Microseismic Source Location with Distributed Reverse Time Migration
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SUMMARY
Traditionally, microseismic source location requires a time-consuming data collection as well as intensive computations, both of which take manpower and resources. Instead, with a sensor network based distributed location algorithm, we can locate the events in a real-time manner. In this abstract, we propose a modified distributed reverse time migration (RTM) method for microseismic source location, which is designed for sensor networks. The distributed system assigns the calculation tasks to several “sinks” (locally central nodes), and every sink only processes the local data and those from its neighboring nodes. Compared with the traditional RTM method, the distributed RTM only requires processing partial data on individual devices, leading to lower computation and communication costs. To further reduce the communication cost, we propose to only exchange the locally stacked RTM imaging results instead of the whole wave fields. Then, the location result is obtained by merging the RTM images from all sinks. The proposed algorithm is shown in detail, and examples demonstrate that our proposed method is promising and able to generate accurate and robust location results.

INTRODUCTION
Subsurface sources include earthquakes, geysers, volcanic activities, and all kinds of human activities (Métaxian et al., 1997). The location of events is meaningful to understand the ground truth, and important for geophysical experiments at all scales (Artman et al., 2010; Maxwell et al., 2010). Determination of event locations and magnitudes leads to estimations of the geometry of the fracture zones and certain dynamics of the fracturing process (Baig and Urbancic, 2010), understanding the efficacy of hydraulic fracture treatments (Maxwell et al., 2002), and reservoir monitoring of thermal processes (Jeanne et al., 2014), drill-cuttings injection (Warpinski et al., 1999), and other processes in oil/gas and mining activities.

Usually, a specifically designed sensor system detects the microseismic events based on the recorded energies generated from the microseismicity (Warpinski et al., 2009; Song and Toksöz, 2011; Li and Song, 2017). Exploration acquisition adopts the controllable active sources, which can produce abundant seismic events. However, the passive source is uncontrollable, so the received data usually have a low signal to noise ratio (SNR). The most common approach for passive source location is the arrival time difference methods (Dong and Li, 2013; Li et al., 2014), while other passive source location methods include range difference based methods (Stehly et al., 2006), cross-correlation based methods (Shapiro et al., 2006) and migration based methods (Nakata and Beroza, 2016). Compared with other methods, migration based methods generate good results especially for situations that the SNR is low (Nakata and Beroza, 2016). To implement the migration based passive source location, the boundary condition needs to be modified. In the reverse time migration (RTM) source location method, all the wave fields individually backward-propagate from each receiver on the surface to coincide the event location spatially and temporally. Sun et al. (2015) discussed the possibility of the distributed RTM for microseismic source location, but without considering the communication costs.

In this abstract, we present a distributed sensor network based RTM algorithm. Instead of sending all raw data to a computation center and applying centralized RTM algorithm on a single device, our algorithm uses local clusters, which process data from themselves and neighboring nodes. The sinks (locally central nodes) apply the RTM algorithm to generate partial wave field images. Then, by exchanging information among sinks, we stack the partial results to obtain a complete image which represents the subsurface source locations. Our proposed algorithm has lower computational and communication costs, making it affordable for distributed sensor networks with limited computation capability to implement real-time imaging.

\[
\frac{1}{c^2_0} \frac{\partial^2 U_B(z,x,t)}{\partial (\text{-}t)^2} = -\nabla^2 U_B(z,x,t)
\]

Distributed RTM for Source Location
As a passive source imaging method, RTM source location generates the concentrated source energy map because the back-propagation wave fields should coincide at the source location (Saenger et al., 2010; Liu et al., 2011). On the energy map, the bright spots will indicate underground activity locations.

Through replacing time \( t \) by \( -\text{-}t \), the time reverse wave equation is expressed as:

\[
\frac{1}{c^2_0} \frac{\partial^2 U_B(z,x,t)}{\partial (\text{-}t)^2} = -\nabla^2 U_B(z,x,t)
\]

Instead of using the free surface boundary condition, RTM method defines a surface boundary condition with the wave field on the surface (Zhu, 2014):

\[
U_B(z = 0,x,t) = U_F(z = 0,x,T - t),
\]
Distributed RTM for Microseismic Source Location

where $U_{B}$ is the backward wave field in time $t$ while $U_{F}$ is the forward wave field on time $T - t$, which is the data recorded at $T - t$ by receivers. When we use the gathered seismic data at $z = 0$ as the boundary condition and start processing from time $t = T$ to time $t = 0$, we can get a time-reversed backward propagated wave field, $T$ is the time length of data. This process is equivalent to stacking the individual backward wave fields generated by one trace of the seismic data.

