Fall 2021 Newsletter

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Texas Consortium for Computational Seismology • The University of Texas at Austin

Welcome to the 22nd *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.

Fall Meeting

Because of continuing pandemic restrictions, we will be delivering the Fall 2021 report individually to each sponsoring company in online meetings, starting on November 1.

While continuing the practice of online engagement, we intend to return to regular meetings in Spring 2022 with a meeting in Houston.

New Member

We welcome Petrobras as a new member of the consortium!

BR PETROBRAS

Presentations at IMAGE 2021

TCCS members made a number of presentations at IMAGE 2021, the First International Meeting for Applied Geoscience & Energy.

The presentations fall into several different subject areas: Acquisition and Survey Design, Machine Learning and Data Analytics: Theory and Special Applications, and Seismic Processing: Multiples, Noise and Regularization, Seismic Velocity Estimation.

Sept. 27	1:45–2:10	Processing (MLDA1)	Physics-constrained deep learning for ground-roll attenuation	Nam Pham and Weichang Li
Sept. 28	9:15–9:40	Inversion 1 (MLDA2)	Boundary conditions for acoustic and elastic wave propagation using deep learning	Harpreet Kaur, Sergey Fomel and Nam Pham
	1:45–2:10	New developments, novel applications and case studies 2 (SPET3)	Approaches to improving 2D simultaneous source acquisition and deblending	Ray Abma
	3:40–4:05	Machine learning applications for noise and multiple attenuation (SPMNR3)	Streaming seismic attributes	Zhicheng Geng, Sergey Fomel, Yang Liu, Qinghan Wang, Zhisheng Zheng, and Yangkang Chen
	4:30–4:55	Interpretation (MLDA 3)	A deep learning framework for seismic facies classification	Harpreet Kaur, Nam Pham, Sergey Fomel, Zhicheng Geng, Luke Decker, Ben Gremillion, Michael Jervis, Ray Abma, and Shuang Gao
	4:55–5:20	Interpretation (MLDA4)	Channel facies and faults multi-segmentation in seismic volumes	Nam Pham, Dallas Dunlap, and Sergey Fomel
Sept. 29	10:45–11:10	Processing and interpretation (MLDA5)	Nonstretching NMO correction using deep learning	Harpreet Kaur and Sergey Fomel
	1:20–1:45	New methodologies and machine learning approaches 1 (SVE1)	A continuation approach for avoiding local minima in seismic velocity picking	Luke Decker and Sergey Fomel

TCCS Sponsors

TCCS appreciates the support of its 2021 sponsors:

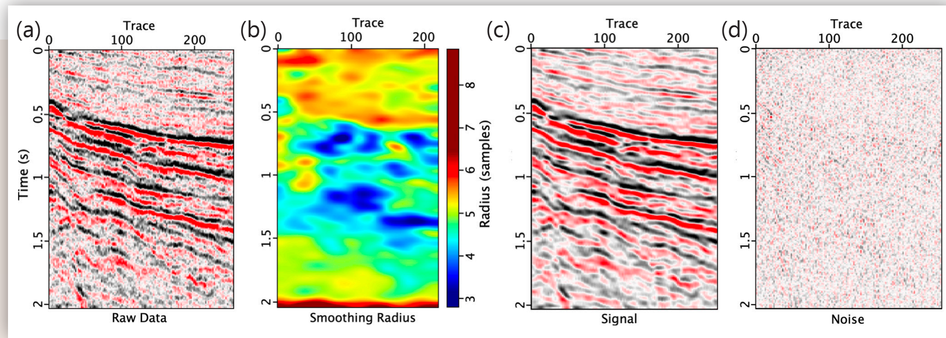
- BP
- Chevron
- ConocoPhillips
- Equinor
- Petrobras
- Saudi Aramco
- Shell
- Sinopec
- TGS

New Course

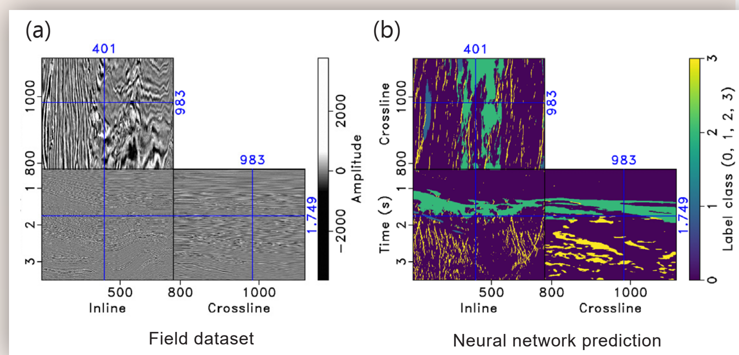
A new graduate course, *Machine Learning Applications in Geosciences*, was introduced in Spring 2020 by Sergey Fomel in collaboration with Jacob Covault and Zoltan Sylvester from the Bureau of Economic Geology's Quantitative Clastics Laboratory. The course provides hands-on exercises with field data to introduce key concepts in machine learning algorithms through their application to geoscience problems. On October 29, a version of this course will be offered to participants of the 17th International Congress of the Brazilian Geophysical Society: https://sbgf.org.br/congresso/short%20courses.php.

