Drift time estimation by dynamic time warping

Tianci Cui and Gary F. Margrave

Outline

- Drift time
- Well-based 1D seismogram models
- Matching stationary and nonstationary seismograms
- Dynamic time warping
- Inclusion of internal multiples
- Conclusions and future work

Drift time estimation by DTW

- **Drift time**
- **Well-based 1D seismogram models**
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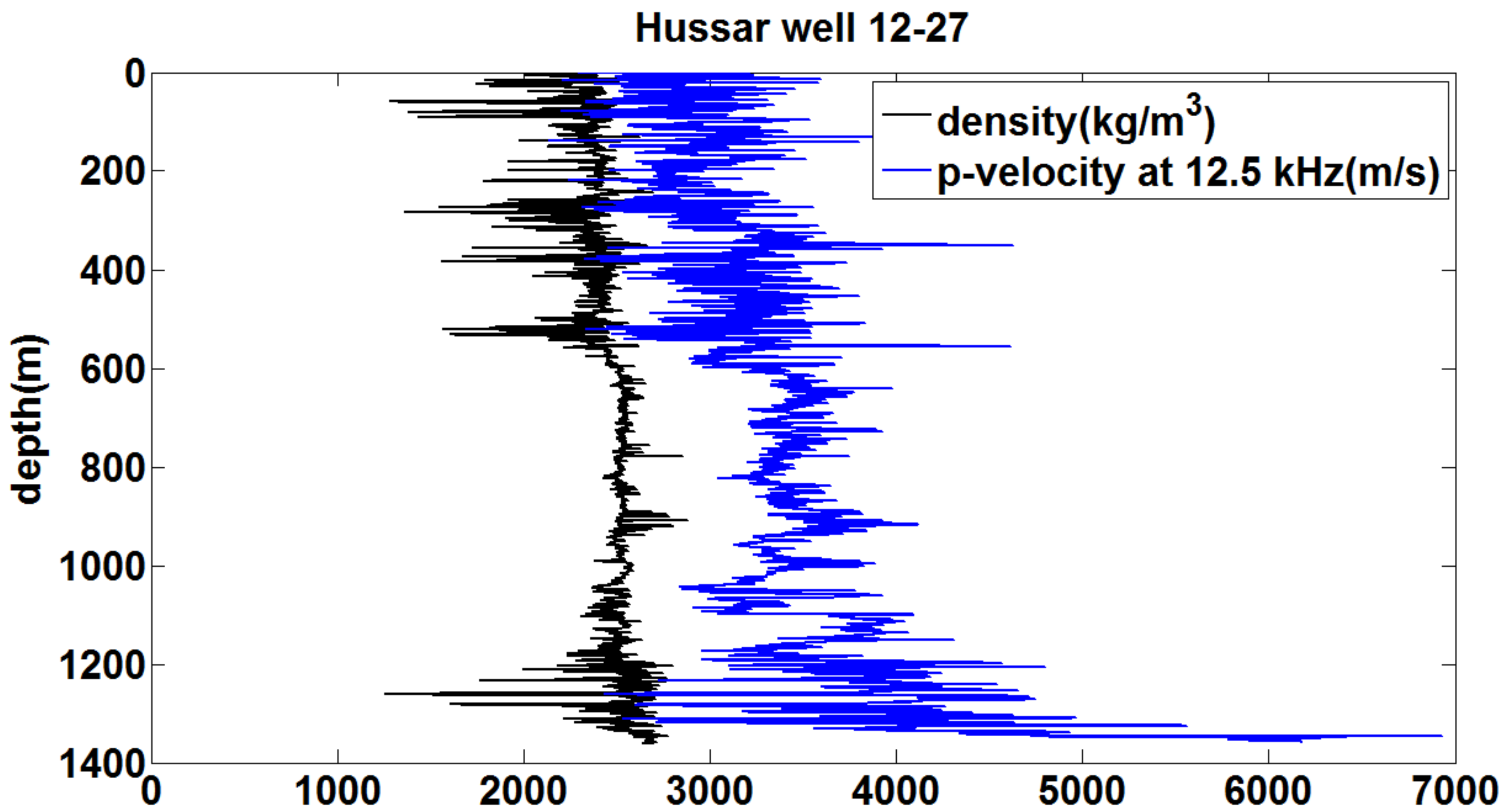
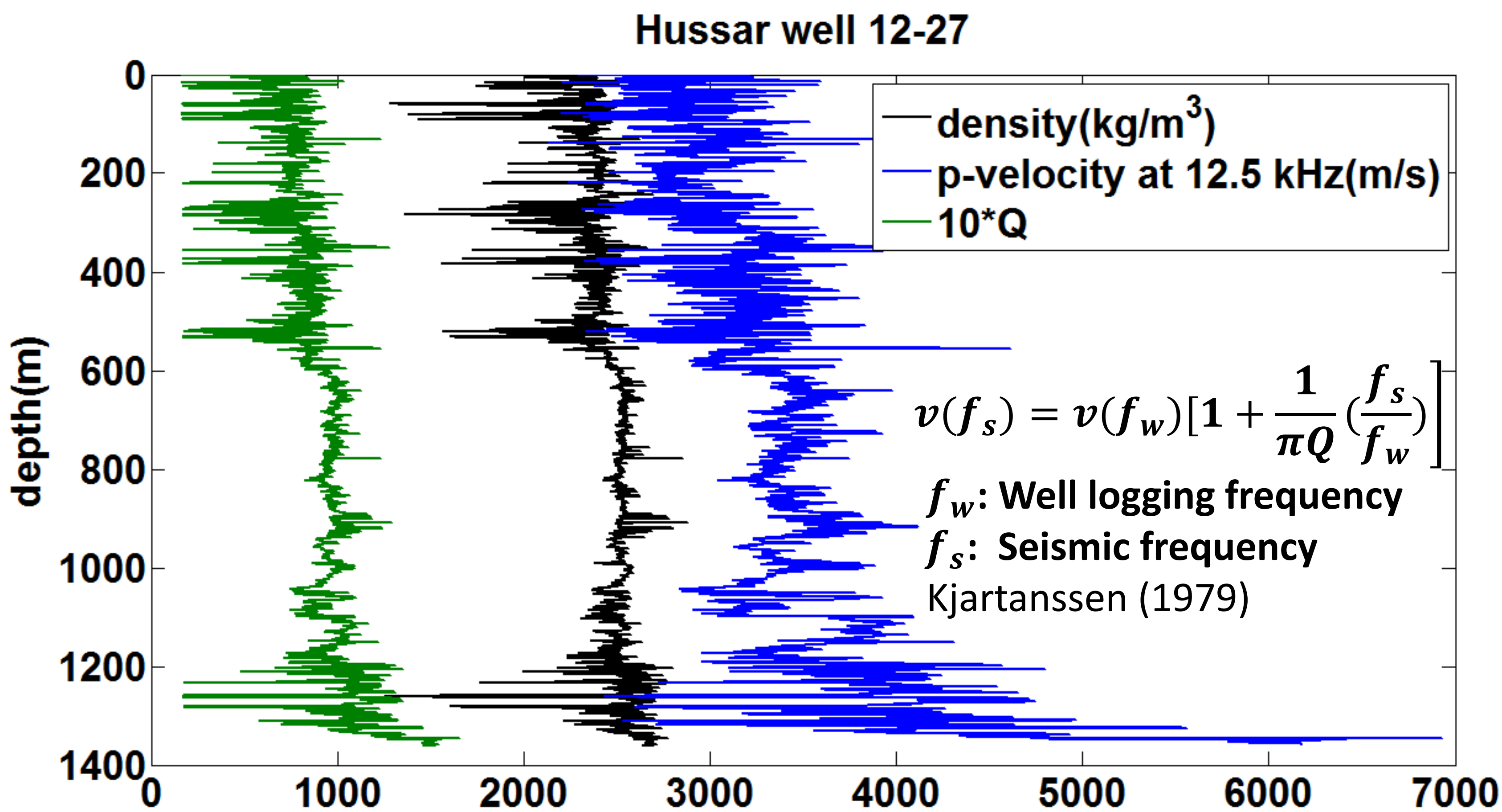
Drift time: well logs



Drift time: fake Q log



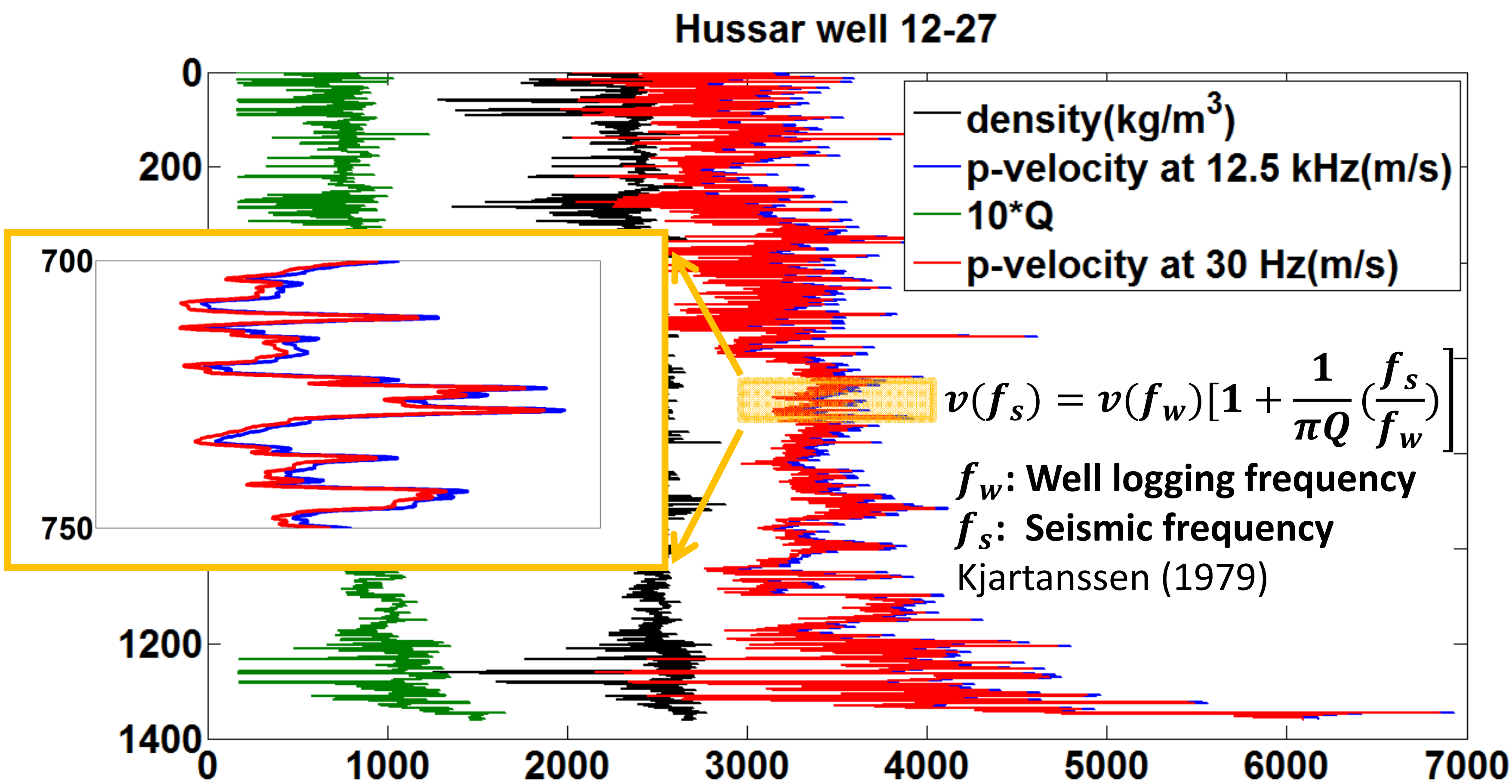
$$v(f_s) = v(f_w)\left[1 + \frac{1}{\pi Q}\left(\frac{f_s}{f_w}\right)\right]$$

