

## Welcome to the 20th TCCS Newsletter!

The Texas Consortium for Computational Seismology is a joint initiative of the Bureau of Economic Geology and the Oden Institute for Computational Engineering and Sciences at The University of Texas at Austin. Its mission is to address the most important and challenging research problems in computational geophysics as experienced by the energy industry while educating the next generation of research geophysicists and computational scientists.

## TCCS Sponsors

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## Fall Meeting

The Fall 2020 Research Meeting of the Texas Consortium for Computational Seismology will take place online during the week of November 9–13.

Representatives of participating companies are invited to register for the meeting by following the link at: <http://www.beg.utexas.edu/tccs/>.



## Presentations at SEG 2020

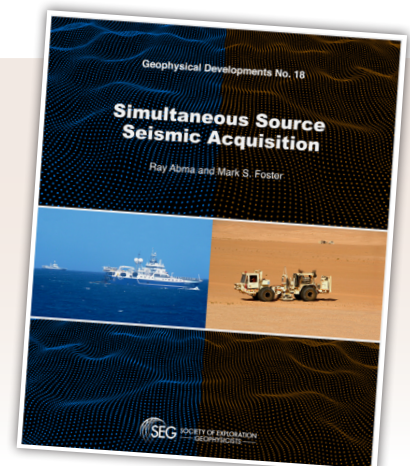
TCCS members and collaborators made numerous presentations at the SEG 2020 Annual Meeting. The presentations fell into four subject areas: Machine Learning and Data Analytics; Seismic Modeling; Seismic Processing: Multiple, Noise and Regularization; Seismic Velocity Estimation.



Day	Time	Topic	Presenters	Description
Monday Oct. 12	3:55 pm	SVE P1: Advancements	Luke Decker and Sergey Fomel	A variational method for picking velocity surfaces from semblance scans
Tuesday Oct. 13	10:10 am	MLDA 2: Processing 1	Harpreet Kaur, Nam Pham, and Sergey Fomel	Separating primaries and multiples using hyperbolic Radon transform with deep learning
	1:50 pm	SS 5: Machine Learning in the Near Surface	Nam Pham and Sergey Fomel	Uncertainty estimation using Bayesian convolutional neural network for automatic channel detection
Wednesday Oct. 14	10:10 am	SM P3 Methods 2: Seismic Modeling	Kristian Jensen, Isabelle Lecomte, Xavier Janson, and Jan Tveranger	Efficient and flexible characterization of paleokarst seismic signatures using point-spread function-based convolution modeling.
	11:25 am	SPMNR 2: Advances in Denoising, Deblending, and Reconstruction	Ray Abma	Enhancing seismic source separation with an Apparition-Inversion hybrid method
	2:15 pm	MLDA P5: Inversion 3	Harpreet Kaur, Alexander Sun, Zhi Zhong, and Sergey Fomel	Time-lapse seismic data inversion for estimating reservoir parameters using deep learning
	3:55 pm	MLDA 4: Modeling and Other Applications 2	Nam Pham, Dmitrii Merzlikin, Sergey Fomel, and Yangkang Chen	Passive seismic signal denoising using convolutional neural network
Thursday Oct. 15	3:30 pm	Workshop W-1, 4D under complex overburden: are we there yet?	Ray Abma	Improving time-lapse measurements with simultaneous sourcing
Friday Oct. 16	10:30 am	Workshop W-18: Machine Learning Blind-test Challenge	Harpreet Kaur (On behalf of TCCS)	Deep learning framework for seismic facies identification

## New book

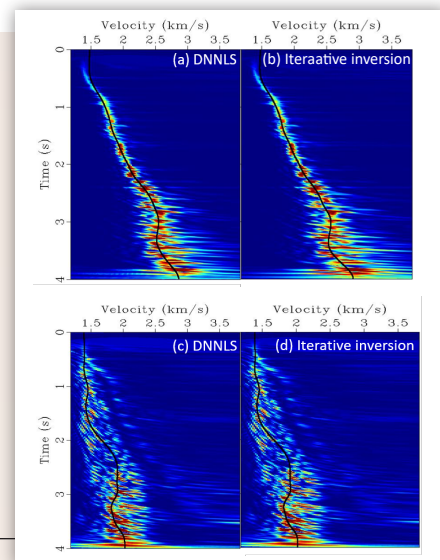
The book, *Simultaneous Source Seismic Acquisition*, by Ray Abma and Mark S. Foster, is published by SEG and should be available this November. It is a practical guide to acquiring and processing simultaneous source seismic surveys. The book covers land and marine simultaneous source acquisition, deblending, and upcoming technologies. Appendices include checklists, deblending codes, and a description of things that can go wrong and how to fix them.