Research Highlights

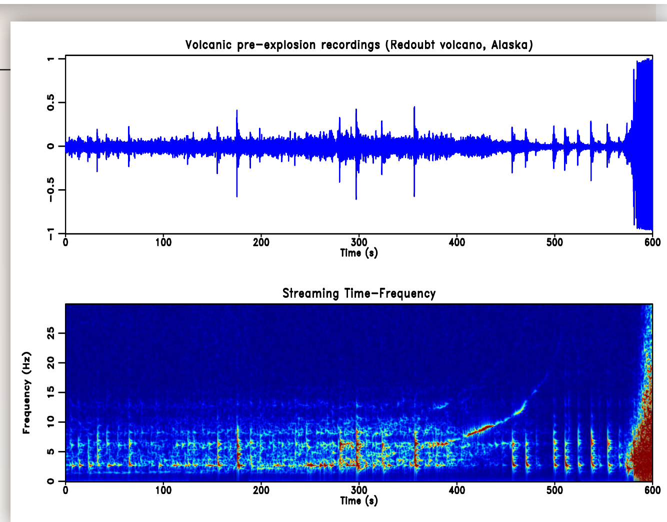
Reem Alomar has been working on a fast and accurate method to estimate the nonstationary triangle smoothing radius for matching seismic data sets. The smoothing radius is estimated by non-linear least-squares inversion using an iterative Gauss-Newton approach. The analytical derivative of the smoothing operator is used to compute the gradient for inversion. The figure shows an application of the method to estimate the nonstationary triangle smoothing constraint for nonstationary local signal-and-noise orthogonalization. Input 2D field data in (a), estimated smoothing radius in (b), estimated signal in (c), and estimated noise in (d).



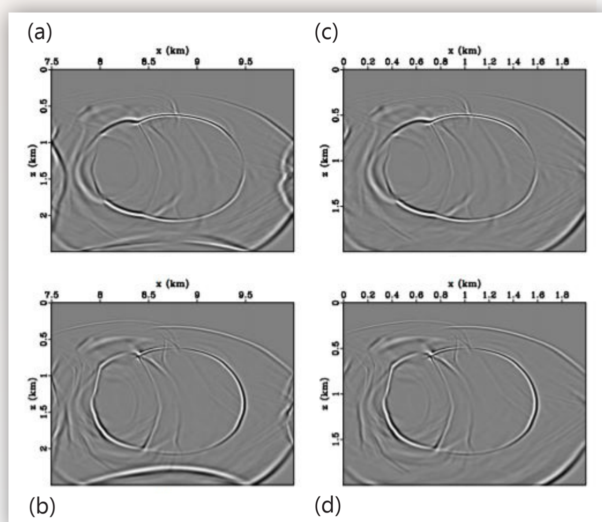
Nam Pham has been working on automatically detecting channel facies and faults simultaneously using an encoder-decoder convolutional neural network. The convolutional neural network is trained with the focal Tversky loss function to easily detect small and thin features such as faults or channel bodies. The workflow also includes the spatial dropout to quantify the model uncertainty and the Grad-CAM algorithm to explain features that the neural network learns in different layers.



Zhicheng Geng has been working on an efficient method for estimating local seismic attributes, including local frequency and local spectrum, using streaming computations. In the proposed approach, the local attributes can be computed by updating the previously calculated attribute value using a single new data point at a time. The proposed method was applied to both synthetic and field data and demonstrated its efficiency and effectiveness to accurately characterize nonstationary seismic signals. The figure shows the time-frequency maps of a volcano tremor (top) and the streaming local spectrum (bottom).



Harpreet Kaur has been working on implementing a deep learning framework to simulate the effect of absorbing boundary conditions for wave propagation in anisotropic media. The network is trained using a few shot locations and time slices, enabling it to learn how to remove boundary reflections and simulate wave propagation for unbounded media. The proposed approach overcomes the challenges associated with stability of conventional implementation of boundary conditions in a tilted transverse isotropic media. The figure shows one of the test slices with horizontal and vertical components of the seismic wavefield in (a) and (b) without absorbing boundary conditions; (c) and (d) with absorbing boundary conditions using the proposed method.



