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Thesis Changes Log

Name of Candidate: Daniel Stephen Wamriew

PhD Program: Petroleum Engineering

Title of Thesis: Location and source mechanism of induced seismic events: A deep learning approach

Supervisor: Prof. Dmitry Koroteev

The thesis document includes the following changes in answer to the external review process.

Dear Jury Members,

Thank you for your comments and suggestions, which have help me to improve the quality of my thesis. Please find the following changes in the final thesis file.

Reviewer: Dr. Pavel Golikov

1. The Background and Theory sections have many similarities especially in parts related to DAS. Some terms are mentioned in Chapter 2.3 but being introduced and explained only in Chapter 3.4. For example, $\phi - OTDR$. I suggest revising the Background section focusing it on the previous works and basic principles.
   - Corrections made.

2. *DAS cable deployment and coupling are one of the most important aspects for the successful DAS acquisition. I recommend adding a couple of paragraphs in Chapter 2.3 describing various options of the DAS cable deployment in general and for microseismic monitoring purposes in particular. Also, it would be great to mention that the quality of the cable coupling to the formation can greatly affect the result of the DAS measurements. The coupling issue could be mentioned in the Chapter 3.4.3 as well.*
   Paragraph added in Chapter 2.3.1 describing deployment options for fiber-optic DAS cables.

3. *In Chapter 2.4, it is worth mentioning briefly what kind of data preprocessing is required to make an input for DL workflow. Can the raw optical data from interrogator be used as an input? The data preprocessing is mentioned in Chapter 4.1.2 and in the Figure 4-2 but no details provided.*
   Added section 3.6 describing data processing for deep learning models.
   For the DAS data modeling and inversion, the synthetic seismograms from raytracing are 150 x 2000 samples (150 receivers with each trace 1s at 0.5ms sampling). Later they were converted into 256 x 256 images for CNN input. How did resampling affect the temporal and spatial frequency content of the data?

4. *What was the rational for selecting different acquisition parameters and different CNN architectures for geophone and DAS data? Why not treat DAS data as single component geophone (before conversion to strain rate)?*
   Rationale: Temporal and spatial dimensions, number of training parameters and input dimensions. Due to their high spatial and temporal resolution, DAS data require deeper models compared to geophone data.

5. *It is not obvious how the FORGE data analysis from the Chapter 4.3 is compared to the one from the Chapter 4.4. Was the same data analyzed? Were the detected microseismic events identical? It would be great to hear more details on this.*
   Chapter 4.4 is a continuation of Chapter 4.3. The same FORGE dataset was analysed. In Chapter 4.4, I re-do forward modelling using the already known velocity models of FORGE. I designed and test several CNN architectures for the inversion of the data and compare their performances. Two of these are chosen for further consideration, the ResNet and Inception-ResNet models. The ResNet model outperforms the Inception-ResNet model in inversion accuracy while the latter outperforms the former in computational efficiency and scalability. Both neural networks detect similar events to those already reported in Chapter 4.3.

6. *Can both the location and the focal mechanisms inversion be combined and performed with one complex DL architecture? How will it affect the performance and the accuracy of the inversion?*
   Technically, yes – both location and moment tensor inversion can be done on the same DL model. However, there would be a huge computational cost for this approach and secondly, the choice of optimum hyperparameters for the neural network becomes extremely difficult. Before deciding to use separate networks for location and moment tensor inversion, I experimented with the single network approach and encountered the aforementioned challenges. While I could get minimal errors for events locations, the errors in moment tensor inversion were in the orders of 43 – 64% making the inversion results unreliable.

7. *Please check the reference formatting style on pages 1 ([Molenaar et al., 2012]) and 9 (Foulger et al. [2018]).*
   - Corrected.

8. *Page 2, Figure 1-1: There are 5 different surface structures that cause induced seismicity in the Figure. 3 of them are briefly explained in the caption. I believe that the other 2 (mining and reservoir impoundment) should be briefly explained too for completeness.*
   - Descriptions for reservoir impoundment and mining added.

9. *Page 7, line 5: Please fix typo in 'theoretical'.*
   - Corrected.

10. *Page 10, paragraph 1: 'It is un- doubtedly challenging to effectively connect all the various disciplines in reservoir characterisation, especially for unconventional* ***reservoirs.****'*
    - Corrected.

11. *Page 12, paragraph 1: The AI abbreviation was not introduced before.*
    - Corrected

12. *Page 13, paragraph 2: The CCUS abbreviation must be introduced first.*
    - Corrected.

13. *Page 15, Chapter 2.3: It would be good to add here some general reference describing basic principles of the DAS recording such as Hartog [2017].*
    - Corrected. Reference added.