f_w: **Well logging frequency**

f_s: **Seismic frequency**

Kjartanssen (1979)

Drift time: frequency-dependent velocity



$$v(f_s) = v(f_w)\left[1 + \frac{1}{\pi Q}\left(\frac{f_s}{f_w}\right)\right]$$

f_w: **Well logging frequency**

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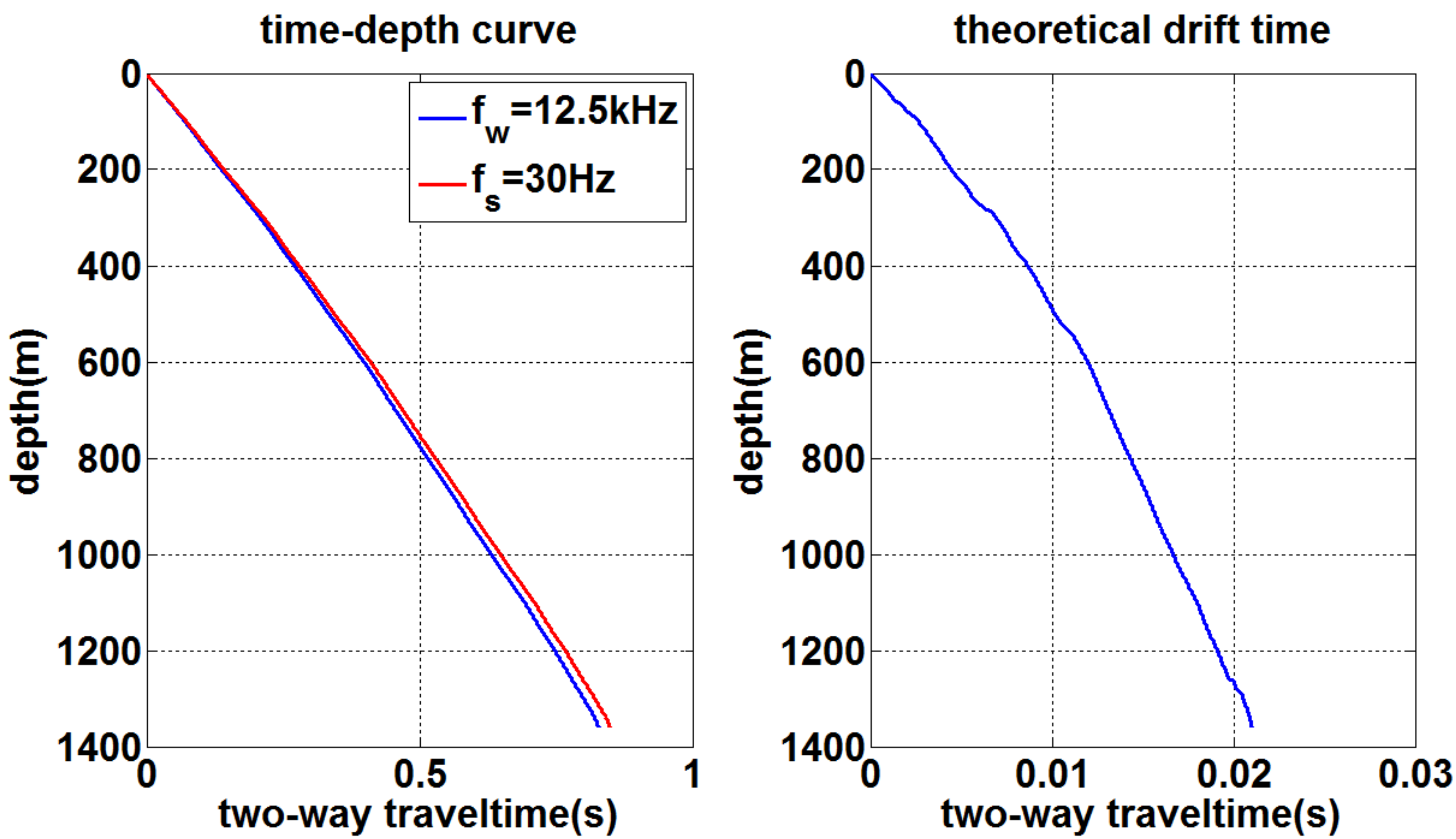
Kjartanssen (1979)

Drift time



time-depth curve
f_w=12.5kHz
f_s=30Hz
depth(m)
two-way traveltime(s)
0
200
400
600
800
1000
1200
1400
0
0.5
1
theoretical drift time
depth(m)
two-way traveltime(s)
0
0.01
0.02
0.03

Drift time estimation by DTW

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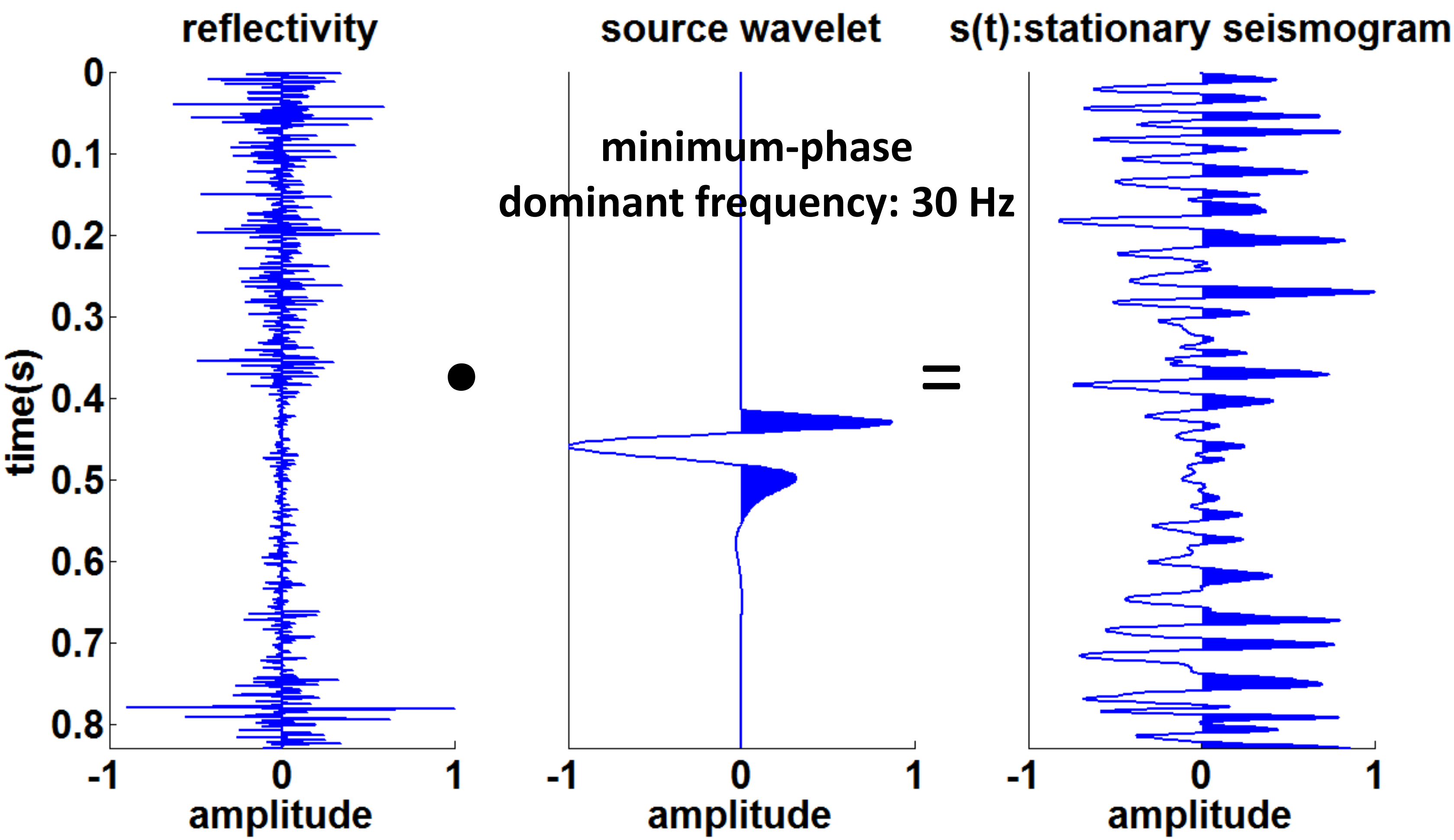
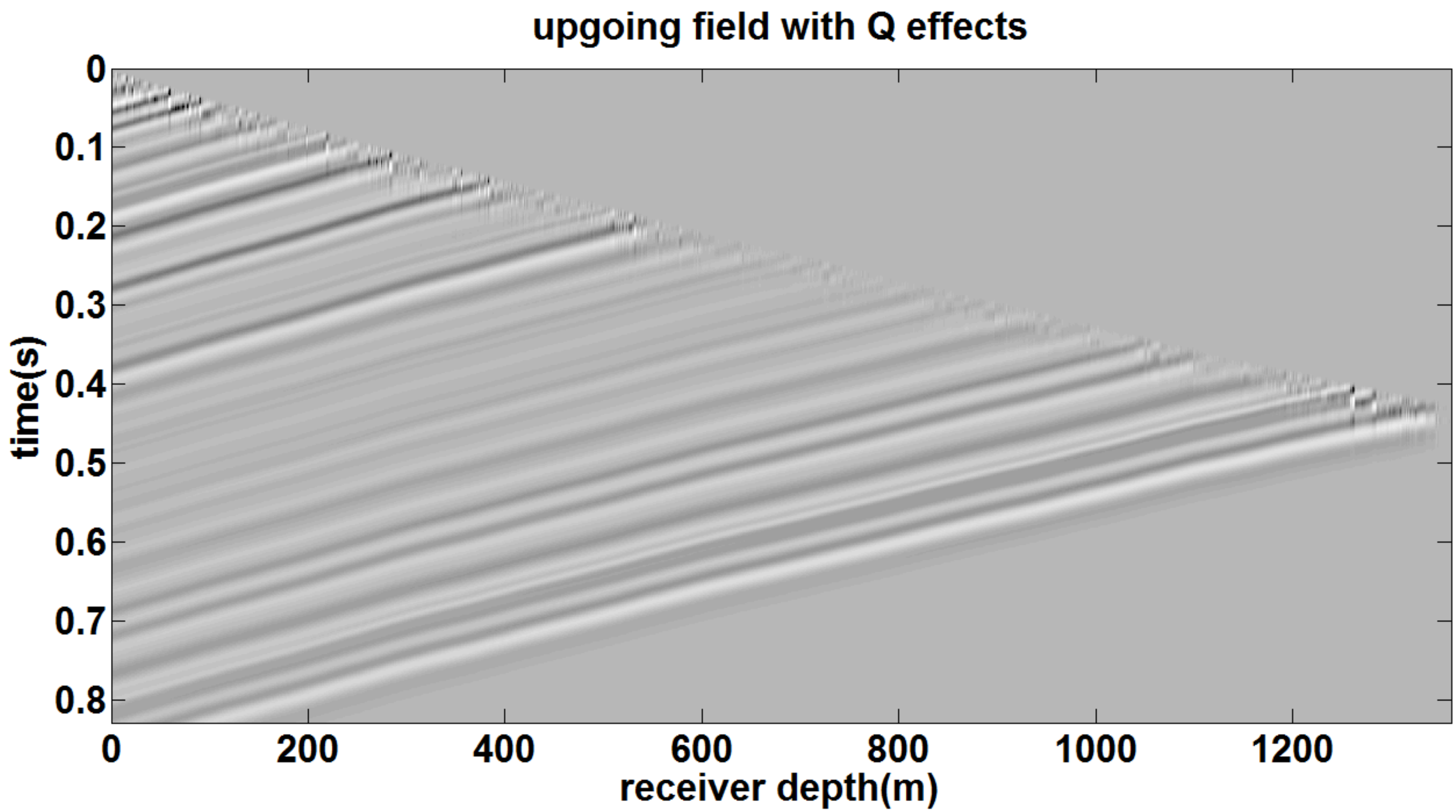
Stationary seismogram: s(t)