Papers Accepted and Published 2020–2021

http://www.beg.utexas.edu/tccs/publications

Accepted

N. Pham and W. Li, 2021, Physics-constrained deep learning for ground-roll attenuation: Geophysics, accepted.

L. Decker and S. Fomel, 2021, A probabilistic approach to seismic diffraction imaging: Lithosphere, accepted.

S. Gao, J.-P. Nicot, P. Hennings, P.L. Pointe, K.M. Smye, E.A. Horne, and R. Dommisse, 2021, Low pressure build-up with large disposal volumes of oilfield water: A flow model of the Ellenburger Group, Fort-Worth Basin, North-Central Texas: AAPG Bulletin, accepted.

Z. Geng, Z. Zhao, Y. Shi, X. Wu, S. Fomel, and M. Sen, 2021, Deep learning for velocity model building with common-image gathers: Geophysical Journal International, accepted.

H. Kaur, A. Sun, Z. Zhong, and S. Fomel, 2021, Time-lapse seismic data inversion for estimating reservoir parameters using deep learning: Interpretation, accepted.

Published 2021

Y. Chen and S. Fomel, 2021, Nonstationary local signal-and-noise orthogonalization: Geophysics, v. 86, V409–V418.

Y. Chen, S. Fomel, H. Wang, and S. Zu, 2021, 5D dealiased seismic data interpolation using nonstationary prediction-error filter: Geophysics, v. 86, V419–V429.

Y. Chen, O. Saad, M. Bai, X. Liu, and S. Fomel, 2021, A compact program for 3D passive seismic source-location imaging: Seismological Research Letters, v. 92, 3187–3201.

S. Fomel and H. Kaur, 2021, Wave-equation time migration: Geophysics, v. 86, 1JF–V89.

P.H. Hennings, J.-P. Nicot, R.S. Gao, H.R. DeShon, J.-E. Lund Snee, A.P. Morris, and others, 2021, Pore pressure threshold and fault slip potential for induced earthquakes in the Dallas-Fort Worth area of north central Texas: Geophysical Research Letters, 48, e2021GL093564.

G. Huang, X. Chen, J. Li, O. Saad, Y. Chen, S. Fomel, C. Luo, and H. Wang, 2021, The slope attribute regularized high-resolution prestack seismic inversion: Surveys in Geophysics, v. 42, 625–671.

H. Kaur, S. Fomel, and N. Pham, 2021, A fast algorithm for elastic wave-mode separation using deep learning with generative adversarial networks (GANs): Journal of Geophysical Research - Solid Earth, v. 126, e2020JB021123.

H. Kaur, N. Pham, and S. Fomel, 2021, Seismic data interpolation using deep learning with generative adversarial networks: Geophysical Prospecting, v. 69, 307–326.

N. Pham and S. Fomel, 2021, Uncertainty and interpretability analysis of encoder-decoder architecture for channel detection: Geophysics, v. 86, O49–O58.

O. Saad, G. Huang, Y. Chen, A. Savvaidis, S. Fomel, N. Pham, and Y. Chen, 2021, SCALODEEP: A highly generalized deep learning framework for real-time earthquake detection: Journal of Geophysical Research - Solid Earth, v. 126, e2020JB021473.

Y. Shi, X. Wu, and S. Fomel, 2021, Interactively tracking seismic geobodies with a deep learning flood-filling network: Geophysics, v. 86, A1–A5.

Published 2020

B. Engquist and D. Peterseim, 2020, Computational multiscale methods: Oberwolfach Reports, v. 16, 2099–2181.

B. Engquist, K. Ren and Y. Yang, 2020, The quadratic Wasserstein metric for inverse data matching: Inverse Problems, v. 36, 055001.

Z. Geng, X. Wu, S. Fomel, and Y. Chen, 2020, Relative time seislet transform: Geophysics, v. 85, V223–V232.

Z. Geng, X. Wu, Y. Shi, and S. Fomel, 2020, Deep learning for relative geologic time and seismic horizons: Geophysics, v. 85, WA87–WA100.

H. Kaur, S. Fomel, and N. Pham, 2020, Seismic ground-roll noise attenuation using deep learning: Geophysical Prospecting, v. 68, 2064–2077.

H. Kaur, N. Pham, and S. Fomel, 2020, Improving resolution of migrated images by approximating the inverse Hessian using deep learning: Geophysics, v. 85, WA173–WA183.

D. Merzlikin, S. Fomel, and X. Wu, 2020, Least-squares diffraction imaging using shaping regularization by anisotropic smoothing: Geophysics, v. 85, S313–S325.