## Research Highlights

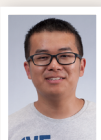
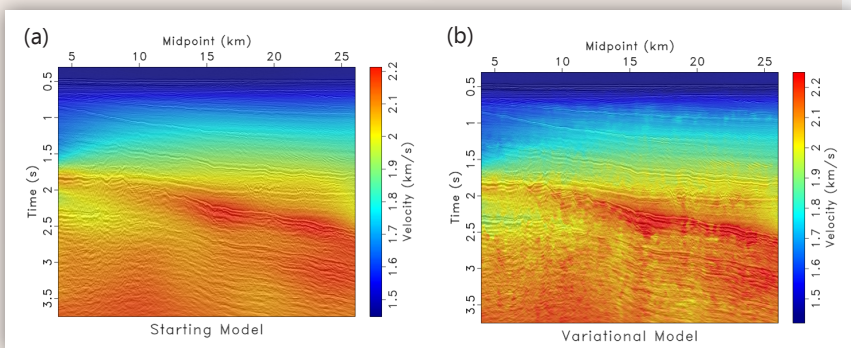


**Harpreet Kaur** has been working on applying a deep neural network (DNN) for computing the hyperbolic Radon transform for separating primary reflections and multiples. The basic idea is to compute the weights associated with the inverse Hessian using the DNN for training datasets, which can then be applied to the adjoint transform of test datasets to obtain an initial model close to the true model. The output of the DNN can then be input into the least-squares framework to obtain an output equivalent to the least-squares solution, but at a significantly reduced cost. Figures (a) and (c) show the primary and multiple semblance scans using the proposed method, and Figures (b) and (d) show the primary and multiple semblance scans using iterative inversion.



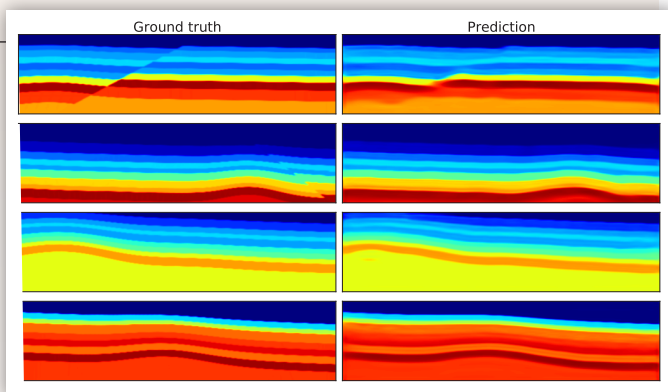
**Luke Decker** has been working on a variational method for picking velocity surfaces from semblance scans. The approach iteratively finds a velocity field

that minimizes the cost of a velocity surface within a semblance scan. This framework enables picked velocity fields to incorporate information from gathers that are spatially near the midpoint in question, and the flexibility of the variational framework allows penalties to be introduced for unphysical velocities. The figures illustrate an application of the method to a field dataset from the Viking Graben. Figure (a) shows the starting interval velocity model overlaid by the corresponding image generated by applying DMO stacking and time migration using the model. Figure (b) shows the model output by the variational method overlaid by its image.



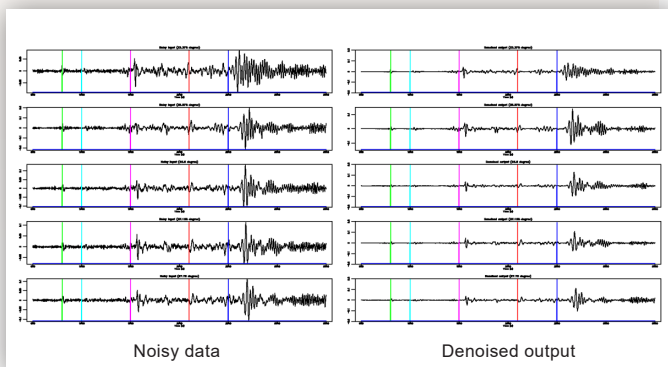
**Zhicheng Geng** has been working on deep learning for velocity model building with common-image gathers (CIGs). The convolutional neural network is able to figure out the relation between shifted images and curved events in CIGs due to an inaccurate velocity model and the corresponding

correct velocity model. Pairs of synthetic input CIGs and output target velocity models are used to train the network. Test results for other synthetic models show the potential of deep learning in velocity modeling.



