Quantitative characterization and monitoring of reservoir properties, pressures, fluids and fractures with multicomponent, quasi-continuous full-waveform seismology

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ABSTRACT

Full waveform (FWI) seismic methods have achieved spectacular industrial and academic successes in image-forming of complex offshore reservoirs, but as practical, regular-use tools for monitoring of onshore conventional and unconventional production, CO2 and wastewater injection, and EOR methods, basic and applied scientific progress is still required. Fortunately, in aid of making such progress, geophysicists now have at hand powerful new geo-computational tools, in the form of HPC and artificial intelligence technology, and powerful new instrumentation and seismic acquisition tools, in the form of permanent controllable sources, broadband geophones and distributed acoustic sensing (DAS, or fibre-optic) seismic sensors, and drillstring acoustic technology. We propose to create the next generation of practical, FWI reservoir characterization and monitoring tools, involving the determination of high resolution maps of rock physics properties – pressures, fluids, fractures and viscosities – through analysis of the elasticity, viscosity, and anisotropy of the complex modern reservoir environment. Our group has carried out significant, though initial, research in broadband and fibre-optic field and laboratory acquisition, practical multi-parameter elastic, viscoelastic and anisotropic FWI method development, rock-physics seismic inversion, near surface characterization, drillstring imaging, machine learning, and HPC methods for large computation/data problems. We propose to grow and expand these early successes, creating a practical reservoir waveform package. FWI involving multicomponent and DAS data, elastic FWI-rock physics sensitivity analysis, surface wave analysis and processing, machine learning for seismic inversion, and new blended acquisition / deblending methodologies, are key outcomes of the research. These efforts will bring about knowledge and technology creation in high-resolution geological mapping. This benefits Canada through technical HQP training, and research with outcomes (high resolution surveillance capabilities) that directly affect resource extraction efficiency, geohazard mitigation, and which contribute to reduction of land, water, and energy use.

INTRODUCTION

Note: what follows is the text component of a proposal CREWES has submitted to the NSERC Collaborative Research and Development (CRD) program for a 5 year grant, matching CREWES sponsor dollars and in-kind support (subject to several restrictions, e.g., that partnering companies must have a significant Canadian footprint). The CRD program is ending, and in fact our proposal was submitted only a few days before the deadline for the last submissions. A new program has been put in place, which CREWES will likely submit proposals to in the future. A high volume of applications to the CRD program as it ended has led to a longer than normal delay in the evaluation of the proposal, according to communications from NSERC. We anticipate based on these communications that the evaluations of our proposal will be complete in late 2019 or early 2020. We are *currently not assuming a commencement of the grant until well into 2020.*

We propose to create a set of new seismic imaging and inversion methods, by combining advances in three areas of seismic geoscience: (1) new acquisition technology based on fibre-optics and distributed acoustic sensing, alone and in combination with broadband sensing; (2) methods for determination of subsurface elastic properties through new formulations of seismic waveform inversion; and (3) development of data analysis/processing methods within newly available computational hardware (including GPUs) and software (including machine learning). In addition, identify two key technology areas that act both as supports for and beneficiaries of these goals. These are (1) near-surface geophysical characterization and (2) seismic-while-drilling and other drillstring and subsurface source imaging methods. We have assembled a group of six co-investigators, each part of or collaborating with the Consortium for Research in Elastic Wave Exploration Seismology (CREWES) research group, which is well positioned to complete this program over the 5 years of the grant.

We are at a pivotal time in the development of seismic technology for exploration and monitoring of hydrocarbon production, enhanced oil recovery, geo-hazards, and CO2 and wastewater injection in geological reservoirs. A surge in research and development of seismic instrumentation, acquisition, data processing, model inference and quantitative interpretation techniques has recently taken place. This is timely, because in oilsands and tight rock resource plays in 2019, to attain real industry relevance it is insufficient to provide seismic monitoring tools that simply delineate reservoir structures (Gray et al., 2016); we need to understand the temperature and distribution of mobile bitumen, and where to best expend water and energy resources on additional steam. We need to identify fracture orientations and weaknesses, and the presence, absence, and type of fluids, and their changes after multiple stages of hydraulic fracturing. We need to identify changes in the state of pressure within reservoir rock and identify potential for failure of the cap-rock and of well-bore integrity. We need to establish the susceptibility of the reservoir volume as a whole and nearby infrastructure to damage from induced seismic events. 3D seismic technology is the only means of characterizing the subsurface with images on a 10km scale with 10m resolution. The question is, can it also provide for these modern, more complex reservoir characterization needs, helping to guide drilling and reservoir engineers? Gray's result is suggestive that, with maximal use of the information content of seismic data, the answer is probably yes – but there is work to be done. The main goal of the 5-year research plan outlined in this proposal is to take maximally high-impact steps towards doing so. Extracting more from seismic data is possible, if we move beyond analyzing partial seismic information (i.e., travel-time and amplitude), and work to explain the data more completely. This effort can be divided up into two categories: first, in which we seek to more completely use data information whose origins we understand, and second, in which we seek to identify and use patterns in the data of which we are unaware. In seismic research today, the exemplar of the first of these is referred to as Full Waveform Inversion (FWI). The exemplars of the second of these are the range of methods referred to as Machine Learning (ML) or Deep Learning. Formulating seismic FWI and ML algorithms, solving the geo-computational problems they involve, and bringing new instrumentation, auxiliary experiments, modelling and acquisition methods together to support them, is the heart of this proposal.

