ISIF

# Perspectives

## On Information Fusion

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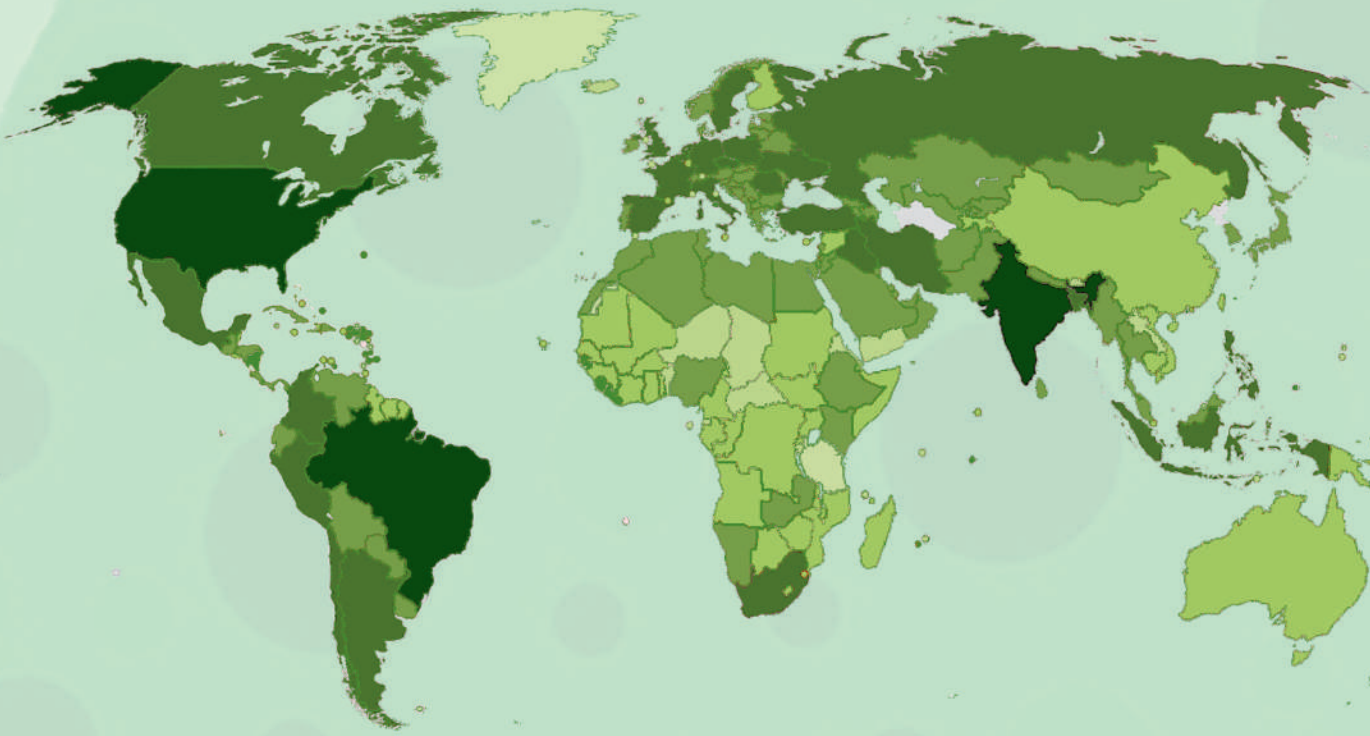

THE ISIF PRESIDENT LOOKS IN THE MIRROR

NPI MODELS EXPLAINED AND COMPLAINED

INFORMATION PROCESSING METHODOLOGIES TO COMBAT THE COVID-19 PANDEMIC

Publication of the
INTERNATIONAL SOCIETY OF INFORMATION FUSION

ISIF

## ISIF Perspectives

***Perspectives*** seeks bridging articles, expository papers and tutorials, classroom notes, and announcements on topics of general interest to the ISIF Fusion community. Fresh points of view on established topics are especially welcome, as are articles on topics of interest to the ISIF annual fusion conference. Papers containing new research should be directed to JAIF or other research journal. The standing Call for Papers (CfP) for ***Perspectives*** can be found at http://isif.org/sites/isif.org/files/CfP%20for%20Perspectives%202019_04APRIL2019.pdf. ***Perspectives*** is published annually by ISIF.

More detailed guidelines and submission instructions for authors may be found at http://perspectives.msubmit.net/cgi-bin/main.plex?form_type=display_auth_instructions. The average length for submissions is approximately six (6) pages (in JAIF two-column format). All submissions will be reviewed for content and style, as well as suitability for ***Perspectives***. All papers accepted for publication will be written in a relaxed, colloquial style that facilitates understanding by a wide audience. Articles containing significant original research should be submitted to JAIF.

**Cover:** Illustration of how the virus became since 2019 a worldwide "data producer", some data being analyzed in papers of this issue. The map displays the cumulated number of cases of COVID-19 from the 1st of December 2019 to the 15th of July 2021. Data accessed from Wikipedia compiling several sources (https://it.wikipedia.org/wiki/Pandemia_di_COVID-19).
Realization: Maya Hamouche.

- 10 000 000+ confirmed cases
- 1 000 000 – 9 999 999 confirmed cases
- 100 000 – 999 999 confirmed cases
- 10 000 – 99 999 confirmed cases
- 1 000 – 9 999 confirmed cases
- 1– 999 confirmed cases
- No confirmed cases / no data


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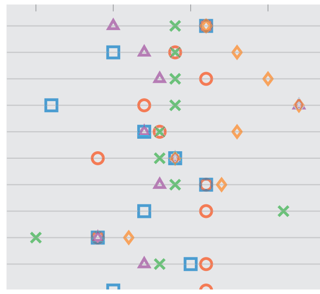
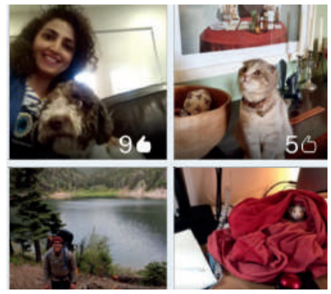
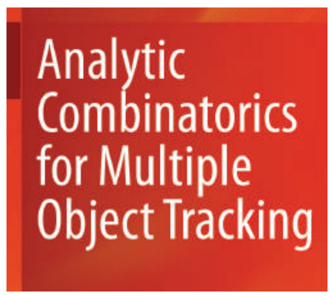






# Introduction to the Issue

## *PERSPECTIVES* MAGAZINE

Welcome to the fourth issue of *Perspectives* magazine.

It is an honor and a real pleasure to take over the role of Editor in Chief (EiC) of the magazine, after the amazing work of Roy Streit since 2015. Roy put *Perspectives* magazine on track and I will do my best to bring it to its next destinations. I would like to sincerely thank him and the International Society of Information Fusion (ISIF) Board of Directors (BoD) for this exciting opportunity.

As roles are changing, I would like also to thank Jason Williams, who has been Associate Editor-in-Chief (AEiC) since 2019, and Kristy Virostek of Conference Catalysts who has been Production Manager (PM) over the same period. Since the magazine would not see the light without such key roles, it is my great pleasure to welcome Roy Streit, who kindly accepted the new role of AEiC and Reta Wehmeier of Conference Catalysts who is now the new PM.

Just before issuing the third edition in Spring 2020, the postscriptum by the EiC, Roy Streit, highlighted the two areas of research, "mathematical modeling of the spread of infectious diseases" and "spatial-temporal data modeling", that would be key in fighting the COVID-19 virus. And indeed since then, from the United Kingdom (UK), to Sweden, to Italy, to the USA, the Fusion community joined forces for this "frontierless" challenge.

So naturally, this fourth issue of *Perspectives* magazine provides us with a large forum for reporting thoughts, ideas, and results of several initiatives. Simon Maskell, the ISIF president "looks in the mirror" at the extraordinary collaborative work of the Liverpool researchers' team since the first lockdown in the UK and draws the path for Data Fusion for 2021. In Sweden, Fredrik Gustafsson (Linköping University) and Kristian Soltesz (Lund University) bring a critical analysis of nonpharmaceutical intervention models, supported by data from Sweden, summarizing work published in *Nature* and previously presented as a plenary session at the Fusion 2020 conference by K. Soltesz. Domenico Gaglione, Paolo Braca, Giovanni Soldi, Nicola Forti, Leonardo Millefiori (NATO STO Centre for Maritime Research and Experimentation), together with Stefano Marano (University of Salerno) and Peter Willett and Krishna Pattipati (University of Connecticut), present results from a collaborative work with predictive analytic models for Italian regions and the state of Connecticut in the USA. These three initiatives provide only a sample of contributions as surely the 2021 Fusion conference will cover the topic with original work and insightful results.

This issue also includes a report on the first ever virtual FUSION Conference in 2020, originally planned in South Africa. The organizing committee, chaired by Pieter de Villiers (University of Pretoria), Fredrik Gustafsson (Linköping University), and Alta de Waal (University of Pretoria), had to invent a new format to allow conference attendees across the world to participate in live Questions & Answers sessions. The FUSION 2020 Best Paper and Best Student Paper awards are themselves presented by N. Rao. A retrospective of the ISIF award program is provided by Dale W. Blair, together with updates about the two active ISIF working groups by Darin Dunham, Erik Blasch, and Simon Maskell: the "Evaluation of Techniques for Uncertain Reasoning Working Group (ETURWG) and the Open Source Tracking and Estimation Working Group (OSTEWG)".

You will also have the pleasure to read a detailed and stimulating review by Christoph Degen (Fraunhofer FKIE) of the book *Analytic Combinatorics for Multiple Object Tracking*, by Roy Streit, Robert Blair Angle, and Murat Efe. The Information Fusion History department focuses on the Canadian Tracking and Fusion Group (CTFG), which celebrates its 10th anniversary this year, with a review of the yearly CTFG workshops since 2011. Finally, several advertisements for future ISIF events are available together with an update of International Conferences and Workshops held, cancelled, or postponed during the pandemic. In particular, the exceptional sanitary conditions due to COVID-19 led the ISIF BoD to give the FUSION 2020 team another opportunity to host the conference in South Africa in 2021, while postponing for one year all successive events. These announcements will hopefully stimulate your next conference's participation.

This fourth issue would not exist without the contributions of all authors, the careful reviews of the Associate Editors Wolfgang Koch, Lyudmila Mihaylova, Murat Efe, Emre Ozkan, and Jesus Garcia Herrero, the precious advice of the AEiC, and the hard work of the PM and the Administrative Editor, David W. Krout. Thank you to all for your time, ideas, and energy. We hope you will enjoy flipping through and reading this new issue of *Perspectives* magazine, maybe during a coffee break in Sun City.

**Anne-Laure Jousselme**
**Editor-in-Chief,**
***Perspectives* Magazine**

# The ISIF President Looks in the Mirror

**Simon Maskell**
University of Liverpool
Brownlow Hill
Liverpool, UK
s.maskell@liverpool.ac.uk

## CONTEMPLATING HOW TO MAKE A DIFFERENCE

Sitting in Liverpool in early 2020, it was clear that COVID-19 was going to present a challenge to global health, and also to global science. The deluge of COVID-19 papers and the apparent inability for that corpus to be rallied to influence reality had already begun to be seen. The question that quickly arose was then: "How could one team in Liverpool make a difference?"

Prior to COVID-19, Liverpool researchers had begun to focus effort on "Big Hypotheses" [1][1], a five year project begun in 2018 to develop a game-changing ability to use large computers to make statistical inferences from noisy data. This activity was initially motivated by the observation that, while the computational resources used to apply Deep Learning are doubling every four months [2], the resources used in the context of numerical Bayesian inference (i.e., Markov Chain Monte Carlo (MCMC)) have stagnated to be those on researchers' desktops. While Bayesian inference can operate effectively in the "data-starved" and "understanding-rich" contexts where Deep Learning can struggle, Bayesian inference needs to evolve to be able to compete. Big Hypotheses' initial aim is to make it possible to use *N* computers to make numerical Bayesian inference run *N* times faster, where *N* might be large (e.g., 86,400: the number of seconds in a day). One might think that this can be achieved by simply implementing MCMC using languages that are amenable to distributed implementation on High Performance Computing (HPC) or in the cloud. Unfortunately, that is necessary but not sufficient: MCMC has an initial burn-in phase which, in general, is very challenging to parallelize since it involves an inherently sequential process of taking a sequence of steps, each of which brings the algorithm a tiny bit closer to convergence.[1] The solution that Big Hypotheses adopts is to replace MCMC with an alternative algorithmic work-horse, the Sequential Monte Carlo (SMC) sampler. The Liverpool team believe that SMC samplers can be configured to implement parallelized numerical Bayesian inference. Indeed, because SMC samplers have different constraints to MCMC, the ultimate (overtly ambitious but, it is believed, achievable) vision for Big Hypotheses is energy-efficiency, whereby one computer can perform numerical Bayesian inference *N* times faster than MCMC.

Strong scaling of an existing algorithm, i.e., making it run faster is, perhaps counter-intuitively, rarely significantly operationally useful; if the algorithm is already being used, it is unlikely that freeing up resources will be game-changing. Strong scaling's utility is more likely to be associated with transforming problems that are assumed to be too time-consuming to be practically useful into operational systems. What strong scaling delivers is an ability to be substantially more ambitious in terms of the complexity or size of problems that can be considered. It is that ambition that is potentially game-changing.

For any game-changing ability to apply numerical Bayesian inference to experience widespread adoption, it would need not only to be readily applied to arbitrary problems but also to deliver benefit relative to existing state-of-the-art solutions that are accessible to the people who need to solve those problems. Probabilistic programming languages (PPL) are widespread across those end-users since they provide a flexible way for end-users to succinctly articulate their probabilistic model in a form that allows a state-of-the-art MCMC algorithm to be applied: the No-U-Turn-Sampler (NUTS) [3] underpins many PPLs and exploits local gradient information to efficiently explore the parameter space (even when it is high dimensional). Big Hypotheses therefore focuses on interfacing to a specific PPL, Stan [4] (named after Stanislaw Ulam), and on articulating benefit in the context of a portfolio of models that have been collated and curated to provide benchmarks for performance comparison [5].

Returning to early 2020, Liverpool researchers were, somewhat fortuitously, already working on combining data from each of multiple sources to detect outbreaks of infectious disease [6]. This work made apparent that there was already a pressing need to calibrate sophisticated models for the spread of infectious diseases. COVID-19 made clear that the world needed Big Hypotheses.

Unfortunately, Big Hypotheses wasn't ready.

## INTRIGUE LED TO ENGAGEMENT

The UK government's response to the need to monitor the spread of COVID-19 was an emergency response; epidemiologists were rallied to inform government decisions. These scientists, and others already working with government who had relevant skills and experience, sensibly made use of tools and techniques that they had to hand or could rapidly produce.

[1] Of course, you can run multiple short MCMC chains in parallel. If you stop each of them before burn-in has completed, this typically (but not always) degrades estimation performance very significantly.

**Figure 1**
The University of Liverpool's Signal Processing Group in mid-2019 (just before COVID-19).

The modelling that was undertaken then helped inform decision making in the UK: the UK entered lockdown #1.

Various governmental bodies stood forward to try to combine the confusing mass of data that was being collated (e.g., from various applications (apps) that were each monitoring intersecting sets of facts about differently biased subpopulations of the UK) and the equally confusing mass of scientific literature and understanding that was beginning to emerge. Meanwhile, the Liverpool research team engaged with some of these government bodies and some of the aforementioned scientists that were helping inform government decisions.

At about this point in time, the vaccines started to emerge and the UK government app, which uses an unscented Kalman smoother to infer close contacts from Bluetooth signal strength [7] and that went on to make a significant impact on COVID-19 [8], was released. Both events were poignant for the Liverpool team: the team had tried to win funding to work on using Twitter to monitor the side effects of vaccines but had been unsuccessful because the reviewers took the view that there was a low chance that vaccines would exist; the team knew some of the developers of the app but were unsure if they should have diverted more of the Liverpool work towards supporting the app developers.

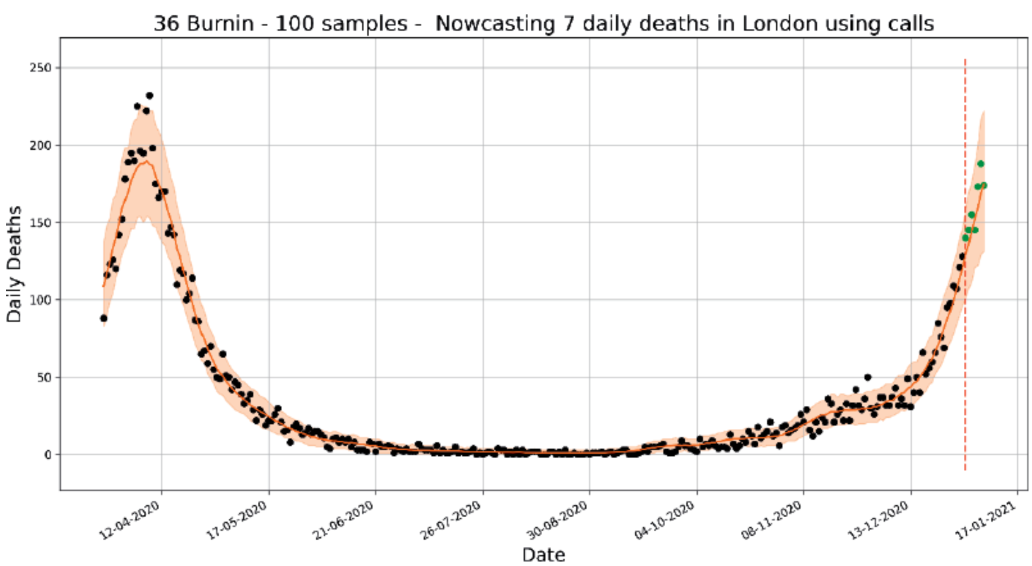



**Figure 2**
Combining low latency and high accuracy feeds can help inform difficult decisions: black dots are observed COVID-19 deaths in London, red line is prediction (with shaded area indicating associated confidence interval), and green dots are (retrospective) actual deaths.

The team had developed a processing chain for monitoring symptoms of COVID-19 reported in Twitter [9] in the hope that the biases present in those data would vary less with time compared to the COVID-19 tests. However, in the UK, the counts of geolocated Tweets that were indicative of symptoms were low. This motivated a focus on combining the high accuracy records of deaths with another low-latency feed: 111 calls and 111 online interactions.[2] By fusing the 111 data and the deaths, it was possible to calibrate the 111 calls as a low-latency forecast (or predictor in statistical language) of future death counts. This use of data fusion combined with Big Hypotheses' vision helped solidify the Liverpool team's engagement with the UK's Joint Biosecurity Centre (JBC): the JBC is charged with transitioning the emergency response into crisis-as-usual and adopting an engineering approach to using the noisy data to inform the difficult decisions that the UK government has to make.

While some epidemiologists were intrigued by the concept of Big Hypotheses, researchers at Imperial College London were arguably the most interested. Imperial had written a paper [10] on simultaneously analyzing multiple geographies to disentangle the impact of different nonpharmaceutical interventions (e.g., shutting schools, closing shops, lockdowns, etc.). They used Stan, but the scale at which they could apply the model was constrained by the inability to use HPC or cloud resources.

Imperial was ambitious. Big Hypotheses was not ready. Then it started to feel like the tide began to turn.

## PROGRESS!

Stan is developed by an international team of researchers but its genesis and the center of gravity for its development is Columbia University in New York. Columbia won National Science Foundation funding to work with the Liverpool team to build COvid DAta MOdels (CODATMO) [11]. CODATMO was a response to different epidemiologists using different programming languages, making it hard to synergize ideas and approaches: CODATMO collates articulations (in Stan) of several Epidemiologists' models, the data they use when assessing such models, as well as frameworks for evaluating the models (including mechanisms for simulating epidemics, such that assessment can exploit known ground-truth). CODATMO aims to make it easier to extend, synergize, develop, and deploy such models. It has been picked up by researchers in Brazil [12] and it has intrigued Stan developers, who have contributed insights that have directly influenced the direction taken by the Liverpool team in their interactions with the JBC. Openness has delivered.

The Liverpool team have also been involved in the analysis (using Stan) of data from wider activities at Liverpool related to UK pilots of mass testing and of large scale events (a business event, a rave, and a festival) with no social distancing. Interest also started to grow in Streaming-Stan [13], a variant of Stan that the Liverpool team had developed, as an off-shoot from Big Hypotheses, as a PPL for tracking problems: the team had several "knocks on the door" of people requesting to be beta-testers.

The sustained hard work of the Liverpool team then started to deliver. Big Hypotheses began to show its potential to achieve strong scaling; promising preliminary results in low dimensions and other promising results in the context of discrete variables emerged. The initial attempt to achieve strong scaling in high dimensions failed: NUTS can generate good samples in high dimensions, but the team couldn't shake off the need for burn-in. The second attempt did successfully avoid burn-in in a few high dimensional examples, but didn't provide the general-purpose Bayesian blunderbuss that the Liverpool team believe they can produce.

Today, the team sense they are close. Big Hypotheses oscillates between being close and feeling far away: it is not yet a reality.

## REFLECTING ON THE PAST AND LOOKING TO THE FUTURE

The reality I now see is that decision makers need to learn how to balance advice from multiple scientists from diverse disciplines: epidemiologists, who understand the impacts of the disease on physical health; psychologists, who understand the impact of interventions on mental health; and economists, who understand the financial ramifications of these interventions. This advice derives from data from each of multiple disparate sources. A common reference frame needs to be defined to triangulate the data and models developed that articulate the scientists' uncertain, imprecise, conflicting, and ambiguous understanding in that reference frame. The parameters of the models need to be estimated from historical data, used to make predictions as time evolves and communicated to decision makers in such a way that they, and the public, can understand. This is Data Fusion for 2021.

So, as I look in the mirror, I ask myself:

1. Was the world lucky that scientists developed vaccines that were more effective than we could have hoped, and that the delta variant only arrived relatively late in the day?
2. Does the Fusion community need to embrace HPC and cloud computing environments, standardized datasets like those associated with CODATMO, and probabilistic programming languages like Stan?
3. Was it ambitious and yet sufficiently realistic to think that a hard-working and purposeful team in Liverpool could mature Big Hypotheses to produce a game-changing ability to perform numerical Bayesian inference for COVID-19?

[2] 111 is the UK telephone number for a public call center that people call for urgent healthcare assistance that does not qualify as an emergency involving an immediate threat to life. The numbers of calls (and interactions with an associated website) that relate to COVID-19 are published by the UK government.

4. Is Big Hypotheses tantalizingly close to demonstrating a revolutionary advance?
5. Is there still lots of interesting, important, and inspiring work left to do?
6. Was COVID-19 the warning shot for the Fusion community?

Yes!

With apologies to JFK: we choose to make Big Hypotheses a reality, not because it is easy, but because it is hard. Indeed, while I wish COVID-19 had not happened, it's fantastic to work with a team that continues to be spurred on by the belief that we are close to making a significant advance and is relentlessly driven forwards by the opportunity to make a difference. I hope the wider Fusion community can learn from our experiences in Liverpool and thereby make a significant contribution to the fight against a common enemy that measures less than a micron across and yet is having an impact that spans the planet. We must coordinate and collaborate if we are to help understand the spread of the pathogen and the utility of different interventions. Only then will we have helped win this fight and positioned the Fusion community to play the pivotal role it should when the next pandemic strikes.