N. Pham, X. Wu, and E. Naeini, 2020, Missing well log prediction using convolutional long short-term memory network: Geophysics, v. 85, WA159–WA171.

Y. Shi, X. Wu, and S. Fomel, 2020, Waveform embedding: automatic horizon picking with unsupervised deep learning: Geophysics, v. 85, WA67–WA76.

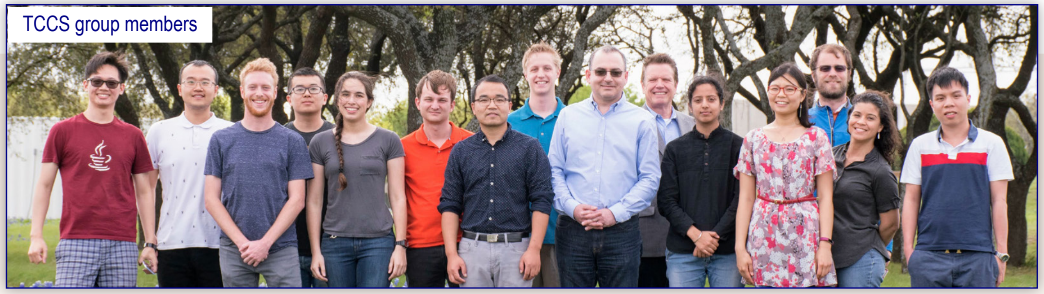
Y. Sripanich, S. Fomel, J. Trampert, W. Burnett, and T. Hess, 2020, Probabilistic moveout analysis by time warping: Geophysics, v. 85, U1–U20.

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: Geophysics, v. 85, WA27–WA39.

Q. Xu, B. Engquist, M. Solaimanian, and K. Yan, 2020, A new nonlinear viscoelastic model and mathematical solution of solids for improving prediction accuracy: Scientific Reports, v. 10, 2202.

TCCS Staff

The TCCS group consists of people from seven countries. Our research staff includes two principal investigators (PI), six Ph.D. students, one M.S. student, one undergraduate student, and two visiting scientists:


TCCS group members

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

Raymond Abma (Visiting Scientist)
Reem Alomar (B.S. 4th year)
Héctor Corzo Pola (M.S. 2nd year)
Björn Engquist (PI)
Sergey Fomel (PI)
Rebecca Gao (Ph.D. 2nd year)
Zhicheng Geng (Ph.D. 5th year)
Ben Gremillion (Ph.D. 3rd year)
Mike Jervis (Visiting Scientist)
Harpreet Kaur (Ph.D. 5th year)
Nam Pham (Ph.D. 3rd year)
Yiran Shen (Ph.D. 5th year)

Testimonials


(Left to right) Tharit Tangkijwanichakul, Dr. Sergey Fomel, and Luke Decker.

Luke Decker

TCCS was a wonderful place to grow and develop as a researcher. The outstanding faculty the University of Texas has in a plethora of disciplines enabled me to take classes directly related to my research interests. The computing resources provided by TACC empowered me to effectively prototype and scale my ideas.

The invaluable mentorship provided by industrial sponsors ensured that my projects were impactful. What is truly unique about TCCS is the collaborative environment, which values ingenuity, integrity, creativity, curiosity, and kindness, bringing together brilliant and compassionate people in a setting where ideas have the opportunity to germinate and can be cultivated to blossom.

Tharit Tangkijwanichakul

TCCS is a unique place for training in seismic processing and imaging. The way TCCS operates, especially the use of Madagascar, has provided a niche for students: it encourages us to open the black box of computational algorithms.

I find that habit persists although now I'm using commercial soft-ware for work. It has been quite an edge to be implanted with this insatiable curiosity in a technical matter and know a little more than just button-clicking.

Of course, the TCCS people are fantastic. My impression is that it was the time when I could ask practically any technical question and could expect a high-quality and supportive answer or discussion, no matter how naive the question was, especially in retrospect.

GPU Workstation

For GPU-intensive deep learning applications, TCCS is using a workstation from Lambda Labs with two NVIDA RTX 3090 GPUs and 32 AMD Threadripper 3970X cores.

TACC Celebrates 20 Years

TACC researchers also use super-computing facilities provided by the Texas Advanced Computing Center (TACC) at UT Austin, which is currently celebrating 20 years in existence. From its humble beginning, TACC grew into the largest academic provider of high-performance computing resources, as well as training for students in scientific and parallel computing. Frontera, TACC's Dell C6420 system with 448,448 Intel Xeon cores and 23.5 Pflops/s performance, is currently listed as the world's 10th most powerful supercomputer. Maverick2, another TACC supercomputer, is dedicated to GPU-accelerated machine learning applications.

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