Nonstationary seismogram: sq(t)

Synthetic zero-offset VSP model with Q effects

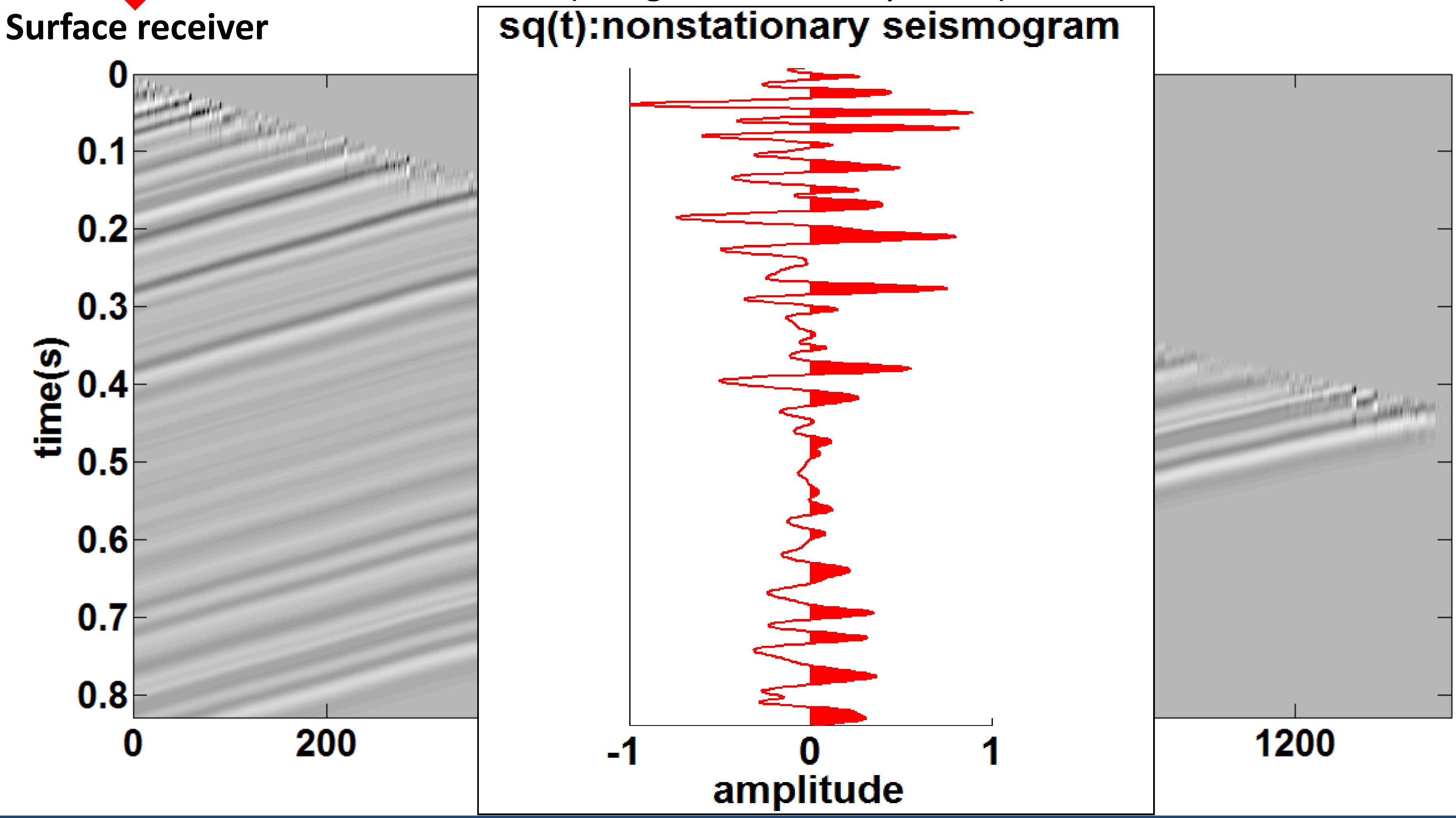
(Margrave and Daley, 2014)



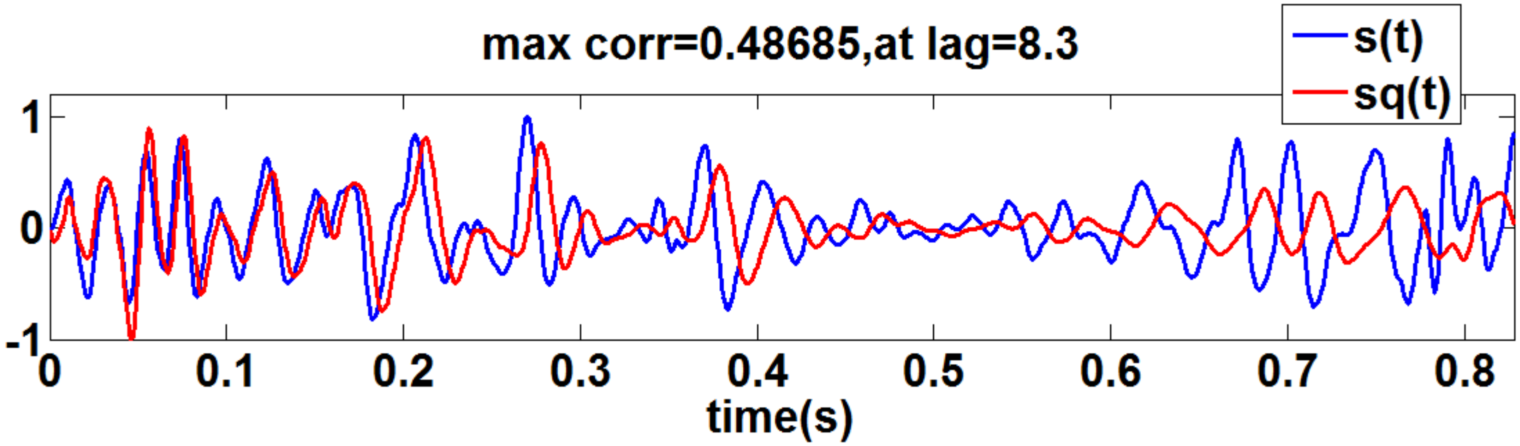
Nonstationary seismogram: sq(t)

Synthetic zero-offset VSP model with Q effects

(Margrave and Daley, 2014)