## REFERENCES


1. Engineering and Physical Sciences Research Council. Grant application. Available: https://gow.epsrc.ukri.org/NGBOViewGrant.aspx?GrantRef=EP/R018537/1.
2. Synced. AI doubling its compute every 3.5 months, https://medium.com/@Synced/ai-doubling-its-compute-every-3-5-months-596b1b60fab.
3. Hoffman, M., and Gelman, A. The No-U-Turn sampler: adaptively setting path lengths in Hamiltonian Monte Carlo. *Journal of Machine Learning Research*, Vol. 15, 1 (2014), 1593–1623.
4. Gelman, A., Lee, D., and Guo, J. Stan: a probabilistic programming language for Bayesian inference and optimization. *Journal of Educational and Behavioral Statistics*, Vol. 40, 5 (2015), 530–543.
5. GitHub. Stan dev, https://github.com/stan-dev/posteriordb.
6. Jenkins, S., Bull, M., Abbs, S., Maskell, S., and Horridge, P. Biosurveillance and data fusion for early outbreak detection and classification. Presented at DTRA CBD S&T 2019, Cincinnati, OH, Nov. 18–21, 2019.
7. Lovett, T., Briers, M., Charalambides, M., Jersakova, R., Lomax, J., and Holmes, C. Inferring proximity from bluetooth low energy RSSI with unscented Kalman smoothers. arXiv preprint, arXiv:2007.05057.
8. Wymant, C., Ferretti, L., Tsallis, D., Charalambides, M., Abeler-Dörner, L., Bonsall, D, et al. The epidemiological impact of the NHS COVID-19 app. *Nature*, Vol. 594, 7863 (2021), 408–412.
9. Symptom Watch UK. Daily counts of UK COVID-19 symptom tweets, https://pgb.liv.ac.uk/~johnheap/.
10. Flaxman, S., Mishra, S., Gandy, A., Unwin, H. J. T., Mellan, T. A., Coupland, H., et al. Estimating the effects of non-pharmaceutical interventions on COVID-19 in Europe. *Nature*, Vol. 584, 7820 (2020), 257–261.
11. GitHub. CODMATO, https://github.com/codatmo.
12. Storopoli, J., Ferreira dos Santos, A. L. M, Guedes Pellini, A. C., and Baldwin, B. Simulation-driven COVID-19 epidemiological modeling with social media. https://arxiv.org/abs/2106.11686.
13. Maskell, S., and Varsi, A. Towards an interface for streaming Stan. Presented at StanCon 2020. https://www.youtube.com/watch?v=8dGhMYmyHnU.


**Simon Maskell** is a Professor of Autonomous Systems at the University of Liverpool. At Liverpool, Simon leads the wider Signal Processing group and is also principal investigator for a number of research projects, mostly funded by EPSRC and Dstl with a focus on synergistic use of next-generation algorithms and parallel computing resources. Simon is also director of the EPSRC Centre for Doctoral Training in Distributed Algorithms, a prestigious grant to train the next generation of data scientists through 60 PhD studentships. Simon has editorial roles for two IEEE journals and one Wiley journal and was general chair for Fusion 2010, co-chair for Fusion 2018, and is now President of the International Society of Information Fusion for 2020–2022. Simon was recently named as a "hero" by the IET for his work to support the UK government's response to COVID-19.

# NPI Models Explained and Complained

***Abstract*—**Numerous modelling efforts have attempted to characterize the effects of different non-pharmaceutical interventions (NPIs) on the Covid-19 spread. Arguably the most famous is one published in Nature by an Imperial College group. A slight variation of it was later published in Science by a group of Oxford researchers. Both publications are based on hierarchical Bayesian modelling that aims to explain observed data by information on enacted NPIs. Due to the Bayesian approach, the models become quite complex and opaque, with many priors that have been assigned more or less ad hoc, and there are even priors on the prior parameters. We show how these models can be recast into the classic linear regression framework. This enables us to transparently analyze basic concepts such as persistency of excitation, identifiability, and model sensitivity.

**Fredrik Gustafsson**
Department of Electrical Engineering
Linkoping University
Linköping, Sweden
fredrik.gustafsson@liu.se

**Kristian Soltesz**
Department of Automatic Control
Lund University
Lund, Sweden
kristian@control.lth.se

## THE SIR MODEL REVISITED

We will refer to the two studied non-pharmaceutical intervention (NPI) models as the *Nature* [1] and *Science* [2] model, respectively. In the presentation we focus on the former, although our methodology remains applicable to either and we will present results obtained using both models.

Within the models, NPIs are typed as school closure, crowd size limit, lockdown, etc. The purpose of the model is then to explain the epidemic trajectory based on enactment of the NPIs.

Before delving into the details of the models, let us briefly revisit the classic Susceptible, Infected, and Recovered (SIR) compartment model [3] that lies at the core of many more advanced epidemiological models, including the ones considered here. It is a lumped-parameter model that can be applied on a societal or subsocietal level and describes how a considered population is partitioned into susceptible $S$, infectious $I$, and removed (recovered and immune ∪ deceased) $R$ fractions.[1] The population is normalized according to (1a), and the dynamics are:

$$1 = S + I + R, \tag{1a}$$

$$\frac{dS}{dt} = -\beta SI, \tag{1b}$$

$$\frac{dI}{dt} = \beta SI - \gamma I, \tag{1c}$$

$$\frac{dR}{dt} = \gamma I. \tag{1d}$$

The equations governing the epidemic trajectory are determined by an infection parameter $\beta$ and a recovery parameter $\gamma$.

The famous basic reproduction number $R_0 = \beta/\gamma$ defines how many secondary infections are expected from one primary infection[2], when $S \gg I$. The adjective *basic* is with respect to some considered action, such as an NPI or set of NPIs. In contrast to the growth *rate*[3] $r_0 = \beta - \gamma$, $R_0$ is unit-less and decoupled from time (making it a less obvious choice for measuring time-dependent growth in the first place).

Arguably the simplest way to model NPI effectiveness is to investigate how enacting an NPI affects the spread parameter $\beta$, which coincides with how it affects $R_0$ (or $r_0$) if $\gamma$ is constant. Since $\beta$ cannot be directly measured (either), an observation model involving a measurable signal related to it is needed. A very simple such observation model would be to assume a constant infection-to-fatality ratio (IFR), and that all deaths occur a fixed time $\tau_{ID}$ following infection.

Figure 1 shows the reported daily deaths in Sweden [4] during the first wave of the pandemic in green. The red curve is fitted using nonlinear least squares (NLS), under the assumption that $\beta$ was constant throughout the first wave. The blue curve is the fit that minimizes the quadratic NLS loss using one NPI (change in $\beta$), with date chosen to optimize curve fit.

Although the results look convincing, the model is useless in all aspects other than for curve fitting.

One artefact is that the parameters generating the red curve explain the decline of the first wave as a consequence of herd immunity, with 99.9% of the population having been infected by October 2020, while the blue curve mainly explains the decline in deaths through an effective NPI enacted on April 7,

[1] The basic SIR model does not distinguish between infected and infectious, but such additional state partitioning is straightforward, as are the partitionings aimed at tracking different subpopulations.

[2] A simple derivation is based on $R_0 = -dS/dR = \beta S/\gamma \approx \beta/\gamma$ when $S \approx 1$, so every removed person gives rise to $R_0$ new infections.

[3] When $S \approx 1$ the solution to (1c) is $I(t) \approx e^{(\beta-\gamma)(t-t_0)} I(t_0)$.

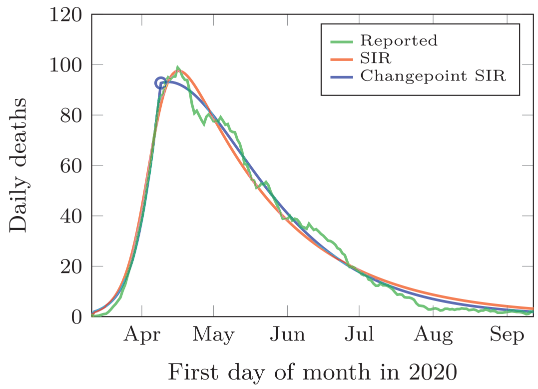



**Figure 1**
NLS fit of the SIR model (1) to officially reported daily deaths in Sweden during the first pandemic wave. Deaths are shown in green, the SIR model fit in red, and the best NLS fit of an SIR model, where $\beta$ is allowed to change twice, is shown in blue. The marker indicates the instance of the parameter change.

2020, with 50% of the population having undergone infection by October 2020.

An important conclusion from this example is that the model fit cannot alone be used to validate a model—not even for the very simple model considered above. The lack of *informative* data for model validation is a fundamental problem, in particular during the early stage of an (infectious disease) epidemic.

## MODELLING FRAMEWORK

The basic dynamics of how NPIs are modeled to affect reported death (or case) data in the *Nature* and *Science* models are illustrated in Figure 2. Both models share the same basic equations as will be outlined in this section. The differences are in the details of NPI types, time span, and the strategies to estimate parameters to fit the data.

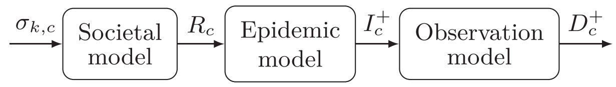



**Figure 2**
Block diagram of the considered NPI models showing their three principal components and intermediate signals: Enactment indicator of NPI $k$, $\sigma_k$, reproduction number $R$, daily infections $I^+$, reported daily deaths $D^+$. Subscript $c$ denotes country.

### SOCIETAL MODEL

NPI $k$ enacted on day $t$ in country $c$ is modeled to induce an undelayed step change of magnitude ($\alpha_{k,c}$) in the reproduction number within the country:

$$R_c(t) = R_{0,c} \cdot \exp\left(-\sum_{k=1}^{N_\alpha} \alpha_{k,c}\sigma_{k,c}(t)\right), \tag{2}$$

where $\sigma$ is the binary indicator function, and $N_\sigma$ is the number of NPI types. The country-specific basic reproduction number $R_{0,c}$ is treated as an unknown parameter to be identified from data together with the effectiveness parameters $\alpha_{k,c}$.

If $\alpha_{k,c} = \alpha_k$ is the same for all countries $c = 1, \ldots, N_c$, the model for each NPI $k = 1, \ldots, N$... is referred to as *fully pooled*. If the effectiveness parameters are allowed full international flexibility, the model is said to be *unpooled*. Models between these extremes are referred to as *partially pooled*. The main differences between the *Nature* and *Science* models reside with the definition of the NPI types, and the pooling assumptions on individual NPIs.

### EPIDEMIC MODEL

Two time-distributions play a central role in the NPI effectiveness modelling. They model the duration $\tau$ between

- primary and secondary infection following the serial (or generation) interval distribution $p_{II}(\tau)$;
- infection and death following the distribution $p_{ID}(\tau)$.

These distributions are assumed to be time-invariant, and prior assumptions on their shape within the *Nature* model are reviewed further below in the section "Priors".

The number of individuals $I_c^+(t)$ that become infectious on day $t$ in country $c$ can now be expressed as

$$I_c^+(t) = \underbrace{R_{0,c}\frac{N_c - \sum_{\tau=0}^{t-1} I_c^+(\tau)}{N_c}}_{R_{e,c}(t)} \sum_{\tau=0}^{t-1} I_c^+(\tau)\, p_{II}(t-\tau). \tag{3}$$

Here, the effective reproduction number $R_{e,c}$ accounts for both NPI and herd immunity effects. Equation (3) constitutes a nonlinear auto-regressive model since previous values of $I_c^+$ are combined in a nonlinear fashion to determine $I_c^+(t)$.

To get some intuition for (3), consider the special case where $p_{II}(\tau) = \delta(\tau - k)$ is a Dirac distribution. That is, each infectious individual spreads the disease to (on average) $R_c(t)I_c^+(t)/N_c$ susceptible individuals, $k$ days after becoming infected. If $R_c$ is constant, the spread can be locally approximated with

$$I_c^+(t) \approx R_c^{(t-t_0)/k} I_c^+(t_0)/N_c, \tag{4}$$

where the exponential growth rate $r_c = \log(R_c)/k$ clearly shows the strong influence of the delay $k$.

### OBSERVATION MODEL

Finally, we have an observation model for reported daily deaths $D_c^+(t)$ in country $c$ on day $t$, based on an assumed distribution $p_{ID}(\tau)$ of the time between infection and death:

$$D_c^+(t) = \text{IFR} \sum_{\tau=0}^{t-1} I_c^+(\tau)\, p_{ID}(t-\tau), \tag{5}$$

If case data is incorporated into the model, the infection-to-case ratio plays an analogous role to the IFR. More generally, each of the distributions of the epidemic model in the section "Epidemic Model" is associated with a normalization factor of this kind, since not all primary infections result in secondary infections, not all infected individuals die, etc.

## MODEL ESTIMATION

The model is defined through (2)–(5). How can it be used to estimate the parameters $R_{0,c}$ and $\alpha_{k,c}$ for $c = 1, \ldots, N_c$ and $k = 1, \ldots, N_\alpha$ from $D_c^+$ time series data?

### BAYESIAN APPROACH

Both the *Nature* and *Science* estimation methods are so-called hierarchical Bayesian models that are fitted using massive Monte Carlo sampling [5]. Our contribution is to recast them into the linear regression framework rather than to analyze the estimation method they originally rely on. However, we believe it is adequate to summarize the main design parameters of the Bayesian approach.

### PRIORS

Prior assumptions on distributions are needed, and in the final published version, the *Nature* model assumes the following priors[4] for the time distributions of the epidemic model reviewed in the section "Epidemic Model":

$$p_{II}(\tau) \sim \Gamma(6.5, 0.62), \tag{6a}$$

$$p_{ID}(\tau) \sim \Gamma(5.1, 0.86) + \Gamma(17.8, 0.45). \tag{6b}$$

Here, $\Gamma(a, b)$ denotes the Gamma distribution with mean $a$, coefficient of variation $b$, and standard deviation $ab$.

The effectiveness prior for NPI type $k$ in the *Nature* model is

$$\alpha_k + \frac{\log(1.05)}{6} \sim \Gamma(1/6, 1),\ k = 1, \ldots, 6, \tag{7}$$

with the motivation that

$$\sum_{k=1}^{6} \alpha_k \sim U(0, 1.05). \tag{8}$$

That is, there is a possibility that the interventions will increase the reproduction number by a factor 1.05, but most of the prior is assigned to a significant decrease.

Finally, the prior for the basic reproduction numbers were chosen $R_{0,c} \sim \mathcal{N}(2.4, |\kappa|)$, $c = 1, \ldots, N_c$ where $\kappa \sim \mathcal{N}(0, 0.5)$.

### REGULARIZING EFFECT OF THE GAMMA PRIOR

As was illustrated by Nic Lewis in his blog [6], the Gamma prior has a regularization effect. Suppose that a pooled model ($\alpha_{k,c} = \alpha_k$) is used and that the data is consistent with a posterior where $\alpha_1 + \ldots + \alpha_{N_\alpha} = 1.75$. This corresponds to a factor $1 - e^{1.75} = 0.83$ decrease of the reproduction number should all NPIs be simultaneously enacted, and it happens to coincide with the median between Markov chain Monte Carlo (MCMC) samples reported in [1]. Then, the prior for the sum becomes orders of magnitude larger if one $\alpha_k$ dominates (e.g., $\alpha_1 = 1.70$), compared to when they all are of similar size (e.g., $\alpha_k = 1.75/N_\alpha$, $k = 1, \ldots, N_\alpha$). This makes the Gamma prior strongly biased towards one (or a few) NPIs explaining the data, and in the case of [1] the lockdown NPI was singled out as the by far dominating explanation of the decrease in viral reproduction. Figure 3 illustrates the effect for the visualizable case of $N_\alpha = 2$.

[4] The reason that $p_{ID}$ is the sum of two Gamma-distributed variables is that the *Nature* model breaks it down into the infection-to-symptom-onset distribution $p_{IO}$ (first term), that is convoluted with the symptom-onset-to-death distribution $p_{OD}$ (second term).

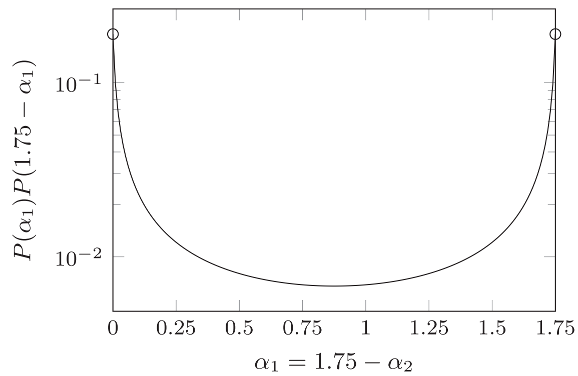



**Figure 3**
Probability for $\alpha_1 + \alpha_2$ for different splits between priors $\alpha_1$ and $\alpha_2 = 1.75 - \alpha_1$, individually distributed according to (7).

### MCMC SAMPLING PRINCIPLE

To compute the (posterior distributions of the) parameters, the *Nature* and *Science* models rely on sampling from the parameter priors, evolving (3) and (2), and then evaluating the likelihood for each sample in a Bayesian MCMC framework, as very sketchily summarized by the following basic steps:

1. Draw a candidate for the parameters from the prior distributions. This is the most important step and there are many different sampling strategies that could be considered.
2. Simulate the model with the parameter candidate.
3. Compute the likelihood for the observed mortality data.
4. Generate a random number $u \sim U(0, 1)$.
5. If the log-likelihood ratio has increased more than $u$, the parameter candidate is accepted, otherwise it is rejected.
6. Continue until a predefined number of parameter candidates have been accepted, excluding the burn-in phase before the MCMC has converged to stationarity.

## LINEAR REGRESSION NPI MODEL

### SOCIETAL MODEL AS A LINEAR REGRESSION

We note that (2) can be cast as a linear regression in the log domain:

$$\log R_c(t) = \log R_{0,c} - \sum_{k=1}^{N_\alpha} \alpha_{k,c}\ \sigma_{k,c}(t). \tag{9}$$

Taking the logarithm of (3) and using it to eliminate $R_c(t)$ yields

$$\log I_c^+(t) = \log R_{0,c} - \sum_{k=1}^{N_\alpha} \alpha_{k,c}\sigma_{k,c}(t) + \log\left(1 - \frac{\sum_{\tau=0}^{t-1} I_c^+(\tau)}{N_c}\right) + \log\left(\sum_{\tau=0}^{t-1} I_c^+(\tau) p_{II}(t-\tau)\right). \tag{10}$$

This fits the classical linear regression framework

$$z_c(t) = h_c(t)\theta + w(t). \tag{11a}$$

The left-hand-side is the auto-regressive process

$$z_c(t) = \log I_c^+(t) - \log\left(\sum_{\tau=0}^{t-1} I_c^+(\tau) p_{II}(t-\tau)\right) \tag{11b}$$

$$+\log\left(1 - \frac{\sum_{\tau=0}^{t-1} I_c^+(\tau)}{N_c}\right). \tag{11c}$$

The right-hand side of (11a) comprises of the regression matrix and parameter vector,

$$h_c(t) = \left[\sigma_{1,c}(t) \ldots \quad \sigma_{N_\alpha,c}(t) \quad e_c^\top\right], \tag{11d}$$

$$\theta = \left[\alpha_1 \ldots \alpha_{N_\alpha} \quad \log(R_{0,1}) \ldots \log(R_{0,N_c})\right]^\top, \tag{11e}$$

where $e_c$ is the $c$th unit vector. Equation (11e) corresponds to the fully pooled model, and partially pooled or unpooled formulations only differ structurally in that they have a larger number of parameters.

Vectorizing the data for the $N_c$ countries, we obtain the more compact form

$$Z(t) = H(t)\theta + W(t), \tag{12}$$

where $Z(t) = \left[z_1(t) \ldots z_{N_c}(t)\right]^\top$ is a function of mortality data and $H(t) = \left[h_1^\top(t) \ldots h_{N_c}^\top(t)\right]^\top$ depends on the NPIs only. The model error $W(t) = \left[w_1(t) \ldots w_{N_c}(t)\right]^\top$ is the realization of an observation noise process, and its variance $\lambda$ can be interpreted as the best model fit for this particular model structure.

## LEAST SQUARES SOLUTION

Assuming that $W$ in (12) consists of independent and identically distributed samples from a Gaussian process, the maximum-likelihood (ML) estimate $\hat{\theta}$ of $\theta$ is obtained by minimizing the quadratic ordinary least-squares (OLS) loss, with closed-form solution

$$J = \sum_t H(t)^\top H(t) \tag{13a}$$

$$\hat{\theta} = J^{-1} \sum_t H(t)^\top Z(t), \tag{13b}$$

$$\mathrm{Cov}\left(\hat{\theta}\right) = \lambda J^{-1}. \tag{13c}$$

Here, $\lambda = \mathrm{Var}\left(z_{t,c}\right)$ denotes the variance of the transformed data, assuming it to be the same for all times and countries, and $J$ is the Fisher information matrix (FIM). Structural identifiability is determined by the rank of the FIM, and persistency of excitation is measured by its condition number.

In the *Nature* and *Science* models, observation noise was not introduced as in (12), but instead implicitly generated through the random variables assigned with priors according to the section "Priors". To understand how the observation noise (or LS residual) $W$ relates to the stochastics of the original model, assume we have access to the posteriors that maximize the likelihood within the Bayesian formulation. Then (in theory) $I_c^+$ can be computed through deconvolution of (5) and used to construct the $X$ and $Z$ of (12). Having access also to the posteriors of $\theta$, $W(t) = Z(t) - H(t)\,\theta$ can be evaluated. It is thus important to note that we cannot (at least directly) use the linear regression formulation for identifying $\theta$. However, and importantly, we can use it to analyze sensitivity of the identified system to small perturbations, that could arise from uncertainty or error in NPI actuation date ($\sigma$) or death ($D^+$) reporting.

## IDENTIFIABILITY OF THE NATURE MODEL

The *Nature* model defined the following $N_\alpha = 5$ NPI types[5]:

1. Social distancing encouraged;
2. Self isolation;
3. School closure;
4. Public events (banned);
5. Lockdown.

Figure 4 (top) shows the dates that the different NPIs were enacted within the published version [1] of the *Nature* model. Countries are labeled by their ISO 3166-1 alpha-2 codes. Note in particular that all NPIs were enacted within a short time window. The corresponding reported daily death time series $D^+$ are also shown in the same figure.

The inverse FIM for the model of the section "Linear Regression NPI Model" has the block structure

$$J^{-1} = \begin{bmatrix} J_{\alpha\alpha}^{-1} & J_{\alpha R_0}^{-1} \\ [2pt] J_{R_0\alpha}^{-1} & J_{R_0R_0}^{-1} \end{bmatrix}. \tag{14}$$

Let us here focus on the block $J_{\alpha\alpha}^{-1} \propto \mathrm{Cov}(\alpha)$ that defines the covariance of the NPI effectiveness parameters.

