Combining asynchronous data sets in regional body-wave tomography

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SUMMARY

Regional body-wave tomography is a very popular tomographic method consisting in inverting relative traveltime residuals of teleseismic body waves measured at regional networks. It is well known that the resulting inverse seismic model is relative to an unknown vertically varying reference model. If jointly inverting data obtained with networks in the vicinity of each other but operating at different times, the relative velocity anomalies in different areas of the model may have different reference levels, possibly introducing large-scale biases in the model that may compromise the interpretation. This is very unfortunate as we have numerous examples of asynchronous network deployments which would benefit from a joint analysis. We show how a simple improvement in the formulation of the sensitivity kernels allows us to mitigate this problem. Using sensitivity kernels that take into account that data processing implies a zero mean residual for each event, the large-scale biases that otherwise arise in the inverse model using data from asynchronous station deployment are largely removed. We illustrate this first with a very simple 3-station example, and then compare the results obtained using the usual and the relative kernels in synthetic tests with more realistic station coverage, simulating data acquisition at two neighbouring asynchronous networks.

Key words: Inverse theory; Body waves; Seismic tomography; Theoretical seismology.

1 INTRODUCTION

Body-wave tomography at regional networks has provided an enormous amount of information on the upper-mantle structure, especially in continental settings, starting with the pioneering work of Aki et al. (1977).

A key factor in this technique is the usage of relative residuals, not absolute ones. It is based on the assumption that traveltimes at stations in a regional network are affected in a similar way by errors in the source location and origin time, as well as by large-scale heterogeneities in the lower mantle, and that by only accounting for the traveltine difference between stations, these effects are considered as removed and the residuals can be inverted in terms of structure beneath the network only (see e.g. Bastow 2012 for a review).

Although a simple approach to measure relative traveltimes would be to use a reference station and measure the traveltine difference between this station and all others, a much more common and robust approach is to use the method proposed by VanDecar & Crosson (1990). In this approach, the traveltine differences between all possible pairs of stations are measured and the residuals at each station that best satisfy in the least-squares sense all traveltine differences are computed. This approach has the advantage of not privileging any single station. Since the obtained residuals are the result of a least-squares inversion, they have minimum norm and correspond in practice to a demeaned set of residuals. The price to pay for demeaning the residuals is well known and recognized: the final velocity model is also demeaned, which means that it is with respect to an unknown vertically varying reference model (Aki et al. 1977; Lévêque & Masson 1999; Bastow 2012).

Another price to pay is that, in the classical formulation of the inverse problem, large-scale biases may arise if combining data obtained with different networks in the vicinity of each other but operating at different times, even though these networks may have some stations in common, for example, permanent stations. This is because the inverted models in the two or more regions may be with respect to different mean models and should not be combined, as the first example in the next section will simply illustrate. This is very unfortunate as we have numerous examples of asynchronous network deployments that complement each other very well for body-wave regional tomography and that, in some cases, have actually been used together (Fouch et al. 2004; Bezada et al. 2010; Rawlinson & Fishwick 2012; Youssouf et al. 2015; Boyce et al. 2016; Liddell et al. 2018). Except in Rawlinson & Fishwick (2012), the possible large-scale biases related to the asynchronous network deployments have usually not been addressed.

Although less severe than when combining data sets from different networks, it should also be recognized that this kind of tomography should be applied only to rather homogeneous data sets.
If not all stations have been deployed at the same time, or that a significant number of stations did not record during a certain period of time, all data from this period should in theory be discarded, as the remaining stations may not cover a region with the same mean structure as the whole network. To know which data to keep is not simple, as the ideal case of all events recorded at all stations of course never happens.

Although, as far as we know, they have never been applied, it is possible and easy to construct kernels which take into account in the inversion that the residuals are demeaned. Maupin & Kolstrup (2015) showed how to construct such kernels and analysed the difference between the usual classical kernels and the demeaned ones, which they called relative kernels. The difference was used to assess the resolution capability of relative residuals to heterogeneities of large lateral dimensions and to quantify the usual assertion that the model is ‘with respect to an unknown reference model’. They did not however analyse if usage of relative kernels instead of classical ones could remedy the limitations of the method in terms of asynchronous station deployment or recording.

