from 2011 to 2013. He also visited the Air Force Research Laboratory Aerospace Systems Directorate in the summer of 2014 and the Munitions Directorate in the summer of 2015. Furthermore, he acted as a consultant to NASA from 2014 to 2016 and to Wichita State University from 2017 to 2018. He is the author of more than 300 journal and proceedings articles.

Rodolphe Sepulchre

TRAVIS E. GIBSON

Q. How did your education and early career lead to your initial and continuing interest in the control field?

***Travis*:** I was first exposed to the control field during the fall semester of my junior year at Georgia Tech. Aldo (Al) Ferri was teaching dynamics and control using Ogata's *System Dynamics*. I immediately fell in love with the compactness of the frequency domain representation of dynamical systems and the figures in Ogata's text. Control is not presented until the end of that book, but that was just icing on the cake by the end of the course. I enjoyed Al's class so much that I asked him what course he was teaching next, and that ended up being one of the most important questions I have ever asked someone. As it turns out, Al's next course was on the calculus of variations (fall of my senior semester). The course is not so important to the story though. At this point, we had become friendly and would chat after class. One day he asked me what I was doing after graduating. I wasn't sure, and he suggested that I apply to graduate school. I knew very little about grad school. At the time, I personally didn't know anyone with a Ph.D., other than the professors in my classes. I didn't know where to apply either, and Al suggested Massachusetts Institute of Technology (MIT) and Stanford. So, with that piece of advice, I scrambled to take one of the last GRE windows before applications were due and applied to Stanford and MIT. I will forever be grateful for that brief conversation with Al. The following March, I received acceptance letters to both programs. Fast forward through accepting the Stanford offer to only then change my mind and politely ask MIT to forget about that last email rejecting their offer, and I ultimately ended up in Cambridge, Massachusetts.

I explored multiple labs during my first semester at MIT before joining Anuradha (Anu) Annaswamy's research group. I didn't know anything about adaptive control at the time, but it was control, and the funding was initially for applications to hypersonic flight, so I was stoked. I was not at all prepared for the mathematical rigor needed to conduct research in control theory though. As most of us do who haven't had a rigorous enough undergraduate education in mathematics, I ended up taking several undergraduate analysis courses at MIT as a graduate student. Anu taught me how be persistent and roll through setbacks. The first two years of my Ph.D. work ended up going nowhere. I proved that what I wanted to prove was impossible. I was devastated. I knew that this would set back graduation by a year or two at least, but Anu seemed unphased and continued to be an ultra-supportive advisor. I would not have survived without her encouragement. I was in search of new ideas after squandering those two years, and that is when Eugene Lavretsky enters the fold. Eugene had been suggesting I study a form of model reference adaptive control where one feeds plant information into the reference model to generate "smoother" transient dynamics. I would end up calling this paradigm of control closed-loop reference model (CRM) adaptive control. The reference model uses feedback from the plant through an observer-like gain to meet the plant "halfway," holding the plant's hand as the adaptive control gains change, as opposed to standard model reference adaptive control, where the reference trajectories are agnostic to the plant state. With my thesis, I was able to provide rigorous transient performance bounds for this new class of adaptive control. Most importantly, I was also able to characterize the no-free-lunch properties of the controller. The CRM observer gain and the adaptation learning rate need to scale 1:1. Deviations from that proportion in either direction can lead to adverse events (peaking or high-frequency oscillations). Kevin Wise of Boeing has generously referred to this "optimal" scaling in my thesis as *Gibson's rule* in one of his publications. This style of reference model/observer has been incorporated into several experimental platforms at Boeing and also flight tested on a manned Learjet-25B at the U.S. Air Force Test Pilot School at Edwards Air Force Base in California.

After completing my Ph.D., I was initially offered a postdoc (postdoctoral research) position with Richard Murray at Caltech (California Institute of Technology). So logically, I completely changed my research focus and instead joined a new lab in the Department of Medicine at Brigham and Women's Hospital and Harvard Medical School that was studying the microbiome (the resident bacteria in and on our body) from a high-level dynamical systems and network perspective. My girlfriend at the time wanted to stay in Boston and was not interested in long-distance dating. So, I chose the relationship over the amazing opportunity to join Richard's group. The postdoc was successful by all standard academic

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metrics. However, I thought that to be truly successful with biological applications, I needed to have more direct experience with experimental biology and clinical applications. So, I did the unthinkable and started a second postdoc. My second postdoc was with Georg Gerber, a physician scientist (M.D.-Ph.D.). With Georg, I got the additional experience I was looking for and was directly involved in designing and carrying out experiments using germ-free mice (mice born without resident gut bacteria) that were subsequently colonized with groups of bacteria that we hand selected, engineered with certain properties, or derived from human donors. Georg's Ph.D. was in Bayesian statistics, so I also learned about statistical machine learning. With the second postdoc, I now had all the tools I needed to conduct novel research in experimental biology, with a unique background in control, dynamics, and statistical machine learning. Oh, and the girlfriend I stayed in Boston for is now my wife, so that worked out too.