1 D seismogram models



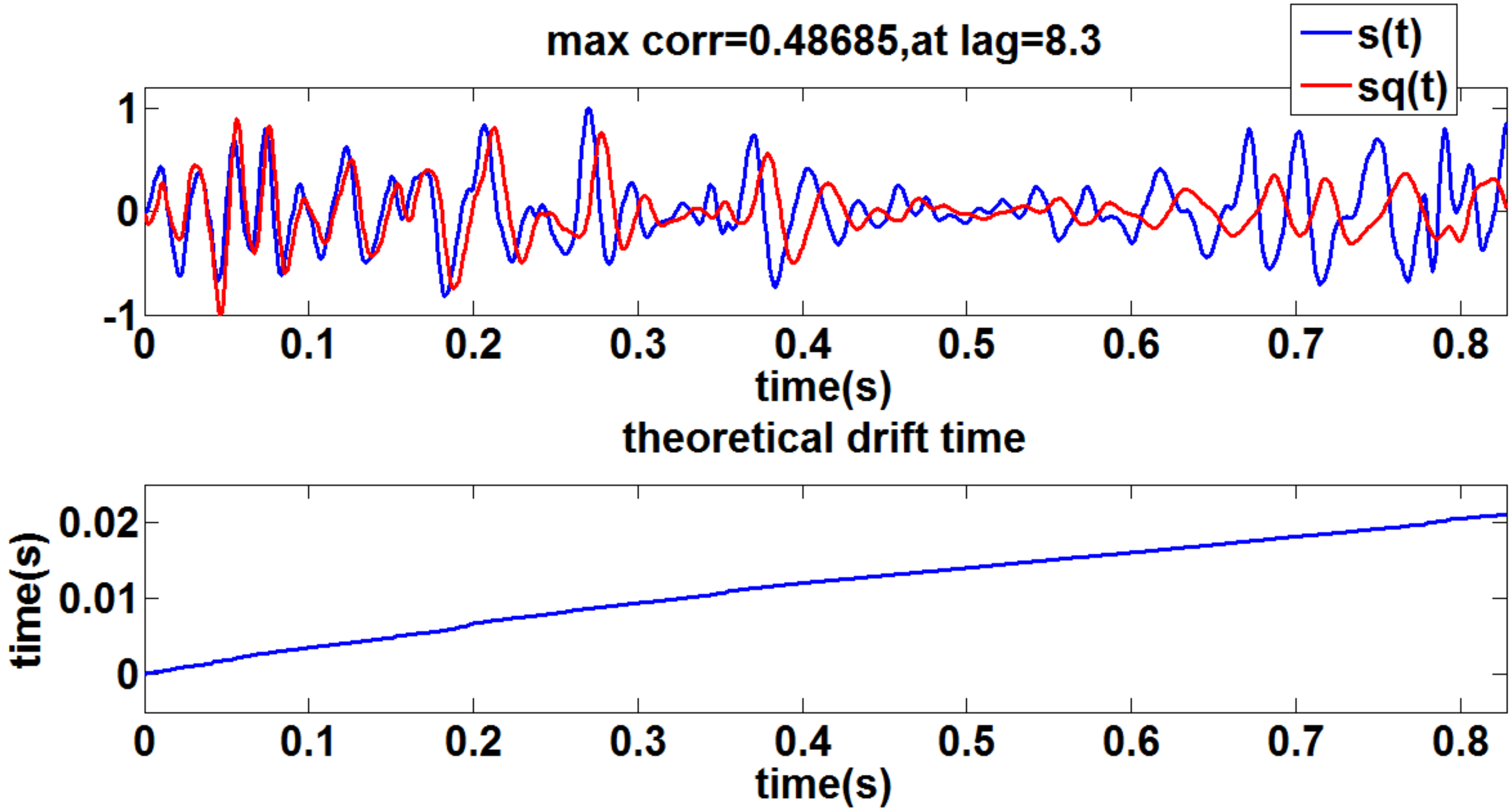
Q effects:

1 Diminishing amplitude

2 Widening wavelets

3 Delaying events ⇦ Drift time

1 D seismogram models



Drift time estimation by DTW

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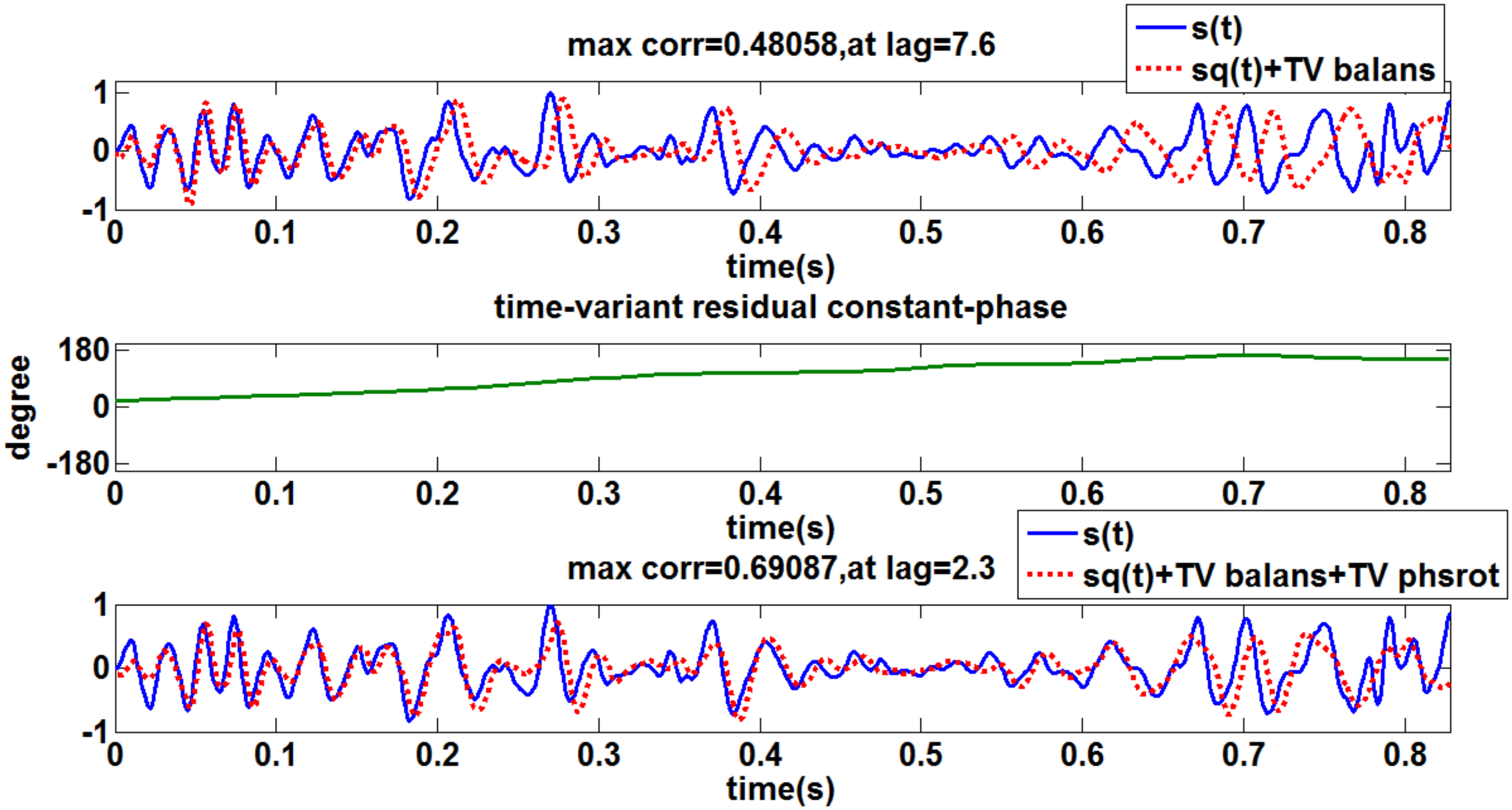
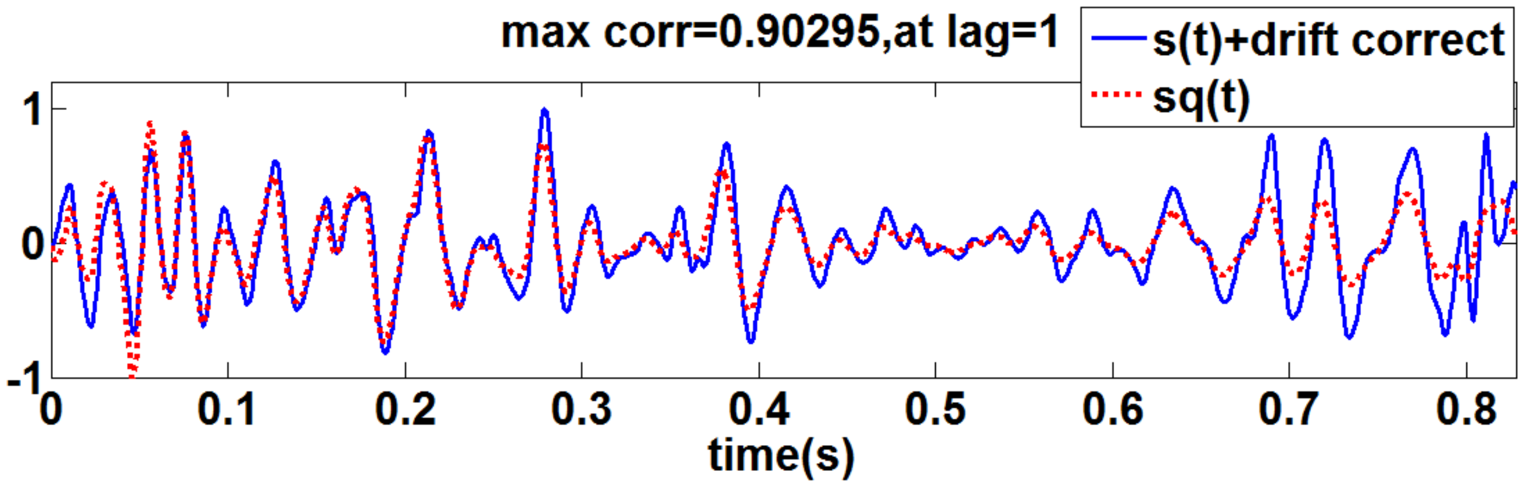
Matching without drift time correction

