High resolution full waveform tomography and seismic tomography with uncertainty quantification in Nankai subduction zone

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1. Nankai subduction zone high resolution full waveform tomography

The Nankai subduction zone has hosted both many devastating earthquakes, such as 1944 Tonankai and 1946 Nankai earthquakes, and various slow earthquakes like tremors and low-frequency earthquakes. The physical properties of the subsurface structure, especially along the plate interface, are key to understand the factor controlling the occurrence of the wide-range of the subduction zone earthquakes.

An active source seismic survey using ocean bottom seismometers (OBSs) is an effective tool to reveal physical properties of the subsurface structure in the seismogenic subduction zones. Conventionally, the active source OBS data have been processed by the traditional ray-based methods such as first-arrival travel time (FAT) tomography (e.g., Zelt and Barton, 1998 [1]). However, the spatial resolution of the FAT tomographic results is not sufficiently high to discuss the physical properties controlling the wide-range of the earthquakes along the plate boundary faults. The full waveform inversion (FWI) that utilizes observed waveform itself is expected to be a good solution to overcome the limits of the FAT tomography.

FWI has been widely used in industry to investigate oil and gas reservoirs. In contrast, FWI has been rarely applied on academic lithospheric scale seismic explorations because the imaging targets of the academic studies are generally much bigger and deeper than those of the industry exploration. The first crust-scale waveform imaging was implemented in the Tokai area of the Eastern Nankai Trough (Dessa et al., 2004 [2]; Operto et al., 2006 [3]), but their results were not clear because the imaging techniques was not enough matured to apply the actual data sets. Later, with the updating of inversion techniques, the resolution and accuracy are greatly improved in the subsequent FWI applications in the Kumano basin (Kamei et al., 2013 [4]) and in the Tokai area (Górszczyk et al., 2017 [5]).

These former results adopted the FWI method implemented in the frequency domain, although the frequency-domain FWI has some shortcomings. Therefore, we perform the time-domain FWI, which could be more efficiency to deal with different frequency contents. However, the time-domain FWI requires much more computing resources than the frequency-domain FWI. And it remains various issues in applying the method to the actual data sets of the lithospheric-scale studies.

In this study, we first aim to establish correct and robust procedures for the FWI. Then, we will apply the FWI to the actual data set. The data set was obtained in 2019 using 100 OBSs deployed at a spacing of 1-km along a 2-D survey line in the central Nankai Trough off the Cape Shiono, Kii Peninsula. Our final goal is to discuss controlling factors on the various fault slip behaviors from the megathrust to the slow slips in this subduction zone.

Since last year, the time-domain FWI program has been successfully run on ES4. In the subsequent period, I conducted continuous testing of various parameters, including but not limited to the evaluation of uncertainties in observed data (rely on signal-to-noise ratio), starting velocity models, and source signatures. Different inputs, as well as inversion parameters, yielded diverse outcomes. To discern the preferred one, I carefully compared and analyzed the various results.

The typical results are illustrated in Fig. 1, based on the starting model obtained by the first arrival tomography (FAT) (Qin et al., 2020 [6]), and chose different misfit functions based on acoustic full waveform inversions. I adopted a frequency continuation strategy, commencing with the low-frequency band and progressively increasing the frequency step by step. Considering the frequency contents associated with the discretized grid size, computational costs rapidly rise when the frequency exceeds 6 Hz, and I have to reduce the iteration number for the higher frequency band inversion. Consequently, the primary computations were carried out in the low-frequency band, with the higher frequency band undergoing fewer than 100 iterations to gain insights into the resolution issue. Uncertainty and spatial resolution tests were conducted, as depicted in the checkerboard test shown in Fig. 2.

Based on our achievements in 2023, additional supporting materials are required to facilitate the interpretation of our results. We plan to conduct various forward modelings to validate the different outcomes. Subsequently, using this foundation, we aim to discuss the physical parameters associated with the diverse fault slip behaviors, ranging from the megathrust to the slow slip within this subduction zone.