If the input data contain a microseismic source signal, the backward wave field at $(z_0, x_0)$ will have the maximum value when energies of all individual wave fields concentrated. We define this value on the energy map as the source location possibility. The stacked wave field of all of the receivers represents the energy distribution of the backward wave field toward time. The RTM source energy map coordinates to the maximum value of the stacked wave field between the same time period. The physical meaning of this image is the maximum energy occurs at the specific time period in the target area:

$$I(z, x) = \max_{t} \sum_{i=1}^{N} R_{i}(z, x, t), \quad (3)$$

where $R_t$ means the backward wave field of a single receiver.

**Algorithm 1 RTM source location image algorithm**

1. Input: data $D$ from device
2. Read window size $w$ from $D$
3. Read time step $dt$ from $D$
4. Input: velocity model $V$ from device
5. Write $D$ as boundary condition on $V$
6. Set $t = 0$
7. For $t$ less than $w$ do
8. Generate backward wave field at time $t$
9. Save wavefield as $S_t$
10. add $dt$ to $t$
11. End
12. Combine wavefield as $S$
13. Calculate the maximum value of $S$ on time scale and save it as image $I$

To make the algorithm distributed, we divide the $N$ receivers to $m$ clusters, and each cluster contains $n$ receivers. And the equation (3) should be rewritten as equation (4). In each cluster, we first calculate a partial source energy map with the nodes inside, and then we propose to stack the energy maps between the different clusters:

$$I(z, x) = \sum_{i=1}^{m} (\max_{t} \sum_{j=1}^{n} R_{i}(z, x, t)). \quad (4)$$

Figure 1 shows the steps of the distributed RTM source location algorithm. We use the surface sensor array to collect raw data generated by the passive seismic source, the red curves are the forward paths of the seismic wave from the source to the receivers. Then, we write time-reversed data as the surface boundary condition and build backward wave field propagation on the nodes. The energies of those wave fields will concentrate on the location of source, which will be shown as a bright spot on the output image. The details of the algorithm can be found in Algorithm 1.

Our distributed RTM algorithm is using the raw data from the node itself and its neighbors as the input data, shown in Algorithm 2. Nodes write boundary conditions based on the data from neighbors and themselves and calculate the backward wave fields, then generate the partial RTM source location images. Finally, the output images are transmitted through the network and stacked to generate the final RTM source location image.

**Algorithm 2 Distributed RTM source location image algorithm**

1. Input: data $d_t$ from neighbors
2. Input: velocity model $V$ from device
3. Write $d_t$ as boundary condition on $V$
4. Apply Algorithm 1
5. Broadcast $I_t$ to other nodes
6. Stack $I_t$ to generate final image $I$

**Computation and Communication Cost**

A typical distributed sensor network structure for RTM imaging method is shown as Figure 2. The green circles are nodes which collect the raw data, and accomplish pre-processing steps. The sensor network is separated to several clusters, and each cluster has one sink (the red circle), which collects data from its neighbors. The sinks apply the local RTM imaging algorithm. We can see the communication benefit of this structure. From the nodes to sinks (shown as green lines in Figure 2), the transmitted data should be one trace of time series seismic data; from the sinks to sinks (shown as red lines), the transmitted data should be a RTM source location image result.

**Figure 2:** Distributed sensor network for RTM source location method (Valero et al., 2017).

Define the time length of raw data as $t$, grid size of velocity model as $z \times x$, the total nodes number as $l$, the average number of neighbor nodes as $n$, the average transmission length as $m$.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Communication Cost</th>
<th>Computation Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Centralized RTM</td>
<td>$t \times l \times m$</td>
<td>$o((z \times x)^2)$</td>
</tr>
<tr>
<td>Distributed RTM</td>
<td>$z \times x \times t \times l \times m$</td>
<td>$o(l \times (z \times x)^2)$</td>
</tr>
<tr>
<td>Proposed Method</td>
<td>$t \times n + z \times x \times m$</td>
<td>$o(l \times (z \times x)^2 / n)$</td>
</tr>
</tbody>
</table>

Table 1 shows the communication and computation costs of
Distributed RTM for Microseismic Source Location

the whole system generated by three different algorithms. The centralized algorithm has the lowest computation cost while distributed RTM algorithm proposed by Sun et al. (2015) has the highest computation cost. In our proposed method, the communication cost depend on the parameters, for example, if the time is long or the sampling rate is high, our algorithm has the lowest communication cost.