Time-variant balancing and time-variant constant-phase rotation



Matching with theoretical drift time correction

Drift time correction



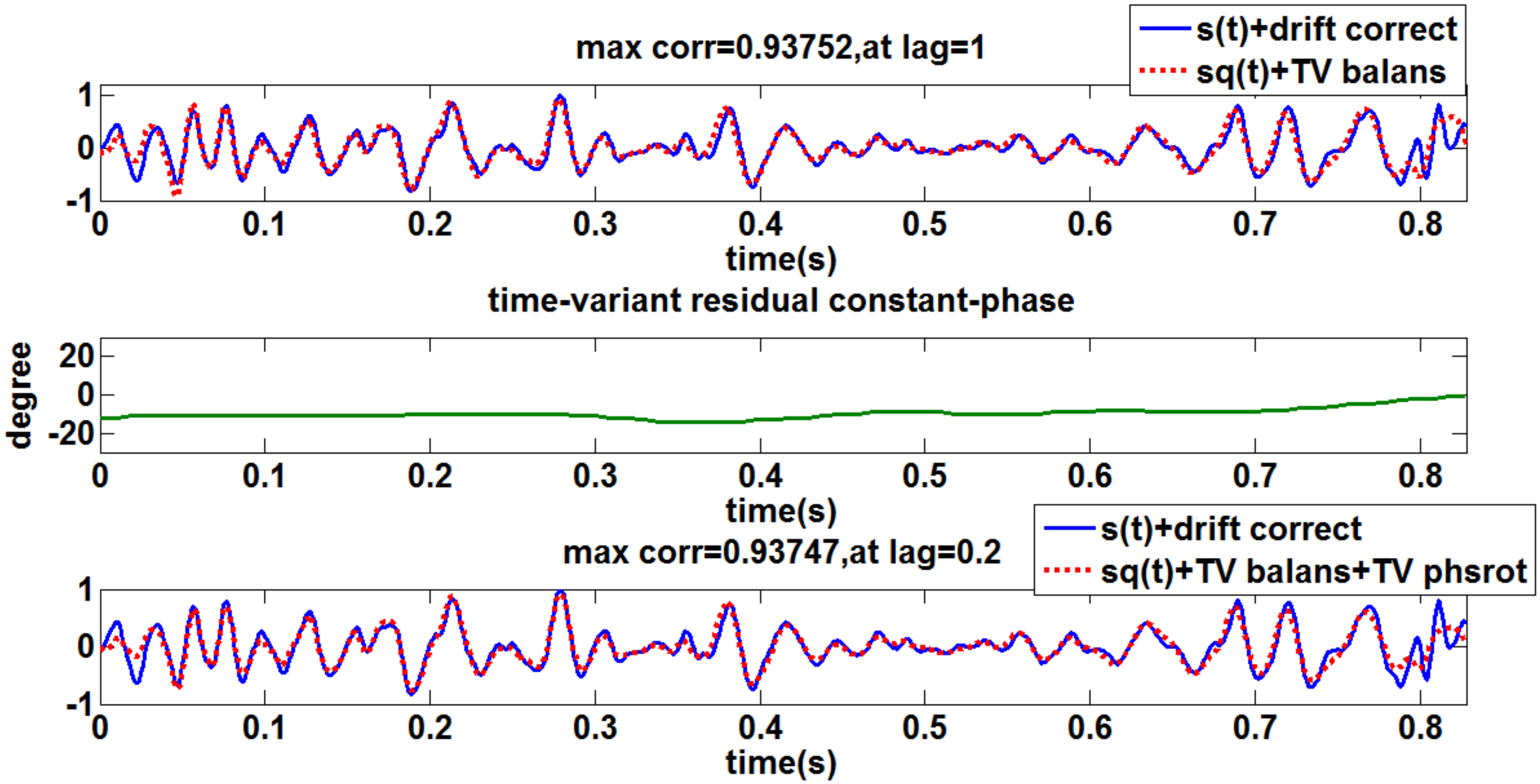
$$s_{corr}(t) = s\,(t + drift(t))$$

$drift(t)$: drift time

$S_{corr}(t)$: stationary seismogram after drift time correction

Matching with theoretical drift time correction

Matching perfection: time-variant balancing and time-variant constant-phase rotation



Matching with theoretical drift time correction

Matching perfection: time-variant balancing and time-variant constant-phase rotation

Drift time correction is necessary to match the stationary to nonstationary seismograms.

Calculation of drift time in industrial practice needs one of these:

- Knowledge of Q or
- A check-shot survey or
- Manually stretching and squeezing the synthetic seismogram

Drift time estimation by DTW

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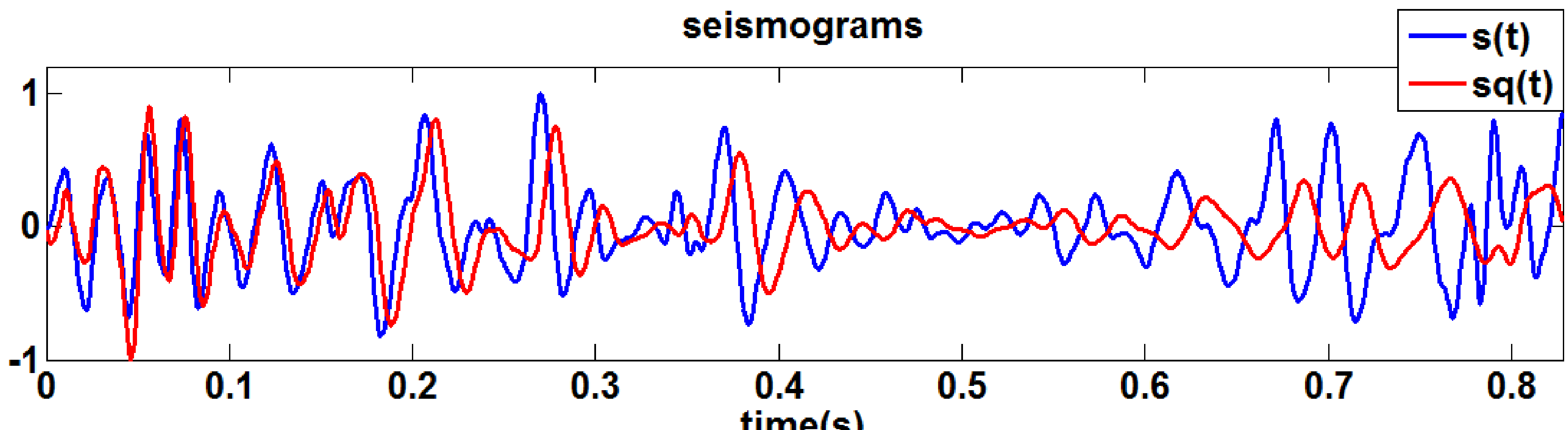
Dynamic Time Warping

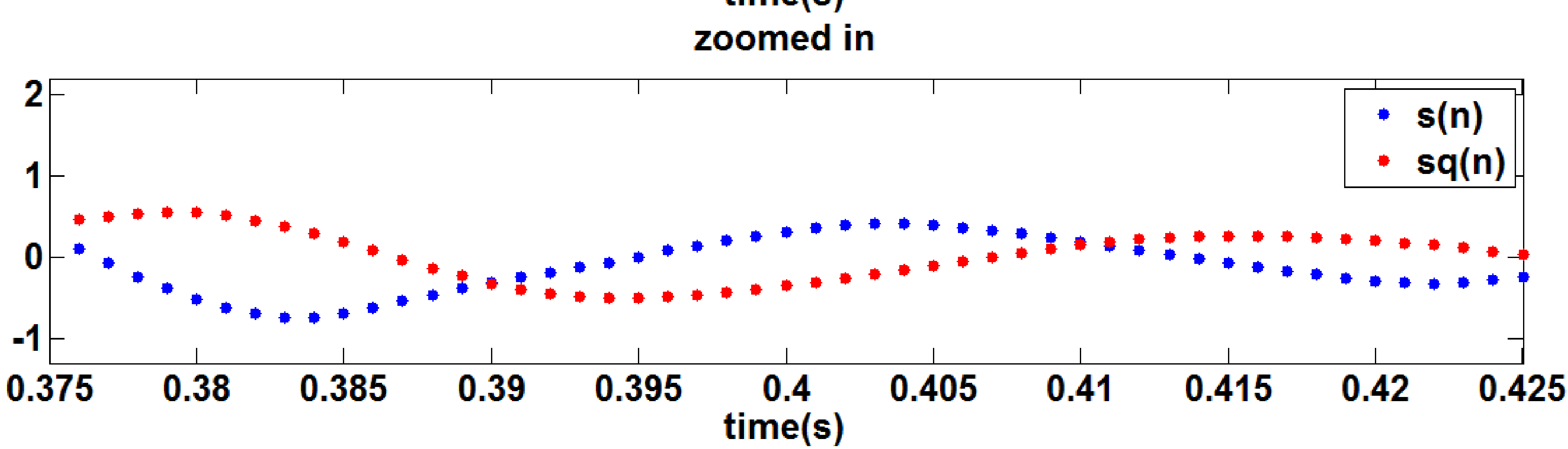
Dynamic time warping (Hale, 2012):

- **Estimates the time shift between two seismograms**
- **Based on constrained optimization algorithm**
- **Realized by dynamic programming**
- **Similar to time-variant crosscorrelation but more sensitive to the rapid-varying time shift**

