigabytes, just one single recording. So the compression abilities, basically like leveraging that sparsity of the data. That's something that neuromorphics like, it's intrinsic to that. So I really see that the natural way for peripheral nerve interfaces at least to move forward is through the like by integrating with neuromorphic designs. And that's not talking about, like all the other benefits that we mentioned about low power and therefore low heat dissipation, which is something super important for implantable devices. The ability to do this online learning and responsive system that can be integrated into closed loop systems. So in my field of bioelectronics for metabolic control. I definitely see that this is the path to move. But one thing that I really want to talk about in the discussion is which is the best way to do this, because this is integrating many different fields. This is something that has been highlighted in the worship as well. We need neuroscientists. We need material scientists, data scientists, of course, electrical engineers. How can we work together? Do we need one lab that has each lab that has different profiles of people? Or is it more efficient to work in specialized labs that collaborate all together. So this is something that I wanted to raise, because I know that it's been mentioned throughout the worship. But we didn't detail on the best way to move forward. So that's it. Thank you.

01:22:02 → 01:22:05

**Ralph Etienne Cummings:** Thank you, Ampero. And I think, yeah, Jennifer. Now I need your help to pull up the slide.

01:22:06 → 01:27:08

**Jennifer Blain:** Oh, sure, I guess I can get started before it's up there. But what I have up there is really a lot of my work which is quite multimodal. So I do things at the scale of trying to measure molecules. I do optical. I do pressure measurements. I do, you know, stimulation recording all of those things. But so I wanted to bring up a couple of points as relates to the multimodal nature of the work that I do, which is that I think there is a really interesting potential for neuromorphic approaches to enable better what we might call sensor fusion in this space. And I haven't. I've heard a little bit of talk about that, but I haven't heard anyone really delve into it. How do we take advantage of neuromorphic techniques to really think about the different timescales involved? So when I think about molecules. That's not the same time scale as an electronic measurement or a pressure measurement or so forth. So how do we use neuromorphic techniques? And can we, you know, as a community. Think about that to leverage some of what neuromorphics has inherently learned to do in our, you know, in human systems and animal systems to better advantage rather than having to come up with de novo. All these algorithms integrate that information. The other thing that came to mind as I, especially as I was listening to all the talks. I have done a lot of work in trying to create these systems. But well, I should say my students do the work. And we're spending a week making one. And this is all from scratch, figuring out, how do you do this? How do you make these things? How can they band? How can we integrate active circuitry into those systems? So we get functionality. We need tools, the way that there are tools for Cmos. If you want to do something in Cmos, there is a very well known, excellent way to learn the tools and the techniques, the textbooks, everything. But for things like this there isn't really a textbook, and I know my colleagues have also developed their own techniques. And there are many of us out there, and they're all somewhat different. We're not having enough conversation, I think, around, how do we take neuromorphic engineering and integrate that with, you know, and come up with ways to create platforms for designing the technologies, the physical hardware technologies that are now soft and flexible like I'm showing here. And so I think you know, having some and some of that was mentioned, but having some of those tools in terms of how do you do the circuit design? How you do the hardware fabrication and so forth, so that we're not spending so much time trying to come up with those de novo every time. You know, and then I hand it off to my neurosurgeon, and they have. Oh, that didn't work. Toss it! That's a whole week, 2 weeks for grad students. Time. No, that one didn't work. I'll grab another one, grab another one, and pretty soon it's 2 months of that grad. Students' time is just tossed away so we can get it into a single animal. And so, you know, it's not efficient. That's not an efficient way to work. So we really need to have better platforms. And there's a little bit of conversation maybe trickling around between some of us about, how do you have it? How do you have techniques for fabrication that aren't every single person trying to come up with their own clean room fabrication protocols to create these devices? So I think those are some of the things that I've been thinking a lot about in terms of the neuromorphics. There is a lot of translational work. So I'm really trying to go. Does the patient get in, you know, at least an animal model. Doing a lot of diagnostics and some of what you see there, and what I'd like is to have less time spent in the fabrication in the clean room before I can actually get to any of that physical testing, any of that animal model human subject testing. And I think that relates to what I've been saying about the fabrication processes and trying to have something that is more integrated. I know I've seen some great people who are trying to make fundamental advances, which I think we really need on the talk from Professor Bell. I remember citing her as a grad student, and she's been doing great work for many, many years. I'm not trying to create the next great polymer material. I want to use it. I want to just take those things, use them and do translational work. Yeah, yeah, wonderful.