In this paper, we demonstrate that using relative kernels, by properly taking into account to which mean each residual is relative to, strongly reduces the problems related to asynchronous and varying station coverage. We first illustrate the advantage of using relative kernels compared to classical ones with a very simple example. We then present the results of a synthetic experiment. Using a simple test structure, we invert together two asynchronous synthetic data sets using a finite-frequency tomography inversion program used and described previously (Hung et al. 2004, 2011; Kolstrup et al. 2015). The kernels used here are the so-called banana-doughnut kernels (Dahlen et al. 2000; Hung et al. 2000), but our demonstration is not dependent on this kind of kernels and could have been done with a ray-based tomographic method. We then analyse the importance of the data distribution for the result of the inversion and conclude with a discussion on the different options when dealing with several data sets in regional body-wave tomography.

## 2 Introducing the Principle with a Simple Example

### 2.1 The usual expression of the forward problem

In order to introduce the problem, let us start with a very simple example: three stations located over a lateral velocity gradient, as shown in Fig. 1, and vertical wave propagation. The classical expression for the relation between the residuals $\delta t_i$ and the model parameters is

$$
\delta t_i = L \delta s_i, 
$$

(1)

where $L$ is the thickness of the heterogeneous region and $\delta s_i$ the perturbation in slowness.

Assuming that we measured the residuals of an event recorded at the three stations, normalizing the length to 1 km for simplicity, the residuals are $\delta t_1 = 1.0$ s, $\delta t_2 = 0.0$ s and $\delta t_3 = 0.0$ s but become $\delta t_1 = 0.67$ s, $\delta t_2 = -0.33$ s and $\delta t_3 = -0.33$ s after demeaning. A simple inversion of these residuals using equation

$$
\delta s_i = \frac{1}{L} \delta t_i 
$$

(2)

yields a prefect recovery of the model, except for a reference level: $\delta s_1 = 0.67$ s km$^{-1}$, $\delta s_2 = -0.33$ s km$^{-1}$ and $\delta s_3 = -0.33$ s km$^{-1}$.

Let us assume now that we have two events, and that event number 1 was recorded only at stations 1 and 2, while event number 2 was recorded at stations 2 and 3. As residuals are relative to a zero mean, the residuals for event 1 are $\delta t_1 = 0.5$ s, $\delta t_2 = -0.5$ s, whereas they are $\delta t'_1 = 0.0$ s, $\delta t'_2 = 0.0$ s for event 2.

This problem has now four data and, as before, three unknowns. Wrongly using eq. (1) to express the direct problem, we obtain the following equation to be inverted:

$$
\begin{pmatrix}
\delta t_1 \\
\delta t_2 \\
\delta t'_1 \\
\delta t'_2
\end{pmatrix} =
\begin{pmatrix}
L & 0 & 0 \\
0 & L & 0 \\
0 & 0 & L
\end{pmatrix} 
\begin{pmatrix}
\delta s_1 \\
\delta s_2 \\
\delta s_3
\end{pmatrix}.
$$

(3)

The least-squares solution to this overdetermined problem is $\delta s_1 = 0.5$ s km$^{-1}$, $\delta s_2 = -0.25$ s km$^{-1}$ and $\delta s_3 = 0.0$ s km$^{-1}$. Although the general trend in the model is correct, the contrast is underestimated and we get a spurious large wavelength variation. The data at station 2 are also apparently incompatible, resulting in a non-zero data misfit.

### 2.2 The correct expression of the forward problem

The flaw in the model obtained in the previous section results from an omission in the formulation of the direct problem: it does not account for the different references in the two sets of data. The first data set measures traveltimes relative to the average traveltimes at stations 1 and 2, whereas the second one measures traveltimes relative to the average traveltimes at stations 2 and 3.