For the data used in [1] and shown in Figure 4, it evaluates to

$$J_{\alpha\alpha}^{-1} = \lambda \begin{bmatrix} 0.044 & -0.019 & -0.015 & -0.007 & -0.005 \\ -0.019 & 0.034 & -0.003 & -0.004 & -0.002 \\ -0.015 & -0.003 & 0.045 & -0.009 & -0.013 \\ -0.007 & -0.004 & -0.009 & 0.027 & -0.006 \\ -0.005 & -0.002 & -0.013 & -0.006 & 0.025 \end{bmatrix}. \tag{15}$$

[5] The careful reader might have noticed that (7)–(8) correspond to $N_\alpha = 6$. This is related to how (a particular version of) the *Nature* model pools data, with a "bonus" NPI for the last intervention introduced in each country, and further explained in [7].

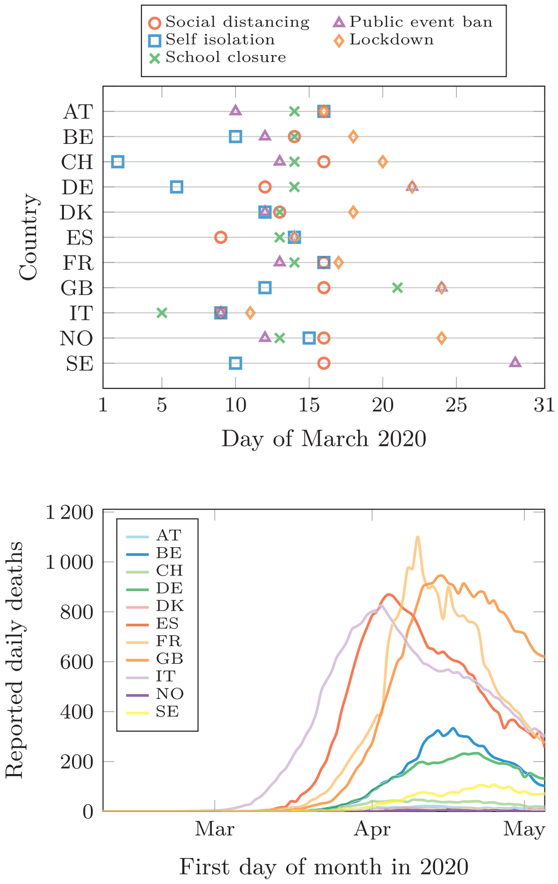



**Figure 4**
NPI enactment dates (top) and reported daily deaths (bottom) used in the published version [1] of the *Nature* model.

The condition number of this matrix is 36, but more severe for the model is that the condition number for the full $J$ matrix is 600. This ill-conditioning[6] can be hard to detect directly from (15), where according to (13c), log $\alpha_k$ can be estimated with a variance less then 0.04 times that of the observation noise $\lambda$ (e.g., model fit).

The SVD of the inverse FIM (covariance matrix) block defined by $J_{\alpha\alpha}^{-1} = U \Sigma U^\top$ is given by

$$\Sigma = \lambda \operatorname{diag}\begin{bmatrix}0.0018 & 0.0649 & 0.0498 & 0.0263 & 0.0331\end{bmatrix}, \tag{16a}$$

$$U = \begin{bmatrix} -0.046 & 0.430 & 0.552 & -0.703 & -0.118 \\ 0.390 & 0.402 & 0.465 & 0.635 & -0.259 \\ 0.467 & -0.021 & 0.231 & -0.097 & 0.848 \\ 0.482 & -0.108 & 0.351 & -0.663 & -0.440 \\ 0.461 & -0.722 & -0.337 & 0.365 & -0.138 \end{bmatrix}. \tag{16b}$$

The first column of $U$, that corresponds to the smallest singular value, points less than 5° from the direction $\sum_k \alpha_k$, indicating that the summed effect of all NPI types constitutes the linear combination that can be identified with highest certainty. This should not be surprising, since all NPIs were enacted within a short time window in all but one country, as seen in Figure 4. Similarly, the last column of $U$ reveals the linear combination of NPIs that is associated with the highest uncertainty (variance).

[6] The Stan code [8] used in the *Nature* model [1] throws a large number of warnings for numerical ill-conditioning; that might be a consequence of this.

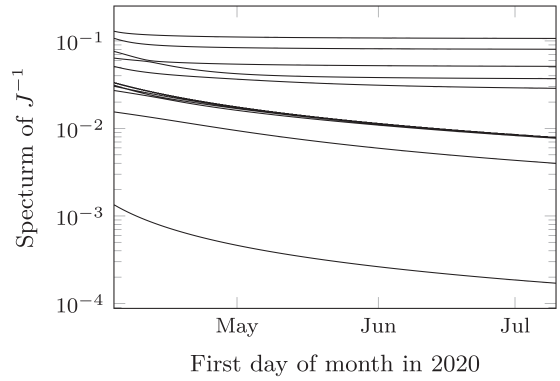



**Figure 5**
Evolution of the 16 ($N_c$ = 11 $R_0$ values, $N_\alpha$ = 5 NPIs) singular values of the full inverse FIM $J^{-1}$ in (13a) for the *Nature* model.

Returning to the unfactored covariance matrix (15) we note that the variance of the normalized sum

$$\operatorname{Var}\left(\sum_{k=1}^{N_\alpha} \frac{\hat{\alpha}_k}{\sqrt{5}}\right) = \frac{1}{5}\operatorname{Var}\left(\mathbf{1}^\top \alpha\right) = \frac{1}{5}\mathbf{1}^\top J_{\alpha\alpha}^{-1}\mathbf{1}\lambda = 0.002\lambda, \tag{17}$$

is an order of magnitude smaller than the smallest diagonal element of the unfactored matrix (15). This further indicates that the summed effect is much easier to identify than the effect of individual NPIs.

## IDENTIFIABILITY OVER TIME

It can be argued that the illustrated identifiability issues result from a lack of data early in the pandemic, and that better estimates could have been obtained if the models were executed at a later time when more data was available. Let us therefore investigate how identifiability of the *Nature* and *Science* models—and a third related model that we are yet to introduce—has evolved throughout (the first pandemic year) 2020. We use exactly the same linear regression framework for all three models; only the NPI definitions and time frames differ.

### THE NATURE MODEL

Figure 5 shows the day-by-day evolution of the singular values of the covariance matrix (15), as more data from the originally used data source [8] became available.[7]

Uncertainty in the principal directions of $J^{-1}$ decreases during the spring of 2020, but then levels out, indicating that iden-

[7] We have blinded out data to emulate past dates. This is very similar, but not exactly identical, to using data causally available on those past dates, since most sources of Covid-19-related time series apply retrospective adjustments.

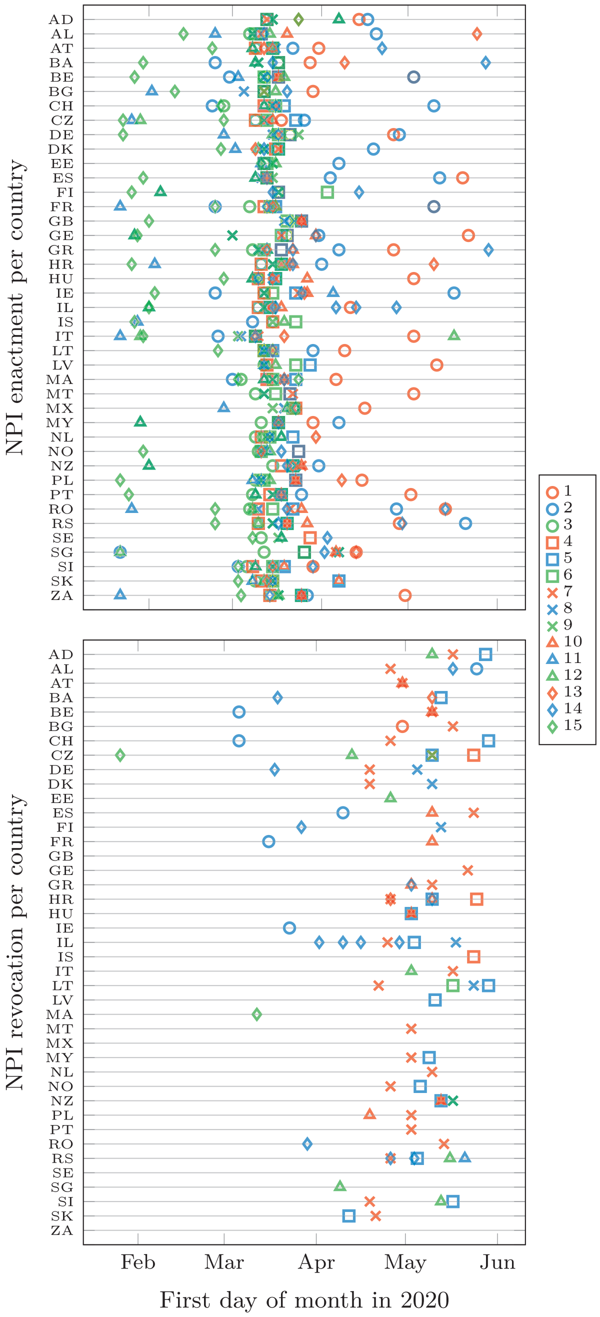



**Figure 6**
Dates when individual NPIs were enacted (top) and revoked (bottom) within the *Science* model. The NPI enumeration is consistent with [2].

tifiability issues, as pointed out in e.g., [7] and [6], have not improved markedly due to data available since the acceptance date of [1].

## THE SCIENCE MODEL

A rule of thumb in system identification, when the regressors can be designed, is that they should resemble white noise. Such a design can be excluded for NPIs in pandemics, but the *Science* model features an input that is more persistently exciting

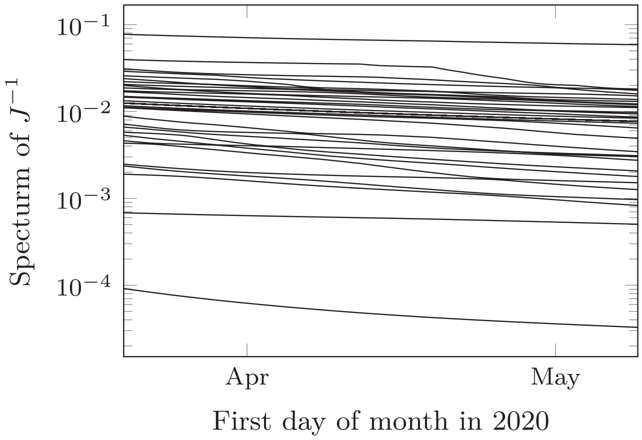



**Figure 7**
Evolution of the 56 ($N_c = 41$ $R_0$ parameters, $N_\alpha = 15$ NPIs) singular values of the full inverse FIM $J^{-1}$ in (13a) for the *Science* model.

than that of the *Nature* model, since the former was secured at a later point in time and has a regressor that keeps track not only of enactment, but also revoking of individual NPIs. The corresponding dates are shown in Figure 6, where it can also be seen that the number of NPI types is larger, compared to the *Nature* model.

The evolution of the singular values of the corresponding $J^{-1}$ is shown in Figure 7. It shows that variance in the least certain principal direction has decreased roughly a factor of three.

## THE INDEX MODEL

A third model [9], here referred to as the "Index" model, differs from the *Nature* and *Science* models in that its individual NPI effectiveness parameters are set by the modellers rather than estimated from data. The sum of these parameters over enacted NPIs at any given time forms the scalar "stringency index", taking values between 0 and 100.

Data to compute the index is taken from an impressive database, further described in [9], that keeps track of over 100 NPI (sub)types. The index is shown in Figure 8 (top). To reduce complexity of the graphics, we picked out the same 11 countries as used in the *Nature* model.

We apply our linear regression framework for the *Science* model (with the selected 11 countries) using this index as the sole NPI. This model thus has one $\alpha$-parameter (the index) and 11 country-specific $R_0$ parameters. The singular values of the inverse FIM are shown in Figure 8 (bottom). Only three distinguishable lines are seen, since 10 of the 12 singular values are identical for this model structure. The careful reader may already have observed that the number of lines in Figures 5 and 7 are fewer than $N_c + N_\alpha$ for similar reasons.

The largest singular value remains steady at a similar level to where the corresponding value of the *Science* model levels out, and roughly 10 times lower than the corresponding level for the *Nature* model. This corresponds to a one-dimensional subspace, within which parameter values can move without affecting the model output much.

## DISCUSSION

### WHAT HAVE WE LEARNT?

The modelling of NPIs as instantaneously changing the reproduction number received much attention early in the Covid-19 pandemic, starting with the Imperial College COVID-19 Response Team (ICCRT) report [10] and subsequent publication [1], that categorized interventions into five NPI types. Identifiability issues due to high sensitivity of the model with the data available at the time (spring of 2020) were apparent and was addressed early in a technical blog post by Nic Lewis [6], and in a response by us [7] published alongside the original work [1]. The focus of that response was on how the partial pooling of national data within the model had incrementally changed in its official code base (8) between publication of the ICCRT report [10] and the *Nature* paper [1], and how these changes resulted in masking an apparent identifiability issue.

Here we have intentionally stayed away from the intricacies of how different models—or versions of the same model—have chosen to pool national data or define the NPI types to include, alongside the criteria associated with enactment of these NPI types within the models. Instead, we have taken one step back and regarded the model structure, and particularly that it is very closely related to a linear regression. Applying standard information theoretic analysis, we have then illustrated that the *information* in the data available in the spring of 2020—and presumably early during possible future epidemics of novel pathogens—is insufficient to uniquely distinguish the effects of (linear combinations of) NPIs.

While both the *Nature* and *Science* models attempt to identify the effects of NPIs on the reproduction number, the Index model instead provides an index based on a carefully curated NPI dataset. Within the herein considered framework, this index corresponds to preassigning the effectiveness parameters rather than identifying them from data. This obviously resolves the identifiability issue, but results in a signal (the index) that correlated very poorly with observed case or death data. This bias is visually apparent when comparing Figure 8 (top) to Figure 4 (bottom).

### HAS IDENTIFIABILITY IMPROVED OVER TIME?

A natural question to ask is if more careful definition of the NPIs and choice of national data pooling could alleviate the aforementioned problem, and whether poor identifiability of NPI effects was merely a consequence of the models being applied too early, when only insufficient data was available. In relation to these questions, it is interesting to note that a model [1] similar to [2] was later published in *Science*. Without additional background, its diametrically differing conclusions regarding the effectiveness of lockdowns in particular (highly effective versus at best mediocre) could be interpreted as the sequel having addressed the above issues. To this end, we have plotted how the singular values of the effectiveness parameter covariance has evolved within the linear regression interpretation of the two models, with more data becoming available. These plots tell us how confidently identifiable the corresponding principal parameter space directions are with respect to the observation noise. Particularly, the condition number, being the ratio between the largest and smallest of them, tells us the identifiability ratio between the least and most certain principal direction. For both models we see that the information remains poorly conditioned, albeit much improved as compared to the spring of 2020. Looking at the corresponding principal directions, we could also see that the most certain principal direction corresponds to the sum of all NPIs within the *Nature* model.

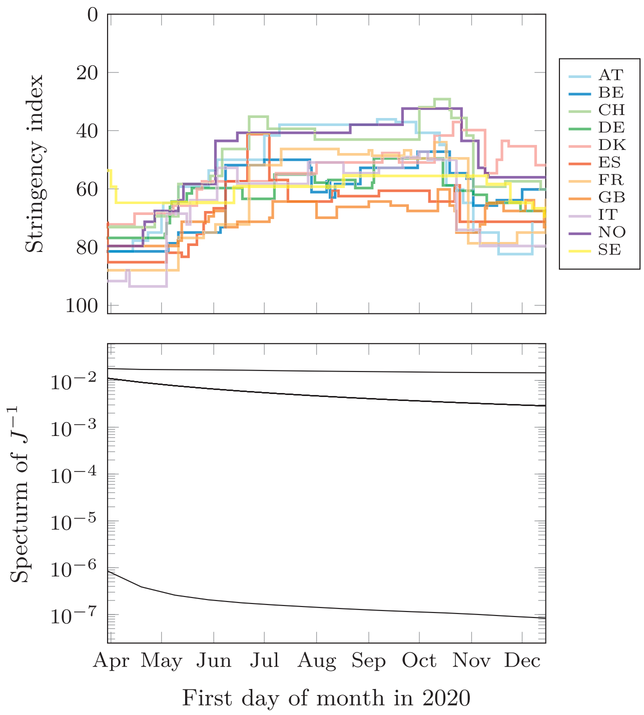



**Figure 8**

Stringency index according to the Index model for the same 11 countries that were included in the *Nature* model (top). Evolution of the 12 ($N_c = 11$ $R_0$ values, $N_\alpha = 1$ NPI) singular values of the full inverse FIM $J^{-1}$ in (13a) for the *Science* model (bottom). Note that 10 of the 12 singular values are identical for this special structure.

### CONCERNS BEYOND THE DATA

So far our analysis has pointed out severe issues with the models while tacitly assuming them to be structurally sound. This is a very generous assumption.

For starters, all three models come with a linearity assumption, in that the combined effect of two NPIs equals the sum of the effects they would inflict if enacted individually. For example, the Index model defines the NPIs “close public transport” and “stay at home requirements”. An educated guess is that the impact on virus spread of the former is decreased should the latter be enacted.

To continue, there is a time-invariance assumption leaving no room for saturation effects or improvements over time within the healthcare sector, mutations resulting in more or less transmissible or harmful pathogen variants, etc.

However, the most pushing point is that of causality. Since neither of the models leave room for any extrinsic variable but the NPIs to explain virus spread, they are bound to explain the decline of the first pandemic wave with the NPIs (and provided that the data is uninformative are most certain about the combined NPI effect). To what extent have changes in behavior, other than those enforced by legislation, affected the pandemic trajectory? What has the role of the change in season been on viral transmission? These are hard questions, and ones that remain unanswerable within the considered models.

## CONCLUSION

In the end, it all comes down to fundamental properties of the true dynamics, the model, and the data:

- Good curve fitting does not validate a model. Cross validation on fresh data is the preferred procedure, and when not possible (for example early in an epidemic), identifiability and sensitivity analyses need to be carefully conducted.
- Good curve fitting does not imply identifiability, only that the model is complex (i.e., flexible) enough to describe observed data.
- Identifiability does not imply good curve fitting, only that the model is not too complex compared to what is measured.
- Uninformative data, resulting from a lack in persistence of excitation, implies that no conclusions whatsoever can be drawn on the model.
- Modelling assumptions directly impact the usefulness of the resulting model. This holds true also for models that can be reliably identifiable from data.

We have demonstrated that several NPI models, including ones published in *Nature* and *Science*, fall short in all these aspects.

## REFERENCES


1. Flaxman, S., Mishra, S., Gandy, Juliette, A. H., Unwin, T., Mellan, T. A., et al. Estimating the effects of non-pharmaceutical interventions on COVID-19 in Europe. *Nature*, Vol. 584, (2020), 257–261.
2. Brauner, J., Mindermann, S., Sharma, M., Johnston, D., Salvatier, J., Gavenčiak, T., et al. Inferring the effectiveness of government interventions against COVID-19. *Science*, Vol. 371, 6531 (2021).
3. Kermack, W., and McKendrick, A. A contribution to the mathematical theory of epidemics. *Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, Vol. 115, 772 (1927), 700–721.
4. Public Health Agency of Sweden. Folkhalsonyndigheten_covid19 [dataset], https://www.arcgis.com/sharing/rest/content/items/b5e7488e117749c19881cce45db13f7e/data, last access May 5, 2021.
5. Meyn, S., and Tweedie, R. *Markov Chains and Stochastic Stability*. London: Springer-Verlag, 1993.
6. Lewis, N. Did lockdowns really save 3 million COVID-19 deaths, as Flaxman et al. claim?, https://judithcurry.com/2020/06/21/did-lockdowns-really-save-3-million-covid-19-deaths-as-flaxman-et-al-claim, last access May 4, 2021.
7. Soltesz, K., Gustafsson, F., Timpka, T., Jaldén, J., Jidling, C., Heimerson, A., et al. The effect of interventions on COVID-19. *Nature*, Vol. 588, E26-E28 (2020).
8. Imperial College COVID-19 Response Team (ICCRT). Covid19model, https://github.com/ImperialCollegeLondon/covid19model, last access Jun. 1, 2020.
9. Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., et al. A global panel database of pandemic policies (Oxford COVID-19 government response tracker). *Nature Human Behaviour*, Vol. 5, (2021), 529–538.
10. Flaxman, S., Mishra, S., Gandy, A., Unwin, H., Coupland, H., Mellan, T., et al. Report 13 UPDATE: Estimating the number of infections and the impact of non-pharmaceutical interventions on COVID-19 in 11 European countries—Technical description update. Imperial College London, Tech. Rep., 2020. Available: http://spiral.imperial.ac.uk/handle/10044/1/77731, last access Apr. 24, 2020.



**Fredrik Gustafsson** is professor in Sensor Informatics at Department of Electrical Engineering, Linköping University, since 2005. He received the M.Sc. degree in electrical engineering 1988 and the Ph.D. degree in Automatic Control, 1992, both from Linköping University. His research interests are in stochastic signal processing and related areas. He is a co-founder of the companies NIRA Dynamics (automotive safety systems), Softube (audio effects) and Senion (indoor positioning systems).



**Kristian Soltesz** is associate professor with the Department of Automatic Control, Lund University, since 2019. He received the M.Sc. and Ph.D. degrees in Automatic Control in 2008 and 2013, both from Lund University. His research interests span various topics within medical control systems. Kristian is a member of the IEEE Committee on Healthcare and Medical systems, has been engaged in several COVID-19-related research topics during the past year and presented a keynote talk on the topic at the FUSION 2020 conference. One year later, he says: "*[…] It is inspiring to see the level of societal engagement […] within many scientific communities, and notably amongst epidemiologists applying statistical signal processing and dynamic modelling methods. […] [M]odelling early in a pandemic could also serve to guide resource allocation, should a similar situation arise in the future.*" —Excerpt from an interview by M. Mihaylova, May 2021.


# Information Processing Methodologies to Combat the COVID-19 Pandemic

**Domenico Gaglione**
NATO STO Centre for Maritime Research and Experimentation (CMRE)
Research Department
La Spezia, Italy
domenico.gaglione@cmre.nato.int

**Paolo Braca**
**Giovanni Soldi**
**Nicola Forti**
**Leonardo M. Millefiori**
NATO STO Centre for Maritime Research and Experimentation (CMRE)
Research Department
La Spezia, Italy

**Stefano Marano**
University of Salerno
Dipartimento di Ingegneria dell'Informazione ed Elettrica e Matematica Applicata (DIEM)
Fisciano (SA), Italy

**Peter K. Willett**
**Krishna R. Pattipati**
University of Connecticut
Department of Electrical and Computer Engineering
Storrs, CT, USA

*Abstract*—Information and signal processing tools are crucial for interpreting coronavirus disease 2019 (COVID-19) pandemic data. These tools allow us to extract, synthesize, and interpret pandemic information, thus providing valuable support to the decision-making authorities. This paper presents an overview of recent advances in information processing methodologies to combat the COVID-19 pandemic. First, we describe the quickest detection procedure designed to detect an exponential growth of positive cases with a mean delay of only a few days and a low risk of erroneously declaring an outbreak. Second, we present a Bayesian approach designed to estimate some features of the pandemic, e.g., the infection rate, and reliably forecast the evolution of the contagion.