In FWI an attempt is made to construct elastic models of the subsurface matching not only arrival times and amplitudes, but the full amplitude and phase information of the measured waveform data. FWI, like seismic technology in general, is at an important developmental stage. In offshore reservoir imaging FWI has achieved an unusual degree of recognition. In April 2017, and again in January 2019, BP in various press releases, quoted the chief executive of global upstream business and the head of upstream technology, referring to the technology as having created the "best images of this [Gulf of Mexico] reservoir we have ever seen." No fundamental limit exists to stop FWI from generating similar value on land and in unconventional reservoirs. However, basic science and non-incremental steps have to be taken before FWI becomes a game-changing technology in US tight oil plays, and Western Canadian oil sands plays, where guiding, measuring, monitoring and validating production, and EOR and CO2/wastewater injection, with high resolution monitoring capability would have a significant impact. In FWI one attempts to recover the physical properties of the subsurface by iteratively minimizing the difference between observed and modeled data generated from the current estimate of the subsurface (Lailly, 1983; Tarantola, 1984; Virieux and Operto, 2009). In principle, FWI is applicable to elastic wave data (i.e., seismic measurements involving more than one component of displacement or velocity) as a means to simultaneously determine three (isotropic-elastic), five (isotropic-viscoelastic), or more (e.g., various anisotropic) parameter distributions in the subsurface (e.g., Tarantola, 1986; Sears et al., 2010), in standard or nonstandard (e.g., Vertical Seismic Profile) configurations (Podgornova et al., 2015). Field examples and feasibility studies of land FWI do exist, in fact applications to problems in reservoir characterization and time-lapse have been reported (Prieux et al., 2013; Raknes and Arntsen, 2014). However, a set of challenges remains. The most serious technical hurdles for practical FWI (computation, source characterization, near-surface/topography, data signal-to-noise ratio and bandwidth) are greatly magnified in land environments. Also, sampling and offsets in land are generally irregular and limited, and these issues (particularly offset limitations) cause critical FWI problems (e.g., local minima). The character of multi-parameter FWI can change dramatically when different parameters or model of wave propagation is adopted; every application is in many ways new. "Good" field multi-parameter elastic FWI results, which do exist, and which have been reported for over 20 years (e.g., Minkoff and Symes, 1997; Pan et al., 2018), tend to be rare, and are tied to "good" datasets, whose goodness is difficult to systematically reproduce. Furthermore, elastic FWI is not typically formulated such that it directly solves the pressing questions of un-conventionals, as set out above. The HQP brought onboard as part of the proposed project will work towards formulating, and validating, with custom acquired datasets, FWI methods which are focused on reservoir specific goals.

Artificial intelligence, ML, and data science have, like FWI, grown rapidly recently. Almost overnight they have taken on a dominant role amongst practicing geophysicists, to go by the session attendance rates of the 2018 Society of Exploration Geophysicists (SEG) Annual Meeting. ML has so far had its greatest geophysical successes within data-rich problems such as facies-classification (Guarido et al., 2018). Fully data-guided activities of this sort seem on the cusp of providing many powerful practical geophysics technologies. However, and this has been pointed out elsewhere (e.g., Karpatne, 2017), a more useful view is that data-guided investigations are one end of a continuum which includes theory-guided investigations (in which data are interpreted as, for instance, samples of fields which satisfy known differential equations) as the other end-member. In the "theory-guided" paradigm, patterns in the data are determined in part by known, and in part by unknown, physics. Downton and Hampson (2018) have presented a compelling approach lying on this continuum, by co-training a reservoir prediction model with real data and with data arising from a physical model of reflection. This motivates us to plan to develop advanced analytics as a means to support waveform methods in seismic monitoring. It connects immediately to our current research into anelastic and anisotropic seismic amplitude inversion for fluid and fracture properties (Chen et al., 2018a,b,c), and is suggestive that full waveform methods may also avail themselves of support from ML. We have taken an initial step into understanding the linkages between FWI and ML. Our group has recently set up FWI as a special case of a recursive neural network ML method, wherein, during training, the iterative determination of the network weights, which represent medium velocity parameters and structures (Sun et al., 2018). In the sense that the weights are co-determined by data and by the assumption that the wave equation holds, this is another example of theory-guided data science applied to seismic inversion. We will expand and explore this important relationship. In particular, we will investigate the ability of this waveform inversion network to determine not only the parameters of the subsurface, but which physical model is optimal. A consequence of our efforts in research in this area will be an expanded ability for the HQP and researchers in our group to grow our capacity for training Canadian geoscientists in geophysical applications of these now indispensable data science / analytics tools. Our research group is in a strong, and unique, position to design, acquire, process, and then analyze field seismic data in custom experiments. This capacity has increased in recent years through our close collaboration with the Containment and Monitoring Institute (CaMI) within Carbon Management Canada (CMC), which is directed by one of the co-investigators on this grant (details below). CaMI maintains a field research site (FRS) near Calgary in Newell County, AB, at which infrastructure for injection of CO2 into two shallow formations has been set up, along with infrastructure for advanced geophysical monitoring. We have carried out a pilot WVSP survey combining fibre-optic sensing and broadband geophone sensing at the CaMI-FRS, leveraging existing infrastructure (observation wells, fibre-optic cables in horizontal trenches and behind borehole casing). CREWES ability to design and acquire full seismic datasets, leveraging the infrastructure of the CaMI-FRS and existing characterization of the site, adds a capacity to validate the theoretical, computational and methodological advances in this proposal which we believe is not duplicated elsewhere.

Focused research areas

We have separated the key scientific and technical obstacles and challenge-areas obstructing next-generation methods like FWI from practical reservoir monitoring, into six major categories.

Continuous, broadband, low-cost seismic acquisition

We will leverage several aspects unique to our investigators: the ability to acquire custom seismic data, to design seismic physical modelling surveys, and to access a field test site in which CO_2 injection is ongoing. Our plan includes acquisition of fibre-optic, broadband 3C, and nodal 3C sensor data, and analyze data from permanent seismic sources. Data arising from these will support reservoir FWI/ML/analytics research.

Subsurface anisotropy and viscoelasticity with full waveform inversion

Many questions are open regarding formulation of elastic-anisotropic-viscoelastic FWI. Our group is in a strong position to examine these in the context of unconventional reservoirs. HQP will study parameter resolution, modelling errors, computation, incorporation of novel datasets (i.e., DAS data), and auxiliary data (well-logs).

FWI and reservoir properties: fluids, fractures and rock physics

As robust FWI is developed, we will connect them with the actual reservoir parameters relevant to fluids, fractures, temperatures, viscosities, and pressures which are usually connected to elastic properties, and thence to seismic data. We will examine short-circuiting this approach, bringing rock physics parameters directly into FWI. This will lead to model construction and also appraisal tools.

Geo-computation: simulation, iterative imaging and machine learning

Each problem we consider has a geo-computational aspect. FWI is computationally intensive, requiring many wave simulations. ML invokes iterative optimization methods, generally on large datasets. 3D seismic data volumes are very large. We will investigate optimizing large simulations in CPU, GPU, and cloud-based programming, characterization of ML algorithms, and advance theory-guided ML for reservoir monitoring.