14. *Page 17, Chapter 2.3.2: "…The DAS system has replaced conventional accelerometers due to its low cost on a large scale…." This is not true. MEMS-based accelerometers are still widely used in surface seismic and to the lesser extent in borehole applications. Moreover, the DAS system is not measuring the particle acceleration directly, thus cannot be direct replacement of the accelerometers.*
    - This statement was retracted.

15. *Page 19, paragraph 2: "The DAS technology has successfully replaced traditional sensing methods across multiple sectors and industries." Perhaps it's too early to talk about full replacement. It's better to use terms: 'complemented' and 'improved'.*
    - Corrected. The term "replaced" was substituted with "complemented".

16. *Page 20, paragraphs 2 and 3: These 2 paragraphs are better be placed at the beginning of this chapter as a brief introduction to the basic principles of DAS measurements.*
    Paragraphs moved to the beginning of subsection 2.3.2.

17. *Page 21: "It is possible to generate reasonable uncertainty in spite of cylindrical symmetry by making several assumptions based on production logs." This sentence is unclear, please reformulate.*
    Statement paraphrased.

18. *Page 42, line 3 from the bottom: "…Equation (3.30), where..."*
    Corrected.

19. *Page 43: Please stick to the same Greek letter when referring to phase.*
    Noted and corrected effectively.

20. *Page 44: The TGD-OFDR term is not explained in the text.*
    Explanation added.

21. *Page 45, Chapter 3.4.3: It is worth mentioning here that DAS directivity issue can be (partially) resolved by utilizing helically wound cables [Kuvshinov, 2016]. Baird [2020] modelled DAS response of the helically wound cables for microseismic applications which is more relevant to the main thesis topic.*
    Mention and references added.

22. *Page 47, paragraph 2: "…the manual and the artificial* ***intelligence*** *systems improved…"*
    Corrected.

23. *Page 48, paragraph 2: "…monitoring of seismic activities in less seismic activities regions…" Please rewrite this sentence.*
    Text edited.

24. *Page 48, last line: "Past cosmic exploration has utilized DAS systems on a mission for different purposes." It would be great to put some relevant references here.*
    - Reference added.

25. *Page 52, paragraph 2: "…alongside other hyperparameters is achieved using trial and improvement…"*
    Corrected.

26. *Page 58, paragraph 2: the ρ sign is missing in the model parameters description.*
    Corrected.

27. *Page 66, paragraph 6: Is the X, Y and Z here denotes seismic components or coordinates of the microseismic event? Clarification is needed here.*
    Thanks for the observation. Clarification made. X, Y, Z are seismic components, while x, y, z denote event location coordinates.

28. *Page 74, paragraph 2: Please correct the reference at [Energy and at the University of Utah, 2019]*
    Corrected.

29. *Page 85, paragraph 2: Please correct the reference at [Energy and at the University of Utah, 2019]*
    Corrected.

Reviewer: Dr. Ariel Lellouch

1. *I think the name of the thesis could be more representative, and in my opinion needs to include some component of machine learning as well as velocity model updates. Also, some of the applications are not for induced seismicity but for microseismic monitoring, so the name is a bit misleading.*
    - Title changed to: Location and source mechanisms of induced microseismic events: A deep learning approach.

2. *The decomposition of the focal mechanism to isotropic, double-couple, and CLVD is also true for isotropic media, as far as I know; I think it would be better suited in that section.*
    True. Correction made in text to include both isotropic and anisotropic media.

3. *Some discussion about the complexity of the subsurface structures (beyond 1-D anisotropy) and the ability of DL methods to handle such previously unmodeled complexities would, I think, be useful. If the field data is affected by a significantly more complicated (and unknown) velocity/density structure, how well will the workflows that you describe perform?*
    This is a very important question. We can consider the use of CNN trained on VTI data to invert data from orthorhombic media as an attempt to answer this question (Section 4.2.6.2). Although the 1-D velocity model is still considered here, I investigated the effect of perturbation of anisotropic parameters of the orthorhombic medium to the accuracy of the CNN inversion. The result showed that the CNN model was capable of extracting both the event location and velocity model parameters of the orthorhombic medium to a reasonable degree of accuracy, even with increasing anisotropy up to about 50% from the initial model. Beyond the 50% increase, the errors in the inversion results were too large. The investigation also revealed that variation of anisotropic parameters least affected the inversion of the velocity model as compared to event locations. We can thus generalize these results to complex medium and hypothesize that the success and or failure of inversion by the CNN model is dependent on how dissimilar is the model under consideration to the model used in training the CNN. More research need to be done however in this direction.