## INTRODUCTION

Since the beginning of 2020 and up to the end of April 2021, the virus known as severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), responsible of the coronavirus disease 2019 (COVID-19) respiratory illness, has infected more than 150 million individuals worldwide and caused the death of more than 3.2 million people. Because of its rapid human-to-human transmission and the presence of highly infectious asymptomatic individuals, the COVID-19 disease was declared by the World Health Organization to be a pandemic on March 11, 2020. Since then, many governments, pushed by the lack of an effective therapy and the imperative need of containing the contagion, have decided to undertake unprecedented extraordinary social measures that have changed many aspects of our lives. These measures, which included travel bans; closure of schools, universities, shops, and factories; and even national lockdowns, effectively slowed the spread of the virus; however, their early relaxation has been causing the recrudescence of the contagion almost everywhere. The implementation of massive vaccination campaigns represents the only way to definitely defeat the pandemic, as shown, e.g., from the evolution of the contagion in Israel, where 85% of individuals older than 60 years had been fully vaccinated after only 2 months into the vaccination campaign [1]. Nevertheless, as researchers are still debating whether new variants can undercut the effectiveness of these first-generation COVID-19 vaccines [2], it is of paramount importance to remain vigilant and assist the authorities in evaluating the implementation of pandemic countermeasures.

Information and signal processing tools, exploiting the vast amount of data collected since the beginning of 2020, can support decision makers in monitoring the contagion and predicting the evolution of the pandemic [3]. This article excerpts from [4]–[8], providing an overview of recent advances in information processing methodologies to combat the COVID-19 pandemic.

## QUICKEST DETECTION OF PANDEMIC WAVES

One aspect to monitoring the COVID-19 pandemic is to detect, as quickly as possible, the outbreak of a new exponential growth of positive cases, which would allow governments and authorities to react in a timely manner [8]. Indeed, on the one hand, the early application of countermeasures, such as social distancing and closure of commercial activities, can save lives; in this context, the delay of intervention needs to be as short as possible. On the other hand, an incorrect detection of an outbreak (i.e., a false alarm), and the consequent imposition of unnecessary restrictive measures, may have huge trust, societal, and economic costs [9]. This risk, mathematically defined as the reciprocal of the mean time between two consecutive false alarms, needs thus to be extremely small.

Leveraging quickest detection theory [10], [11], we have developed in [4], [5], and [6] a variation of the celebrated Page's test [12], called the mean-agnostic sequential test (MAST), designed to detect the transition from a controlled regime of the pandemic, characterized by a limited number of daily new positive cases, to a critical regime, in which the infection spreads exponentially fast. MAST is based on the recursive computation of a decision statistic that depends only on the observed growth rate, computed daily as the ratio between two consecutive new positive counts (details in [5]). This statistic is then compared to a threshold—selected to trade off mean decision delay and risk—and, if it is crossed, an outbreak is declared.

An extensive analysis of MAST when applied to data of the COVID-19 second wave from several countries is presented in [4]. Here, we report in Figure 1 the operational curve—risk versus mean delay—for the 14 countries considered. We observe that for a reasonable risk, e.g., $10^{-4}$ days$^{-1}$, which means that an erroneous decision is made, on average, once every 27 years, the mean delay in declaring the onset of the second wave is always less than 20 days. Additional analyses are available in [13].

MAST was shown in [6] to also be effective when used on data from a smaller community (e.g., a region or a province) and, after minor modifications, for detecting the termination of a pandemic wave [14]; this information may be crucial, e.g., to safely relax the restrictive measures. As an example, we report in Figure 2 the growth rate computed for the Lombardia region of Italy from February 24, 2020, to February 26, 2021, and in Figure 3 the MAST statistics used to detect, in the same time interval, the onset of the second and third pandemic waves and the termination of the second wave. Here, the value of the threshold corresponds to a risk of $10^{-5}$ days$^{-1}$, which means that a false change of regime is declared, on average, once every 270 years. We observe that the onset of the second wave is declared on August 20, 2020, with its termination on December 3, 2020. A third wave is detected on February 25, 2021. Exact dates on which the second and third waves began are clearly not available. Nevertheless, we can argue that the detection delay is reasonably small for the third wave [15], whereas the second wave is largely anticipated by MAST, with the restrictive measures implemented only more than 2 months after August 20, 2020 [16].

## ADAPTIVE FORECAST OF THE INFECTION

Once an exponential growth of positive cases is detected, to understand how the pandemic will evolve is essential information for policymakers to plan their future actions, e.g., increase hospital bed capacity and relocate health care personnel. Equally important is the forecast of the infection in a controlled regime that can support planning for the gradual reopening of commercial, industrial, and social activities.

In the introduction to the third volume of *ISIF Perspectives on Information Fusion* in May 2020 [17], Dr. Streit rightly foresaw that "two areas of research will naturally beckon for our attention in the coming days and months. One area is the mathematical modeling of the spread of infectious diseases" that "began in the 1920s with differential equation compartmental models of the numbers of Susceptible/Infectious/Recovered (SIR) individuals. […] The other area concerns spatial-temporal data modeling". Compartmental epidemiological models are—still today—commonly used to study the spread of infectious diseases. They assume that a given population is partitioned into a predefined number of compartments (population subgroups), in which each compartment represents a pandemic state that an individual can

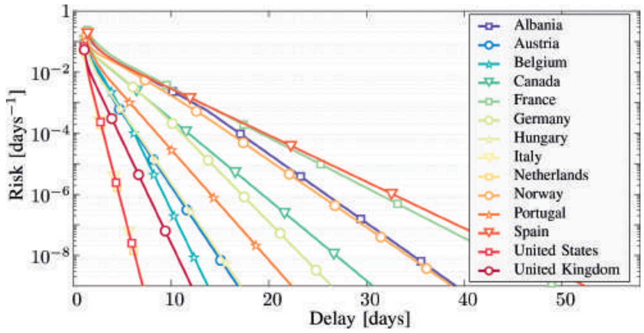



**Figure 1**
From [4], operational curve—risk versus mean delay for decision—for 14 countries.

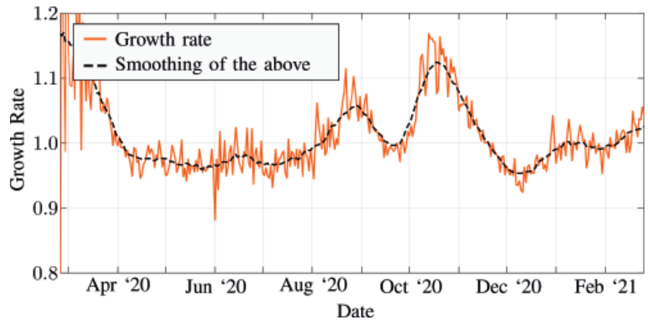



**Figure 2**
From [6], growth rate of the pandemic in the Lombardia region of Italy, computed from the averaged daily new positive cases (orange solid line) from February 24, 2020, to February 26, 2021; for easier visualization, we also show its smoothed version obtained through a noncausal moving average filter with uniform weights of a length of 21 days (black dashed line).

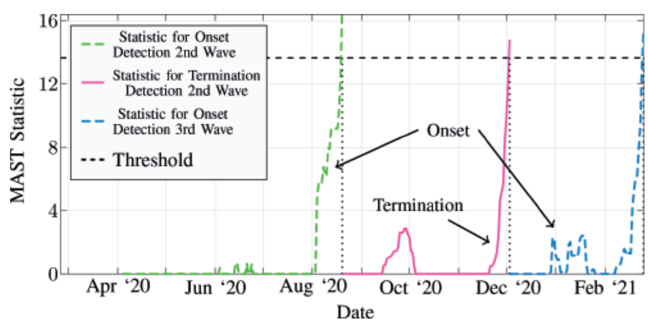



**Figure 3**
From [6], MAST statistics computed for the Lombardia region of Italy, starting from April 4, 2020, for the onset detection of the second wave (green dashed line) and the third wave (blue dashed line) and for the termination detection of the second wave (magenta solid line). The threshold (black dashed line) corresponds to the risk of $10^{-5}$ days$^{-1}$. The onset and termination of the second wave are declared on August 20 and December 3, 2020, respectively. The onset of the third wave is declared on February 25, 2021.

occupy, and the flow dynamics from one compartment to another are modeled as a set of differential equations [18]. The pioneering study on mathematical theory of epidemics mentioned by Streit dates back to 1927 and proposes an epidemiological model in which the entire population of, e.g., a city, a region, or a nation is constant and divided into three mutually exclusive compartments, namely, susceptible (S), infected (I), and recovered (R) individuals, and known as the SIR model [19], [20]. An infected individual infects a susceptible one at a given infection rate $\beta$. Once infected, the individual is removed from the compartment of susceptible individuals and enters the infected compartment. Each infected person runs through the course of the disease and eventually is removed from the number of those who are still infected, either by recovery or death, thus exiting the system at recovery rate $\gamma$; the recovered people are considered permanently immune. More complex extensions of the SIR model have been developed over the years, and the COVID-19 pandemic has motivated researchers to further investigate the topic [21]–[24].

The parameters that rule the dynamics from one compartment to another, e.g., infection rate $\beta$ and recovery rate $\gamma$ in the SIR model, are usually time invariant, and several approaches have been proposed for tuning or estimating them [25], [26], [27]. We have developed in [7] a Bayesian approach that sequentially estimates the compartmental model's parameters by exploiting data made publicly available daily by national authorities, such as the number of new positive cases, the number of recovered people, and the number of fatalities. The approach is based on discretization of the continuous stochastic differential equations that describe the compartmental epidemiological model [28] and on basic principles of Bayesian sequential estimation that involve a prediction step and an update step. The estimated model's parameters are then used to forecast the evolution of the COVID-19 pandemic via ensemble forecasting, i.e., a Monte Carlo approach that produces a set (or ensemble) of forecasts. This forecasting approach also requires hypothesizing about the future—i.e., not observed yet—evolution of the infection rate (see details in [7]). The effectiveness of the proposed method has been evaluated in [7] through its application on data from the first pandemic wave in the Lombardia region of Italy and in United States. Here, we report in Figure 4 the estimated infection rate in Lombardia from February 24 to June 30, 2020; the decrease in the infection rate, which represents the slowdown of the pandemic, clearly reflects the restrictive measures established by the Italian government on March 8, 2020. Figure 5 instead shows the forecast of the pandemic evolution performed on April 13, 2020; we observe that accurate estimation of the time-varying infection and recovery rates facilitates reliable prediction of the evolution of the infection, with a forecasted number of infected individuals that closely follows future observations.

As mentioned above, the proposed forecasting approach requires hypothesizing about the future evolution of the infection rate. The infection rate models the interaction between people; therefore, its future evolution depends on how authorities react to the progress of the contagion and how people respond to the imposed restrictions. Thus, modeling its future evolution is still an open issue. In [8], we proposed a solution that employs MAST, hence providing a comprehensive, decision-directed estimation-detection-forecasting tool. Specifically, when an outbreak is declared through MAST, the hypothesized infection rate slope (i.e., the derivative of the infection rate) is positive (or zero), whereas when the termination of a pandemic wave is declared, the hypothesized infection rate slope is negative (or zero).

Detection and forecast of the second and third waves in United States are analyzed in [8]. Here, we report in Figure 6 the mean absolute percentage error (MAPE) of the forecast computed on different days from June 22, 2020 (day of detection of the second wave in the United States), and for two time horizons, i.e., 2 and 4 weeks. The results are compared with an alternative approach that employs a nonlinear least squares fitting algorithm that, using the number of infected and recovered individuals, computes the parameters of an epidemiologi-

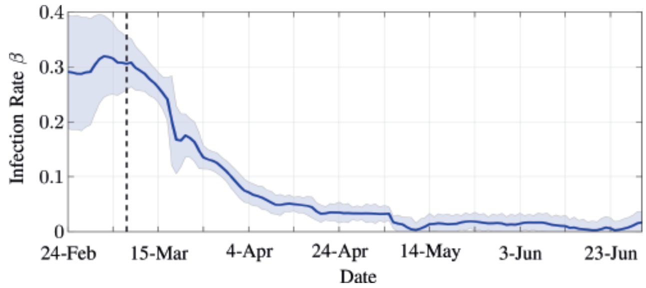



**Figure 4**

From [7], estimated infection rate $\beta$ for the Lombardia region of Italy from February 24 to June 30, 2020. The vertical dashed line indicates March 8, 2020, the beginning of the lockdown imposed by the Italian government during the first pandemic wave. The shaded areas represent the 90% confidence interval.

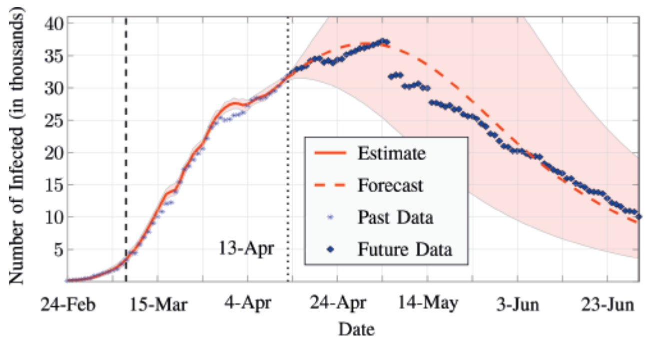



**Figure 5**

From [7], estimation and forecasting in solid and dashed lines, respectively, of the number of infected individuals in the Lombardia region of Italy. The date corresponding to the end of the estimation and the beginning of the forecast, that is, April 13, 2020, is marked by a vertical dotted line. The leftmost vertical dashed line marks March 8, 2020, the beginning of the lockdown imposed by the Italian government during the first pandemic wave. The shaded area represents the 90% confidence interval. The large step in the number of infected individuals observed on May 6, 2020, is due to inaccurate reporting of the data by local authorities.

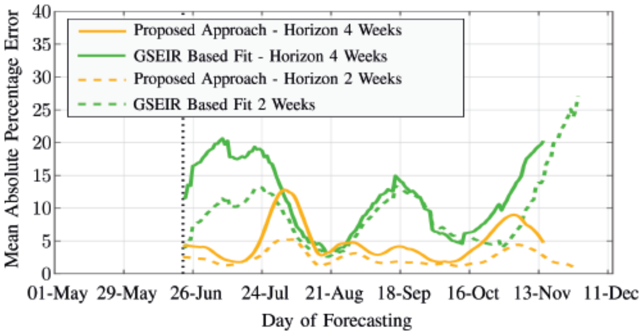



**Figure 6**
From [8], MAPE of the forecast of the pandemic evolution in the United States performed with the proposed algorithm and the GSEIR-based fit approach on different days (abscissa) and for different time horizons, i.e., 2 and 4 weeks (depicted with solid and dashed lines, respectively).

**Table 1**

**Time-Averaged MAPE of the Forecast of the Epidemic Evolution**

| Algorithm | 2 Weeks (%) | 4 Weeks (%) |
|---|---|---|
| Proposed | 2.39 | 4.82 |
| SIR-based fit | 101.83 | 137.17 |
| SIR-X-based fit | 25.86 | 27.53 |

cal model, known as generalized SEIR (GSEIR) [29], with four more compartments than SIR that account for insusceptible people, exposed (but not infectious) people (E), quarantined people, and deaths. We observe that the proposed forecast algorithm outperforms the GSEIR-based fit approach for both forecast horizons of 2 and 4 weeks, and that, apart from the time interval of roughly between July 19 and August 13, the proposed approach presents a MAPE that is always below 10%.

An additional comparison is reported in Table 1. The SIR- and SIR-X-based fits represent approaches similar to the one described for GSEIR that use, respectively, the classical SIR model and the SIR-X model [30]; the latter directly accounts for restrictive measures by removing susceptible individuals from the disease-spreading process. The results show significant performance improvements by the proposed forecast algorithm in terms of time-averaged MAPE.

## CONCLUSION

Leveraging known concepts from related fields, we provided an overview of the recent advances on information processing methodologies to combat the COVID-19 pandemic. First, we described a quickest detection procedure, known as MAST, designed to detect an exponential growth of positive cases with a mean delay of few days and, at the same time, with a low risk of erroneously declaring an outbreak. In addition, MAST was shown to be suitable—with proper adjustments—for the detection of the termination of a pandemic wave. The effectiveness of MAST has been demonstrated through extensive analysis of COVID-19 data of second and third waves from different countries, as well as from smaller communities.

Second, we reported a Bayesian approach that estimates the features of the pandemic, e.g., the infection rate, and reliably forecasts the evolution of the contagion. This estimation-forecasting approach has been demonstrated on COVID-19 data of first and second waves, achieving low MAPEs for forecasts of up to 4 weeks and favorable comparison with alternative approaches.

## REFERENCES


1. Rossman, H., Shilo, S., Meir, T., Gorfine, T., Shalit, U., and Segal, E. COVID-19 dynamics after a national immunization program in Israel. *Nature Medicine,* Vol. 27, 3 (Apr. 2021), 1055–1061.
2. Fontanet, A., Autran, B., Lina, B., Kieny, M. P., Karim, S. S. A., and Sridhar, D. SARS-CoV-2 variants and ending the COVID-19 pandemic. *Lancet,* Vol. 397, 10278 (Mar. 2021), 952–954.
3. Pretz, K. Using modeling to understand how COVID-19 preventive measures work: washing hands, wearing masks: does it help?—[spectral lines]. *IEEE Spectrum,* Vol. 57, 10 (Oct. 2020), 4.
4. Braca, P., Gaglione, D., Marano, S., Millefiori, L. M., Willett, P., and Pattipati, K. Decision support for the quickest detection of critical COVID-19 phases. *Scientific Reports,* Vol. 11, 1 (Apr. 2021), 8558.
5. Braca, P., Gaglione, D., Marano, S., Millefiori, L. M., Willett, P., and Pattipati, K. Quickest detection of COVID-19 pandemic onset. *IEEE Signal Processing Letters,* Vol. 28 (Mar. 2021), 683–687.
6. Braca, P., Gaglione, D., Marano, S., Millefiori, L. M., Willett, P., and Pattipati, K. MAST: a quickest detection procedure for COVID-19 epidemiological data to trigger strategic decisions. In *Proceedings of EUSIPCO-21,* Dublin, Ireland, Aug. 2021.
7. Gaglione, D., Braca, P., Millefiori, L. M., Soldi, G., Forti, N., Marano, S., Willett, P., and Pattipati, K. R. Adaptive Bayesian learning and forecasting of epidemic evolution—data analysis of the COVID-19 outbreak. *IEEE Access,* Vol. 8 (Sep. 2020), 175244–175264.
8. Soldi, G., Forti, N., Gaglione, D., Braca, P., Millefiori, L. M., Marano, S., Willett, P., and Pattipati K. Quickest detection and forecast of pandemic outbreaks: analysis of COVID-19 waves. *IEEE Communications Magazine*. [Online]. Available: https://arxiv.org/abs/2101.04620 Jul. 2021.
9. Millefiori, L. M., Braca, P., Zissis, D., Spiliopoulos, G., Marano, S., Willett, P. K., and Carniel, S. COVID-19 impact on global maritime mobility. *Scientific Reports* (under review). [Online]. Available: https://arxiv.org/abs/2009.06960 2021.
10. Basseville, M., and Nikiforov, I. V. *Detection of Abrupt Changes: Theory and Application*. Englewood Cliffs, NJ: Prentice Hall, 1993.
11. Poor, H. V., and Hadjiliadis, O. *Quickest Detection*. Cambridge, United Kingdom: Cambridge Univ. Press, 2009.
12. Page, E. Continuous inspection schemes. *Biometrika,* Vol. 41, 1/2 (Jun. 1954), 100–115.
13. Braca, P., Gaglione, D., Marano, S., Millefiori, L. M., Willett, P., and Pattipati, K. MAST: COVID-19 pandemic onset test—multi-country analysis and visualization. Available: https://covid-mast.github.io 2020.
14. Marano, S., and Sayed, A. H. Decision-making algorithms for learning and adaptation with application to COVID-19 data. [Online]. Available: https://arxiv.org/abs/2012.07844 May 2021 (submitted).
15. Winfield, N. Italy's Lombardy again in virus crisis as Brescia sees surge. *AP News*. [Online]. Available: https://apnews.com/article/europe-italy-

coronavirus-pandemic-coronavirus-vaccine-national-governments-e4d4ab04ed7f0de06f454cdf718dfd48 Feb. 2021.

16. BBC. Coronavirus: Italy imposes regional lockdown as Europe battles surges. [Online]. Available: https://www.bbc.com/news/world-europe-54839429 Nov. 2020.
17. Streit, R. Introduction to the issue. *ISIF Perspectives on Information Fusion,* Vol. 3, 1 (May 2020), 3.
18. Daley, D., and Gani, J. *Epidemic Modelling: An Introduction*. Cambridge, United Kingdom: Cambridge Univ. Press, 2001.
19. Kermack, W. O., McKendrick, A. G., and Walker, G. T. A contribution to the mathematical theory of epidemics. *Proceedings of the Royal Society of London,* Vol. 115, 772 (Aug. 1927), 700–721.
20. Bjørnstad, O. N., Shea, K., Krzywinski, M., and Altman, N. Modeling infectious epidemics. *Nature Methods,* Vol. 17, 5 (Apr. 2020), 455–456.
21. Giordano, G., Blanchini, F., Bruno, R., Colaneri, P., Di Filippo, A., Di Matteo, A., and Colaneri, M. Modelling the COVID-19 epidemic and implementation of population-wide interventions in Italy. *Nature Medicine,* Vol. 26, 6 (Jun. 2020), 855–860.
22. Bertozzi, A. L., Franco, E., Mohler, G., Short, M. B., and Sledge, D. The challenges of modeling and forecasting the spread of COVID-19. *Proceedings of the National Academy of Sciences of the United States of America,* Vol. 117, 29 (Jul. 2020), 16732–16738.
23. Adiga, A., Dubhashi, D., Lewis, B., Marathe, M., Venkatramanan, S., and Vullikanti, A. Mathematical models for COVID-19 pandemic: a comparative analysis. *Journal of the Indian Institute of Science,* Vol. 100, 4 (Oct. 2020), 793–807.
24. Xiang, Y., Jia, Y., Chen, L., Guo, L., Shu, B., and Long, E. COVID-19 epidemic prediction and the impact of public health interventions: a review of COVID-19 epidemic models. *Infectious Disease Modelling,* Vol. 6 (2021), 324–342.
25. Skvortsov, A., and Ristic, B. Monitoring and prediction of an epidemic outbreak using syndromic observations. *Mathematical Biosciences,* Vol. 240, 1 (Nov. 2012), 12–19.
26. Sheinson, D. M., Niemi, J., and Meiring, W. Comparison of the performance of particle filter algorithms applied to tracking of a disease epidemic. *Mathematical Biosciences,* Vol. 255 (Sep. 2014), 21–32.
27. Shahtori, N. M., Scoglio, C., Pourhabib, A., and Sahneh, F. D. Sequential Monte Carlo filtering estimation of Ebola progression in West Africa. *2016 American Control Conference (ACC)* Jul. 2016, 1277–1282.
28. Allen, L. J. A primer on stochastic epidemic models: formulation, numerical simulation, and analysis. *Infectious Disease Modelling,* Vol. 2, 2 (May 2017), 128–142.
29. Peng, L., Yang, W., Zhang, D., Zhuge, C., and Hong, L. Epidemic analysis of COVID-19 in China by dynamical modeling. *arXiv*. [Online]. Available: https://arxiv.org/abs/2002.06563 Feb. 2020.
30. Maier, B. F., and Brockmann, D. Effective containment explains subexponential growth in recent confirmed COVID-19 cases in China. *Science,* Vol. 368, 6492 (May 2020), 742–746.