**Nam Pham** has been working on denoising passive seismic data in the local time-frequency domain with complex-valued neural networks. The network is trained with synthetic datasets created by the reflectivity method using the Thomson-Haskell propagator matrix. Tests on a USArray dataset of a

New Zealand earthquake prove that the denoised outputs can help automatic pickers identify different phase arrivals more easily. A dropout layer is used to quantify model uncertainty. Uncertainties are related to waveform complexity and the relative positions of stations to the earthquake epicenter.



Accepted	<p>S. Fomel and H. Kaur, 2020, Wave-equation time migration: <i>Geophysics</i>, accepted.</p> <p>H. Kaur, N. Pham, and S. Fomel, 2020, Seismic data interpolation using deep learning with Generative Adversarial Networks: <i>Geophysical Prospecting</i>, accepted.</p> <p>Y. Shi, X. Wu, and S. Fomel, 2020, Interactively tracking seismic geobodies with a deep learning flood-filling network: <i>Geophysics</i>, accepted.</p>
Published 2020	<p>L. Decker and Q. Zhang, 2020, Quantifying and correcting residual azimuthal anisotropic moveout in image gathers using dynamic time warping: <i>Geophysics</i>, v. 85, 071–082.</p> <p>B. Engquist, K. Ren, and Y. Yang, 2020, The quadratic Wasserstein metric for inverse data matching: <i>Inverse Problems</i>, v. 36, 055001.</p> <p>Z. Geng, X. Wu, S. Fomel, and Y. Chen, 2020, Relative time seislet transform: <i>Geophysics</i>, v. 85, V223–V232.</p> <p>Z. Geng, X. Wu, Y. Shi, and S. Fomel, 2020, Deep learning for relative geologic time and seismic horizons: <i>Geophysics</i>, v. 85, WA87–WA100.</p> <p>H. Kaur, S. Fomel, and N. Pham, 2020, Seismic ground-roll noise attenuation using deep learning: <i>Geophysical Prospecting</i>, v. 68, 2064–2077.</p> <p>H. Kaur, N. Pham, and S. Fomel, 2020, Improving the resolution of migrated images by approximating the inverse Hessian using deep learning: <i>Geophysics</i>, v. 85, WA173–WA183.</p> <p>D. Merzlikin, S. Fomel, and X. Wu, 2020, Least-squares diffraction imaging using shaping regularization by anisotropic smoothing: <i>Geophysics</i>, v. 85, S313–S325.</p> <p>N. Pham, X. Wu, and E. Naeini, 2020, Missing well log prediction using convolutional long short-term memory network: <i>Geophysics</i>, v. 85, WA159–WA171.</p> <p>Y. Shi, X. Wu, and S. Fomel, 2020, Waveform embedding: automatic horizon picking with unsupervised deep learning: <i>Geophysics</i>, v. 85, WA67–WA76.</p> <p>Y. Sripanich, S. Fomel, J. Trampert, W. Burnett, and T. Hess, 2020, Probabilistic moveout analysis by time warping: <i>Geophysics</i>, v. 85, U1–U20.</p> <p>X. Wu, Z. Geng, Y. Shi, N. Pham, S. Fomel, and G. Caumon, 2020, Building realistic structure models to train deep convolutional neural networks for seismic structural interpretation: <i>Geophysics</i>, v. 85, WA27–WA39.</p> <p>Q. Xu, B. Engquist, M. Solaimanian, and K. Yan, 2020, A new nonlinear viscoelastic model and mathematical solution of solids for improving prediction accuracy: <i>Scientific Reports</i>, v. 10, Article 2202.</p>
Published 2019	<p>S. Bader, X. Wu, and S. Fomel, 2019, Missing log data interpolation and semiautomatic seismic well ties using data matching techniques: <i>Interpretation</i>, v. 7, T347–T361.</p> <p>B. Engquist and D. Peterseim, 2019, Computational multiscale methods: <i>Oberwolfach Reports</i>, v. 16, 2099–2181.</p> <p>D. Merzlikin, S. Fomel, and M. Sen, 2019, Least-squares path-summation diffraction imaging using sparsity constraints: <i>Geophysics</i>, v. 84, S187–S200.</p> <p>N. Pham, S. Fomel, and D. Dunlap, 2019, Automatic channel detection using deep learning: <i>Interpretation</i>, v. 7, SE43–SE50.</p> <p>Y. Shi, X. Wu, and S. Fomel, 2019, SaltSeg: Automatic 3D salt segmentation using a deep convolutional neural network: <i>Interpretation</i>, v. 7, SE113–SE122.</p> <p>A. Stovas and S. Fomel, 2019, Generalized velocity approximation: <i>Geophysics</i>, v. 84, C27–C40.</p> <p>Y. Sripanich, S. Fomel, and A. Stovas, 2019, Effects of lateral heterogeneity on time-domain processing parameters: <i>Geophysical Journal International</i>, v. 219, 1181–1201.</p> <p>C. Wang, Z. Zhu, H. Gu, X. Wu, and S. Liu, 2019, Hankel low-rank approximation for seismic noise attenuation: <i>IEEE Transactions on Geoscience and Remote Sensing</i>, v. 57, 561–573.</p> <p>X. Wu and Z. Guo, 2019, Detecting faults and channels while enhancing seismic structural and stratigraphic features: <i>Interpretation</i>, v. 7, T155–T166.</p> <p>X. Wu, L. Liang, Y. Shi, and S. Fomel, 2019, FaultSeg3D: Using synthetic data sets to train an end-to-end convolutional neural network for 3D seismic fault segmentation: <i>Geophysics</i>, v. 84, IM35–IM45.</p> <p>X. Wu, L. Liang, Y. Shi, Z. Geng, and S. Fomel, 2019, Multitask learning for local seismic image processing: fault detection, structure-oriented smoothing with edge-preserving, and seismic normal estimation by using a single convolutional neural network: <i>Geophysical Journal International</i>, v. 219, 2097–2109.</p> <p>X. Wu, Y. Shi, S. Fomel, L. Liang, Q. Zhang, and A. Yusifov, 2019, FaultNet3D: Predicting fault probabilities, strikes, and dips with a single convolutional neural network: <i>IEEE Transactions on Geoscience and Remote Sensing</i>, v. 57, 9138–9155.</p> <p>Z. Xue, H. Zhang, Y. Zhao, and S. Fomel, 2019, Pattern-guided dip estimation with plane-wave destruction filters: <i>Geophysical Prospecting</i>, v. 67, 1798–1810.</p>