01:27:09 → 01:27:27

**Ralph Etienne Cummings:** We might want to open it up a little bit now for some discussion with the audience. Please stop the microphones. But let me start with Tony, Tony. You had a, you know, reaction to Pam's position. So please. You know. State your point.

01:27:30 → 01:28:27

**Tony Lewis:** Yeah, no. The only point is if you look at a human being. How much power do they take? So it's probably roughly around 100 watts or so. This half of my body. 50 watts, you know, probably my legs much less than that. So if you, if you try to put something on it which is like a conventional Gpu. You're going to suck all the power out of the system pretty fast. When you're driving. It probably takes between 10 and 20 horsepower so that you know at a minimum, maybe about what? 7,500 watts just, you know, and it rolls around right? And if you take two you know, Rtx, 4 40 nines on board, you're sucking a thousand watts. You're going to impact your gas mileage. It's going to become something, you know, like a critical deficit. So that was my only point. It was just. It's probably taking things off topic.

01:28:30 → 01:28:47

**Sunny Bains:** Can I just add to that? That what you might want is an ambient power source, right, so you might want to not have to rely on the battery at all. But use stuff that's flowing around the body, anyway, or movement, in which case, you really want to get low power. So I agree.

01:28:53 → 01:29:10

**Andreas Andreou:** Putting Tesla on the full autopilot, and driving on a long distance cuts down to about 20% of your mileage. Yes. One of my ex students did this experiment driving to from La to Washington state

01:29:11 → 01:29:15

**Ralph Etienne-Cummings:** Any other comments from the panelists before I move to a slightly different topic?

01:29:18 → 01:30:31

**Sihong Wang:** Yeah, yeah, along this line of, you know, the power requirements. I also do agree that you know power is one of the biggest development requirements for eventually being able to use such systems, probably more important for implantable cases for longer periods. Not like, you know, today. For a pacemaker, you have to go to the hospital to do another surgery in 5 to 10 years. So one solution would be probably taking energy from the human body, like, for example, inside the human body. There are 2 types of energy commonly available. One is biomechanical, coming from, you know, the organ movements or the blood flow, and then the other is about chemicals. So this is also like one thing that my group has been working on. I don't have time to talk about that part to try to, you know, come up with a device design that can convert this type of energy. So what we are working on so far is mainly mechanical energy into electricity, so that it can be used to replenish the power consumption in the battery in the sense that the battery could, you know, never run out. So of course, right? This also needs to be coupled with the entire system having much less power. Consumption is more power efficient. I think that's where the neuromorphic will play a big role.

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**Andreas Andreou:** The challenge is not really to harvest the energy. The challenge is to store it, and so do an amazing job in doing that. So I'm gonna play devil's advocate here. Also, I'm gonna play devil's advocate and ask anybody that wants to do a new room.A bio inspired, or whatever device. Go to go and get a microcontroller from St. Micro one of their St. 32 c. Series and try to do that, and then challenge yourself to actually see if you can do it in a different way. So I think there's challenges there. I think there's no value, that neuromorphic can be low power. But I will also take Pamela's viewpoint that maybe this whole power thing is a little bit oversold.

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**Ralph Etienne-Cummings:** Okay, I have one question that came up during the discussion a little bit earlier about the cost of developing, you know, silicon specific? You know, devices right? And there was kind of some conflict right in the sense of one person, you know, we had a person say, Hey, it's 30 million dollars at least 2 million dollars if you don't go into the most aggressive nodes. But then your gut said, No, no, we can't do it, for like nothing. Right? So the question is, what is the reality? And I and Andreas, I know you've spent a lot of time thinking about this.

01:32:00 → 01:33:30

**Andreas Andreou:** So. And I think that's why the idea of these neural chiplets. I did some consulting for Medtronic a while back and they bought their own packaging and low end Fab facility because they didn't want to go and certify FDA, certify every single device that they put in the body. And so that's an enormous cost. So you need to have something modular that gets certified IP, or whatever someone owns that, and people come and use it and reuse it to build scalable systems. And I think that's the whole idea of the chiplet, which is really kind of an advanced packaging technology. The silicone itself, the cost of design is the cost. But once you've done that, you have it there, and you can reuse it. And I think that's really the idea. I think we also need a new place. Really, that is more about system integration and not cheap design, not just chip design. Cheap design doesn't get you a product. The fact that Apple has a good product in this, in the same apple silicon or Nvidia has a good product is because they have this amazing packaging technology, which is really the, I mean, if we look at supply supply manufacturing supply shortages. That's really where all the shortcuts are not in chip design.