Taking into account that the measured residuals are demeaned, the expression for the direct problem should be

$$
\delta t_i = L \delta s_i - \frac{1}{N} \Sigma_\alpha L \delta s_\alpha, 
$$

(4)

where the second term on the right-hand side represents the mean over the residuals measured together with $\delta t_i$, that is, belonging to the same event. The direct problem becomes

$$
\begin{pmatrix}
\delta t_1 \\
\delta t_2 \\
\delta t'_1 \\
\delta t'_2
\end{pmatrix} =
\begin{pmatrix}
L/2 & -L/2 & 0 \\
L/2 & -L/2 & 0 \\
0 & L/2 & -L/2 \\
0 & -L/2 & L/2
\end{pmatrix} 
\begin{pmatrix}
\delta s_1 \\
\delta s_2 \\
\delta s_3
\end{pmatrix}.
$$

(5)

This system of equations is singular, but can be inverted in the least-squares sense by introducing a small component of damping. The solution is $\delta s_1 = 0.67$ s km$^{-1}$, $\delta s_2 = -0.33$ s km$^{-1}$ and $\delta s_3 = -0.33$ s km$^{-1}$. Except for the global average, the model is now...
Body-wave regional tomography

3 COMBINING TWO DATA SETS IN RESOLUTION TESTS

In order to test a more complex and realistic set-up, we analyse the results of resolution tests using synthetic data made by combining two real configurations of data acquisition in two neighbouring regions of southern Scandinavia. The two data acquisitions have no time overlap but partial geographical overlap (Fig. 2). The main goal of the experiment is to analyse the consequences of the lack of common events if these two data sets are used in a joint inversion. The station configuration for the early events corresponds to the MAGNUS temporary deployment in 2006–2008 and covers mostly southern Norway (Weidle et al. 2010). Supplemented by permanent stations, this data set was used in several regional body-wave tomographies (Medhus et al. 2012; Kolstrup et al. 2015), among other studies. We have chosen 25 azimuthally well-distributed events from this data set to perform our resolution test. The station configuration for the late events corresponds to the southernmost stations from the Scanarray experiment (2012–2017; Thybo et al. 2012), which, also supplemented by permanent stations, is the basis for ongoing tomography analysis. The selected stations cover mostly southern Sweden and we have also chosen a subset of 25 events from this data set. We can see from Fig. 2 that the partial geographical overlap is mostly related to some permanent stations common to the two data sets and to a few site reuses. The two sets have however quite distinct barycentres.

As seen in the simple example in Section 2, the main problem which may arise when combining asynchronous adjacent data sets is the difference in reference structure in the two regions. We expect therefore more problems with large-scale features than small-scale ones. In the present case, it has been shown by several studies that the upper mantle has a significantly lower velocity in southern Norway than in southern Sweden (review in Maupin et al. 2013). We have therefore constructed a resolution test with a zone of low P-wave velocity (−2.5 per cent) from 100 to 250 km depth in a 330 km × 440 km wide area in southern Norway, as shown in Fig. 3, ensuring a different average structure in the two regions covered by the two data sets.

We produce synthetic P-wave data for this structure using finite-frequency kernels (Dahlen et al. 2000; Hung et al. 2000). Although finite-frequency studies usually apply several frequency bands to the data, we use here only one high-frequency range of 0.5–2.0 Hz for simplicity and for consistency with most P-wave tomography studies. The choice of kernel is not decisive here and ray-based kernels could also have been used. A very important step to mimic real data acquisition is that the synthetic residuals are demeaned for each event separately. Gaussian noise with a standard deviation of 0.02 s is added to the data. In order to test the influence of the level of noise, an additional example with a higher noise level of 0.05 s is shown in the Appendix.

3.1 The kernels

We use two kinds of kernels to invert the data. The usual kernels $K_i$, which we call absolute kernels, are those expressing the dependence on the structure of each event-station traveltime $i$. The relative kernels $K'_i$ take into account the fact that each residual is relative to the average residual for that particular event and depend on the absolute...
ones as follows (Maupin & Kolstrup 2015):
\[
K'_i(\tilde{x}) = K_i(\tilde{x}) - \frac{1}{N} \sum_{j=1}^{N} K_j(\tilde{x}),
\]
(6)
where \(N\) is the number of residuals for that particular event and \(j\) their indexes.