The near surface: seeing the reservoir through it, and the geohazards within it

The upper 10-100m of the subsurface affects the propagating wave in a complex manner. This must be accounted for to analyze the waveforms interacting with reservoir geology. We will compare and analyze novel seismic, electrical, and joint seismic-electrical geophysical methods, with the aim of predicting/removing near surface effects, including slow-moving and aliased waves. This project, which supports the FWI research, will build from Lauer's existing geo-hazard detection research.

New raypaths: seismic monitoring of the smart reservoir

Drillstring seismic technology is being analyzed and developed by Shor. We will use these seismic sources to enrich the raypaths illuminating the subsurface. Seismic while drilling data can be incorporated within iterative imaging to sharpen reservoir images. We will extend this to base it on FWI, building from the other parts of this research, and in doing so generate several benchmark laboratory scale seismic-while-drilling datasets.

Detailed proposal

Continuous, broadband and low-cost seismic acquisition

The goal of making more complete use of waveform information in seismic exploration and monitoring is not achievable without vigorous research in: seismic sensor design, sensitivity testing, source design, and analysis of sampling, bandwidth and repeatability in field experiments. We refer to this broadly as seismic acquisition. Several acquisition technologies have very recently become available for testing and appraisal, each of which could increase the feasibility and potential of waveform methods. Distributed Acoustic Sensing (DAS) involves the rapid measurement of strain or strain-rate along a fibre-optic cable through pulsed laser light. The pulsed laser light is sent from and measured at a specialized acquisition system referred to as an interrogator. Because seismic motions involve strain perturbations, as a wave passes a DAS fibre, the fibre acts as a quasi-continuous sensor (Kuvshinov, 2016), and DAS acquisition systems are now generating seismic records that are comparable to standard geophone systems (Parker, 2014). Industrial investment into DAS research has been significant, spurred by the possibilities of low-cost production monitoring (Chalenski et al., 2016) and microseismic monitoring; academic applications are also growing in number, with applications in earthquake monitoring (Lindsey et al., 2017), ambient noise (Ajo-Franklin et al., 2015), and traffic monitoring (Martin et al., 2016). However, serious bottlenecks exist, particularly cost (Chalenski, 2016), directionality (Mateeva et al., 2012; 2014), and sensitivity (Daley et al., 2013). The issue of increasing the sensitivity and thus signal-to-noise ratio of DAS measurements is the subject of intensive industrial research at present (Correa et al., 2017). The directionality issue is traceable to the fundamentals of DAS measurements. DAS fibres are sensitive to axial strain only. Seismic P-waves incident broadside on DAS fibre, for instance, cause a weak signal because they carry strain orthogonal to the sensitivity direction (Kuvshinov, 2014). Currently the main approach to addressing directional insensitivity is to introduce shaped fibres, for instance the Helical-Wound Cable or HWC (Mateeva et al., 2014). However, shaped DAS fibres introduce new questions. If a complex wave impinges on a fibre with a complex geometrical shape, and if the data are to be analyzed quantitatively, precisely what has been measured becomes a difficult question. A geometrical DAS sensing model designed to answer this question has been introduced (Innanen, 2017a), and used to set up multicomponent sensing (Innanen, 2017b) and to distinguish wave modes (Innanen and Eaid, 2018). The model has also been coupled to a 3D anisotropic finite difference wave simulation model (Eaid et al., 2018), and used to simulate the response of an arbitrary DAS fibre to an arbitrary microseismic focal mechanism (Eaid and Innanen, 2018). Concurrently, our group in collaboration with CaMI has carried out a range of sensitivity tests and DAS-geophone comparison tests for both vertical borehole and horizontal trenched fibre. The directionality question has led to the design, deployment and initial validation of the first ever prototype multicomponent DAS sensor loop (Innanen et al., 2019). We now propose to build on this, to carry out research projects in which DAS and its potential play a decisive role. First, DAS may be a powerful complementary dataset to support elastic FWI in addition to standard 3-component geophones. Elastic FWI requires high fidelity, densely sampled and broadband (especially low frequency) multicomponent data. Current DAS technology produces measurements which (a) are relatively low SNR, single-component, and have directionality restrictions; but (b) are inexpensive, spatially quasi-continuous, and with a clear low frequency response. Current multicomponent seismic sensor technology is multicomponent and has a high SNR, but has limited sensitivity below 3-4Hz and is expensive to sample densely. Thus, neither DAS nor standard 3C phones alone supply all that FWI requires; but together, they do. We will investigate various formulations of joint FWI in which residuals determined from the two concurrently acquired datasets are reduced simultaneously.

DAS will form an important aspect of our full 5 year plan for field seismic research. In September of 2018, we designed and carried out a large walkaway-walkaround VSP experiment in collaboration with CaMI. This dataset will enable several of the research projects at the outset of our proposed research; refinements and repetitions of the survey to enable time-lapse research will occur roughly yearly. The CaMI-FRS has shown signs of requiring anisotropic and viscoelastic models for its full description. These datasets will support the research projects and HQP engaging in multiparameter FWI (see Section 3.0). The deployment of the prototype multicomponent DAS sensor, a loop of fibre with well-characterized segments along various lateral coordinate directions (Innanen et al., 2019), will also be expanded. The design derived from theoretical research we have carried out showing that such loops have the capacity to determine up to 6 independent components of strain in the output traces (Innanen, 2017). If sensor loops can be designed without dramatically increasing the cost of deployment, this approach could expand DAS to include multicomponent sensing. Multicomponent data being critical to elastic FWI, this step if successful would close the loop on the use of DAS data to support FWI. We propose to carry out a systematic seismic illumination of the prototype sensor system now in place. Several theses will arise from the use of these data to create multicomponent DAS workflows. As the gauge lengths available in DAS acquisition through our industry partners reduces, smaller versions of similar DAS loops will be deployed at the CaMI-FRS.