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**Jennifer Blain:** I add one thing to that. I think one thing that's been missing in the Chips Act is every conversation about packaging has nothing to do with the kind of packaging that people want to do for medical devices.

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**Ralph Etienne-Cummings:** Wonderful should post it so we can all learn about it. Wonderful. I want to switch a little bit and think about, you know, applications in the hospital, for example. Right? So let's start with Roberts, and then we'll go to Bob and to Brad, and and think about it in 2 ways, right? So bringing in technologies into the hospital to test with actual patients is not an easy task. Right? So. And that's one way that we could, you know, verify some of the technologies that we're talking about here now, bringing in technologies that are not your typical technology, you know. And we start thinking about neuromorphics and things of that sort. So how do you see the path forward in terms of you know, I mean, there are docs like you, who are, you know, tech forwards, and we appreciate those. But we can't necessarily, you know, always convince the infrastructure to allow us access right? So how do we? What do we do?

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**Robert Stevens:** Yeah. So I mean, there, there's many layers to the answer for your question. I think, certainly there, or layers or barriers, whatever you want to call them. But there's, you know, the sort of organizational strategic layer which involves, you know, putting together the right teams of individuals who could deploy these devices? In a, you know, effective way, that is, you know, safety that evaluates feasibility, that determines safety, that is able to demonstrate benefits, not just in terms of patient outcomes, but also in terms of, you know, potentially reduced cost. And you know, greater efficiencies in clinical workflows. So that's 1 layer. There's obviously a very important regulatory and ethical layer, which is, you know, in the sort of clinical setting that is usually governed by the institutional review boards, data, trusts, and other, you know, sort of supervisory bodies that are. You know, especially with regards to the implementation of, you know, neuromorphics and new devices that are going to obviously exert significant scrutiny and are going to be very, very you know, difficult initially and hard to convince. I think there's the issue of, you know, global financing and cost. And who's going to invest in testing these devices in a healthcare setting. Is it going to be exclusively in the domain of, you know Federal funding? And you know, Nsf, nih, Darpa, Arpa, H. Or are we going to get, you know, substantive investments from industry, which I think is probably the way to go. We need the industry to really push this forward, and they have the resources and capabilities. And then I think there's a lot of additional questions which have to do with this sort of broader impact. Right? So I mean, for example, if we think that more and more computing devices used in the healthcare setting is going to lead to greater energy expenditure. What is the impact on the environment? How do we manage that? Also? The presence of, you know, neuromorphics and other sort of edge computing devices on patients. What is the impact on patients? Of course, we want, we are hoping for better outcomes. But what about health care workers? Are we making their task easier, simpler, or making it more complex? How do we integrate the healthcare workers, the doctors, the nurses, the other protagonists in the healthcare setting so that they can optimally, you know, benefit from from the use of these systems and not be potentially harmed because the health care environment right now is sufficiently complex and onerous that many healthcare workers are, you know, experiencing different things like burnout wanting to leave the go into other domains, so can we make their their environments, you know, safer better, so that they, you know, people are attracted, for example, to to this domain. I think that's another important aspect of this.

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**Ralph Ettiene-Cummings:** Thank you. And well, Erica, I mean the connection between, yeah, the healthcare industry.

01:38:10 → 01:40:50

**Erika Shmitt:** And well, I think a lot of that is kind of that change management concept. It is the idea that I think is kind of related to that change management concept. And how do you engage people in the ecosystem? And I think the comfort level with neuromorphic technology is low. And to Sunny's point, yesterday language matters. And I think it's because when you ask for a review paper on what neuromorphic technology is. Which one do you send? You know, and I think I think that has applications. I think people don't really have an intuitive understanding of what continuous processing really means. The idea of having something in your body or something that's continuously monitoring your behavior feels freaky until it feels helpful. And it's kind of like pushing the rock up the hill until it starts to go down the other side. But from an industry investment point of view that is not typically where VCs are going to be investing, where private industry is going to be investing unless they see a really really clear application. And that's where that kind of obfuscation is the direct impact clear enough and the packaging definable enough that you don't really talk about the fundamentals and how they're completely different. And then I think it's sort of once you get there, being able to say, Oh, by the way, this is on a you know, this is predicated on a novel system. This is a system called neuromorphics. Look at all of the things that it's unlocked for you. And I think that really is.You know, it's that kind of pragmatic approach. But if you know it's having the conversations here, but then there's like the sales aspect of it, and it's selling to the users it's selling to the ecosystem it's selling to the funders. And you know, I think we need in industry all of the groundwork that's been laid in R&D. But it's really, how do you kind of meet in the middle? And continue to build on those foundations? One thing that I meant to say, and I think I failed to say is a challenge that we have, is that our secret sauce is the kind of core mathematical loop at the neuron level. But there's a lot that we can open source around that for collaboration and kind of figuring out where that middle ground is, I think, would help with. How do you think about making this a flexible kind of model design, where people can mix and match regions to applications outside of hearing in multimodal, eventually in that SDK, that obscures sort of the IP but allows people to build applications that are flexible.