**Domenico Gaglione** is currently a Research Scientist with NATO STO Centre for Maritime Research & Experimentation (CMRE), La Spezia, Italy. His research interests include statistical signal processing with emphasis on state estimation, data fusion, and multisensor multitarget tracking, and radar (sonar) signal processing.

**Paolo Braca** is a Senior Scientist with the Research Department and a Project Manager of the Data Knowledge and Operational Effectiveness (DKOE) Program. He conducts research in the general area of statistical signal processing with emphasis on detection and estimation theory, wireless sensor network, multiagent algorithms, target tracking and data fusion, adaptation and learning over graphs, and radar (sonar) signal processing.

**Giovanni Soldi** is a Scientist with the Centre for Maritime Research and Experimentation (CMRE), La Spezia, Italy. His current research interests include statistical signal processing with a focus on state estimation, data fusion, and multisensor-multitarget tracking techniques.

**Nicola Forti** is currently a Scientist with the Research Department, NATO Science & Technology Organization Centre for Maritime Research and Experimentation (CMRE). His current research interests include state estimation and control theory, statistical signal processing, machine learning, target tracking, and data fusion.

**Leonardo M. Millefiori** is a Research Scientist with the Research Department with the NATO Science and Technology Organization Center for Maritime Research and Experimentation (CMRE), La Spezia, Italy. His research interests include target motion modeling, statistical learning and signal processing, and target tracking and data fusion

**Stefano Marano** is a Professor with DIEM, University of Salerno, Italy. His current research interests include statistical signal processing with emphasis on distributed inference, sensor networks, and information theory.

**Peter K. Willett** is a faculty member in the Electrical and Computer Engineering Department at the University of Connecticut. His primary areas of research have been statistical signal processing, detection, machine learning, communications, data fusion, and tracking.

**Krishna R. Pattipati** is with the Department of Electrical and Computer Engineering, UConn, where he is currently the Board of Trustees Distinguished Professor and the UTC Chair Professor in systems engineering. His research interests include proactive decision support, uncertainty quantification, smart manufacturing, autonomy, knowledge representation, and optimization-based learning and inference.

# ISIF Awards

**W. Dale Blair**
Georgia Institute of Technology
Georgia Tech Research Institute
Smyrna, GA, USA
dale.blair@gtri.gatech.edu

## ISIF AWARD PROGRAM

To encourage excellence and advancements in the research community for information fusion, the International Society of Information Fusion (ISIF) sponsors awards for significant achievements in the field of information fusion. This field is diverse and composed of target tracking, detection, estimation, sensor fusion, applications of information fusion, image fusion, information fusion systems architectures, classification, learning, Bayesian and reasoning methods, and data mining. The ISIF Awards Committee for 2021 includes Chee-Yee Chong, Lawrence Stone, Yaakov Bar-Shalom, Craig Agate, Paulo Costa, and Dale Blair as chair.

ISIF proudly sponsors three society awards and two conference awards. These are as follows:

- ISIF Yaakov Bar-Shalom Award for a Lifetime of Excellence in Information Fusion
- ISIF Young Investigator Award for Contributions in Information Fusion
- ISIF Robert Lynch Award for Exceptional Service
- ISIF Jean-Pierre Le Cadre Best Paper Award
- ISIF Tammy Blair Best Student Paper Award

All awards are presented annually at the award banquet at the International Conference on Information Fusion (ICIF), or simply FUSION conference, and this article shares additional details of these awards. Additional details of the award and selection processes are available at www.isif.org.

The premier ISIF award is the ISIF Yaakov Bar-Shalom Award for a Lifetime of Excellence in Information Fusion. This award is given for a lifetime of contributions to information fusion. It was first given in 2015 and subsequently named in 2016 for the first recipient, Yaakov Bar-Shalom, whose career began in the pre-internet days of punched cards. The ISIF Yaakov Bar-Shalom Award recognizes a researcher or engineer for outstanding contributions to the field of information fusion throughout his or her career. Contributions include technical advances, technical vision and leadership, education and mentoring, novel applications of information fusion and associated engineering achievements, and service to ISIF. This award may be given annually, if outstanding candidates are nominated, but it is expected to be given at least once every 3 years because individuals with the anticipated level of contributions to information fusion throughout a career will be rare. The selection process is managed by the ISIF Awards Committee. Nominations are solicited from the ISIF membership, and nominees must have been a member of ISIF for at least 10 years. Anyone qualified to appraise the candidate's contributions may formally nominate the candidate. Dr. Chee-Yee Chong was the 2016 recipient of the ISIF Yaakov Bar-Shalom Award, and Dr. Pramod Varshney was the 2018 recipient.


Yaakov Bar-Shalom at FUSION 2000 in Paris, France.

Pramod Varshney, recipient of the 2018 ISIF Yaakov Bar-Shalom Award.

Nominations are typically due by January 31 in the year of the award, and the award is presented at the annual ICIF. Due to changes in the timing of the 2021 ICIF, award nominations were due in 2021 before September 30.

The ISIF Young Investigator Award is sponsored by ISIF to grant international recognition for outstanding contributions to the art of information fusion by a young ISIF member. The goals of ISIF in granting this award are to encourage individual effort and to foster increased participation by younger researchers and engineers. This ISIF award consists of a commemorative recognition plaque and travel grant to receive the award. An eligible candidate must be no older than 40 years of age on the first day of January for the year in which he or she will be honored, and the recipient must also be a member of ISIF, with at least 3 years of ISIF membership. Nominations are solicited from the ISIF membership, and the selection process is managed by the ISIF Awards Committee. Anyone qualified to appraise the candidate's contributions to the art of information fusion may formally nominate the candidate. The ISIF Young Investigator Award is presented at the annual FUSION conference. In 2016, the first year of the ISIF Young Investigator award, Dr. David Crouse was the recipient. Dr. Marcus Baum from the University of Göttin-

Marcus Baum, recipient of the 2017 ISIF Young Investigator Award.

Dr. Karl Granstrom, recipient of the 2018 ISIF Young Investigator Award.

gen in Germany was the 2017 recipient, and Dr. Karl Granstrom of Chalmers University of Technology in Sweden was the 2018 recipient. A full nomination package that includes an exhaustive curriculum vitae and at least three endorsement letters is typically required by January 31 in the year of the award. Due to changes in the timing of the 2021 ICIF, award nominations were due before September 30.

In 2016, ISIF introduced the ISIF Robert Lynch Award for Exceptional Service to recognize an individual who has provided great service to the society. The award was established in memory of Robert (Bob) Lynch who contributed regularly over many years to the organization of the annual FUSION conference and tirelessly to the founding and production of the *Journal for Advances in Information Fusion* (JAIF), the founding of *ISIF Perspectives on Information Fusion,* and the maintenance of the ISIF website. Good candidates for the service award would have numerous contributions that might include active and prolonged participation in the annual FUSION conference, exceptional leadership in the organization in ICIF over many years, service to the ISIF Board of Directors in either elected or appointed positions, publications in JAIF, leadership and contributions to the JAIF editorial board and its production, support of the ISIF website and working groups, and other activities that promote ISIF and the area of information fusion. This award may be given annually, if outstanding candidates are nominated, but it is expected to be given once every 3 years because individuals with the anticipated level of contributions to ISIF will be rare. The nominee will have made a series of major contributions to ISIF and the information fusion community over multiple years. Nominees must have 10 years of membership in ISIF. Anyone qualified to appraise the candidate's contribution or contributions may formally nominate the candidate. A full nomination package that includes an exhaustive curriculum vita is provided to the chair of the ISIF Awards Committee prior to January 31 in the year of the award. Due to changes in the timing of the 2021 ICIF, award nominations were due this year before September 30.

Robert (Bob) Lynch.

Jean-Pierre Le Cadre at FUSION 2000 in Paris, France.

The ISIF Jean-Pierre Le Cadre Best Paper Award recognizes excellence among researchers and scientists in information fusion. Jean-Pierre Le Cadre's career was highly motivated by his pursuit of excellence in his research. Beginning in 2010, the Jean-Pierre Le Cadre Award has been for the best paper of the FUSION conference and includes a certificate and an honorarium. The Jean-Pierre Le Cadre Award is managed by the organizing committee for FUSION conference for that year. Each year, the best paper and two runner-up papers are recognized. In 2020, the ISIF Jean-Pierre Le Cadre Best Paper Award went to Susanne Radtke, Benjamin Noack, and Uwe D. Hanebeck for their paper titled “Fully Decentralized Estimation Using Square-Root Decompositions.”

Students are the lifeblood of ISIF and the future of information fusion. Tammy Blair played a key role in the organizing committee for multiple FUSION conferences and was passionate about involving students. Tammy Blair died in San Diego, California, during the week following the 2009 FUSION conference, where she contracted the swine flu. The ISIF Tammy Blair Best Student Paper Award encourages the involvement of young researchers and scientists in information fusion. It honors Blair's commitment to ISIF and her efforts to involve students in the annual FUSION conference. In addition to the best student paper, as judged by the ICIF organizing committee, two runners-up are recognized annually. All awardees receive certificates and honorariums. Student authors of finalist papers are required to attend the ICIF. In 2020, Tammy Blair Best Student Paper Award went to Keith LeGrand and Silvia Ferreira for their work “The Role of Bounded Fields-of-View and Negative Information in Finite Set Statistics (FISST).”

Tammy Blair at FUSION 2006 in Florence, Italy.

The ISIF Board of Directors is committed to promoting excellence and achievement in the area of information fusion, and a strong ISIF awards program is considered to be a critical piece of that vision.

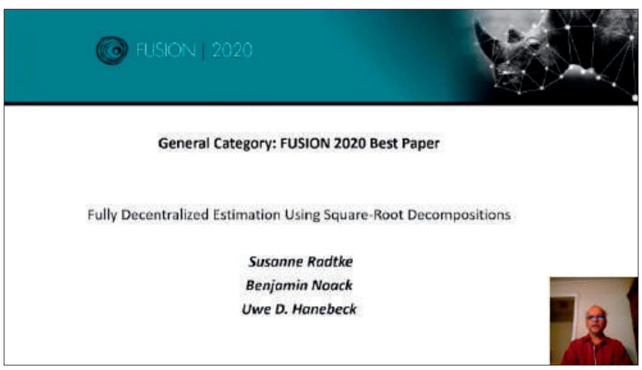
# FUSION Conference Awards

## FUSION 2020 BEST PAPER AWARDS

**Nageswara Rao**
Oak Ridge National Laboratories
Oak Ridge, Tennessee
raons@ornl.gov

Since its inception, ISIF has promoted a high-quality technical program at FUSION. One way to encourage this excellence is to promote the paper awards program. Accordingly, each year the conference includes recognition of the best regular papers and the best student papers. Student papers are those for which the lead author is a full-time graduate (or undergraduate) student at an accredited university. As mandated by the ISIF Board of Directors, the best paper receives the Jean Pierre Le Cadre Award. The best student paper receives the Tammy L. Blair Award. These awards honor the efforts and commitment of both Jean-Pierre and Tammy to the international fusion community over many years.

The FUSION 2020 Awards Co-Chairs were Wolfgang Koch, Nageswara Rao and Pramod Varshney. They began the selection process by examining the reviews of 231 papers by the Technical Program Committee led by the Technical Co-Chairs Paulo Costa, Anne-Laure Jousselme, Thia Kirubarajan, Simon Godsill, Lyudmila Mihaylova and Zhansheng Duan. To avoid the possibility of conflicts of interest, all papers co-authored by any FUSION 2020 Organizing Committee member were excluded from further consideration. Based on reviewer scores, the Awards Co-Chairs selected 15 regular papers out of 122, and 15 student papers out of 109, for detailed assessment. They conducted a thorough review and quantitative scoring of these papers, leading to a set of six regular and six student papers for further analysis. Subsequently, the Awards Co-Chairs formed the Awards Committee consisting of Donald Bucci, Stefano Coraluppi, Henry Leung, Mahendra Mallick. Ruixin Niu, Xiaojing Shen, Lauro Snidaro and Jason Williams. All eight committee members ranked both sets of six regular and six student papers. No committee members were co-authors on any papers that they evaluated, and no conflicts of interest were identified. The sum of scores led to overall rankings that were ratified by the Awards Co-Chairs. The scores for second runners-up in the regular papers category are too close to call for two papers, both of which were selected.



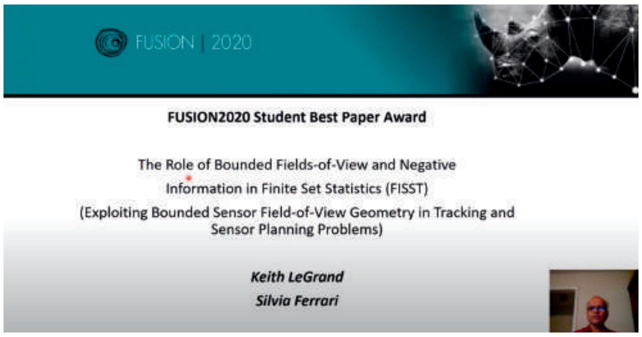

The best regular papers were the following:

- Best Paper: Susanne Radtke, Benjamin Noack, Uwe D. Hanebeck, "Fully Decentralized Estimation Using Square-Root Decompositions"
- First Runner-Up: Victor Wattin Håkansson, Naveen K. D. Venkategowda, Stefan Werner, "Optimal scheduling policy for spatio-temporally dependent observations using Age-of-Information"
- Second Runners-Up: (two listed in no particular order)
- Simone Servadio, Renato Zanetti, and Brandon Jones, "Nonlinear Filtering with Polynomial Series of Gaussian Random Variables"
- Yitzchak Solomon and Paul Bendich, "Geometric Fusion via Joint Delay Embeddings"

### BEST PAPER AWARD

Susanne Radtke, Benjamin Noack, Uwe D. Hanebeck, "Fully Decentralized Estimation Using Square-Root Decompositions"

Abstract—Networks consisting of several spatially distributed sensor nodes are useful in many applications. While distributed processing of information can be more robust and flexible than centralized filtering, it requires careful consideration of dependencies between local state estimates. This paper proposes an algorithm to keep track of dependencies in decentralized systems where no dedicated fusion center is present. Specifically, it addresses double counting of measurement information due to intermediate fusion results as well as correlations due to common process noise and common prior information. To limit the necessary amount of data, this paper introduces a method to bound correlations partially, leading to a more conservative fusion result while reducing the necessary amount of data. Simulation studies compare the performance and convergence rate of the proposed algorithm to other state-of-the-art methods. Index Terms—Decentralized estimation, data fusion, sensor networks.




The best student papers were the following:

- Best Paper Award: Keith LeGrand and Silvia Ferrari, "The Role of Bounded Fields-of-View and Negative Information in Finite Set Statistics (FISST) (Exploiting Bounded Sensor Field-of-View Geometry in Tracking and Sensor Planning Problems)"
- First Runner-Up: Thomas Kropfreiter, and Franz Hlawatsch, "A Probabilistic Label Association Algorithm for Distributed Labeled Multi-Bernoulli Filtering"
- Second Runner-Up: Max Ian Schöpe, Hans Driessen, and Alexander Yarovoy, "Multi-Task Sensor Resource Balancing Using Lagrangian Relaxation and Policy Rollout"

These papers were recognized during the FUSION 2020. Nageswara Rao announced the winners and award certificates were virtually presented by General Co-Chair Pieter de Villiers. The selection process to decide FUSION paper awards is an important stage that complements the larger paper-review process. The awards selection is conducted with great thoroughness, identifying research of significant value that is deserving of the attention of fusion researchers and practitioners. On behalf of ISIF, congratulations to the authors of all seven papers for their hard work and impressive achievement.

## BEST STUDENT PAPER AWARD

Keith LeGrand and Silvia Ferrari, "The Role of Bounded Fields-of-View and Negative Information in Finite Set Statistics (FISST) (Exploiting Bounded Sensor Field-of-View Geometry in Tracking and Sensor Planning Problems)"

Abstract—The role of negative information is particularly important to search-detect-track problems in which the number of objects is unknown a priori, and the size of the sensor field-of view is far smaller than that of the region of interest. This paper presents an approach for systematically incorporating knowledge of the field-of-view geometry and position and object inclusion/exclusion evidence into object state densities and random finite set multi-object cardinality distributions. The approach is derived for a representative set of multi-object distributions and demonstrated through a sensor planning problem involving a multi-Bernoulli process with up to one-hundred potential targets. Index Terms—Bounded field-of-view, Gaussian mixtures, Gaussian splitting, random finite set theory.

# ISIF Working Groups Report

**Simon Maskell**
University of Liverpool
Liverpool, UK
s.maskell@liverpool.ac.uk

**Erik Blasch**
Air Force Research Lab
WPAFB, OH, USA
erik.blasch@gmail.com

**Darin Dunham**
Vectraxx, Inc.
Glen Allen, VA, USA
darin@vectraxx.com

## UPDATES ON WORKING GROUPS

The International Society of Information Fusion (ISIF) sponsors working groups by providing recognition and status. The working groups bring together researchers who share a common interest. For more information on working groups, or for submitting a proposal for a new working group, please see the ISIF website[1] or contact Darin Dunham, Vice President Working Groups (darin@vectraxx.com).

Currently, there are two active working groups sponsored by ISIF, and a report of their recent activities is included.

## STONE SOUP DEVELOPMENT CONTINUES APACE

Stone Soup was described in the March 2019 issue of *Perspectives*. It has continued to both grow and develop over the last year. It is now supported via ISIF's Open-Source Tracking and Estimation Working Group (OSTEWG) as well as a North Atlantic Treaty Organization (NATO) Exploratory Team activity (SET-ET-124). Stone Soup also has now a digital object identifier (DOI):10.5281/zenodo.4663993. With biweekly user-focused telecons, an active Slack workspace, 105 "stars"[2] (see Figure 1), a peak of 164 downloads in a single day, 50 forks, and 15 active developers contributing 15,392 insertions (and 4,594 deletions) to the repository[3] in the last year, Stone Soup now includes, for example: a vectorised implementation of a particle filter; multiframe assignment; square-root and iterated Kalman Filters; particle flow implementations; and tree-based data structures for very efficient gating. These enhancements have led to Stone Soup being applied across a growing variety of domains spanning countering drones (in which context it was used by two of the winners of a Kaggle challenge[4]), analysis of air traffic, sonar processing, global maritime surveillance, and space situational awareness. Training courses at the UK University Defence Research Collaboration's summer school (in June 2021) and at Fusion 2020 have taken place and the material from those sessions is online.[5] Current development includes a focus on development of user interfaces, further enhancing the set of state-of-the-art algorithms that Stone Soup implements, and on configuring Stone Soup to operate effectively in sensor management contexts. For example, under the auspices of ISIF OSTEWG, an international workshop on Stone Soup for sensor management was convened virtually at various ends of the day on 2 November 2020. This drew contributions from academia, government, and industry participants. The activity at the workshop has culminated in amendments to the Stone Soup code base, to sensor classes which are now actionable, and most obviously to new sensor management classes. These are to be augmented with novel, more efficient methods in 2022. More generally, new contributors wanting to integrate their algorithmic advances into an increasingly mature open-source library and/or compare their new algorithms with ever-more sophisticated preexisting baselines are very welcome. Similarly, users wanting a taste of Stone Soup's algorithmic gastronomy should get in touch: visit https://isif-ostewg.org/; or highlight barriers to use as "issues"[6]; or initiate or engage in discussions.[7] Help us to enable Stone Soup to help you!

*—By Simon Maskell*

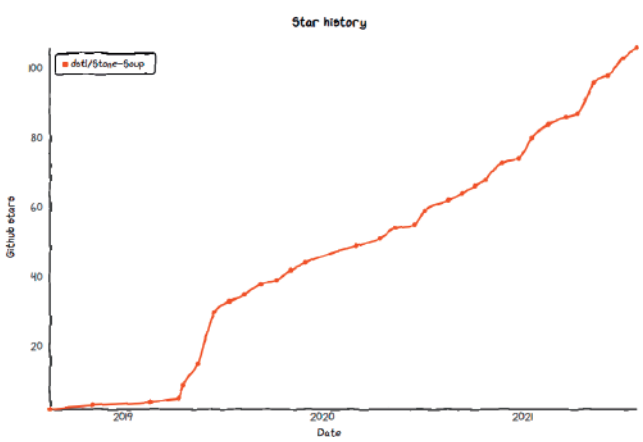



**Figure 1**
Stone Soup has consistently grown in maturity since its March 2019.

## UPDATES ON THE ETUR WORKING GROUP ACTIVITIES

The Evaluation of Techniques for Uncertainty Representation Working Group (ETURWG) is an official activity of ISIF with the products posted at https://eturwg.c4i.gmu.edu/. The ETURWG is going on 10 years of collaboration continuing to refine, update, clarify, and implement the Uncertainty Representation and Reasoning Evaluation Framework (URREF) ontology. On

1 https://isif.org/working-groups/isif-working-groups
2 https://star-history.t9t.io/#dstl/Stone-Soup
3 https://github.com/dstl/Stone-Soup
4 https://www.ncia.nato.int/about-us/newsroom/agency-announces-winners-of-drone-data-challenge.html
5 https://stonesoup.readthedocs.io/en/v0.1b5/auto_tutorials/index.html
6 https://github.com/dstl/Stone-Soup/issues
7 https://github.com/dstl/Stone-Soup/discussions

average, 15 people participate at the biweekly meetings. The ETURWG activities include developing a URREF tutorial, incorporating artificial intelligence and machine learning (AI/ML), and defining metrics.

The first activity developed a tutorial that advocates for the URREF, the implementation, and use cases. Since the ETURWG URREF tutorial was organized from the group discussions, it incorporates the perspectives from many activities of ISIF members. Given the Fusion 2020 format, the tutorial is recorded and the results available to the community.

The second major point lies in the current ETURWG discussions. AI and ML are two areas of constant attention with many overlaps with data fusion. Still, some challenges remain with the understanding of deep learning, much as situation assessment in information fusion. Hence, the group sought to align the uncertainty analysis to that of emerging metrics in AI/ML of *explainability*, *interpretability*, and *transparency*. The 2021 ETUR Special Session is focused on trust and its connections with uncertainty representation and reasoning within the Information Fusion context. Topics covered include human-machine teaming, cognitive security, hybrid systems, explainability and interpretability, autonomy, multiple intelligence, and decision making.