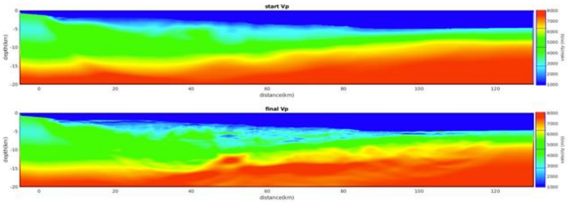

Fig. 1 Starting velocity model (FAT) and the FWI velocity model.

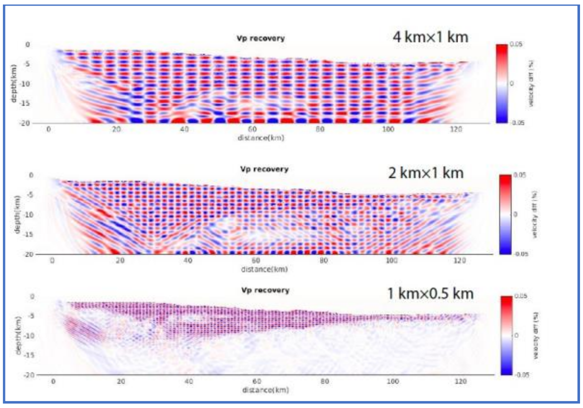

Fig.2 checkerboard resolution test by using three different grid sizes.

2. Bayesian first-arrival travel time tomography using physics-informed neural networks for seismic refraction survey data in the Nankai subduction zone

First-arrival travel time tomography (FAT) using refraction seismic data is a crucial and useful technique for understanding the seismic wave velocity structure at depth. In order to ensure the reliability of the estimation, it is essential to quantify the uncertainty of seismic velocity estimates in tomography. For this purpose, Bayesian estimation has been introduced to seismic tomography to estimate the posterior probability distribution function (P-PDF) of the velocity structure based on errors in travel time data and prior information (e.g., [7]). All of these previous studies introduce a grid- or mesh-based discretization of the analysis domain for calculating the travel time using a numerical method and parametrizing the velocity for Bayesian estimation. Since this estimation problem is nonlinear, sampling methods such as Markov chain Monte Carlo (MCMC) are commonly used.

Physics-informed neural networks (PINN) [8], which solves partial differential equations and inverse problems with neural networks (NNs) constrained from the equations, has attracted much attention in recent years. It has been also applied to seismic tomography [9]. This is a mesh-free framework that leverages continuous functions represented by NNs, which are plausible and flexible for modeling the velocity structure. Considering this advantage, we have developed a novel and efficient Bayesian estimation framework for PINN-based seismic tomography [10]. In this study, we applied the proposed method to first-arrival travel time data acquired in a marine seismic refraction survey conducted in the Nankai subduction zone.

We studied seismic refraction data available along the line KI03 located off Mie Prefecture, which were obtained by using a tuned airgun array and ocean bottom seismometers (OBS) (Fig. 3). We estimated two-dimensional (2D) P-wave velocity structure and its uncertainty using 14,146 first-arrival travel times manually picked from the refraction data by using the PINN-based ensemble estimation method [10]. This method represents seismic velocity structure and travel time function using NNs instead of grid or mesh. The travel time NN can be trained for the seismic velocity structure represented by the velocity NN through the PINN framework by minimizing the residual of the Eikonal equation, which simulates wavefront propagation and determines travel time, evaluated straightforwardly with the help of automatic differentiation of the NN outputs. An ensemble of velocity NNs that represents the posterior probability for the travel time data formulated by Bayes' theorem, i.e., the stochastic property of estimation uncertainty, were generated through the combined use of PINN-based travel time calculation and function-space particle-based variational inference (ParVI) [11][12]. We employed ParVI because it is known as a Bayesian estimation method suitable for parallel computation.

From the 256 velocity NNs obtained via the ensemble estimation (Fig. 4A), we obtained the mean model (Fig. 4B) and standard deviation (Fig. 4C) of the seismic velocity structure. The obtained mean seismic velocity models clearly show the north-dipping surface of the subducting oceanic plate and low velocities areas corresponding to an accretionary prism and the forearc basin without introducing any prior information. These features are in general good agreement with existing seismic structures modeled by deterministic tomographic methods [13]. The standard deviation of the ensemble, i.e. the uncertainty of the seismic velocities, is generally small in the area covered by the ray-path of the first arrivals. It shows spatial variations even within the ray-coverage area, suggesting the uneven distribution of the ray-paths. To obtain this single result, we ran calculation using 16 NVIDIA A100 GPU equipped in the Earth Simulator for about 100 hours. We additionally performed a number of runs for parameter studies of Bayesian estimation.