EXAMPLES

In this section, we first present a noise free test on a horizontally layered velocity model, which proves that our algorithm is theoretically correct and can detect the source location. Then we apply our method on a portion of Marmousi model to simulate a more realistic condition. We also discuss the computation and communication performances of our algorithm in the multi-source condition.

Layered Model

Figure 3 shows the synthetic velocity model, where the grid size is $300 \times 300$, and the depth interval $dz$ and width interval $dx$ are both 5 m. The velocity model contains two layers: the velocity in first layer is 2500 m/s and the velocity in second layer is 3500 m/s. The event locates at the second layer with the red circle shows the location of the event. The observation system contains 300 receivers, and each receiver can be considered as a node in a sensor network. We have 9 clusters indicated by green triangles to apply the proposed algorithm, and each cluster contains 30 nodes.

Figure 4 shows the result of the centralized RTM source location method and the proposed method. We set a source at $(x, z) = (750 \text{ m}, 750 \text{ m})$, the time length of recorded data is 1 s. In Figure 4(a), when all of the 300 traces of observed data are set as boundary conditions, we can get a clear bright spot on the source energy map, and Figure 4(b) shows the stacked source energy map from 9 sinks. The individual source energy map on the 1st and 9th clusters are shown in Figure 4(c) and Figure 4(d), where the individual source energy map generated by one sink looks like a beam. We get a bright spot on the stacked energy map in Figure 4(b), but not as concentrated as the centralized one in Figure 4(a), because in the stacked process only 9 clusters are used while the centralized RTM used all the data from all receivers. However, considering about the computation and communication save, our proposed method has its own advantages.

Marmousi Model

The second example is on a portion of Marmousi model (shown in Figure 5). The grid size is $300 \times 300$, with width and depth intervals are 4 m. The surface sensor array collected 300 traces. There are 9 clusters and each cluster contains 60 traces.

First, we generate a forward seismic record with only one source, the source location is $(z_0, x_0) = (750 \text{ m}, 750 \text{ m})$, the time length of recorded data is 1 s. Figure 6(b) shows the result of stacked energy map of 9 sinks. The individual source energy map on the 1st and 9th clusters are shown in Figure 6(c) and Figure 6(d), where the individual source energy map generated by one sink looks like a beam. We get a bright spot on the stacked energy map in Figure 6(b),
the energy map. Note that the energy concentration in Figure 6(b) is better than Figure 4(b). The possible reason is that the Marmousi model is complex, so the interfering energies could be diffracted or canceled. Next, 0 dB Gaussian noise is added to the recorded data (shown as Figure 7(a)). As we can see in Figure 7(b), the source image result is similar as the noise free result.

Figure 6: (a) Noise free recorded data; (b) Source image result of single source experiment.

Second, we perform a multi-source test on the same Marmousi model. The observation system remains the same parameters. There are 6 sources and the locations of sources are shown in Figure 5 using red spots. The time length of the recorded data is 1 s. Figure 8(a) shows the data collected from the surface sensor array. In this experiment, we compensate the wave energies to make sure that the signals from different sources have similar amplitudes. Figure 8(b) shows the stacked energy map, there are six clear bright spots, and the local maximum energy values on this energy map are consist with the real locations of the six sources. This result shows that our algorithm can detect multiple sources simultaneously. Figure 9(a) shows the multiple source data with 0 dB random noise. Figure 9(b) shows the energy map generated with the noisy data. It is almost the same as the result in the noise free test. This experiment shows that our algorithm is robust even when SNR is low.

We can also calculate the reduction of communication cost by using the proposed algorithm. The grid size of partial RTM image is the same as the velocity model, which is $300 \times 300 = 90000$. The size of raw data used to generate RTM image in each local center node is $n \times T / dt = 60 \times 1 / 0.0005 = 120000$, which is bigger than the output. It is obvious that when the time length is large, our algorithm can reduce the communication cost significantly while the resolution of output is still acceptable. This benefit is very important when the algorithm is running in real sensor networks.

CONCLUSIONS

We propose a distributed RTM source location method that generates the source energy map and detects the hypocenters of the microseismic sources. By separating the sensor nodes to smaller clusters, the partial RTM source energy maps are transmitted instead of the whole wave fields, which can reduce the communication cost. The source location image produced by this algorithm provides a clear indication for a single source or multiple sources. In addition, the algorithm is robust even in low SNR situations. The proposed sensor network based algorithm is promising for subsurface imaging in real time.

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