The third development is exploring the URREF to support explainability, interpretability, and transparency. Since the URREF supports a system-level understanding of the data pedigree and the reasoning strategy, the ETURWG put together a few papers addressing the elements of transparency that include data handing, data reasoning, and data reporting. Hence, data turned into information should incorporate the system contextual knowledge that supports the information fusion pipeline.

The ETURWG continues to explore new topics in data and information fusion processing, reasoning, and decision making with the focus on uncertainty analysis. The URREF ontology semantically captures the many elements for deploying information fusion systems, while at the same time explores metrics of analysis, use cases, and philosophical elements of the community. All ISIF members are welcome to join the discussions and to propose future topics aligned with the ETURWG interests.

*—By Erik Blasch*

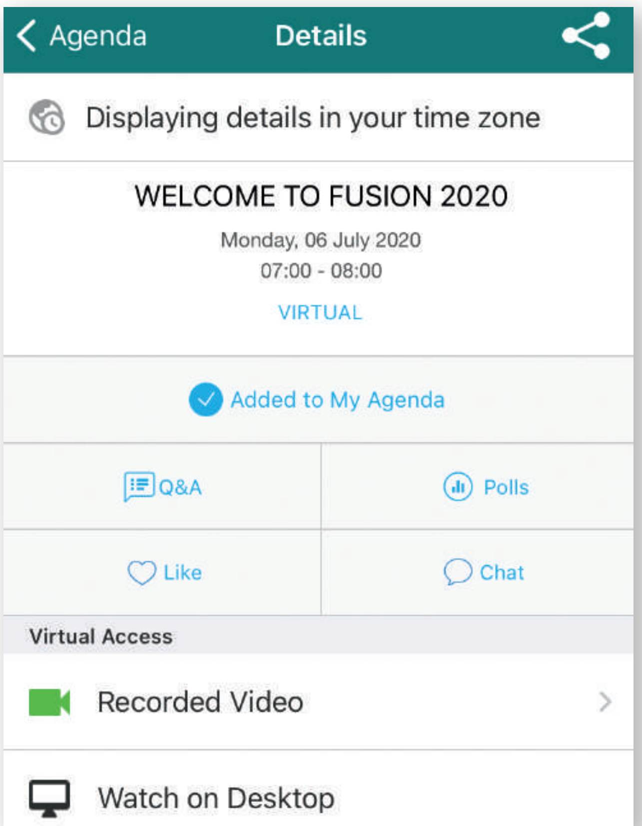
# FUSION 2020 REPORT


**Alta De Waal**
BMW Group
Pretoria, South Africa
alta.dewaal@gmail.com

## REPORT ON THE 23RD INTERNATIONAL CONFERENCE ON INFORMATION FUSION

The International Society of Information Fusion (ISIF) hosted its 23rd International Conference on Information Fusion online from 6 to 9 July 2020. On 2 April 2020, ISIF Board of Directors, and the South African Local Organising Committee, in consideration of the effects of the COVID-19 pandemic, decided to proceed with the Fusion 2020 Conference hosted as a virtual online event.

Dr. Paulo Costa, the 2020 ISIF President announced "… witnessing the strong participation of our community, ISIF and the Fusion 2020 organization jointly opted for conveying the conference in a virtual format only, while keeping all the technical program intact."




The programme did not deviate substantially from the original conference agenda, with the only component omitted being the social events. The conference was attended by 278 people, featured 16 tutorials, and 169 papers that were viewed by attendees from 24 countries.

## TUTORIALS

Sixteen tutorial presentations were made available as a series of 20-minute video presentations to mitigate screen fatigue. The tutorial registration included access to prerecorded videos and two live Questions and Answers (Q&A) sessions of 40 minutes each to accommodate attendees from different time zones. The Eastern Sessions made provision for attendees from Australasia and Asia and the Western Sessions made provision for attendees from Africa, Europe, and the Americas.

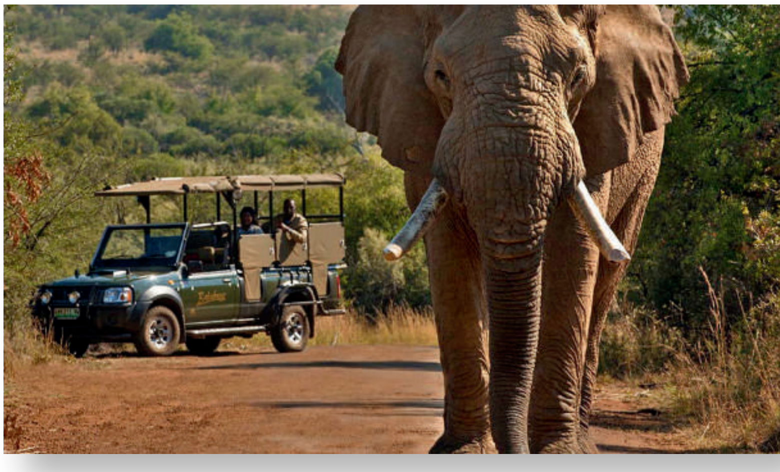
During each of these Q&A slots there were 20 parallel virtual rooms (one per tutorial), where attendees could drop in and out to ask questions. The tutorial material and presentations were released a week prior to the conference to allow attendees sufficient time to watch the videos before the live Q&A sessions on Monday, 6 July 2020. Lecturers reported active Q&A sessions, with a lot of participation from the attendees

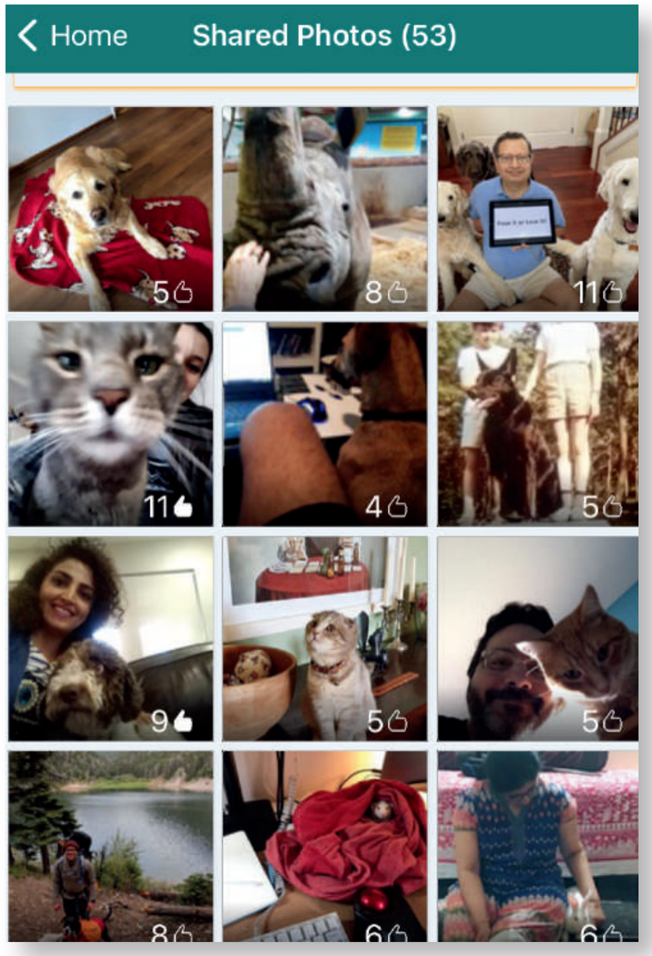
## KEYNOTE SPEAKERS

The conference organisers decided to invite different keynote speakers than those that were originally scheduled to speak to better address the current concern of the COVID-19 pandemic. We wish to thank our keynote speakers for their inspiring words in the run-up to each conference day's proceedings and the very pertinent addresses considering the world-wide pandemic. This year's speakers were Maj. Gen. Johan Jooste, retired from the South African Army in 2006 after 35 years of active service on "Technology Makes Things Possible, Only People Can Make It Happen"; Dr. Jian Chen, the founder and CEO of CreditWise Technologies, Co. Ltd. on "Fusion of Finance and Epidemiology Models"; and Associate Prof. Kristian Soltesz with the Department of Automatic Control at the Lund University in Sweden on "Fusion in the Fight Against COVID-19: Possibilities and Limitations".

## TECHNICAL PROGRAMME

The Fusion2020 technical program committee included eight members and was cochaired by Paulo Costa, Anne-Laure Jousselme, Thia Kirubarajan, Simon Godsill, Lyudmila Mihaylova, and Zhansheng Duan. It provided at least three expert reviews for each of the 230 submitted papers; many papers had more






than three reviews. The result was 167 papers (with an acceptance rate of 73%). A complete list of presentations can be found on the Fusion 2020 conference website (fusion2020.org) and on IEEE Xplore.[1]

Each conference day consisted of three blocks of five parallel sessions. All presentations were prerecorded. The recorded paper presentations were released on the day prior to which the paper was scheduled to be presented. In so doing, attendees in all time zones were given the chance to view the presentation before a "live" Q&A session. Each block of sessions had a 20-minute live Q&A session which was divided into two sessions: an Eastern Session to accommodate attendees from Australasia, Asia, Africa, and Europe, and a Western Session to accommodate attendees from Africa, Europe, and the Americas.

## ORGANISATION

All welcome addresses, awards sessions, and closing remarks were prerecorded and presented online. In closing, ISIF President Paulo Costa added:

> *"The online virtual conference still enabled us to experience tutorials, special sessions, regular sessions, keynote presentations, award ceremonies, participation in discussions, and other events that ordinarily form part of Fusion conferences— all at the level of quality we have been used to. Earlier in 2020 this outcome would have been considered unlikely, given the challenges and limitations imposed by the Global Pandemic. The ISIF Leadership was confident, and today we can report on our very first virtual Fusion conference that turned out to be an extremely successful event. The community showed its support, and the Fusion 2020 organization committee excelled—Pieter de Villiers, Fredrik Gustafsson, Alta de Waal, and the entire team did an excellent job. We end this conference with a message of hope. There is much uncertainty in what may await us in the year ahead, but this conference showed us that we can face great challenges and emerge stronger. I look forward to seeing all of you next year in South Africa!"*

[1] https://ieeexplore.ieee.org/xpl/conhome/9183728/proceeding

## BUILDING ON PAST EXPERIENCES

The success of the online conference can be greatly attributed to a vibrant information community that attended the event, and a local organising committee that spent many hours considering and implementing solutions for the best possible online conference experience. All of us have attended past Fusion conferences and our aim was to offer nothing less than an event of technical excellence. We wish to thank all our committee members and other volunteers for their selfless contributions in time and expertise, and the assistance from past organisers whose input was truly invaluable. Nothing can unfortunately replace the social aspect of an on-site conference, even with initiatives such forums for special interest groups and the fun pets photo competition! We hope that you will be able to join us for Fusion 2021 at the Sun City Conference Centre in South Africa, from 1 to 4 November 2021, where we intend to make up for lost social and networking opportunities.


**Welcome to the 25th International Conference on Information Fusion in Linköping, the Fusion Capital of Sweden!**

Linköping has for the past 100 years been the aerospace capital in Northern Europe, with two airfields, aircraft manufacturing industries, airforce training and a whole echo-system around this, including the C3ISR branch of the Swedish Defence Research Agency (FOI), and the Swedish Airforce Museum. You will find a beautiful city center with walking distance between conference venue and the hotels.

Linköping University was started in the 1960's to support SAAB with engineers but it has sparked the whole city to grow with 150% since then. The Science Park has 350 companies and 7000 employees, with focus areas in automotive safety, telecom, MedTech and IoT. Linköping University with its EE, CS and ME departments have contributed hundreds of papers to Fusion over the years. It is part of the 500 million USD research program WASP, focusing on autonomous systems (AS) and machine learning (ML). Fusion 2021 will aside from the traditional scope of the conference also highlight AS and ML in its plenaries, tutorials, special sessions and exhibitions.

Linköping is a historic place, dating back more than 700+ years. It hosts the bishop of one of Sweden's first and most important dioceses (1107) and a beautiful 800 year old cathedral. The cathedral, nearby Vreta Abbey, and the town of Vadstena (home of Saint Bridget) makes it a popular pilgrimage destination. In July you will enjoy nightless days with 18 hours of daylight and 6 hours of dusk, and an average high of 22.6 degrees Celsius.

Please visit www.isif.org/fusion2022 for more information!

Fredrik Gustafsson and Gustaf Hendeby
General Chairs of Fusion 2022



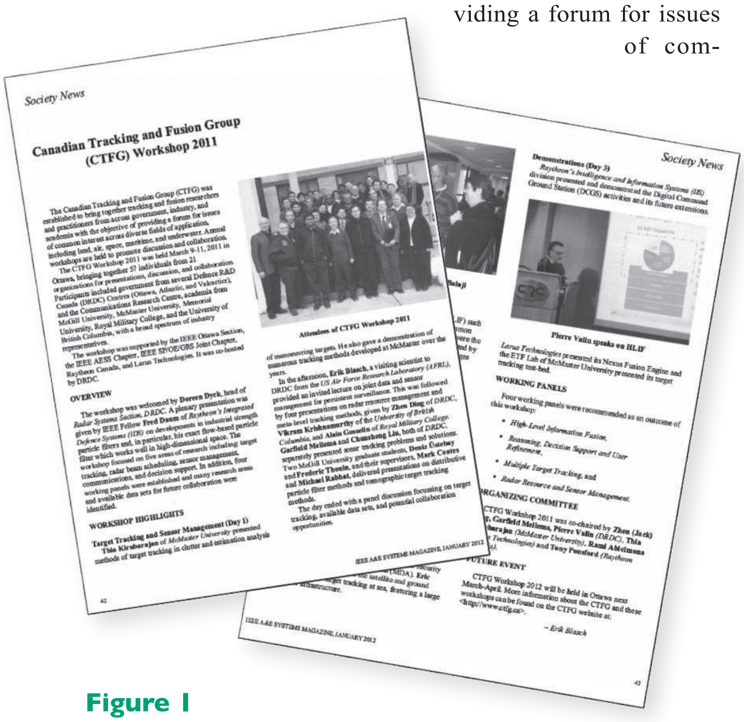

# The Canadian Tracking and Fusion Group Across the Years: The 10th Anniversary

The Canadian Tracking and Fusion Group (CTFG) was born in the fall of 2010. In May of that year, Garfield Mellema had hosted the two-day North Atlantic Treaty Organization (NATO) Research and Technology Organization (RTO) Sensors and Electronics Technology Panel (SET)-157 lecture series on *Multisensor Fusion: Advanced Methodology and Applications* in Halifax. The series was presented by Peter Willett, Stefano Coraluppi, Wolfgang Koch, and Roy Streit. All experts in the field and well-known to International Society of Information Fusion (ISIF) members. The meeting room was packed, with attendees from across the country. At lunch on the second day, Garfield Mellema, Jack Ding, and Bhashyam Balaji (all of whom work for Defence Research & Development Canada (DRDC)) were noting the level of interest in this field and discussing what could be done to both encourage it and to support collaboration in Canada. Jack Ding got the ball rolling with an email list, then a Google group. Soon after that, an organizing committee was formed and the CTFG Workshop series began.

The CTFG was established to bring together tracking and fusion researchers and practitioners from across government, industry, and academia with the objective of providing a forum for issues of common interest across diverse fields of application, including land, air, space, maritime, and underwater. This diversity was reflected in the composition of the initial organizing committee, which was composed of Zhen (Jack) Ding (DRDC Ottawa), Garfield Mellema (DRDC Atlantic), Pierre Valin (DRDC Valcartier), Thia Kirubarajan (McMaster University), Tony Ponsford (Raytheon Canada), and Rami Abielmona (Larus Technologies).

Discussions focused on aspects of target tracking and fusion, including sensors, signal processing, detection, tracking, low-level fusion, high-level fusion, classification, resource management, information flow, performance evaluation, fusion architectures, decision support systems, registration, software, data sets, benchmarks, and data modeling. Through the years, the discussions have been fed by stimulating keynote talks from fusion scientists, military, or Canadian research programme directors.

To mark the first decennial anniversary, we present here a review of the CTFG's activities across the ten years of its existence through the lens of the annual workshops.



Society News

**Canadian Tracking and Fusion Group (CTFG) Workshop 2011**

The Canadian Tracking and Fusion Group (CTFG) was established to bring together tracking and fusion researchers and practitioners from across government, industry, and academia with the objective of providing a forum for issues of common interest across diverse fields of application, including land, air, space, maritime, and underwater. Annual workshops are held to promote discussion and collaboration.

The CTFG Workshop 2011 was held March 9-11, 2011 in Ottawa, bringing together 57 individuals from 21 organizations for presentations, discussion, and collaboration. Participants included government from several Defence R&D Canada (DRDC) Centres (Ottawa, Atlantic, and Valcartier), and the Communications Research Centre, academia from McGill University, McMaster University, Memorial University, Royal Military College, and the University of British Columbia, with a broad spectrum of industry representatives.

The workshop was supported by the IEEE Ottawa Section, the IEEE AESS Chapter, IEEE SP/OE/GRS Joint Chapter, Raytheon Canada, and Larus Technologies. It was co-hosted by DRDC.

OVERVIEW

The workshop was welcomed by **Doreen Dyck**, head of *Radar Systems Section, DRDC*. A plenary presentation was given by IEEE Fellow **Fred Daum** of *Raytheon's Integrated Defence Systems (IDS)* on developments in industrial strength particle filters and, in particular, his exact flow-based particle filter which works well in high-dimensional space. The workshop focused on five areas of research including: target tracking, radar beam scheduling, sensor management, communications, and decision support. In addition, four working panels were established and many research areas and available data sets for future collaboration were identified.

WORKSHOP HIGHLIGHTS

**Target Tracking and Sensor Management (Day 1)**

**Thia Kirubarajan** of *McMaster University* presented methods of target tracking in clutter and estimation analysis

Attendees of CTFG Workshop 2011

of manoeuvring targets. He also gave a demonstration of numerous tracking methods developed at McMaster over the years.

In the afternoon, **Erik Blasch**, a visiting scientist to DRDC from the *US Air Force Research Laboratory (AFRL)*, provided an invited lecture on joint data and sensor management for persistent surveillance. This was followed by four presentations on radar resource management and meta-level tracking methods, given by **Zhen Ding** of *DRDC*, **Vikram Krishnamurthy** of the *University of British Columbia*, and **Alain Gosselin** of *Royal Military College*. **Garfield Mellema** and **Chunsheng Liu**, both of *DRDC*, separately presented sonar tracking problems and solutions. Two McGill University graduate students, **Deniz Üstebay** and **Frederic Thouin**, and their supervisors, **Mark Coates** and **Michael Rabbat**, delivered presentations on distributive particle filter methods and tomographic target tracking methods.

The day ended with a panel discussion focussing on target tracking, available data sets, and potential collaboration opportunities.

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IEEE A&E SYSTEMS MAGAZINE, JANUARY 2012

Society News

**Demonstrations (Day 3)**

*Raytheon's Intelligence and Information Systems (IIS)* division presented and demonstrated the Digital Command Ground Station (DCGS) activities and its future extensions.

Pierre Valin speaks on HLIF

*Larus Technologies* presented its Nexus Fusion Engine and the ETF Lab of McMaster University presented its target tracking test-bed.

WORKING PANELS

Four working panels were recommended as an outcome of this workshop:

- *High-Level Information Fusion,*
- *Reasoning, Decision Support and User Refinement,*
- *Multiple Target Tracking,* and
- *Radar Resource and Sensor Management.*

FUTURE EVENT

CTFG Workshop 2012 will be held in Ottawa next March-April. More information about the CTFG and these workshops can be found on the CTFG website at: <http://www.ctfg.ca>.

– *Erik Blasch*

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IEEE A&E SYSTEMS MAGAZINE, JANUARY 2012

**Figure 1**
CTFG Workshop 2011 report, E. Blasch, IEEE A&E Systems Magazine, Jan 2012, pp. 42–43.

**Mihai Florea**
Thales Digital Solutions Inc.
Québec, Canada
mihai.florea@thalesgroup.com

**Rami Abielmona**
Larus Technologies
Ottawa, Canada

**Bhashyam Balaji**
**Zhen (Jack) Ding**
Defence Research and Development Canada (DRDC) Ottawa
Ottawa, Canada

**Melita Hadzagic**
**Elisa Shahbazian**
OODA Technologies
Montreal, Canada

**Steven Horn**
Defence Research and Development Canada (DRDC)
Centre for Operational Research and Analysis (CORA)
Ottawa, Canada

**Anne-Laure Jousselme**
NATO STO Centre for Maritime Research and Experimentation
La Spezia, Italy

**Thia Kirubarajan**
**Ratnasingham Tharmarasa**
McMaster University
Hamilton, Canada

**Garfield Mellema**
Defence Research and Development Canada (DRDC) Atlantic
Halifax, Canada

**Tony Ponsford**
AM Ponsford Consulting
Manotick, Canada

**Sreeraman Rajan**
Carleton University
Ottawa, Canada

**Figure 2**
CTFG Workshop 2012 attendance, DRDC Ottawa.

**Figure 4**
CTFG Workshop 2014 attendance, DRDC Ottawa.

CANADIAN TRACKING AND FUSION GROUP (CTFG)

CTFG WORKSHOP 2013

HOME ORGANIZING COMMITTEE INVITED SPEAKERS PROGRAM ANNOUNCEMENT VENUE CONTACT

TECHNICAL PROGRAM

| 10 September 2013, DAY 1 (Technical Presentations) | | | | |
|---|---|---|---|---|
| 08:00-08:40 | Registration | | | |
| 08:40-08:50 | Thia Kirubarajan | Announcements | McMaster University | |
| 08:50-09:50 | Tony Ponsford | Keynote Address | Raytheon Canada | Maritime Domain Awareness |
| **9:50-10:10** | **Coffee Break** | **Sponsor** | **AUG Signals** | |
| **Session: Sensors (Chair: Garfield Mellema, DRDC Atlantic)** | | | | |
| 10:10-10:30 | Jack Ding, Peter Moo and Edwin Riseborough | Presentation | DRDC Ottawa | Electronic Protection for Naval Phased Array Radar |
| 10:30-10:50 | Maria Rey | Opening Remarks | DRDC Ottawa | |
| 10:50-11:10 | Alain Gosselin*, Jack Ding^ and Yongkui Wang* | Presentation | ^DRDC Ottawa, *RMC | Multiple Criteria Optimization for Phased Array Radar Resource Management |
| 11:10-11:30 | Jing (Jane)* He and Qingsheng Zeng^ | Presentation | ^CRC, *Carleton University | Maximal Length Sequence and Perfect Sequence in UWB Radar Applications |
| 11:30-11:50 | Sutharsan Sivagnanam and Michel Pelletier | Presentation | FLIR Radar | Experimental Results and Demonstration of the R20SS Digital Beamforming Surveillance Radar |
| 11:50-12:00 | **Group Picture** | | | |
| **12:00-13:00** | **Lunch: Executive Dining Room, CRC Cafeteria (not provided)** | | | |
| **Session: Tracking (Chair: Jack Ding, DRDC Ottawa)** | | | | |
| 13:00-13:20 | Bhashyam Balaji^, Kai Wang*, Anthony Damini^, Martie Goulding* and Kurt Hagen* | Presentation | ^DRDC Ottawa, *MDA | Comparison of Filtering and Smoothing Algorithms for Airborne Radar Data |
| 13:20-13:40 | Abhijit Sinha | Presentation | AUG Signals | Robust Detection and Tracking Procedure for Weak Targets On and Near Roadways |
| 13:40-14:00 | Garfield Mellema | Presentation | DRDC Atlantic | Use of Feature Information for Improved Multistatic Sonar Tracking |
| 14:00-14:20 | Dominic Schaub | Presentation | DRDC Atlantic | Estimating Target Identity in Wide-Area Surveillance |
| 14:20-14:40 | Jack Ding and Bhashyam Balaji | Presentation | DRDC Ottawa | Comparison of the Unscented and Cubature Kalman |

CTFG Homepage

English French

IMPORTANT DATES

**August 15, 2013:** Submission of proposals

**August 20, 2013:** Notification of acceptance/rejection

**September 4, 2013:** Submission of final presentations and workshop registration

**September 10-11, 2013:** CTFG 2013 Workshop

SPONSORS

IEEE Ottawa Section

ISIF

Airborne Underwater Geophysical Signals

LARUS TECHNOLOGIES

ooda TECHNOLOGIES

**Figure 3**
Excerpt of the CTFG Workshop 2013 technical programme.

## BUILDING THE COMMUNITY

The first event (CTFG Workshop 2011) took place at DRDC Ottawa at the Communications Research Centre Canada (CRC). Focusing on research areas of target tracking, radar beam scheduling, sensor management, communications, and decision support, CTFG Workshop 2011 gathered around 40 participants over three days while discussions were stimulated by invited lectures, working panels, technical sessions, and live demonstrations. Keynote talks from four invited speakers set the tone for this first CTFG workshop. Fred Daum from Raytheon Integrated Systems (IDS) US talked on the first day about industrial strength nonlinear filters. Erik Blasch from the US Air Force Research Laboratory (AFRL), visiting scientist at DRDC Valcartier at that time, presented his lecture on the second day about the performance evaluation of seismic and acoustic track and identification fusion. Pierre Valin from DRDC Valcartier detailed the issues and challenges that exist in the field of High-Level Information Fusion (HLIF), while the last lecture was provided by Tony Ponsford, Technical Director at Raytheon Canada Limited at that time, who spoke about the effective maritime domain awareness based on appropriate layered surveillance and a multilevel decision support system. The technical programme gathered more than twenty presentations over the two first days covering low-level and high-level fusion topics, such as methods for high-level information fusion including user coordination, situation awareness from a common reference, and standards to promote interoperability. Four working panels addressed topics on reasoning, decision support and user refine-

**Figure 5**
CTFG Workshop 2015 attendance, DRDC Ottawa.

ment, multiple target tracking, and radar resource and sensor management. Finally, three live demonstrations of tools and technologies illustrated operational implementation of some solutions: Raytheon's Digital Command Ground Station (DCGS) activities and its future extensions, Larus Technologies' Nexus Fusion Engine, and McMaster University's High Performance Multitarget Tracker and Tracking/Fusion Testbed.