4. *The coupling between moment tensor inversion and the velocity structure is known to be potentially significant. Could you elaborate on how your approach would work with only a reasonably accurate model?*
   Preliminary studies have revealed the difficulty of joint inversion of the moment tensor and velocity model using a single CNN model. The difficulty arises in tuning the hypaparameters of the neural network and could be attributed to the non-uniqueness of the focal plane solutions. However, as demonstrated in Chapter 4.5, it is possible to use two distinct CNN models for both velocity model and moment tensor inversion.

5. *Along the same line, I think that describing potential limitations of using ray tracing in generating a complete training dataset would be beneficial. There are cases (for instance, you can see some of my work on guided waves, but there are other cases) in which ray-based approaches cannot accurately represent recorded data.*
   Limitations of raytracing have been described in Chapter 4, last paragraph of subsection 4.3.7.1.

6. *In the FORGE dataset, there is a "ground truth" estimation coming from microseismic monitoring performed by Schlumberger. I know the work has already been published, and it may be too late, but it would be useful to compare your results to the microseismic catalog.*
   In-deed, the analysis done in section 4.4 takes notes of both the velocity models (now available in the FORGE data repository) and the event catalogs for DAS dataset by Schlumberger. We compare a subset of the presented events catalogs and out of this; we detect 6 new events missing from this catalog as mentioned in section 4.4.8.

7. *I do not ask to modify the thesis, but many of the validation examples are guilty of what is often called the "inverse crime" (using the same modeling tool for forward and inverse problems). I think that, for example, generating a testing dataset through wave equation modeling (instead of the same ray-tracing used for the training dataset) would be beneficial.*
   I agree, and as demonstrated by the results in section 4.2.6.2, we can consider the use of coherent noise (Bazulin et. al., 2021) a plausible approach (or a working substitute) in the absence of full-wave inversion, although the latter would be more appropriate.

   Reference:
   Bazulin, M., Sabitov, D., & Charara, M. (2021). Determination of the elastic parameters of a VTI medium from sonic logging data using deep learning. *Computers & Geosciences*, *152*, 104759.

Reviewer: Prof. Sergey Tikhotskiy

1. *The review of the microseismicity is very comprehensive and present a lot of examples. Meanwhile, the shortcoming of the presented considerations is that it does not pay attention to the principal difference between the "triggered" and "induced" seismicity (though the mentioned terms are not widely accepted). The former relies to the triggering of the natural tectonic stress release by artificial influences: fluid injection, mining, etc. Here the small changes in the pore pressure or external load led to the loss of stability in pre-stressed media and, in most cases – shear fracturing. While the latter corresponds to the true artificial stress induced by the intense and fast pressure increase (as in the course of the HF) or drop (while drilling). In this case, the pre-stress of the media and additional stress change are of the same magnitude and thus the focal mechanisms more variable, including those leading to dilatation and compaction. These two cases must be considered independently to clarify the physics and obtain better fit between the theory and experiment. Specifically, the same amount of the injected fluid will lead to very different microseismic events depending on the rate of pumping: fast, as in the course of HF, or low, as in the course of waste disposal.*

A general approach has been adopted in this work in order to avoid the subjective distinction between "triggered" and "induced" seismicity since a proper distinction of the two would requires an in-depth geomechanical analysis/discussion which would then go beyond the scope of the this study. The microseismic causes such as mining, fluid injection, waste disposal and hydraulic fracturing are thus discussed with this subcategorization. Nonetheless, the study of "triggered" and "induced" seismicity with respect to source parameters is of great importance and should be considered in future.

2. *Regarding the following review of the DAS technology, it is worth to mention that it starts from the historical mistake. In fact, the acoustic and electromagnetic waves propagation including the effects of scattering is studied since the XVII century, not from the beginning of the XX century, as stated. Specifically, the Raleigh scattering that is the base for the DAS technology was recovered and explained by Raleigh in 1871. Of course, this is a very obvious but not really important mistake. The review of the DAS application in different fields and in reservoir characterization is very comprehensive and interesting.*

   Thank you. I have reviewed the statement to focus only on acoustic sensing.

3. *Chapter 2 ends with the conclusion that two cutting-edge technology is used for the study: DAS and DL. Well, it is true, but the shortcoming of the approach is the absence of the critical comparison of this choice with other possibilities. What will be if I used 3-component velocimeters downhole array with the similar CNN DL technique? And so on.*

   Text added in the conclusion section of Chapter 2 to include also 3-C geophones downhole array as the application of DL technique has also been extended to 3-C geophone data as demonstrated in Chapter 4 sections 4.2 and 4.5.