## TCCS Staff

The TCCS group consists of people from seven countries. Our research staff includes 2 principal investigators, 7 Ph.D. students, 1 M.S. student, an undergraduate student, and 2 visiting scientists:



TCCS group members at a socially distanced picnic in Austin's Zilker Park

For more information, see <http://www.beg.utexas.edu/tccs/staff>.

Raymond Abma (Visiting Scientist)  
 Hector Corzo Pola (M.S. 1st year)  
 Luke Decker (Ph.D. 5th year)  
 Björn Engquist (PI)  
 Sergey Fomel (PI)

Rebecca Gao (Ph.D. 1st year)  
 Zhicheng Geng (Ph.D. 4th year)  
 Ben Gremillion (Ph.D. 2nd year)  
 Mike Jervis (Visiting Scientist)

Harpreet Kaur (Ph.D. 4th year)  
 Nam Pham (Ph.D. 2nd year)  
 Yiran Shen (Ph.D. 4th year)  
 Tharit Tangkijwanichakul (B.S. 4th year)

## Testimonials

### Yunzhi Shi

*Not many decisions in my life I would never regret, but joining TCCS is definitely one of them. Dr. Fomel is a nice supervisor and mentor. He is also a kind friend one can count on: whenever I knocked on his door, he was always ready to help with his relieving smile. Being part of TCCS, I am thrilled to be surrounded by like-minded colleagues who are so talented and passionate. Like a family, they've cheered me up during my bad times and shared happiness*

*during the good times. Since TCCS was established 10 years ago, it has always been innovating in geophysics research, delivering techniques to its sponsors, and embracing new ideas to lead the scientific cutting edge. This success can be attributed to a tenet present since TCCS's foundation: reproducibility. Reproducible research helps this consortium stand on the shoulders of giants and see further. I will cherish my memories here for life and look forward to the fruitful future of TCCS.*



Yunzhi Shi during his online graduation ceremony.

## Professional Awards

TCCS members received a number of professional awards at the 2020 SEG Meeting.



**Ximing Wu**, a TCCS visiting Ph.D. student and postdoc in 2015–2019 and currently a professor at the University of Science and Technology of China, received the J. Clarence Karcher Award, a major SEG award for young geophysicists. Xinming was also recognized as the 2020 SEG Honorary Lecturer for South and East Asia. His lecture was "Deep learning for seismic processing and interpretation."



**Sergey Fomel** was recognized as the SEG Distinguished Lecturer for Spring 2020. His lecture was "Automatic seismic data analysis and interpretation."

In 2020, Sergey Fomel was also elected an Honorary Member of the Geophysical Society of Houston (GSH).