CaMI (of CMC Research Institutes Inc.), in conjunction with the University of Calgary, has developed a comprehensive Field Research Station (FRS) in southern Alberta, Canada, to facilitate and accelerate research and development leading to improved understandings and technologies for geological containment and secure storage of CO2 (Lawton et al., 2019). The injection at this pilot site is designed to simulate leakage of CO2 from a deeper and larger reservoir by being injected at shallow depth (300m). CREWES has been closely involved in seismic surveys that have already been acquired to characterize the subsurface and will be used as baselines for the monitoring of CO2 injection (Isaac and Lawton, 2016). CaMI and CREWES are now developing new seismic technologies to monitor the CO2 injection program, with an emphasis on time-lapse seismic analysis. Changes in rock properties through fluid substitution impact seismic velocity and density of the target formation which can be detected as a change in the reflection amplitudes between baseline and monitor surveys (after gas injection) (e.g. Lumley 2010). Numerous papers demonstrate the potential of using 4D seismic to monitor the evolution of the gas plume in a large-scale CO2 reservoir (e.g. Lawton, 2009; Ivanova et al. 2012; White 2013; Roach et al. 2017). The CaMI site has already been instrumented with optical fibre for Distributed Acoustic Sensing (DAS) in wells and in a 1.1 km long trench. CREWES has participated in several VSP DAS surveys, yielding promising baseline images of the target reservoir around the CO2 injection well (Gordon et al., 2018; Hall et al., 2018). Recently a new, permanent seismic source has been installed at the CaMI site (Spackman and Lawton, 2018) that will enable rapid and frequent time-lapse VSP surveys to be undertaken, leading to a new paradigm of continuous seismic monitoring. This facility available to CREWES through collaboration with CaMI will enable testing and real data applications of research described in Sections 3-4, for imaging subtle changes in the injection reservoir after CO2 injection. We envision this being the starting point for research into dedicated sparse and quasi-continuous low frequency sources for FWI. Our research group has the capacity to explore sampling design in acquisition, both with the aim of supporting new inversion methods and of reducing cost. One way by which geophysicists can decrease the acquisition costs is by simultaneous shooting (Beasley et al. 1998, Beasley 2008, Berkhout, 2008, Abma et al., 2015). Acquiring such data brings, however, difficulties because most processing algorithms use a unique source location, either by working on shot gathers or other groups derived from acquisition coordinates. To process blended data, it is necessary to either separate the information coming from different shots, which is known as "de-blending", or redesign the processing flow to process blended data. When these are stably in place, reductions in sampling requirements can occur. The first approach is common because many standard de-noising tools can perform deblending. However, these techniques often use data properties that are not well defined before processing. For example, methods based on coherence may not work in raw data before static corrections. Deblending tools have some similarities with those of regularization/interpolation. In fact, deblending can be handled with standard sparse transforms (Sacchi and Ulrych, 1995, Trad et al., 2003), also known as compressive sensing (CS) (Lin and Herrmann, 2008), or interpolation (Cheng and Sacchi, 2015). The main difficulty comes from its occurrence at the outset of processing, before denoising/statics. An approach that may be more robust but which requires prior information is migration-demigration. An additional complication comes from an extension to elastic (converted wave) data. In marine acquisition, ocean bottom nodes (OBN) have significantly improved the quality of 4D surveys. Similarly, in land acquisitions, 3C-3D data are increasingly in demand. For elastic processing, improving the sampling by interpolation and/or regularization is difficult because of midpoint approximations, which in elastic data are time variant. Motivated by these considerations, we will investigate deblending for acoustic and elastic data, for 2D and 3D land surveys and marine OBN. We will examine three different approaches:

1. The denoising approach: data are sorted in domains where the blended energy is random (Moore et al, 2008, Mahda et al, 2011). Blended energy is the signal coming from a shot whose location is not the one used in the processing coordinates. This approach is straightforward but limits data/geological complexity. We will investigate this approach in different surveys and geological models. In particular we will look at different shooting schemes and processing dataflows.

2. The inversion approach: a sparse transformation maps blended data to a domain where a few coefficients represent the bulk of the signal. The inverse transform maps back to the deblended data space, effectively inverting a blended matrix (Berkhout et al., 2008, Abma and Yan, 2009). These techniques are referred to as "compressive sensing" (Candes et al. 2006, Lin and Herrmann, 2008), but they are mostly an evolution of multidimensional interpolation / regularization (Liu and Sacchi, 2004, Trad, 2009), where the sampling operator is generalized to a blending operator. A promising approach is low rank or Singular Spectrum Analysis, or SSA (Cheng and Sacchi, 2015). We will implement and compare deblending with Fourier and SSA.

3. The migration/demigration approach: like inversion but with a more complex transformation that uses all prior information. Typical transformations are migration/demigration algorithms and least squares migration (Trad, 2003, Trad et al., 2012, Ibrahim and Sacchi, 2014, 2015, Trad 2015). We will investigate this approach for Kirchhoff and Reverse Time Migration operators.

Subsurface anisotropy and viscoelasticity with full waveform inversion

The first major step needed to set up multi-parameter FWI for reservoir analysis is to formulate and practically apply extensions to elastic FWI incorporating anisotropic and viscoelastic models, i.e., such that some combination of elastic-isotropic (e.g., VP-VS-density), anisotropic (e.g., Thomsen parameters), and viscoelastic (e.g., QP-QS) parameters are determined from data; we will refer to this as AVFWI. Formulations of these exist, but general results and guidelines on how to implement them, re-parameterize them, and apply them practically from one dataset to another do not. In the next section we will discuss alterations for direct application to reservoir problems; here we will discuss solving AVFWI formulation problems for, and field trials of, several different experimental configurations, surface, Vertical Seismic Profile (VSP), Walkaway VSP (WVSP), and WVSP with DAS. Three-parameter isotropic elastic FWI algorithms have been in existence as long as FWI itself (e.g., Tarantola, 1986). However, there exist only a small number of compelling field cases in which the waveform information clearly produced model information of value (e.g., Minkoff and Symes, 1997). Although 3-parameter isotropic FWI does not directly connect to the physical mechanisms of importance in unconventional reservoirs (viscosities, fracture directions, etc.), it connects seismic data with reservoir rock physics (e.g., Russell et al., 2003; 2011), and it is the simplest possible seismic wave model within which multicomponent elastic data can be explained (see, e.g., Foster et al., 2010). Our group has recently generated one of the small number of isotropic-elastic field data examples whose results are clearly correlated with expected rock physics models (Pan et al., 2018); this was carried out on a WVSP data set co-acquired by our group and an anonymous company over a producing Western Canadian heavy oil field. We have carried out feasibility studies regarding the use of well-log data to calibrate acoustic FWI updates in the absence of long-offset data (Margrave et al., 2011; Romahn and Innanen, 2017; 2018), and will as part of the proposed research now validate applications of the approach to field data (Romahn, 2019). Through various industrial collaborations, we have produced some of the first practical workflows for field application of elastic FWI (Pan et al., 2019; Cova et al., 2019). These are promising, but they amount to first steps only. In particular, the 1-parameter nature of the method of Romahn, though successful, must be extended to 3-parameter elastic. We will develop and validate well log-calibrated isotropic elastic FWI. Log-validated FWI, because of its apparent robustness, will also the basis for our first foray into time-lapse FWI. Time lapse FWI (e.g., Yang et al., 2015) puts a high demand on repeatability and data uncertainty, and the computational speed, use of pre-critical reflection data, and stability of log-validation, gives this the best chance of success.