An example of relative kernel is shown in Fig. 4. This is the relative kernel for a \(P\)-wave residual belonging to the western data set, recording the event close to Madagascar at the station located at \((60.8^\circ, 8.3^\circ)\). This event has been recorded by 31 stations, a typical number of recording stations for the events we have used. On the left-hand side of the figure, where the kernel is shown in full scale, one can basically only see the positive values of the kernel main lobe centred close to the station in the upper layers and getting wider and moving laterally towards the event with depth. The kernel is also shown to the right with a clipped colour scale to enhance the visibility of the small values. At the shallow levels, some negative features appear as dots at the locations of the other stations of the network, merging into a more diffuse negative value at the deeper levels. These negative values are only of the order of a few percent of the maximum value of the kernel, and do not exceed the negative values associated with the kernel second Fresnel zone.

For comparison, the absolute kernel for the same residual is shown in Fig. 5, and the relative kernel for another residual belonging to the data set recorded in the eastern part of the region is shown in the Appendix (Fig. A1).

### 3.2 The resolution tests

Fig. 6 shows the results of the resolution test using the usual absolute kernels for a noise level of 0.02 s and a damping value of 2000. The misfit reduction is 92 per cent in this case.

Considering that the test structure does not have a zero mean and that regional tomography is not expected to inform the absolute velocity but the contrasts between regions, we do not expect to recover just a low velocity, but the contrast between a lower velocity region surrounded by a higher velocity background.

Although the vertical profile shows that the depth resolution is limited, lateral resolution is on the other hand rather good and the low-velocity zone is well delineated horizontally. The velocity anomaly in the low-velocity zone is of course smaller than in the synthetic model, with a value of about \(-1.0\) per cent. If we consider the structure West of 12° east, we see that the contrast between the low-velocity zone and its faster outskirts, with a velocity anomaly
Figure 4. The relative kernel of the $P$-wave residual at station located at (60.8°N, 8.3°E) for the event close to Madagascar. The left-hand plots show depth slices of the amplitude of the kernel with respect to its maximum value. The right-hand plots apply a clipped colour scale to enhance the visibility of the small values.

at about ±0.6 per cent, is quite well rendered. In the maps at 125 and 200 km depth, we can however note that the East coast of Sweden shows as a slightly slow region, with a velocity anomaly of −0.1 to −0.2 per cent, in contrast to the fast outskirts of the main low-velocity zone. This region is the location of the set of stations which have recorded only the late events. These events have not been recorded to the West and almost do not sample the low-velocity zone. The structure in this region is therefore only affected indirectly
by the low-velocity zone: the inversion puts low velocities to the far east in order to compensate for the higher velocities close to the Norwegian–Swedish border and ensure a close-to-zero average in that part of the model. This introduces a spurious long-wavelength anomaly.

Results with other damping values and noise levels, as shown in the Appendix in Figs A2 and A3, show similar results. The result of the inversion without demeaning the residuals is also shown in the Appendix (Fig. A4). In that case, which of course does not comply with real data processing procedures, the apparent velocity

Figure 5. The same as Fig. 4 but for the absolute kernel.
Figure 6. Inversion with absolute kernels. Horizontal and vertical slices of the $P$-wave velocity model obtained by inversion of the synthetic data using the absolute kernels. The damping level is set to 2000 and the noise level on the data to 0.02 s.

The main difference between the results of the two resolution tests is the reduction of the large-scale bias between east and west using the relative kernels. It is remarkable that, despite its small amplitude, the difference between the absolute and relative kernels is able to affect the result of the inversion significantly. This difference is very distributed, especially at depth, relating it to the resolution of large-scale features, as already noted by Maupin & Kolstrup (2015).

4 RESHUFFLING THE DATA

In order to test the importance of the geographical distribution of the data in the final result, we have performed inversions with tworeshuffled data sets. These data sets consist of the same events as in the previous section, but we have exchanged some of the stations at which the events are registered. For example, the events which were actually registered at station ASKU located to the east at (58.9°N,14.8°E), which all belong to the late set of events (blue in Fig. 2), are supposed in this first reshuffled data set to be registered instead further West at station NWG15 situated at (60.7°N,6.9°E), and the opposite for the early events originally registered at NWG15. The exchange of stations was done to ensure that all events were registered rather uniformly in the whole region, still keeping the same total number of residuals than in the previous section. The resulting data distribution in this distributed set-up is shown in Fig. 8(a).