Profile of Travis E. Gibson

- *Current position*: instructor in pathology, Brigham and Women's Hospital and Harvard Medical School.
- *Visiting and research positions*: research affiliate, Computer Science and AI Lab, Massachusetts Institute of Technology.
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- *Notable awards*: NIH Maximizing Investigators' Research Award (2021).

Q. What are some of your research interests?

***Travis*:** In my current research, I am trying to integrate rigorous computational and inferential thinking with the notions of robustness and stability that have propelled the success of control applications to better model, design, and learn about biological systems from data. There are three main pillars to this work: the development of flexible statistical machine learning models for biological dynamics, efficient and robust optimization schemes for models using biological and health-care data, and using control principles and machine learning to design in vivo microbial communities for therapeutic applications.

The measurements we take in biology are usually far from Gaussian and are often discrete as well. We also don't usually have conjugate probability relationships between model components if we naively, but faithfully, capture the underlying biological processes that are occurring. Furthermore, we don't want our inference scheme to require a significant amount of analysis overhead to be

Travis in front of the National Museum of Mathematics in New York.

Travis fishing on Ossipee Lake in New Hampshire.

Travis introducing his son to the Triumph.

made efficient for just one experimental setup. Our measurement modality might change between experiments because of advances in technology, or the experiment itself may dictate the change. In this line of work, we employ variational techniques and discrete relaxations to overcome some of these challenges.

In my lab, our second main research direction involves using Lyapunov stability techniques and insights from adaptive control to design provably robust (and accelerated) gradient descent methods for optimizing biological and clinical machine learning models. The hope is that we may one day be able to certify the optimization and training process, so that *if* a model is deployed in a real time or clinical setting, there is some degree of robustness engineered into the optimization scheme. This may aid in the certification and approval of these methods as they are deployed in different health-care systems or are trained on data collected from different institutions.

In the third main thrust of my lab's research, we are designing bacteriotherapies (groups of bacteria for therapeutic applications) using principles from control theory. The role of feedback and robustness are central to the design of these communities, and we both derive and test these communities with longitudinal in vivo experiments using germ-free mice. The hope is that by deploying a top-down approach that begins with in vivo experiments, we can overcome some of the challenges encountered when insights from in vitro experiments (from culturing bacteria in a well) aren't recapitulated in the complex environment of a mammalian gut.

Q. What are some of the most promising opportunities you see in the control field?

***Travis*: ** It is hard to predict these things, so please disregard this if (in a few years) I am completely wrong. One area that may be very impactful in the near future is the intersection of statistical learning and adaptive control. As control applications become increasingly more data driven, I don't know how we can make further progress without becoming more comfortable with statistical thinking and the tools and techniques that come from high-dimensional statistics, online learning, and Bayesian inference. I wish I had been exposed to more statistics during my time in school at all levels of education.

Many investigators in our field have already begun to incorporate control theory with experimental and synthetic biology, and I don't see this area of research slowing down anytime soon. To have impact in biological applications though, I would suggest picking systems where it is becoming easier to take temporal measurements, and similarly, working with a system where you will have the ability to design your own experiments. It will probably seem obvious, but without those two ingredients (and I really mean both), it may be hard to be impactful. Having data alone isn't enough. Given your training in control, you will likely design experiments that are wildly different from how an experimental biologist may think to conduct them. You will also have different questions that will necessitate these experimental differences. Otherwise, you will be theorizing about the most complex of complex systems.

Q. What are some of your interests and activities outside of your professional career?

***Travis*: ** Outside of my professional life, I spend my time fishing, playing soccer, and riding my motorcycle. Having a motorcycle in Boston is one of the easiest ways to commute between the hospitals in Boston and the Harvard and MIT campuses in Cambridge. There are tons of "free" parking spots as well. I highly recommend it, and if you get heated riding gear, you can ride year round. I also recently I became a father. Playing with my son beats any Zoom meeting, hands down.

Q. Thank you for your comments.

***Travis*: ** Thank you for letting me tell my story and share my work.