4. *The major issue with the chapter 4.2 («Location and velocity inversion in real time», published in «Computers and geosciences») is the forward modelling procedure. Author uses the dynamic ray tracing algorithm, i.e. the ray-theoretical assumption is implied. The travel times and amplitudes are calculated and then convolved with the Ricker wavelet. According to the equation 4.1 the ray-theoretical displacements are calculated. It is not clear from the text how these displacements were converted to the signal that will be recorded by DAS. It is known that the DAS is recording the deformation along the cable axis averaged over the GL (or deformation rate depending on DAS pre-processing). There are no signs that these deformations were really calculated. The above-mentioned problem with the frequency response of the DAS line comes out here. According to the text the central Ricker wavelet frequencies were chosen in the range 50-500 Hz. The mean P-wave velocity is about 4500 m/s. I.e., the shortest wavelength is about 9 m which may be difficult to record by modern DAS line without the significant distortion. Moreover, the different frequency wavelets coming at different angles will be recorded with different distortions. This issue must be taken into account, because the NN must be trained on data that are adequate to the real field data.*
   The above-mentioned shortcoming is resolved to some extent in the chapter 4.3 ("Detection, location and velocity model inversion", published in "Sensors"). Here the synthetic displacement data are converted to DAS signal via the calculation of strain rate (equation 4.4). Nevertheless, the actual frequency response of the DAS line is not considered and analyzed, and this issue is not mentioned in the section 4.3.7.1 "Limitation of DAS", though this is a very important limitation.

Chapter 4.2 deals with deep learning inversion of data acquired by conventional geophones. Therefore, the particles displacements were not converted to DAS since the focus of this work was to perform inversion on 3-C geophone data by use of deep learning.
With regards to frequency response of DAS, most present DAS instruments have a wide range of frequency response up to a few kHz, (e.g Tang et al., 2021, Titov et al., 2022).
Section 4.3.7.1, discusses the less sensitivity of DAS records to broadside signals.

References:
Tang, J., Cai, L., Li, C., Yang, M., Guo, H., & Gan, W. (2021). Distributed acoustic sensors with wide frequency response based on UWFBG array utilizing dual-pulse detection. *Optical Fiber Technology*, *61*, 102452.

Titov, A., Fan, Y., Kutun, K., & Jin, G. (2022). Distributed Acoustic Sensing (DAS) Response of Rising Taylor Bubbles in Slug Flow. *Sensors*, *22*(3), 1266.

Reviewer: Prof. Vladimir Chevarda

1. *In the introductory part of the dissertation, Daniel quite fully describes the current level of development of this direction in relation to the Earth sciences. However, in my opinion, insufficient attention is paid to the description of the application of these methods in seismology, in particular for monitoring the process of stress accumulation in seismically active areas. In my opinion, the problem of controlling the stressed state of the medium in relation to ensuring the safety of such complex engineering structures as bridges, tunnels and others deserves more attention. Undoubtedly, the use of machine learning and DAS to monitor the state of hydrocarbon reservoirs is a very important and demanded task, but processes such as stress accumulation and the formation of areas of increased fracturing caused by this are also a very important and interesting task.*

   Thank you. In section 2.3.2, a brief review of applications of DAS to monitoring complex engineering structures is provided. This does not in any way downplay the importance of

2. *I will add that it seems to me appropriate in the part devoted to modeling the wave field, to present in more detail the specific numerical algorithms used by the author. Apparently, this is a ray method, so I would like to see a description of its applicability in terms of the requirements for the geometric structure of the boundaries in the model used. Here it would be interesting to know the author's expectations for the applicability of more accurate algorithms, primarily finite differences or spectral elements. In this case, it would be interesting and important to find out the influence of the choice of the method for numerical simulation during training. Namely, when conducting training, use the ray method, then apply the constructed neural network to the data obtained by finite-difference modeling. At the same time, choose a model such that the data for processing contains events that are not described by the ray method, for example, the presence of diffracted waves. Thus, the influence of the perturbation in the training data set on the result of its application to a specific problem will be studied.*

   The dynamic ray tracing routines used for synthetic data generation were based on Cervený, (2001). Section 4.8.4 , second-last paragraph, discusses the limitations of raytracing, key among them is that it can only be applied in smooth varying media but can fail, or provide misleading results in singular regions. For investigating the robustness of the deep learning approach, we tested the trained network with microseismic signal from orthorhombic medium model (section 4.2.6.2). Since the model was trained with signal from VTI medium, the orthorhombic media signals present events whose properties are alien to the neural network. The perturbation of the anisotropic parameters further distorts the signal. The inversion stability of the model diminishes when the perturbation exceeds 50% of the initial model. The proposal for testing the CNN on data generated by a different method is timely and will be included in future work.

Reference:

Cervený, V. (2001). *Seismic ray theory* (Vol. 110). Cambridge: Cambridge university press.

Reviewer: Prof. Elexey Cherimisin

1. *I recommend making the changes highlighted in the attached thesis with comments.*
   All highlighted changes have been corrected accordingly in the text.