Seismic velocity structure models serve as the basis of other seismic data analysis such as hypocenter determination and seismic reflection methods. By using the obtained ensemble velocity model as an input to these subsequent analyses, we can accurately consider uncertainty propagation, resulting in more accurate estimates. We performed such analyses for an earthquake occurred in the vicinity of the survey line as an example and confirmed the positive effect of considering the uncertainty propagation in hypocenter determination. A manuscript based on these results has been submitted to a scientific journal and is now under review.

Based on these developments, we plan to extend the framework to three-dimensional (3D) analyses in FY2024, so that more realistic velocity structure model as the basis for hypocenter determination can be obtained.

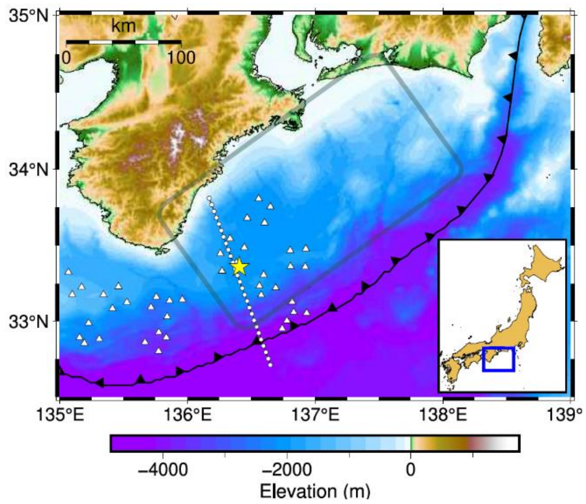

Fig. 3. A map of the study area. The circles and triangles denote the locations of OBSs which were installed in the survey line KI03 and the DONET observation nodes, respectively. The yellow star denotes the epicenter of the 2016 Mw 5.9 earthquake occurred in the vicinity of the line KI03. The gray rectangle denotes the approximate focal region of the 1944 Tonankai earthquake.

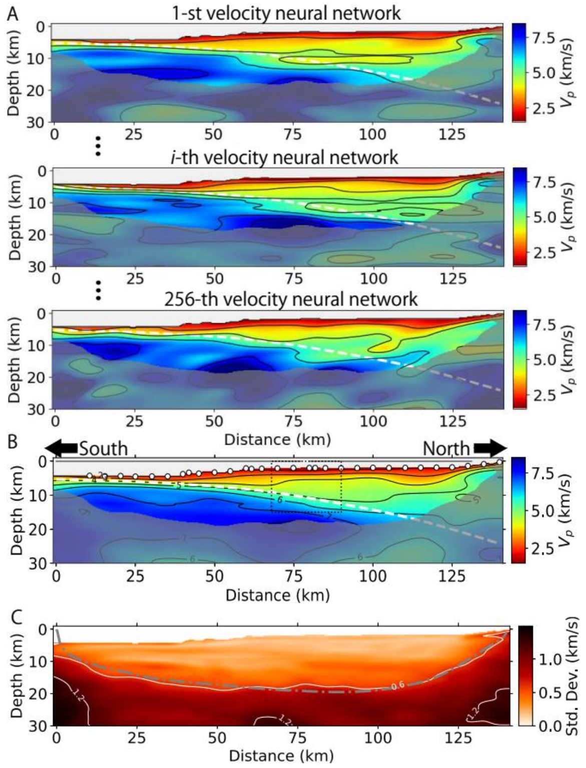

Fig. 4. (A) 256 velocity models along the KI03 line represented by NN ensemble members trained by combination of PINN and ParVI. In (A) and (B), the gray shaded area denotes the region where standard deviation is larger than 0.6. In (A) and (B), the white dashed line denotes the plate boundary model of [14]. (B) The mean velocity model calculated based on the estimated ensemble. (C) The standard deviation calculated based on the estimated ensemble. The gray dot-dashed line denotes the bottom of ray coverage for the mean model.

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