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**Bradley Aimone:** So you know, I think this, you know kind of what you're saying Eric is really important is that we don't fully grasp what this computing paradigm will mean. And if you go back and you think about when you know cell phones 1st came out 20 years ago, and people were like you'd hear, like, you know. Steve Jobs saying, this is what they're going to be used for, right. If you go back and look at that stuff from 20 years ago half of it came true, and half of it. No one, nothing ever happened with. You know the tables at the restaurants that you order from, or whatever. And then there's these millions of things that we're using them for, that no one ever anticipated. And so, if you know, one of the things we've learned from neuromorphic algorithm development is that these systems are infinitely more powerful and capable of things than anyone has. An appreciation of people are like, I built this chip to do resnet or something, and it's like, No, it's terrible at resnet. But it's actually really good at this, this, this and this. And so I think once the technology gets its way into the field, as long as we don't screw it up on the way, which is the important piece, then we possibly will open doors that we can't even imagine right now. But if we over engineer it to be only for a very narrow little application, you know. Then I think the impact becomes very, very narrow, and we've basically lost a big opportunity. So I think we need to resist the urge to over engineer any particular thing that looks good tomorrow. And I think I really like that. You know what I've been hearing here is like, it's a long path. And I think that's where we need to sit.

01:42:48 → 01:44:13

**Tony Lewis:** So this might be a little bit controversial. But, you know the term neuromorphic and an over reliance on the term to sell your technology can actually be fatal. You know, when we go talk to people, you know, it's like you're neuromorphic. Oh, no, we don't want any of that and do you have to overcome that barrier? When I was running the neuromorphic program at Qualcomm, I went to the head of R. And D, and I said, Hey, so I know you're worried about power. That's why we're doing neuromorphic, he said. No, we can build low power stuff. That's not, that's not an issue. Can you do something magical? And so, really okay, they could be a bunch of money making magic. So really the and and if you get caught in a situation where you're doing a spreadsheet challenge, you know where the customer says, fill out the spreadsheet. Put where your power numbers are. There, put your functionality. You're dead. You're dead. It's a nightmare. Okay? So the question for the panel is, how do we get out of this? How do we do something that is magical in neuromorphic, where other people can't do it? And that's when we're going to, you know, really make an impact.

01:44:14 → 01:44:20

**Ralph Etienne-Cummings:** Thank you, Tony, and yes, we ran out of time. So that's why I want to ask Peril whether you have anything to add.

01:44:22 → 01:45:55

**Amparo Guemes Gonzalez:** I can try to answer that magical question. I think exploiting neuromorphics is the best way, and actually selling it the best way, as Erica was suggesting, is the way to show that this is medical. This is enabling things that can't be done with other technology, and it's showcasing that benefit and basically overcoming the harms so that harm benefit analysis. So it's overcoming the harms that are basically intrinsic to any medical product through showcasing the benefits that this can provide in front of all the technologies. That's basically that magic technology that people are looking for. And if we think about it a few years ago. Just the idea of opening the skull of a person implanting away and letting the person go that was crazy like no one will have in a rational mind don't do it. But the fact that that will improve the quality of life of that person makes it progress, and neuromorphics enable things that way. So, I think, yeah, like the potential is huge. The marketing has to be improved. And the technology has to. Of course. Keep progressing, but I feel like we're on the wood path.

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**Ralph Etienne-Cummings:** Thank you so much. And I'm really happy that we're not talking about killer apps anymore. But we're talking about magic apps. So thank you guys, let's move forward. We'll have some coffee, and then we'll come back for another wrap-up. Thank you. Oh, we'll come back in half an hour. Yup.