Similarly, we have reshuffled the data in order to make a disjoint set-up (Fig. 8b), in which the data distribution is even more separated into a western group and an eastern group than in the original data set, and in which no station has registered both sets of events. Let us note that although the data set is disjoint at the surface, the sensitivity kernels from both sets partly overlap at depth.

The result of the inversions of these data sets using both absolute and relative kernels is compared to those of the original data set in
In all cases, the low-velocity zone is well delineated. Using absolute kernels, we observe with the disjoint set-up (right upper plot) an east–west velocity bias as we did with the original data set (middle upper plot). The bias has disappeared with the distributed set-up (left upper plot), proving that the data distribution is at the origin of this bias. Using relative kernels, the data distribution has basically no influence on the resulting model.

An intriguing observation is that the models derived with the relative kernels are on average slow, contrary to the usual understanding that using demeaned residuals automatically implies that the inverted model has zero mean. It is particularly interesting to discuss the difference in average structure between the two models derived with well-distributed data (Fig. 9, left plots), in which case the absolute kernels provide a non-biased inverted model very similar to the model derived with the relative kernels, but with an average much closer to zero.

This difference comes from the fact that, since the relative kernels are zero-mean, a model derived with relative kernels does not need to be zero-mean to accommodate the zero-mean nature of the residuals, as it does when using absolute kernels. Whereas the model is forced to zero mean in order to fit the data in the case of absolute kernels, it does not in the case of relative kernels. The choice of regularization plays therefore a much larger role in defining the average value in the relative-kernel case. Minimum-norm-damping regularization will commonly lead to a close-to-zero average model.

In this study, we do not use a classical norm-damping regularization, but a data-adaptive regularization scheme based on wavelet decomposition of the model (Hung et al. 2011). This is likely the reason why our relative-kernel models are not zero-mean. As the data do not contain any information about the average model, this non-zero average has however no value and only contrasts should be interpreted.

Another interesting feature is the ability of the disjoint data set to resolve the contrast between east and west despite the lack of common stations. Although the data are recorded in distinct regions, their kernels overlap at depth and this overlap offers a link between the model to the west and the model to the east. Using relative kernels, as discussed above, changing the average of the model in a region covered by a given data set does not alter the fit to the data. The inversion will therefore tend to adapt the difference in average between east and west in order to get model parameters in the region of overlap that fit both sets of data simultaneously. This phenomenon is similar to what we see in the simple example in Section 2. If instead of one station above the middle cell, we had put two stations recording two different events, the direct problem would have been formulated exactly the same way as with one station (eq. 5) and we would have recovered the model perfectly well. As long as the kernels have a reasonable amount of spatial overlap, they are therefore able to handle data sets which are rather disjoint at the surface.
5 DISCUSSION

Merging asynchronous data sets which cover adjacent regions into one regional body-wave tomography leads to challenges regarding possible biases in large-scale structure. This has been pointed out before (Rawlinson & Fishwick 2012). We have shown here that this bias can be largely removed by taking into account that each residual is in practice with respect to the mean residual for each particular event, and using relative kernels instead of the usual absolute ones in the inversion. To calculate the relative kernels from the absolute ones is very easy. They account for the data processing better than the absolute ones and can of course be also beneficial in tomographies with one single period of data acquisition but somewhat irregular data quality so that some stations miss many events. The only challenge is that the kernels have a non-negligible amplitude in a much larger volume than the absolute ones, increasing significantly both the required disk space and inversion time. In the examples presented in this work, the relative kernels require about 9 times more disk space than the absolute ones and the inversion takes 15 times longer to perform (but are still done in 15 min on a standard server).

An important point to make here is that traditional resolution tests will not unravel the lack of large-scale resolution in a merged data set. One reason is that resolution tests like checkerboard or spike tests are usually geared at finding the size of the smallest resolved features and not in checking the resolution of the larger scale features (Lévêque et al. 1993; Rawlinson & Spakman 2016). But the main reason is more fundamental: resolution tests are usually done by producing synthetic data with the forward operator used in the inverse problem, namely the absolute kernels in the case of regional body-wave tomography. This does not produce demeaned residuals and therefore does not simulate data acquisition correctly. As we have shown (Fig. A4), the model is not biased if the residuals are not demeaned. To be fully valid, resolution tests should include a demeaning of the residuals per event, even without considering merging data sets.