There are close relationships between multi-parameter FWI and AVO inversion (Innanen, 2014); the latter guides the creation of more complete versions of the former, and provides insight into feasibility. Standard amplitude inversion methods will play an important role in our proposed research. Recent efforts indicate that determination of reservoir-scale parameter classes, in particular anisotropic-elastic, are critical for characterization (e.g., Chen et al., 2018a; b; c). We propose to formulate amplitude methods along the lines of Chen, and and from this base move into the FWI determination of reservoir anisotropic properties and thence fracture characteristics. Our 2018 W-VSP field data set, which we will repeat and add to over the course of this proposed research both to monitor time lapse changes and to refine our methods, has been shown to contain non-negligible azimuthal anisotropy (Hall et al., 2018; 2019). Early FWI work within our group (Pan et al., 2019) suggests that multicomponent W-VSP data containing evidence of anisotropy (in Pan's case, VTI) can be practically incorporated into a multi-parameter FWI algorithm to create interpretable results. This motivates a plan to include the azimuthal component of anisotropy at the CaMI-FRS using the W-VSP data as the next step. The creation of practical elastic FWI should be thought of as a problem in toolbox construction. A practical FWI algorithm, able to handle a large number of sources and a high-resolution model, will often require a time-domain approach. The elastic VTI-FWI result of Pan et al. (2019) is an example of time-domain FWI. However, in order to investigate the parameter resolution of VTI-FWI (or TTI-FWI), frequency-domain methods are also critical. As we create various types of elastic FWI algorithm, each of which can be realized in these two different ways, and each of which can involve a range of different optimizations, e.g., Truncated Newton (e.g., Metivier et al., 2015), it is evident that we will require a range of forward modelling and simulation tools. We have been active recently to develop these especially for use in FWI workflows.

Next, although anisotropic parameters are the most high impact components of the Earth model needed for reservoir characterization (for fractures, fluids and pressures), FWI for land unconventional reservoirs must address attenuation, because of the impact seismic Q has on amplitudes and waveforms, and because of the variability of its mechanisms. Our group has analyzed several aspects of the viscoacoustic and viscoelastic FWI problem (Keating and Innanen, 2017; 2018; Pan et al., 2019). This has been geared towards understanding cross-talk between the most heavily coupled parameters, VP and QP (e.g., Hicks and Pratt, 2001; Innanen and Weglein, 2007; Mulder and Hak, 2011; Malinowski, 2011; Kamei and Pratt, 2013; Metivier et al., 2015; Plessix et al., 2016). We have formulated multi-scale acoustic frequency-domain QFWI such that discrepancies between the assumed and actual attenuation mechanism cause minimal error (Keating and Innanen, 2017a; b; Keating and Innanen, 2019). With this approach in hand, we propose to extend this to the isotropic-viscoelastic case, to analyze the fundamental problems of (1) resolving QP and QS models, and (2) protecting model estimates of VP, VS and density from leakage due to attenuation and dispersion. One of the major conclusions of the isotropic-elastic WVSP example (Pan et al., 2018) was that significant data residuals remained in the final simulated data because of strong QP and QS in the near-surface, which agrees with standard attenuation analysis (Montano et al., 2015). That same data has been used for practical viscoelastic FWI (Pan et al., 2018; 2019). The formulation of Keating and the procedure of Pan must now be brought together to produce a practical, cross-talk suppressing FWI. We will carry this out such that the proposed CREWES-acquired surveys validate the waveform determination of QP/QS.

Subsurface anisotropy and viscoelasticity with full waveform inversion

A standard approach to seismic interpretation involves an inversion step, wherein seismic amplitudes are used to infer impedances, followed by an interpretation step, wherein these intermediate quantities are used to infer lithological and rock physics parameters. Recent efforts have been made to progress this science with at least two broad approaches: first, with more complex models (beyond isotropic-elastic) within standard AVO inversion workflows, and second, by avoiding the serial process of inverting seismic amplitudes, and then inverting these for rock physics properties: instead, developing direct relationships between rock properties and data (Goodway, 1997; Russell et al., 2003; 2011). Our group has recently focused on the first of these, by incorporating anisotropy and viscoelasticity into the physics, and incorporating rock physics models to determine fracture weaknesses, pressures, fluids, and integrated attenuation factors (Chen et al., 2018a, 2018b, 2018c). However, the first approach has admirable traits, amongst which is the provision of qualitative insight into the character of the problem. Because of its directness, the AVO formulation of Russell and Gray (2003; 2011) not only estimates the numerical values of the fluid term, but it also tells us directly about the sensitivity of a particular seismic experiment is to the fluid property. The first approach, in other words, comes with an internal appraisal mechanism in addition to providing the numbers in a model. A larger question, relevant to these developments, was recently posed, and partially answered, by Gray et al (2016). How do we ensure that our seismic technology solves problems we actually face in unconventional reservoirs? The answer Gray and co-authors provided was that rock physics modelling alongside maximally complete seismic data (including 3C, and time-lapse coordinate), led to powerful prediction and monitoring technology.