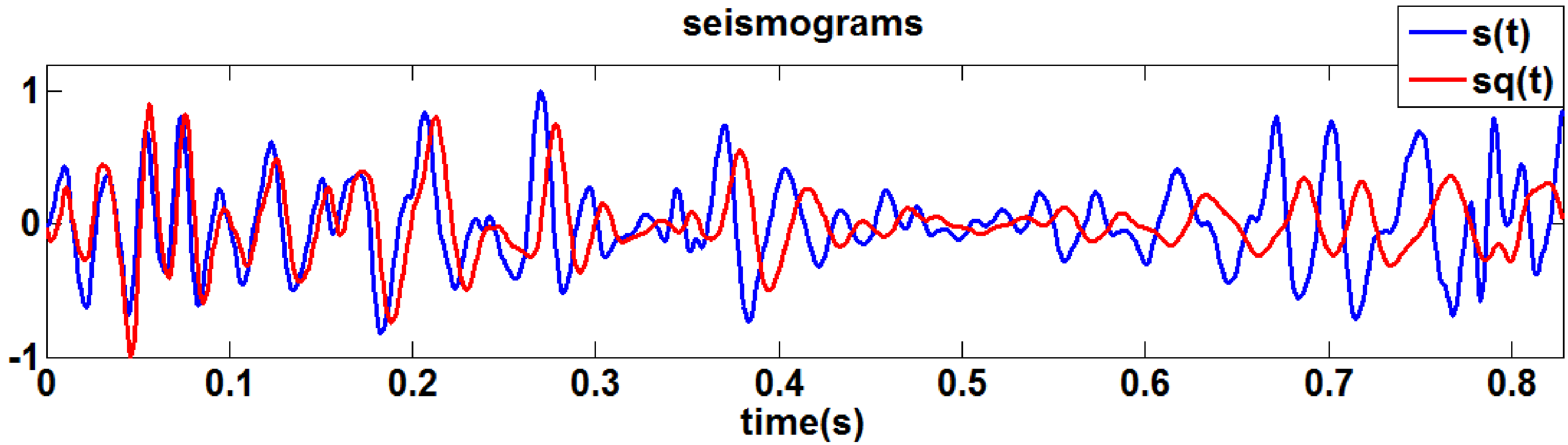
We use dynamic time warping (DTW) to estimate the drift time between the stationary and nonstationary seismograms caused by anelastic attenuation