Even though using relative kernels reduces the regional biases very efficiently, the increased computational cost might be a challenge for large data sets, and we may want to examine other alternatives.

First of all, the example shown above is rather extreme, with a large-scale large-amplitude anomaly right where one of the two data sets is located. It has been chosen as an extreme case to illustrate the problem. Still, it shows that regional differences, if they exist, will not be well recovered in the model, and that it will anyway be difficult to interpret with confidence regional differences which coincide with the locations of the two networks. This will reduce the value of a common inversion compared to two separate ones as it introduces a risk of misinterpretation, especially by non-seismologists, but little additional information on the fine-scale structure that is as well resolved in both cases.

Although this is not common practice, anchoring the residuals to those at one or a few permanent stations which have registered all the events could be an option to avoid the problem. Although this has the advantage of providing a common reference to all residuals, it has the disadvantage of privileging one or some stations. The kernel that should be used for each residual in such a data set is actually

$$K^*_r(\vec{x}) = K_r(\vec{x}) - K_r(x_0),$$

where $K_r$ is the absolute kernel at the reference station. This shows that the structure around the reference station gets a prominent role in the inversion process, a feature that might lead to uneven resolution. The advantage of the method of VanDecar & Crosson (1990) is that traveltime differences between all pairs of stations are taken into account in an equal way in computing the residuals, avoiding the predominance of a reference station. By anchoring the residuals to a reference station, we lose this advantage, but gain computationally by using a kernel more restricted in space than the relative ones.
Figure 9. Comparison of the inverted models for different data coverage set-ups. Horizontal slices at 200 km depth for models obtained using absolute kernels (upper row) and relative kernels (lower row). Left-hand plots: data set-up of Fig. 8(a). Middle plots: data set-up of Fig. 2. Right-hand plots: data set-up of Fig. 8(b).

Rather than anchoring to one station, one can also anchor the residuals to a global model, moving from relative residuals to absolute ones. Although the purpose has not been to combine data from asynchronous networks, several authors have proposed methods to access absolute traveltime information from data at regional networks (Chevrot 2002; Weidle et al. 2005; Burdick et al. 2008; Boyce et al. 2017). Although the large-scale features are not biased, the model produced with relative kernels is still with respect to an unknown average structure. Using absolute residuals is of course a good alternative that removes this limitation, but does require to couple regional issues to global ones and complexifies the data analysis.

The issue when merging data sets is related to different average background models. Information from other sources concerning the large-scale structure, for example from surface waves, can be used as a priori model, letting the body waves adjust only the small-scale features of the model. This has in addition the advantage of providing absolute information on the velocities. Although usually applied only to provide a correct 1-D average reference model to tomographies (Lévêque & Masson 1999), this technique has been used in 3-D to avoid large-scale biases in the inversion of residual data acquired by a moving array in Australia (Rawlinson & Fishwick 2012). The penetration depth of surface waves will however limit usage of this technique to relatively shallow lithospheric studies, or to data sets where particularly long-period surface waves or overtones are available.

6 CONCLUSION

Merging residual data sets acquired at different times in different regions of a study area causes problems concerning resolution of the large-scale structure derived from regional body-wave tomography. We have shown that using relative kernels instead of absolute ones helps mitigating this problem and has computational cost as the only drawback.

We do not aim at giving a general rule in terms of geographical overlap and number of stations as to when relative kernels should be used compared to absolute ones. We think that relative kernels should be used whenever possible, even without merging data, as they provide a more correct representation of the data processing. If they cannot be used, we simply recommend to examine possible biases in inversions with absolute kernels by doing resolution tests in models appropriate for the tectonic setting of the study area.
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APPENDIX: ADDITIONAL FIGURES
Figure A1. The same as Fig. 4 but for the $P$-wave residual at station located at (60.5°N, 15.8°E) for an event in the Philippines.
Figure A2. The same as Fig. 6 but with noise level of 0.05 s and damping of 1000.
Figure A3. The same as Fig. 6 but with noise level of 0.05 s and damping of 3000.
Figure A4. The same as Fig. 6 but without demeaning the data before inversion.