In light of these remarks, and of the part of our research program described in Section 3.0, three natural research directions arise. First, rock physics properties, and lithological facies, are currently determined using reflection amplitude information and an amplitude-variation-with-offset approach, and not full waveform information. Can we formulate FWI algorithms which do something similar? This has been discussed in terms of FWI with lithological and/or petrophysical constraints included either explicitly (Rocha and Sava, 2018) or via regularization (Kamath et al., 2017). However, in existing approaches, the updating and the sensitivities underlying it, remain in terms of elastic coordinates VP, VS and density. Theoretical and computational FWI algorithms generated by our group (Innanen, 2015, Keating and Innanen, 2018a,b) have been specifically designed to accommodate any variant or re-parameterization of the elastic problem. This plays a critical role in reservoir model construction (Pan et al., 2018a;b). This can be the starting point for an FWI version of reformulating amplitude modelling in terms of new parameters, e.g., those of Russell and Gray, or of Goodway. In such a formulation, the actual updating and parameter resolution analyses are carried out directly in terms of rock-physics relevant properties. A key step in our proposed research is to implement elastic FWI in these terms, leading to reservoir rock physics model-building, but also methods for sensitivity and parameterization analyses along the lines of those our group has assembled for elastic FWI. Second, the issue of mixing rock physics modelling with 4D seismic. We propose to incorporate a time-lapse dimension to these method developments, such that the constraints such as temperature and mobility of bitumen from seismic would derive from FWI. This would realize Gray et al.'s philosophy. The third natural research direction has to do with the practicalities of involving time-lapse analysis in elastic land FWI. The robust and practical form of FWI as introduced by Margrave et al. (2011) has been developed and refined to the point where meaningful results are being derived on land field data example; see earlier discussion of the work of Romahn (2017; 2018). Observation of the robustness of this procedure motivates us to choose this as a practical FWI formulation to be set up in a time-lapse form. In the proposed research, we will investigate the use of well-logs as supporters of baseline FWI only. We will make use of the CaMI-FRS infrastructure, CREWES acquisition capacity, and the CO2 injection (see Section 2), for a set of field experiments supporting algorithm development.

Geocomputation: HPC, modelling, inversion and machine learning

In solving the above problems, and those of the coming sections, computation plays a key role, both because the calculations and simulations are resource intensive, and because the datasets are very large. To deal with large volumes of data, geophysicists have developed many different approaches to simplify processing and inversion. A common example is the subdivision of data into groups that can be processed as units, either physical (e.g., shot gathers), or practical (windows, common midpoints, offset gathers). This involves several approximations that more complete methods avoid; e.g., interpolation, which was performed in groups until the last decade, when 5D interpolation came online (Trad, 2009). In more complex processing tasks it is difficult to use the full dimensionality of the seismic data. 3D migration algorithms, for instance, take days to complete even in powerful computer clusters. Adding to the computational burden, modern migration is often performed iteratively, optimizing data fit (Tarantola, 1984). Least-squares migration (LSMIG) can take 10 times longer than migration, and FWI can take 10 times longer than LSMIG. Thus, most academic work is done on synthetic 2D data sets. Practical application and validation of novel techniques in industry requires extending these algorithms to 3D, which is a key disconnect between academic and industry seismic research. We will reduce this gap, taking advantage of advances that computer science has brought through parallelism (cloud computing, clusters, graphical processing units or GPUs). These make full 3D versions of seismic algorithms possible for academia, to a degree. However, the use of parallel resources comes at the cost of more complexity in programming, a field known as High-Performance computing (HPC). Using distributed memory architectures introduces overhead in programming time, skill-development and debugging. Coding for GPUs introduces even greater difficulty, often requiring a complete re-writing, debugging and optimization of existing serial code. We will expand our efforts to make these skills available to HQP through efficient parallel software development training with compiled languages and development of reusable parallel libraries. On the other hand, high-level languages (e.g., Python, Julia, Matlab) use abstraction techniques to facilitate the use of optimized libraries and are convenient for certain types of computations, like Machine Learning (ML). Therefore, in addition to geo-computation research using efficient low-level coding (for, e.g., large data iterative inversions), we will include effort in HPC using high-level languages for ML and data mining applications. These two goals are essential for several projects in this proposal; below as exemplars we describe a few specific directions.

Low-level geo-computation is critical for least squares inversion techniques, which are used for estimation of reflectivity, velocities, and elastic parameters (LSMIG and FWI). The most computationally expensive aspect of these calculations is the forward modeling of data to be compared with the acquired data. This modeling is performed either in the time or frequency domains; each has its own advantages / disadvantages. In the time domain, parallel data decomposition permits several seismic gathers to be computed simultaneously, reducing time by factors of 10-100. Alternatively, the subsurface can be divided into blocks through model decomposition, which although slower than data decomposition because of communication overhead, permits inversion of large models. Model decomposition is more common in the frequency domain, where parallel solvers are required for the large matrix equations (Virieux et al, 2009). We will continue developing model and data decomposition data-flows for its use in large computations. Although computer science has provided geophysics with the means to realize these computations, challenges remain to perform them correctly. Iterative techniques use differences between predicted and acquired data to calculate update gradients. This assumes that errors in the data prediction can be reduced by changing the magnitudes calculated during the inversion, and by ignoring modelling errors (Schuster, 2017). Unfortunately, data components often cannot be properly predicted without incurring large computational expenses. There is a continuous trade-off between proper modeling of the acquired data and practical calculation. The accuracy of modelling operators, and the degree towhich they approximate reality with (e.g.) elasticity, attenuation and anisotropy, are the most important factors that limits accuracy of inversion results (Virieux et al, 2009). Geophysicists have developed many approximations of physical phenomena using variants of finite differences and finite elements. These remain unfeasible for simulating large 3D data, and only the promise of extreme speed ups through HPC, or beyond, through quantum computers (Moradi et al, 2018), can address this; in practice, other avenues must be followed. One approach is data simplification (Trad, 2018), in which we track information in residuals to detect data components that are not properly explained by forward modeling. Our proposed research involves fast iterative parallel solvers combined with machine learning techniques (see below), to attenuate from the data space unpredicted components to achieve better information from our models.