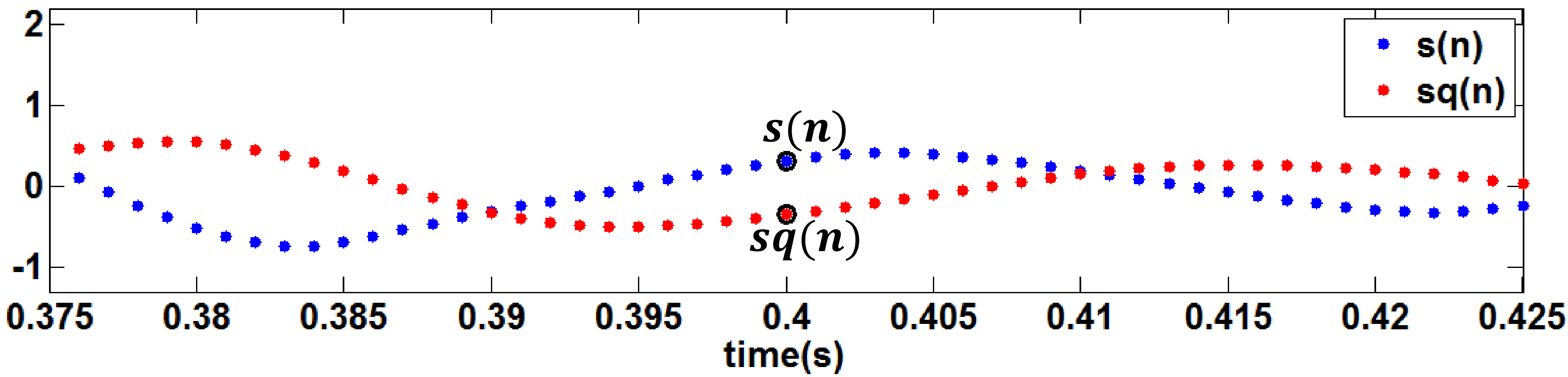
DTW: drift time estimation



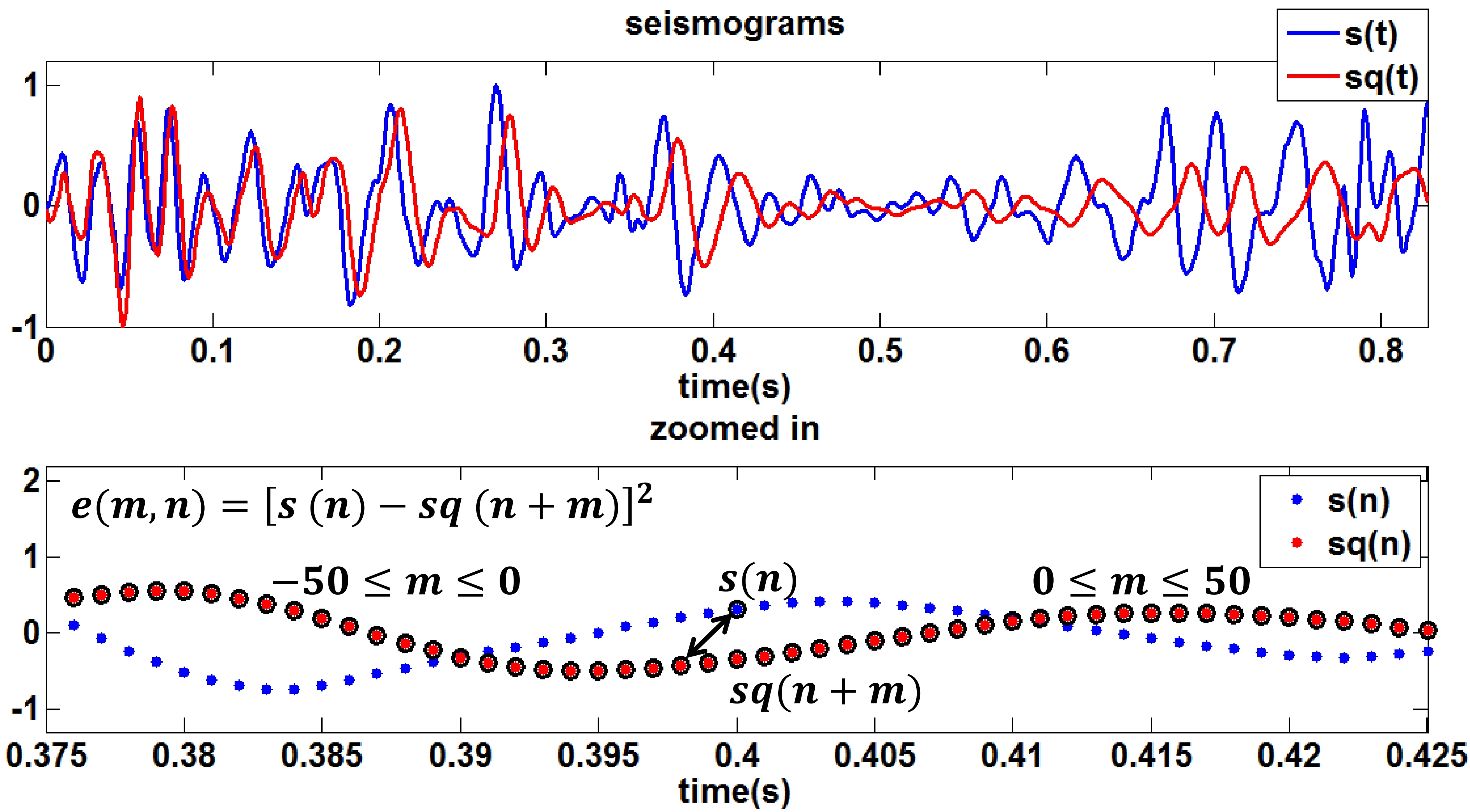


DTW: drift time estimation





DTW: drift time estimation



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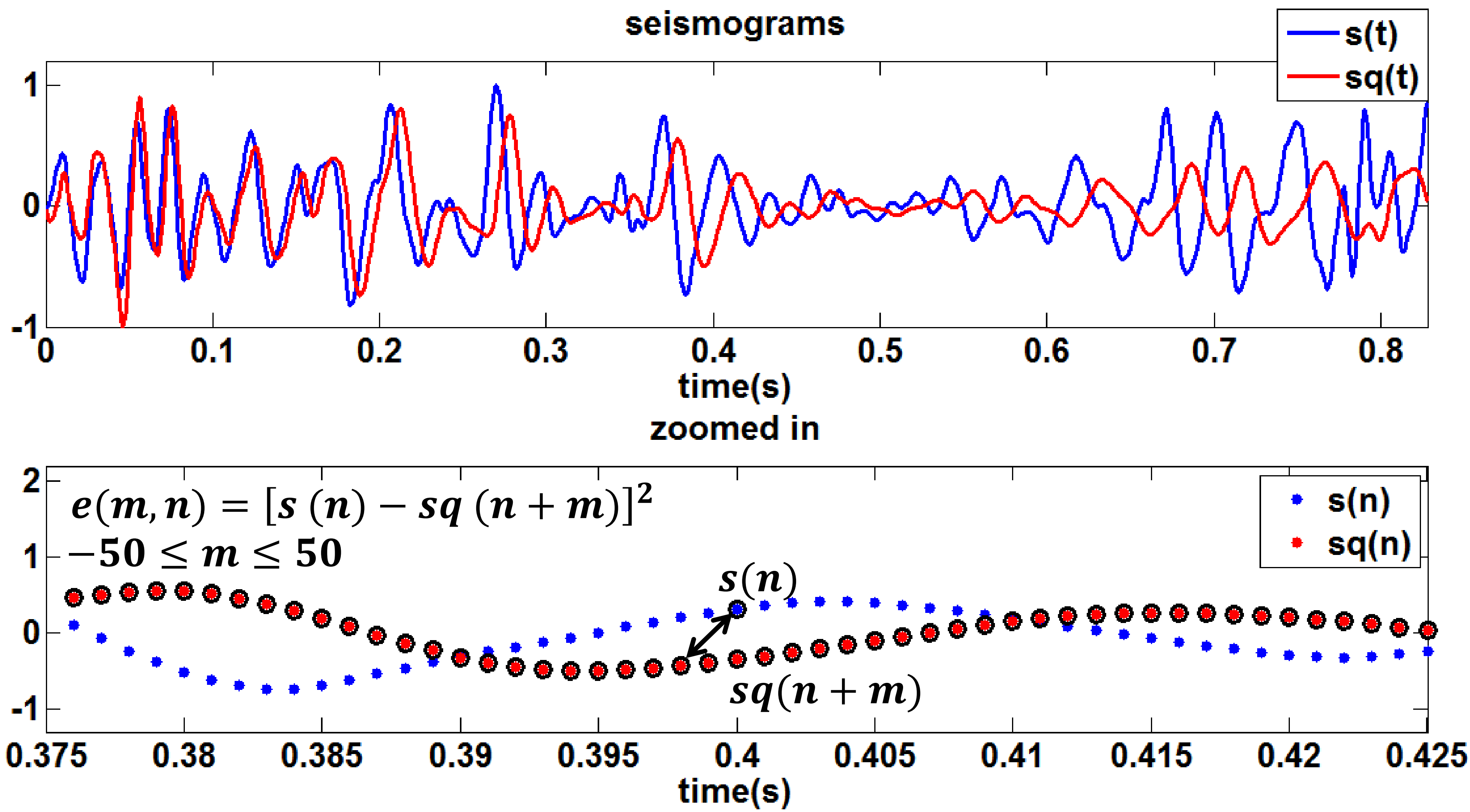
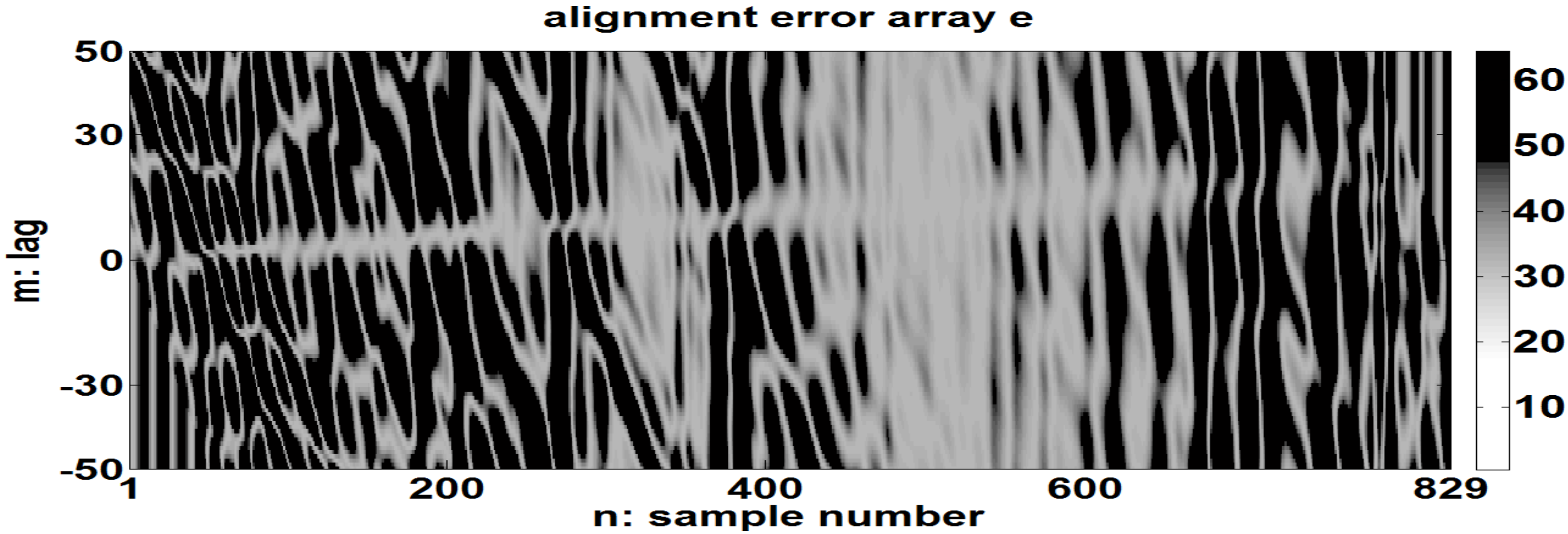
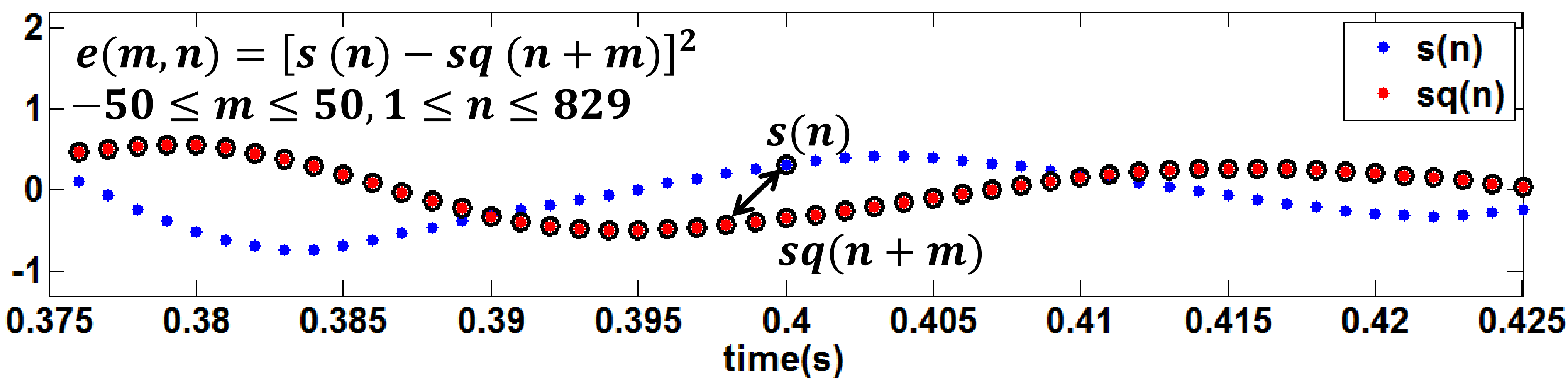
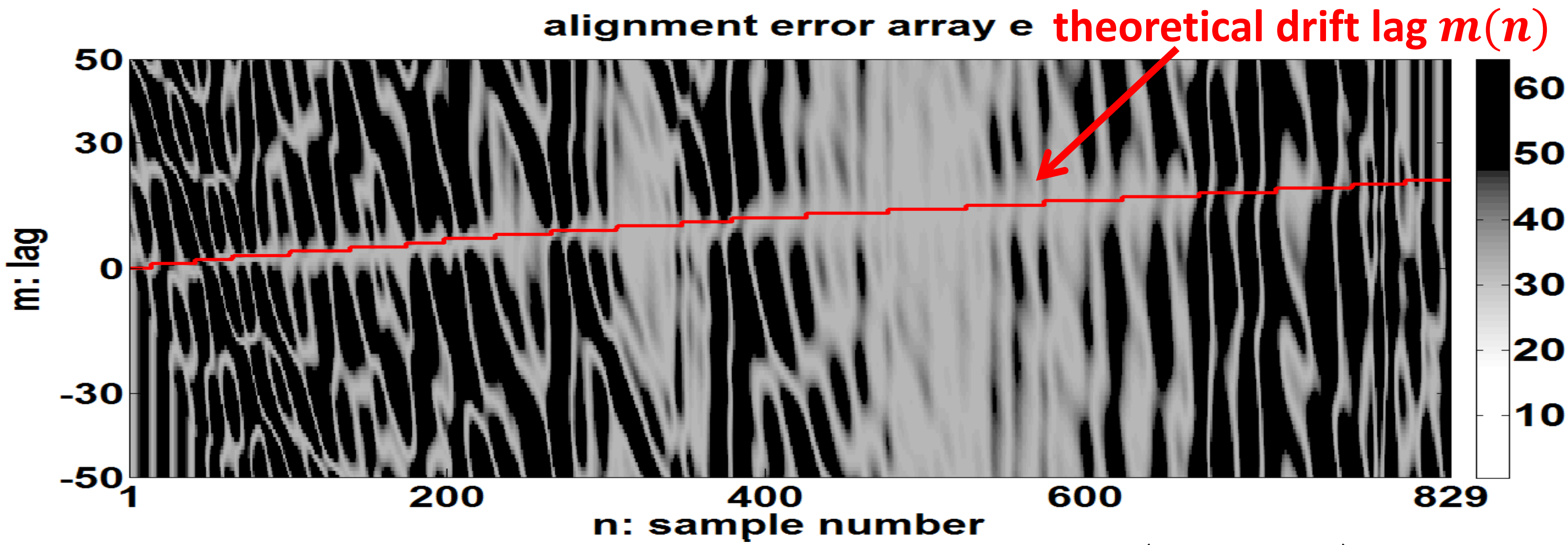