A year later, the CTFG Workshop 2012 gathered about 50 participants, featuring more than thirty presentations. The first day of the workshop was focused more on the low-level fusion and tracking while the second day of the workshop addressed more high-level fusion topics, reflected in the two keynote talks from two experts from the fusion community. Yaakov Bar-Shalom from the University of Connecticut (US) explained how to get the most out of sensors through target tracking and data fusion. James Llinas from the State University of New York (US) talked about algorithmic, architectural, and employment concept challenges involved in the Hard and Soft data fusion problems. The workshop concluded with five live demonstrations from Canadian companies: McMaster University's *High Performance Multitarget Tracker and Tracking/Fusion Testbed*, FLIR Radars Canada's *Dual-Mode Perimeter Surveillance Radar Systems*, the National Research Council of Canada's *Interactive Virtual Reality Visualizations for Multi Sensor/Multi Source Information Fusion*, Larus Technologies' *Risk Management Framework*, and Thales Raytheon System's *BCS-F Tracking and Fusion in Support of NORAD Air and Maritime Missions*.

## FROM TRACKING TO SITUATION AWARENESS

The CTFG Workshop 2013 was held under the theme of *Maritime Domain Awareness*, while covering classical topics such as sensors, tracking, and fusion. Tony Ponsford (Raytheon Canada), the first invited speaker, talked about the Maritime Domain Awareness and chaired a panel discussion on the same topic, in conclusion of the workshop. Two other invited speakers were Éloi Bossé from Laval University who presented the fusion of information to improve dependability in cyber-physical and social systems (CPSS), while Cdr. Rob Hudson from the Canadian

**Figure 6**
Andre Dupuis, presenting the Conformational Analyzer with Molecular Dynamics and Sampling (CAMDAS) program at the CTFG Workshop 2016, Ottawa.

Department of National Defence (DND) talked about the information and decision advantage within DND. During the demonstration session, Thales Canada presented the *tactical picture compilation (TPC) demonstrator tool* and *FUSEWARE*–a data/information fusion service to be used in a service-oriented architecture. TrackGen Solutions presented a *Tracking, Fusion, Resource Management and Situational Awareness Toolset* and Larus Technologies presented the *Total::Insight™ High Level Information Fusion Engine (HLIFE)*.

The CTFG Workshop 2014 continued in a two-day format driven by two major lectures providing Canadian operational perspectives. Col. Gregory D. Burt from the Canadian Forces Intelligence Group presented a keynote talk, the Canadian Forces Intelligence Command (CFINTCOM) providing a perspective on information related challenges. He presented a view from the standpoint of the end-user, which drives the value of a system while the value of information is measured by its effectiveness in achieving the end-result. In the context of defence intelligence, Col. Burt raised the question of how information fusion could provide more effective tools to shift the balance of human activities from searching to analysing. Kurt Salchert, retired captain from the Royal Canadian Navy (RCN) and part of the Beyond the Border Consulting, provided unique insight into the end user's view of information fusion in the context of naval surveillance and security. The technical programme complemented these operational views with 14 authors presenting recent research in four specific topics: source evaluation and performance, target tracking and filtering, detection and localization algorithms, and video processing and surveillance.

In 2015, after being hosted by the DRDC Ottawa for the first four years, the workshop venue moved to the Shaw Centre in downtown Ottawa. It has stayed in downtown Ottawa ever since, alternating between the Shaw Centre and the Les Suites Hotels. CTFG Workshop 2015 was cohosted with the NATO Lecture Series IST-134 *Advanced Algorithms for Effectively Fusing Hard and Soft Information*, offering participants to attend both events and exchange on synergic topics. Fifteen presentations across three ses-

**Figure 7**
High attendance for the presentation of Hossein Chahrour (DRDC Ottawa & Carleton University) during CTFG Workshop 2017, Ottawa.

sions focused on maritime applications for tracking and situational awareness, while still exhibiting contributions on general target tracking. A special session on space provided the opportunity for five invited speakers to present the challenges and opportunities related to the Earth Observation and the surveillance of the Canadian borders. The workshop concluded with a panel discussion on trends, gaps, and requirements in tracking and fusion.

## BRIDGING THE DOMAINS

Held under the theme of *Tracking and Fusion for Intelligence Based Decision Support*, the CTFG Workshop 2016 featured about 30 technical presentations and keynote talks. A special session was dedicated to the *All-Domain Situation Awareness* (ADSA) Canadian program, a five-year program which intended to enhance domain awareness of air, surface, and subsurface approaches to Canada's northern regions. Pierre Lavoie, Assistant Deputy Minister (ADM) (Science & Technology (S&T)) Director General Science and Technology Force Employment, introduced the ASDA program followed by Maria Rey and Andre Dupuis who shared the floor for reporting a feasibility study conducted on behalf of the Canadian Space Agency and DRDC Ottawa on the development of a concept of operations and high-level system architecture for a Canadian All-Source Maritime Domain Awareness System (CAMDAS). Finally, Jim Chan (DRDC Centre for Operational Research and Applications (CORA)) presented the ADSA Underwater Surveillance–Underwater Environment in Northern Canada, discussing aspects of submarine navigation, bathymetry in the Arctic Archipelago, and analysis of choke points where underwater surveillance could be focused, and seasonal characteristics of sea ice in the region. James Llinas (University of Buffalo) concluded this special session with a US perspective on *All Domain Situational Awareness and Information Fusion Technology—Achieving Agility*. His presentation offered a range of ideas and issues associated with developing multidomain robustness and cost-effective approaches to agile Information Fusion capabilities. James Llinas provided a second presentation entitled *Designing and Developing a Data Fusion Capability into an Internet of Things Framework* which offered some thoughts on the systems engineering approach to designing a Data Fusion (DF) process into the Internet of Things (IoT) environment.

**Figure 8**
Participants of CTFG Workshop 2018, Ottawa.

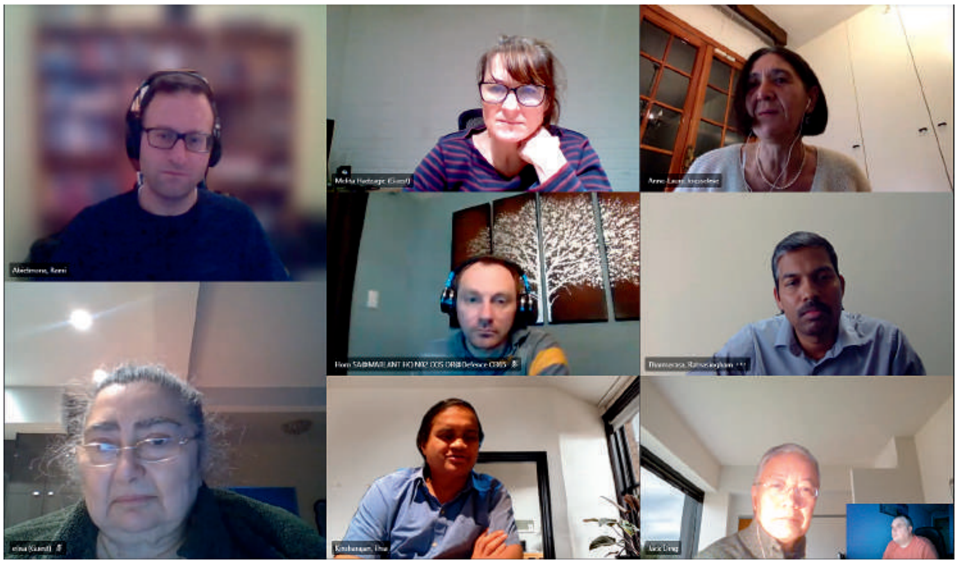


**Figure 9**
CTFG committee meeting after CTFG Workshop 2020+, January 2021.

He discussed using defined architectural primitives for both DF and the IoT as one basis for such designs, and addressed Middleware and Information Quality issues that will impact the realization of good designs for any DF process within an IoT environment. The second and last day hosted a special session on *human factors related to tracking and fusion enabled capabilities within Canada's fleet of CP-140 aircraft*, with a presentation from Christopher Bryan from the Canadian Armed Forces.

| **The CTFG Committee** | | **Chair** |
|---|---|---|
| Rami Abielmona | Larus Technologies | 2011, 2020+ |
| Bhashyam Balaji | DRDC-Ottawa | 2021 |
| Zhen (Jack) Ding | DRDC-Ottawa | 2011, 2015 |
| Mihai Florea | Thales Canada | 2016, 2017 |
| Melita Hadzagic | OODA Technologies | 2018 |
| Steven Horn | DRDC-Atlantic | 2018 |
| Anne-Laure Jousselme | NATO STO CMRE | 2014 |
| Thia Kirubarajan | McMaster University | 2011 |
| Garfield Mellema | DRDC-Atlantic | 2011, 2012 |
| Tony Ponsford | Raytheon Canada Limited | 2011, 2013, 2015 |
| Sreeraman Rajan | Carleton University | 2021 |
| Ratnasingham Tharmarasa | McMaster University | 2020+ |
| Elisa Shahbazian | OODA Technologies | 2016, 2017 |
| Pierre Valin | DRDC-Valcartier | 2011 |

In 2017, the seventh annual CTFG workshop included four special talks by invited speakers and 28 regular talks divided into four tracking sessions (sensor and resource management, detection and tracking, and clutter, estimation, and fusion) and four fusion sessions (optimisation and planning, system design and concepts, and high-level fusion). Eric Fournier, Director General S&T Strategic Decision Support provided information about the Innovation for Defence Excellence and Security (IDEaS) program The IDEaS program is an augmentative approach to accessing innovation allowing Canada's military to better tap into extraordinary talent and ingenuity resident in Canada. James Llinas (University of Buffalo) talked about the knowledge requirements for the design of distributed multisensor multitarget tracking systems. During the second day, Roy Streit from Metron presented the *Analytic combinatorics in tracking and information fusion*. Finally, the last keynote talk was provided by Mr. Srikanth, associated with the Build in Canada Innovation Program (BCIP) which is a research and development (R&D) procurement program aimed at procuring, testing, and evaluating R&D precommercialized goods and services in the late stage development.

## TOWARD EMERGING TECHNOLOGIES AND NEW APPLICATION AREAS

Over two days in October 2018, with the increased number of participants (70), the CTFG Workshop 2018 continued the trend from the previous years of extending the usual workshop topics covering multitarget and video tracking, sensor fusion, resource management to the topics of high-level fusion, hard and soft data fusion, and also including the new topics addressing emerging technologies such as machine learning, deep learning, and blockchain, where the main application domains were maritime, air, and space. The importance of emerging technologies, hard and soft data fusion, and distributed computing in current and future decision support systems were supported by the three plenary talks given by Dale Reding, Director General Science and Technology Air Force and Navy (DGSTAN), DND Canada, who discussed the main S&T trends for Canadian Armed Forces (CAF) and highlighted the significance of emerging technologies such as quantum science, nontraditional sensing, and their impact on the future of computing and digital devices (deep learning, artificial intelligence, next generation encryption, etc.), and the future of decision making. Galina Rogova, a Research Professor at the State University of New York at Buffalo presented the challenges and computational approaches for higher level fusion and situation management while Chee-Yee Chong provided an overview of forty years of distributed filtering. CTFG Workshop 2018 held in Ottawa also presented a good networking opportunity for the 2019 edition of the International Conference on Information Fusion (FUSION 2019) which was to also be held in Ottawa, Canada, and created a perfect forum for the FUSION 2019 organizing committee to discuss the upcoming conference in person.

Indeed, since the FUSION 2019 conference was held in Canada (Ottawa), the CTFG organizing committee decided to encourage participation in this international event and chose not to hold a CTFG workshop in 2019.

In 2020, due to the COVID-19 pandemic, the CTFG Workshop 2020+ was held in January 2021 using an online format for the first time, with a record attendance of 100 participants. The workshop focused on Tracking and Data, Information and Knowledge Fusion for a New Era, and was divided in four half-day presentations instead of two full days. Two invited speakers talked about the link between artificial intelligence/machine learning and data fusion (Erik Blasch, AFRL) and about the IDEaS Program, two years after the beginning of this program which provides funding mechanisms to assist Canadian innovators in solving defence and security challenges (Eric Fournier, Director General Innovation for DND Canada). Thirty-four presentations covered classical topics of video tracking, multitarget tracking, signal processing, sensor fusion, high level fusion, resource management, but also COVID-19 prediction, satellite scheduling, machine learning, as well as biomedical engineering.

Over the 10 years of the CTFG's existence, the Canadian Tracking and Fusion research community has matured as the result of the connectivity and visibility into the advanced data/information fusion solutions supporting the decision making in a multitude of domains in Canada and internationally provided by the CTFG. The CTFG community has also grown, involving new researchers and practitioners from across government (e.g., DRDC agency), industry (e.g., Larus, OODA Technologies, TrackGen), and academia (e.g., Universities of Ottawa, Carleton, McMaster, and Dalhousie), involved in research on new state of the art topics, supporting the requirements of applications of interest to governmental organizations, as well as medical, environmental, financial, and other domains. Since its birth, the CTFG maintains a close relationship with the ISIF experts outside Canada who stimulate fruitful discussions and ideas, within the rooms, during the coffee breaks, and during dinners. We would like to thank Yaakov Bar-Shalom, Erik Blasch, Chee-Yee Chong, Fred Daum, James Llinas, Galina Rogova, and Roy Streit for their enthusiastic participation and support over the years.

The growth of the tracking and fusion research community in Canada has been possible thanks to the ongoing support of the International Society of Information Fusion (ISIF) to the CTFG Workshop series. The IEEE Ottawa Section, and its Computer and Computational Intelligence Chapters, have also been great supporters of the CTFG Workshop over the years. CTFG Workshop 2021 is planned to be held in December in Ottawa.

Information about past and future activities of the CTFG can be found at www.ctfg.ca. Presentations are available upon request.

# Conference Report

## INTERNATIONAL CONFERENCES AND WORKSHOPS DURING THE PANDEMIC

Here is a summary of the status of conferences that might be of interest to the ISIF community as of June 2021.

| Conference | 2020 Status | 2021 Status | 2022 Status |
|---|---|---|---|
| **AeroConf**<br>IEEE Aerospace Conference | March 7–14, 2020<br>Big Sky, MT | Virtual, March 6–13, 2021 | March 5–12, 2022<br>Big Sky, MT |
| **BELIEF***<br>International Conference on Belief Functions | Postponed to 2021 | Hybrid, October 15–19, 2021<br>Shanghai, China | Date to be confirmed<br>Paris, France |
| **CDC**<br>IEEE Conference on Decision and Control | Virtual, December 14–18, 2020 | Virtual or hybrid, December 13–15, 2021<br>Austin, TX | December 6–9, 2022<br>Cancun, Mexico |
| **CogSIMA**<br>IEEE Conference on Cognitive and Computational Aspects of Situation Management | Cancelled, then postponed to 2021 | Virtual, May 14–22, 2021 | TBA |
| **CTFG***<br>Canadian Tracking and Fusion Group Workshop | Virtual, postponed to January 18–21, 2021 | December 2021 (TBC) | TBA |
| **FUSION***<br>International Conference on Information Fusion | Virtual, July 6–9, 2020 | Hybrid, November 1–4, 2021<br>Suncity, South Africa | July 4–7, 2022<br>Linköping, Sweden |
| **ICASSP**<br>IEEE International Conference on Acoustics, Speech, & Signal Processing | Virtual, May 4–8, 2020 | Virtual, June 6–11, 2021 | May 22–27, 2022<br>Singapore |
| **ICML**<br>International Conference on Machine Learning | Virtual, July 12–18, 2020 | Virtual, July 18–24, 2021 | July 17–23, 2022<br>Baltimore, MD |
| **ICRA**<br>IEEE International Conference on Robotics and Automation | Virtual, May 31–June 15, 2020 | Virtual, May 30–June 5, 2021 | May 23–27, 2022<br>Philadelphia, PA |
| **MFI**<br>IEEE International Conference on Multisensor Fusion and Integration | Virtual, September 14–16, 2020 | Hybrid joint event with SDF, September 23–25, 2021<br>Karlsruhe, Germany | TBA |
| **MLSP**<br>IEEE International Workshop on Machine Learning for Signal Processing | Virtual, September 21–24, 2020 | Virtual, October 25–28, 2021 | TBA |
| **NIPS**<br>Conference on Neural Information Processing Systems | Virtual, December 6–12, 2020 | Virtual, December 6–14, 2021 | November 26–December 4, 2022 |

| Conference | 2020 Status | 2021 Status | 2022 Status |
|---|---|---|---|
| **NWOLAS*** Nordic Workshop on Localization for Autonomous Systems | Cancelled | Cancelled | TBA |
| **SDF*** Sensor Data Fusion Symposium | Cancelled | Hybrid joint event with MFI, September 23–25, 2021 Karlsruhe, Germany | October 2022 Karlsruhe, Germany |
| **SSP** IEEE Statistical Signal Processing Workshop | Postponed to 2021 | Virtual, July 11–14, 2021 | July 3–6, 2022 Hanoi, Vietnam |
| **UAI** The Conference on Uncertainty in Artificial Intelligence | Virtual, August 3–6, 2020 | Virtual, July 27–30, 2021 | TBA |
| **VTC** IEEE Vehicular Technology Conference | Virtual, May 25–28, 2020 | Virtual, April 25–28, 2021 | June 19–22, 2022 Helsinki, Finland |

NOTE: Conferences are listed in alphabetic order. TBA, to be announced; TBC, to be confirmed.
*Conferences that received ISIF support in the past years.






# 2022 IEEE Aerospace Conference

Technical Cosponsors: AIAA & PHM Society

Yellowstone Conference Center in Big Sky, Montana

March 5 - 12, 2022

## Call for Papers

**Abstract Due Date (300 - 500 words) : will be accepted until September 2021**

**Paper (6 - 20 pages) Deadline : October 15, 2021**

**Reviewed Paper Returned to Author : November 15, 2021**

**Final Paper Due Date : January 14, 2022**

All submissions are electronic at : www.aeroconf.org

**Registration Opens: October 1, 2021**

The 43rd in a series of annual, week-long, winter conferences designed for aerospace experts, academics, military personnel, and industry leaders will be held in Big Sky, Montana March 5 -12, 2022. The Conference promotes interdisciplinary understanding of aerospace systems, their underlying science and technology, and their applications to government and commercial endeavors. Attendees enjoy exceptional access to authors and invited speakers in a setting ideal for developing lasting relationships benefiting participants, their organizations, and the engineering, scientific, and aerospace communities.

## TECHNICAL PROGRAM

This Call invites submission of papers reporting original work or state-of-the-art reviews that enhance knowledge of: (1) aerospace systems, science, and technology; (2) applications of aerospace systems or technology to military, civil or commercial endeavors; (3) system engineering and management science in the aerospace industry; and (4) Government policy that directs or drives aerospace programs, systems, and technologies. The technical program will present key innovations and achievements in aerospace technologies and their current and future applications.