The second challenge of geo-computation that is gathering momentum in the geophysical community is machine learning (ML). This branch of artificial intelligence (AI) has become extremely important in many areas of science because of a data explosion produced by information exchange through the internet. In geoscience, there has been a renewed interest on ML because of its ability to combine information with different formats, resolutions, sampling and physical origins. Global geoscience relies in large part on data based on different physical phenomena and collected by different types of sensors (Karpatne et al, 2017). In applied geophysics, ML has brought significant interest as well, and many applications have been published recently, like facies classification (Hall, 2016), salt identification (Lewis and Vigh, 2017), fault detection (Araya-Polo et al., 2017), tomography (Araya-Polo, 2018), common midpoint point velocity analysis (Smith, 2017), amplitude variation with offset (Russell et al. 2002). These algorithms take the form of classification or clustering, regression, deep neural networks, random forest tree ensembles and support vector machines. The big promise of ML is the possibility to capture hidden features and relationships between different physical phenomena and data for which traditional modeling based on physical laws becomes very difficult. Maximizing information extraction from geophysical data is a challenge because of our limitations to model complex aspects of seismic data. ML provides an intriguing but unclear path into filling this gap, by providing ways to detect and remove complexities that prevent inversion from working correctly (data simplification). Older examples, without ML, involve linear and non-linear filters to match poor predictions to complex data and matching filters used in multiple attenuation and FWI (Verschuur et al, 1992, Romahn and Innanen 2017, Warner and Guash, 2016, Zhu and Fomel, 2016), combinations of operators to extract signal from noisy data (Trad, 2015). We will improve this with the flexibility of ML. This component of the proposal also involves investigation into the uses of ML as a component of FWI. In principle ML can be used to match step length calculations with auxiliary data, such as well-logs, adding to the work of Romahn and Innanen (2017). However, there are some deeper possibilities that we will analyze. We have shown (Sun et al, 2019) that FWI can be re-posed as a recurrent neural network ML problem, in which the wave propagation and the medium properties are encoded into the weights, the process of training fixing the latter. This is now being extended to reverse time migration imaging, using ML to map between reflectivity and impedance (Niu et al, 2019). With these steps in place, we will investigate the potential of ML algorithms to seeks new patterns in seismic data. FWI extracts information from data assuming full knowledge of the origins of those patterns, which are traceable to pre-selected partial differential equations. An FWI algorithm encoded within a neural network naturally accommodates an initial state in which not only are the parameters of the medium unknown, but so are in the rules by which the waveforms propagate. A key advance we will seek, on the backdrop of these initial results, is a hybrid FWI-ML procedure which selects the wave physics model and the model parameters based on the data. This can be considered an alternative formulation of the modelling-error mitigation work of Keating and Innanen (2018, see Section 3).

All examples above come from the deterministic signal processing community based on the predictive power of linear filters. Techniques like neural networks (NN) add non-linearity to these filters. The main obstacle for these applications is the lack of training data. In spite of the large volumes of seismic data, each has unique characteristics and cannot in general be used to train an NN applicable to any data set. A theory-guided solution to this is NN training by synthetic models (Downton and Hampson, 2018). Another problem in geophysics that we will explore by ML is the combination of data sets with different resolutions and physical properties. A typical example is the merging of Vertical Seismic Profile (VSP) data (conventional or Digital Acoustic Sensing or DAS) with surface data. This problem involves combining different transfer functions to explain the same kind of model.

The near surface: seeing the reservoir through it and the geo-hazards within it

A key issue in all elastic/multicomponent seismic in land settings, but of particular importance for elastic FWI, is the near surface. The near surface is a complex agglomeration of loose till, unconsolidated sediments, variable water table depths, and surface topography; in vertical seismic profiling the seismic wave must traverse this complex system once, and in surface/reflection seismic profiling the wave must traverse it twice. The near surface acts as a complicated lens system which must either be accommodated directly in simulating or processing wave data, or corrected for, such that the data may be treated as having been acquired on a planar datum above competent rock. It also conducts seismic energy in the form of surface and guided body waves, whose amplitudes are generally much larger than those of the waves that interact with the reservoir zones. These waves must be accounted for in land data analysis and inversion. In principle, FWI would, from data associated with waves having travelled through the complex near surface, simultaneously determine it along with the deeper geological model structures. However, in reality, much of the pre-processing carried out on deeper refracted arrivals, diving waves and reflections is inconsistent with proper treatment of the surface and shallower refracted arrivals, and one must assume that the near surface system and the deeper systems are different. In addition, other geophysical methods, incapable of illuminating deeper geological structures, are capable of supporting seismic inversion in the top 100m; thus certain combinations of geophysical methods are applicable to the near surface but not elsewhere.

The elastic and fluid properties of the near surface in isolation are, furthermore, decisive in determining the consequences of natural and anthropogenic seismicity, and other geohazards. Significant resources are currently being expended to understand and quantify induced seismicity, with both industrial and government/regulatory consequences (Eaton, 2018). However, the degree of damage a seismic event of a given magnitude will cause to infrastructure is largely determined by the shallow P- and S-wave velocity profiles. A complete characterization of seismic hazards, induced and natural, requires high resolution near surface elastic property models. Recent research carried out by CREWES HQP has begun "waveform based" near surface characterization based on interferometric methods, focused on S-wave velocity model building. For elastic FWI and multicomponent seismic in general, the near surface S-wave velocity, which can be extremely low (e.g., Cova et al., 2017), has a strong influence on proper modelling. HQP in our group has introduced new inversion methods based on full waveform statics solutions (Cova et al., 2017; 2018) for the computation of VS profiles. We will use this as a base for elastic FWI starting models. However, a range of relatively robust near surface elastic model inference methods exist (e.g., Krohn and Routh, 2017). As part of this proposal, we will survey these, add to and modify them, and incorporate them in our prototype FWI methodologies.