## 14 Tracks

1. Science & Aerospace Frontiers: Eight Plenary Sessions

*(Key addresses by leading scientists and leaders in government and industry)*

2. Space Missions, Systems, and Architecture
3. Antenna, RF/Microwave Systems and Propagation
4. Communication & Navigation Sys. & Technologies
5. Observation Systems and Technologies
6. Remote Sensing
7. Avionics and Electronics for Space Applications
8. Spacecraft, Launch Vehicle Sys. &Technologies
9. Air Vehicle Systems and Technologies
10. Software and Computing
11. Diagnostics, Prognostics, and Health Management
12. Ground and Space Operations
13. Management, Systems Engineering and Cost
14. Govt. Plans, Policies & Education - High Level Panels

*(>100 Technical Sessions—See "Call for Papers" at www.aeroconf.org)*

JUNIOR ENGINEERING AND SCIENCE CONFERENCE

A concurrent conference for junior engineers, grades 1-12

See "Junior Engineering" at www.aeroconf.org/junior-engineering

| **More information:** | **www.aeroconf.org** | |
|---|---|---|
| Conference Chair | Kendra Cook | Chair@aeroconf.org |
| Technical Program | Richard Mattingly | Richard.Mattingly@jpl.nasa.gov |
| | Karen Profet | Karen.Profet@aeroconf.org |
| | Jeff Webster | Jeff.Webster@aeroconf.org |
| | Erica Delonno | Erica.Deionno@aeroconf.org |
| Registration | Monica Panno | Registration@aeroconf.org |

# Book Review

**Christoph Degen**
Fraunhofer FKIE
Wachtberg, Germany
christoph.degen@fkie.fraunhofer.de

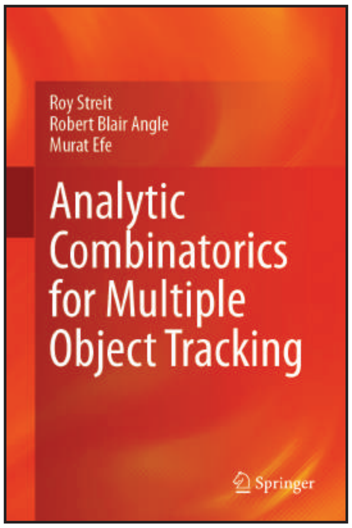
## Analytic Combinatorics for Multiple Object Tracking

**Roy Streit, Robert Blair Angle, and Murat Efe**
Springer, 2021
ISBN: 978-3-030-61191-0

## INTRODUCTION

Analytic combinatorics (AC), probability-generating functions (PGFs), and probability-generating functionals (PGFLs) provide a universal, exact, and intuitive approach for the structure, design, and derivation of multitarget tracking filters. This book is a must read for anyone who wants to learn the following:

- The mechanics of Bayesian tracking filters
- How existing tracking filters differ and what they have in common
- How to intuitively design a customized tracking filter
- How to derive the exact a posteriori filter equations
- How to effectively implement tracking filters based on AC and PGFLs




In particular, a closer look should be taken by engineers who want an overview of the broad field of multiobject target tracking or engineers who are often confronted with nonstandard tracking challenges and need to find customized new filter solutions to their tracking problem. It provides everything needed to understand how existing tracking filters can be extended or new filters can easily be designed. The appendix and the references provide all mathematical details to understand this innovative approach for formulating tracking filters.

> **"It provides everything needed to understand how existing tracking filters can be extended or new filters can easily be designed."**

Combinatorics is a broad field of classical mathematics that comprises problems from diverse applications, ranging from theoretical considerations to highly relevant challenges in applications where, for example, objects have to be counted or enumerated, such as the measurement-to-target assignments in multiobject target tracking. Indeed, one of the main issues confronting a tracking engineer in daily work is the data association problem: which measurement (or even multiple measurements) belongs to which track? Depending on the number of measurements, the way a target generates measurements (single source [1], extended target [2], and generalized measurement model [3]), the statistics, the properties and output of the sensor(s) used, the time evolution of the target(s), the environment, etc., an immense amount of different tracking problems arise. This steady increase of challenges in multitarget tracking implied the derivation of an enormous number of different multiobject target tracking filters in past decades. Consequently, even experienced experts might find it difficult to stay on top of the developments and to distinguish benefits and drawbacks of the different approaches. The diversity of tracking filters enables a tracking engineer to solve problems in state estimation and tracking with a great level of detailed modeling. In addition, AC for multitarget tracking provides a toolbox of concepts that can be combined, extended, and generalized to solve new tracking tasks or to improve information extraction for given data. This directly implies that it is often unknown to a tracking engineer whether a solution to a new tracking scenario exists or whether related concepts can be used to derive a tailormade solution to the problem. An overview of the range of tracking approaches is hard to attain because most tracking filter derivations differ in their approach and a unified framework of representation is missing.

The authors provide the unification of such multiobject tracking filters by applying the theory of point processes, generating functions and functionals that encode the measurement-to-target data associations for several assumptions. Furthermore, the authors explain different approaches to decode the information via differentiation, including highly relevant methods for implementation of tracking filters via particle filtering. A unification of different tracking approaches thereby not only helps in understanding differences and similarities in existing approaches but is also a valuable contribution in the derivation of new and practically relevant tracking solutions.

## BACKGROUND

The book covers the essential aspects of the derivation and representation of tracking filters using PGFLs. In the past decade, first author Roy Streit brought several aspects of this promising field to the tracking community after the invention of the intensity filter (iFilter) using Poisson point processes (see, for example, [4] and [5]). Therein, Streit lay the foundation of a universal representation of multiobject tracking filters by PGFLs for the design, comparison, and derivation of existing and new, customized tracking filters. Based on the well-understood theory of point processes [6], [7] and the classic publication of Moyal [8], in which finite point processes are first characterized using PGFLs, Streit derived several tracking filter representations and aspects using PGFLs and AC. In particular, [4] and [5] give a first overview of the potential of generating functional representation for the comparison and derivation of multiobject tracking filters. Simple and finite point processes, which are random variables (RVs), represent a set of points. These points are variable in their number and spatial distribution, representing the set of targets, measurements, or clutter. Furthermore, the authors use PGFs and PGFLs to encode the Bayesian probability structure of the point process model. Finally, the well-understood tool of a functional derivative decodes the probabilities and yields the statistics needed to describe and implement the respective tracking filter. This approach is modular and divides the tracking filter into different modeling aspects, which makes it an ideal choice for the design and derivation of new filters. In addition, it is a unique choice to understand and compare existing tracking filters, which makes it an ideal approach for engineers new to the topic of target tracking.

The reviewed book combines aspects of previous publications, adds important details, and provides an excellent didactical structure, starting from the easiest and most accessible example using discrete state spaces, and therefore generating functions, and ending up with a general description of several state-of-the-art filters from past decades. Furthermore, the authors discuss the practical relevance and present options for the efficient numerical implementation of AC-derived tracking filters. The appendix presents the broad mathematical background of the unifying approach without interrupting the didactic concept of the main body. If the reader is interested in further details, the references are exhaustive. An excellent overview and the technical details on AC can be found in [9], the technical details on point processes, which are used to model targets and measurements, can be found in [6] and [7].

## OUTLINE OF ANALYTIC COMBINATORICS FOR MULTIPLE OBJECT TRACKING

The book contains six main chapters plus three additional chapters on the mathematical background in the appendix. In the following, the individual chapters in the main body are briefly discussed.

### CHAPTER 1

In the first chapter, the authors explain how to describe a tracking filter with a single function using the simplest example of a single-target problem: The state of the object of interest is modeled such that it might or might not exist, and a single sensor might or might not produce a single detection of the object on a discrete grid. The state space of the target is discretized, making the possible state estimates countable and enabling the authors to present the idea of the approach by the application of a PGF, the well-known and discrete version of a PGFL, which can be described as "a clothesline on which we hang up a sequence of numbers for display" [10]. Herbert Wilf's quote shows what the idea of generating functions is about: A single function encodes the statistics of the underlying RV in a compact, clear, and comparable way. If needed, the moments, i.e., the statistics of the underlying RV, can be decoded using ordinary differentiation. In this way, the relevant statistical information, which is needed to implement a tracking filter, can be extracted.

***"...enabling the authors to present the idea of the approach by the application of a PGF..., which can be described as 'a clothesline on which we hang up a sequence of numbers for display' [10]."***

The authors start their description of tracking filters using generating functions after a short introduction to AC, sensor and object models in tracking, likelihood functions, and measurement-to-target assignments in a didactically elegant way. First, the authors model the existence and detection of a target using a Bernoulli RV, that is, they consider the following problem: "Statement A. At most one object exists and, if it does exist, the sensor may or may not generate one measurement" [11]. This simplest example (Statement A) suffices to explain the main idea of the concept of a generating function. In parallel, the reader can study the mathematical foundations of the discussion in Appendix A. This enables the authors to present their concepts without interrupting the common goal to make the main idea clear. Using this simple example, the authors discuss the important topics of a conditional (how does the measurement generating function look if one object exists) and the marginal PGF of the number of measurements. In addition, the authors explain the branching form of a generating function, making the benefit of using AC for the design, derivation, and unification of tracking filters obvious. In the second and third examples, the authors add gridded random measurements and consider the following problem: "Statement B. At most one object exists and, if it does exist, the sensor may or may not generate a random measurement Y" [11]. Afterward, the authors add gridded random object states to the problem, which yields the more advanced tracking-related example: "Statement C. At most one random object exists and, if it does exist in state X, the sensor may or may not generate a random measurement Y" [11]. Afterward, the authors present the PGF for the Bayes theorem and derive it for the three statements, e.g., what does the generating function for the number of existing targets look like if the number of measurements is known? This sets the stage for Bayesian tracking filters. Finally, the authors incorporate different models of object existence and detection (multiple object existence, random number of object existence, and false alarms) into the generating function of the original problem. They give a first impression of how easily an engineer can adapt the generating function and therefore the tracking filter to a specific tracking challenge. Illustrative examples make the considerations clearer and demonstrate the principle of Wilf's clothesline.

## CHAPTER 2

The second chapter sets the stage for the complex multiobject target tracking filters by introducing "filters that track a single target" [11] on a continuous state space, that is, the classical Bayes-Markov [12], probabilistic data association (PDA) [12], and integrated PDA (IPDA) [13] filters. Because most applications presume a continuous target state and/or measurement space, the authors introduce PGFLs. To this end, the authors determine the PGF for the Bayes theorem and take the small cell limit of the two grids that, by becoming infinitesimally small, yields the PGFL for the Bayes theorem on a continuous state and measurement space. Afterward, the authors define the basic PGFL of the Bayes–posterior point process and use it to set up a broad collection of multiobject tracking filters.

The first example is the Bayes-Markov filter, whose extension yields the PDA filter, which additionally models clutter and optionally gating. Afterward, the authors present the IPDA filter, which integrates a model of object existence into the PGFL and simultaneously demonstrates how the adaption or extension of an existing PGFL is performed intuitively. Finally, the classical Kalman filter [1] is formulated using PGFLs. For each filter, the authors apply the technique of secular functions introduced by Streit in [14] to compute the functional derivatives by ordinary differentiation in order to derive the respective exact Bayesian posterior distribution.

## CHAPTER 3

The third chapter extends the considerations of the second chapter with the introduction of "filters that track a specified number of targets" [11], starting with the well-known extension of the PDA filter, the joint PDA (JPDA) [15]. Because multiple potential measurement origins exist, various measurement-to-target assignment configurations appear. However, in contrast to the traditional derivation of the JPDA filter, which starts by defining all possible measurement-to-target assignments, the AC approach reveals its elegance by first characterizing the statistical properties of measurements and objects. The possible assignments are revealed when the derivatives computed. Thus, the authors demonstrate systematically that AC is "an alternative way to conceptualize these filters combinatorially [sic]" [11]. The authors explain this nontrivial filter derivation and its properties by extending the results of the single-target PDA derivation using AC. An interested reader should be able to follow the arguments of the authors easily (by studying the appendix in parallel) and learn the main ingredients of an AC-tracking filter derivation. The benefit of the AC approach becomes obvious when the authors introduce the famous joint integrated PDA (JIPDA) [16] filter. Modeling track initiation and termination, the number of assignments results in a complex derivation using the traditional path (any engineer who has tried to implement the JIPDA filter will agree on its complexity). However, the AC approach presents the PGFL of the JIPDA in a short and elegant way as the core of the implementation. The complexity of the measurement-to-target assignment becomes apparent when the posterior density is derived using functional derivatives. At a first glance, this seems to be complicated, but the computation of derivatives can be performed automatically using automatic differentiation. A variant of the JPDA filter that models unresolved measurements from two targets demonstrates the potential of the AC approach in the design and adaption of new or existing filters to a specific problem. An illustrative numerical example of the tracking of targets with unresolved measurements using the JPDA filter closes the third chapter.

***"Thereby, the concept of AC not only shows its power in the derivation of a new tracking filter by simple operation on the PGFL but also shows relationships between existing filters, like the JPDA with superposition (JPDAS) and the cardinalized probability hypothesis density (CPHD) filter."***

## CHAPTER 4

The JIPDA has great complexity because each target (and thus its state space) possesses an identifier and because it models the events of track termination and initiation. Therefore, an application of the JIPDA in numerically complex applications usually is restricted. Furthermore, of important relevance for practical applications are filters that "track a variable number of targets" [11]. To this end, the authors apply an efficient concept to the JPDA filter that ignores distinguishable targets; that is, they perform superposition of target state spaces. The lack of information brings a highly applicable multiobject tracking filter to life. Thereby, the concept of AC not only shows its power in the derivation of a new tracking filter by simple operation on the PGFL but also shows relationships between existing filters, like the JPDA with superposition (JPDAS) and the cardinalized probability hypothesis density (CPHD) filter. After introducing state-dependent models for object birth, death, and spawning, the authors show that the famous probability hypothesis density (PHD) filter [17] is a special case of the CPHD filter. Having seen the derivations of tracking filters using superposition, the interested reader should be able to understand further tracking filters (e.g., [18] and [3]) and be ready to derive a problem-specific customized approach. The chapter closes with a numerical efficient particle implementation for superposed AC-derived tracking filters using complex step differentiation [19], [20], [21], which not only makes AC a concept for the design, unification, and understanding of tracking filters but also shows that the concept is interesting for deriving numerical efficient particle–based implementations.

### CHAPTER 5

In an analogous way to Chapter 4 and the relationship between the JPDA and the CPHD filters, the authors demonstrate the relationship between the JIPDA and the multi-Bernoulli (MB) filters using AC. The authors thereby talk about the small but fine difference between the MB filter and the CPHD filter. Each of the Bernoulli models within the MB filter is a sequential detector for a single object (due to the model of target existence within the JIPDA filter), whereas the model of the CPHD filter makes it an estimator of the number of object detection decisions. The authors present variants of the MB filter, including the multi-Bernoulli mixture (MBM) filter originally presented in [22]. The authors discuss several other MB filter variants, including labeled MB and MBM filters, and name a large list of relevant references. The authors apply AC to show that there is a close relationship between "Multi-Bernoulli Mixture and Multi-Hypothesis Tracking filters" [11], [23] for one scan. Finally, the chapter closes with a numerical investigation of the newly derived JIPDA with superposition (JIPDAS) filter.

*"After reading the book, readers can design their own tracking filters using AC, compare them in a unified fashion with existing filters, and efficiently implement particle versions of the filters."*

### CHAPTER 6

In the last chapter, the authors first summarize their results of applying AC to multiobject tracking filters and visualize the connection with the specific filter in a single figure. Afterward, possible extensions of the application of AC to the field of target tracking are discussed, including multiobject trajectory filters, tracking with multiple unresolved objects, and evaluation of further statistics like spatial and temporal correlation. Furthermore, the authors propose two techniques (saddle point approximation [24] and complex step differentiation [19], [20], [21]) for an efficient particle implementation of the filters. Finally, the authors use the alternative way of formulating tracking filters by assignments (see, e.g., [25]) to discuss the applicability of AC to solve integer linear programming problems.

## SUMMARY

The authors give a broad overview of the possibilities and benefits of an application of AC to the world of Bayesian target tracking in their book *Analytic Combinatorics for Multiple Object Tracking* in a didactically excellent way. This book can be recommended to all tracking engineers, independent of whether they are at a beginner or expert level. The list of benefits is long. AC provides the following:

- Unification and representation of tracking filters in a single PGFL
- Understanding of the similarities and differences between existing tracking filters by consideration of a single functional
- Derivation of tracking filters without explicitly enumerating all possible assignments
- The possibility of applying highly efficient numerical implementations
- An adaption and simple, customized design of multiobject tracking filters
- Straightforward evaluation of several summary statistics, like factorial moments
- Reduction of notational burden of multiobject tracking filters

The authors derive the most important tracking filters using AC and use only as much mathematical theory as is essentially necessary to follow the main thread. In addition, all of the mathematical theory the reader needs for the details is contained in the appendix, and the authors name useful references to understand the mathematical theory. After reading the book, readers can design their own tracking filters using AC, compare them in a unified fashion with existing filters, and efficiently implement particle versions of the filters. Overall, the book is a pleasure to read and shows its relevance in several publications on the topic of AC for target tracking.

## REFERENCES


1. Bar-Shalom, Y., Li, X.-R., and Kirubarajan, T. *Estimation with Applications to Tracking and Navigation*. John Wiley & Sons, Inc., 2001.
2. Koch, W. *Tracking and Sensor Data Fusion—Methodological Framework and Selected Applications*. Springer, 2014.
3. Degen, C., Govaers, F., and Koch, W. Tracking targets with multiple measurements per scan. In *Proceedings of the 17th International Conference on Information Fusion,* Spain, 2014.
4. Streit, R. How I learned to stop worrying about a thousand and one filters. In *IEEE Aerospace Conference,* Big Sky, MT, 2017.
5. Streit, R. Analytic combinatorics in multiple object tracking. In *2017 Workshop on Sensor Data Fusion: Trends, Solutions, Applications (SDF),* Bonn, Germany, 2017.
6. Davey, D. J., and Vere-Jones, D. *An Introduction to the Theory of Point Processes, Volume 1: Elementary Theory and Methods*. Springer, 2003.
7. Davey, D. J., and Vere-Jones, D. *An Introduction to the Theory of Point Processes, Volume 2: General Theory and structure*. Springer, 2008.

8. Moyal, J. E. The general theory of stochastic population processes. *Acta Mathematica,* Vol. 108 (1962), 1–31.
9. Flajolet, P., and Sedgewick, *R. Analytic Combinatorics*. Cambridge Univ. Press, 2009.
10. Wilf, H. *Generatingfunctionology*. Academic Press, 1994.
11. Streit, R., Angle, R. B., and Efe, M. *Analytic Combinatorics for Multiple Object Tracking*. Springer, 2021.
12. Bar-Shalom, Y., and Fortmann, T. E. *Tracking and Data Association*. Academic Press, 1988.
13. Musicki, D., Evans, R., and Stankovic, S. Integrated probabilistic data association. *IEEE Transactions on Automatic Control,* Vol. 44, 1 (2008), 11–126.
14. Streit, R. A Technique for deriving multitarget intensity filters using ordinary derivatives. *Journal of Advances in Information Fusion,* Vol. 9 (2014), 3–12.
15. Bar-Shalom, Y., and Li, X.-R. *Estimation and Tracking—Principles, Techniques, and Software*. Storrs, CT: YBS Publishing, 1995.
16. Musicki, D., and Evans, R. Joint integrated probabilistic data association: JIPDA. *IEEE Transactions on Aerospace and Electronic Systems,* Vol. 40, 3 (2004), 1093–1099.
17. Mahler, R. P. S. Multitarget Bayes filtering via first-order multitarget moments. *IEEE Transactions on Aerospace and Electronic Systems,* Vol. 39, 4 (2003), 1152–1178.
18. Schlangen, I., Degen, C., and Charlish, A. Distinguishing wanted and unwanted targets using point processes. In *Proceedings of the 21st International Conference on Information Fusion,* Cambridge, United Kingdom, 2018.
19. Squire, W., and Trapp, G. Using complex variables to estimate derivatives of real functions. *SIAM Review,* Vol. 40, 1 (1998), 110–112.
20. Lyness, J. N., and Moler, C. B. Numerical differentiation of analytic functions. *SIAM Journal on Numerical Analysis,* Vol. 4, 2 (1967), 202–210.
21. Higham, N. "Differentiation with(out) a difference" [Online]. Available: https://sinews.siam.org/Details-Page/differentiation-without-a-difference. 1 June 2018, last access 7 June 2021.
22. Vo, B.-T., and Vo, B.-N. Labeled random finite sets and multi-object conjugate priors. *IEEE Transactions on Signal Processing,* Vol. 61, 13 (2013), 3460–3475.
23. Reid, D. An algorithm for tracking multiple targets. *IEEE Transactions on Automatic Control,* Vol. 24, 6 (1979), 843–854.
24. Streit, R. Saddle point method for JPDA and related filters. In *Proceedings of the 18th International Conference on Information Fusion,* Washington, DC, 2015.
25. Poore, A. B. Multidimensional assignment formulation of data association problems arising from multitarget and multisensor tracking. *Computational Optimization and Applications,* Vol. 3, 1 (1994), 27–57.


## *ISIF VISION STATEMENT*

The International Society of Information Fusion (ISIF) is the premier professional society and global information resource for multidisciplinary approaches for theoretical and applied INFORMATION FUSION technologies. Technical areas of interest include target tracking, detection theory, applications for information fusion methods, image fusion, fusion systems architectures and management issues, classification, learning, data mining, Bayesian and reasoning methods.

## *ISIF Journal of Advances in Information Fusion (JAIF)*

The Journal of Advances in Information Fusion (JAIF) is the flagship journal of ISIF. JAIF is an open-access, peer-reviewed, semi-annual, archival journal published electronically and distributed via the internet. JAIF was founded in July 2006. The journal is indexed at SCOPUS, free for authors, and freely available for readers at http://www.isif.org/journals/all. Authors are invited to submit both regular papers as well as short correspondences describing advances, applications, and new ideas in information fusion, both theory and application. Authors of papers presented at our annual International Conference on Information Fusion are strongly encouraged to consider submitting expanded versions of their papers to JAIF. Manuscripts can be submitted at http://jaif.msubmit.net.


Charleston, South Carolina, will be home to the 26th ISIF Fusion Conference from June 27-30, 2023. The historic southern city was founded in 1670 and has preserved a rich history from the American Revolutionary and Civil Wars. Charleston is characterized by cobblestone streets, horse-drawn carriages, southern plantations, historic churches, world renowned restaurants and all the sights of a waterfront port city and prior naval base. The conference venue is located in downtown Charleston, which is known for its walkability, at the historic Belmond Charleston Place in the center of the King Street historic district. The venue is adjacent to the City Market and within a short distance of the Old Exchange, Provost Dungeon, Gibbs Museum of Art, and plenty of pubs and restaurants to satisfy any cravings! There are landmark Battery Promenade and Waterfront Parks overlooking the Charleston Harbor and Fort Sumter, where the first shots of the Civil War were fired. Since 2013, Charleston has been named the No. 1 city in the United States by Travel + Leisure magazine and the No. 2 city in the world in 2017!

In addition to the numerous attractions and activities located in the downtown area of Charleston, many more are within a few miles. Fort Sumter is located on an island in Charleston Harbor which can be visited by boat tour, whereas Fort Moultrie is located on Sullivan's island that can be accessed by car. Fort Sumter and Fort Moultrie incorporate several historical sites around the Charleston Harbor, which tell the unique stories that shaped the United States of America. Patriot's Point Naval and Maritime Museum features a World War II aircraft carrier, USS YORKTOWN, a fleet of National Historic Landmark ships, a Cold War Memorial and Vietnam Experience Exhibit, the Congressional Medal of Honor Society, and a Medal of Honor Museum. The H. L. Hunley was the first submarine to sink an enemy ship, the USS Housatonic, off the coast of Charleston and is on display at the Warren Lasch Conservation Center in North Charleston. The Citadel is the military college of South Carolina, established in 1842, located on the northwest side of Charleston. There are also numerous historic plantations, renowned golf courses, barrier island beaches, national parks, and art museums.

We look forward to welcoming you to South Carolina!

*See you soon!*