In addition to analysis and extension of existing near surface methods as above, our plan is to build additional tools for "pre-FWI" near-surface characterization, guided by projects within Sections 2-4 above, and in particular by building on two research areas which are the domain of expertise of one of the PIs of this proposal (Lauer). The first is a set of results connected to geophysical identification and characterization of fugitive gas emissions from energy wells, due to failures in the well casing. This is a well-documented geo-hazard. In 2018, a study on methane detection and migration in a homogeneous sandy aquifer, in Borden, Canada, was carried out by Lauer and her group (Cary et al., 2018). Detection research included a suite of geophysical methods, including seismic refraction, vertical seismic profiling (VSP), electrical resistivity tomography (ERT), and distributed temperature sensing. Baseline data were collected from two ERT lines parallel and perpendicular to regional groundwater flow, a seismic refraction line parallel to groundwater flow, and a walkaway VSP survey conducted parallel to groundwater flow in a borehole eight meters from the injection. Continuous methane injection at a rate of 1.5m3 per day started in mid-June and is planned for 100 days total. After nine days of injection, resistivity increases of up to 15% above background are seen in close proximity to the injection point. Data from day 21 show resistivity increases of 10-15% that extend from the injection depth towards the surface, matching interpreted preferential pathways to surface identified on the background survey. VSP acquisition is ongoing and early conclusions are that combinations of geophysical measurements may be critical to creating clear models of near-surface environments undergoing production-related and seasonal changes. Further to this, new research is indicative that surface seismic experiments contain subtle but useful information for near surface characterization within both surface and guided-wave modes. This combination of geophysical methods to detect and characterize subtle changes in the near surface is suggestive that multi-physics is a powerful approach to create near-surface models to support deeper seismic characterization. The second area of near surface characterization we will draw from, in our reservoir analysis research, is Lauer's group's analysis of "soap holes" – localized occurrences of viscous clay, silt, sand and water encrusted by a thin layer of dried soil. Since first being noted by ranchers in the early 1900s, hundreds of soap holes have been located, manifesting either as a mound or a flat region of quick material (Toth, 1963). Morphologically soap holes are analogous to terrestrial mud volcanoes, which are commonly associated with hydrocarbon resources and methane release (Toth, 1963; Kopf, 2002). This suggests soap holes may represent a significant source of natural methane not included in the existing global methane budget and climate models (Etiope, 2004; Etiope et al., 2009). They are also detrimental to farming operations by killing livestock, destroying machinery, and rendering surrounding soils unusable (Toth, 1963; Toth, 1966). A combination of long-term hydrologic monitoring, ERT profiling and seismic methods has been formulated to determine the physical properties of the near surface in these areas. We will develop variants of these methods as starting points for near surface geophysical characterization in aid of deeper reservoir sensing.

New raypaths: seismic monitoring of the smart reservoir

Resolution of subsurface imagery is often limited by the relatively low frequency of the signal source, the high attenuation of the transmitting medium and large distances between the source, receiver and reflection. Is it possible to reduce these distances and increase frequencies by using subsurface sources or receivers while reducing the time necessary to image by using the drilling process itself? There has been significant work done over the past 40 years to understand the behavior of a steel drillstring as a wave guide, both at higher frequencies (up to 4 kHz) and at lower frequencies (up to 50 Hz). At higher frequencies, acoustic signals may be used for data transmission, however, the geometry of the drillpipe creates passbands and stopbands which must be accounted for (Drumheller, 1989; 1993; 2002). At lower frequencies, waveguide behavior becomes partially nonlinear due to friction between the drillpipe and the borehole wall, but recent work has shed new light on the phenomena (Aarsnes and Shor, 2018). The mechanical action of the drill-bit on rock formations is complex, and information-rich, and the response, which radiates elastically, is observable at points along the drillstring, within nearby boreholes, and/or on the surface of the Earth. By using the known behavior of the drillstring, the acoustic signature may be inverted for utilizing surface sensors during drilling operations, allowing for single waveform inversion techniques to be used to image the formation between the drillbit and either surface receivers or downhole receivers in adjacent wells. Seismic-while-drilling technology has been in existence for some time (Kostov, 1990; Rector and Marion, 1991; Meehan et al., 1993; Dubinsky, 2000; Petronio and Poletto, 2002; Meehan et al., 1993; Poletto et al., 2004), but additions based on new waveform and iterative imaging methods are possible. One of the investigators in the current proposal has led a research project in which proof-of-concept tests verifying that the additional ray-paths provided to surface and/or borehole seismic data from the drill-bit can significantly improve reservoir imaging in general [8]. We have an opportunity to carry out research which merges the growing waveform based imaging and inversion activities (see Sections 3-4), geo-computation activities (Section 5), with the drillstring modelling and engineering research. This will grow from our initial research into use of least-squares imaging approaches (Kazemi et al., 2018), accommodating FWI formulations. We regard the likely outcomes of such research not only to be new technology, but to include enriching connections between geophysics and unconventional drilling, and the HQP developing skills in both areas. In addition, our research group maintains a physical modelling laboratory (Igonin et al., 2018) which is currently undergoing significant expansion, to permit much larger 3D datasets, to augment the lab capacity to carry out multicomponent (shear plus vertical) acquisitions, with reduced transducer footprint. We will engage in significant benchmark dataset creation to support initial validation of the SWD-supporting techniques. This can be accomplished by designing a scale model, excavating a drill-path within it, and inserting a transducer such that it couples with the end of the path as it is created. The resulting data sets will be unique as tools for academic research and industry collaboration.

Our specific SWD research plan is as follows. Given the limited number of sources and receivers at the surface and using the interaction between rock and drill bit as a seismic source for SWD, our goal is to identify strategies to utilize joint FWI inversion to obtain precise images of the subsurface structure. In essence, we deploy seismic sources at the surface along with SWD sources in the well and record the seismic wave fields, generated by these sources, with sensors to solve the joint FWI inversion with low uncertainties. The proposed framework reduces the environmental impact of oil/gas exploration and improves production. Drilling parameters resulting in useful seismic radiation patterns is also a goal, though this must occur on the backdrop of an overall industry attempt to lower costs through reduced drilling times. Understanding the interaction mechanism between rock and drill bit in generating seismic wave filed is an important and crucial step of the proposed framework. These radiation patterns have been studied by Poletto and Bellezza (2006) for simple media. More research is needed to address the radiation patterns in complex subsurface environments. The proposed framework will enhance future energy exploration, development, and production. According to the statistics reported in the SPE distinguished lecture series by Roland Chemali (2011), proper well-placement can result in up to 10 times more production from the reservoir. Proper well-placement requires an advance geosteering technology. Proactive geosteering is only possible given high-resolution subsurface images of the subsurface. The proposed joint FWI of surface seismic and SWD data can provide such an image. The improved accuracy and detailed subsurface image provided by the FWI framework helps the drilling process in terms of optimal well-placement and lowering the drilling risks. Therefore, it reduces the drilling costs and improves the oil/gas production substantially. We will examine a range of seismic modes originating (e.g.) from long-reach horizontal wells, to help overcome signal strength issues; current drillbit technology has been refined such that they produce less noise – which is the signal SWD expects to use. However, we note that the dynamics in such situations will be more complex.

CONCLUSIONS

This is the text component of the proposal CREWES submitted to the Canadian government's NSERC Collaborative Research and Development funding program in May 2019. We look forward to the grant being awarded and for this funding to form a key element of CREWES support from 2020-2024.

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