DTW: drift time estimation





DTW: drift time estimation

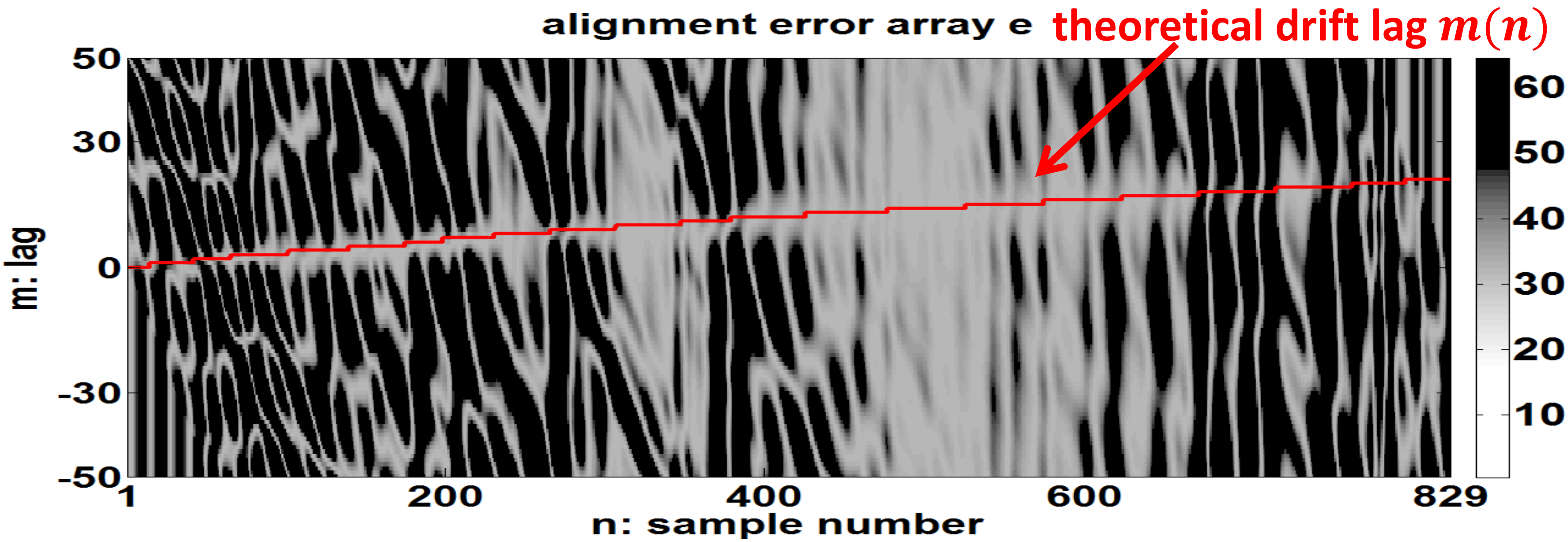


$$e(m,n) = [s\,(n) - sq\,(n+m)]^2$$
$$-50 \le m \le 50, 1 \le n \le 829$$

$$m(n) = round\left(\frac{drift(n)}{dt}\right)$$

n: sample number, dt: time sample rate
$drift(n)$: drift time, $m(n)$: drift lag

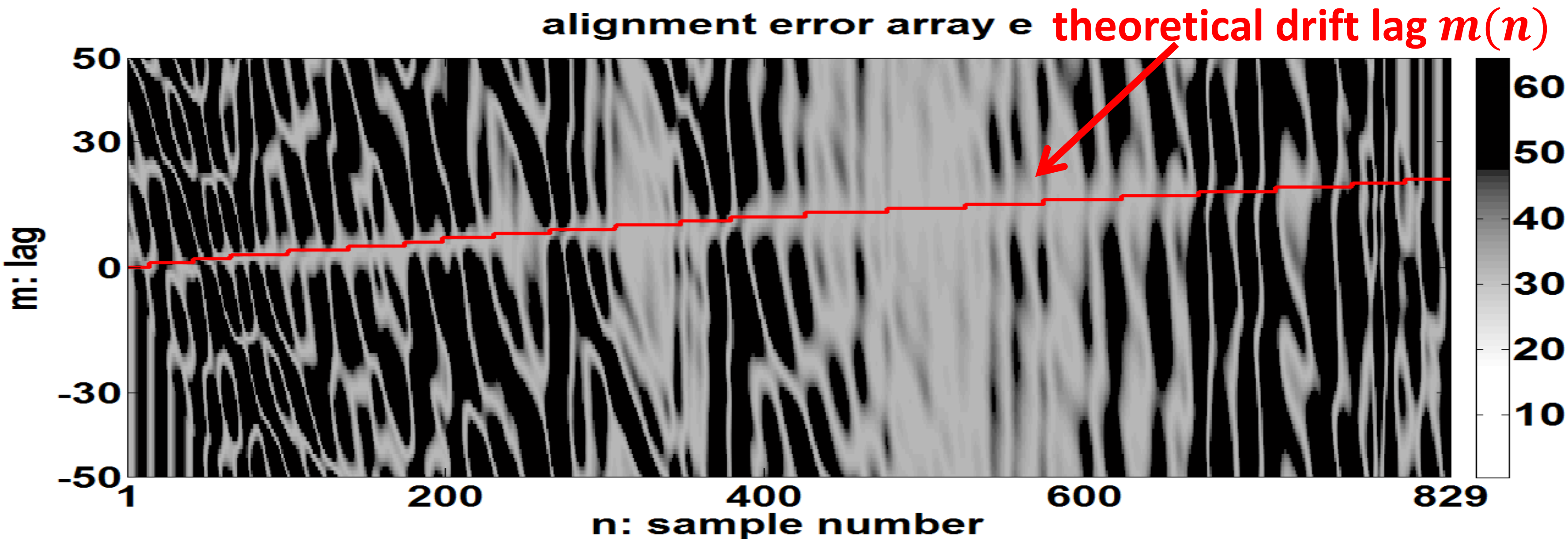
DTW: drift time estimation



- The alignment error is nearly zero along the theoretical drift lag.

- Choose a path traveling from $n = 1$ to 829, sum alignment errors along this path. The estimated drift lag sequence is the path of the minimal cumulative alignment error.

DTW: drift time estimation



101^{829} ⇨ infinite

Constraint: $|m(n) - m(n-1)| \leq 1$

Dynamic Programming

Alignment error array

m \ n	1	2	3
1	4	7	1
0	3	5	8
-1	6	2	9

27 possible paths

Dynamic Programming: accumulation

Alignment error array

m \ n	1	2	3
1	**4**	**7**	**1**
0	**3**	**5**	**8**
-1	**6**	**2**	**9**

27 possible paths

Cumulative alignment error array

m \ n	1	2	3
1			
0			
-1			

Dynamic Programming: accumulation

Alignment error array

m \ n	1	2	3
1	4	7	1
0	3	5	8
-1	6	2	9

27 possible paths

Cumulative alignment error array

m \ n	1	2	3
1	4	?	
0	3		
-1	6		

Constraint: $|m(n) - m(n-1)| \leq 1$

Dynamic Programming: accumulation

Alignment error array

m \ n	1	2	3
1	**4**	**7**	**1**
0	**3**	**5**	**8**
-1	**6**	**2**	**9**

27 possible paths

Cumulative alignment error array

m \ n	1	2	3
1	**4**	**?**	
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Dynamic Programming: accumulation

Alignment error array

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1	4	7	1
0	3	5	8
-1	6	2	9

27 possible paths

Cumulative alignment error array

m \ n	1	2	3
1	4	?	
0	3		
-1	6		

Constraint: $|\boldsymbol{m(n) - m(n-1)}|$ **≤1**

Dynamic Programming: accumulation

Alignment error array

m \ n	1	2	3
1	4	7	1
0	3	5	8
-1	6	2	9

27 possible paths

Cumulative alignment error array

m \ n	1	2	3
1	4	10	
0	3		
-1	6		

Constraint: $|m(n) - m(n-1)| \leq 1$

Dynamic Programming: accumulation

Alignment error array

m \ n	1	2	3
1	**4**	**7**	**1**
0	**3**	**5**	**8**
-1	**6**	**2**	**9**

27 possible paths

Cumulative alignment error array

m \ n	1	2	3
1	**4**	**10**	
0	**3**	**?**	
-1	**6**		

Constraint: $|\boldsymbol{m(n) - m(n-1)}|\leq \mathbf{1}$

Dynamic Programming: accumulation

Alignment error array

m \ n	1	2	3
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27 possible paths

Cumulative alignment error array

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27 possible paths

Cumulative alignment error array

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Dynamic Programming: accumulation

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0	3	5	8
-1	6	2	9

27 possible paths

Cumulative alignment error array

m \ n	1	2	3
1	4	10	
0	3	8	
-1	6	5	

Constraint: $|m(n) - m(n-1)| \leq 1$

Dynamic Programming: accumulation

Alignment error array

m \ n	1	2	3
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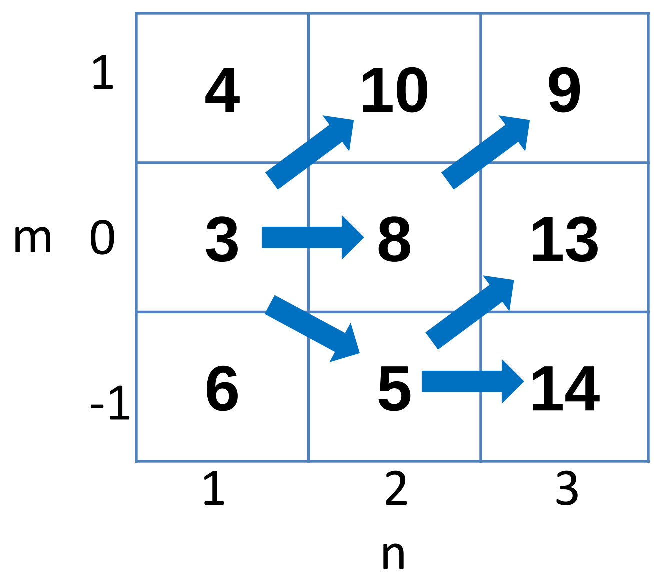
0	3	5	8
-1	6	2	9

27 possible paths

Cumulative alignment error array



3 possible paths

Constraint: $|m(n) - m(n-1)| \leq 1$

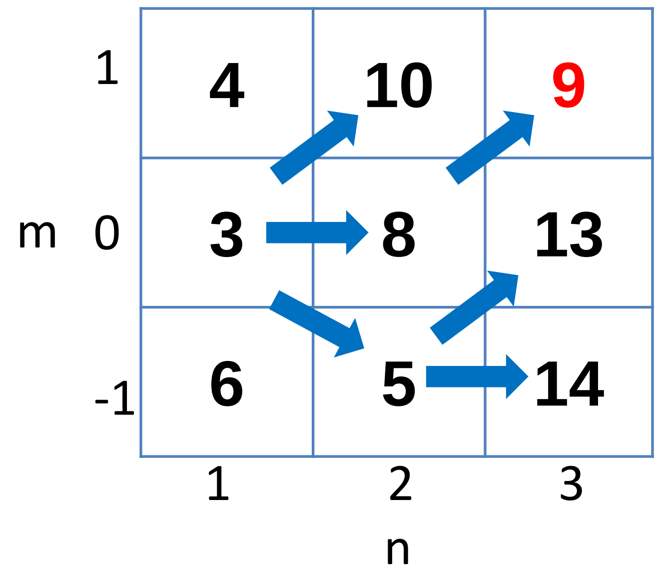
Dynamic Programming: backtracking

Alignment error array

m \ n	1	2	3
1	4	7	1
0	3	5	8
-1	6	2	9

27 possible paths

Cumulative alignment error array



3 possible paths

Constraint: $|m(n) - m(n-1)| \leq 1$

Dynamic Programming: backtracking

Alignment error array

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1	4	7	1
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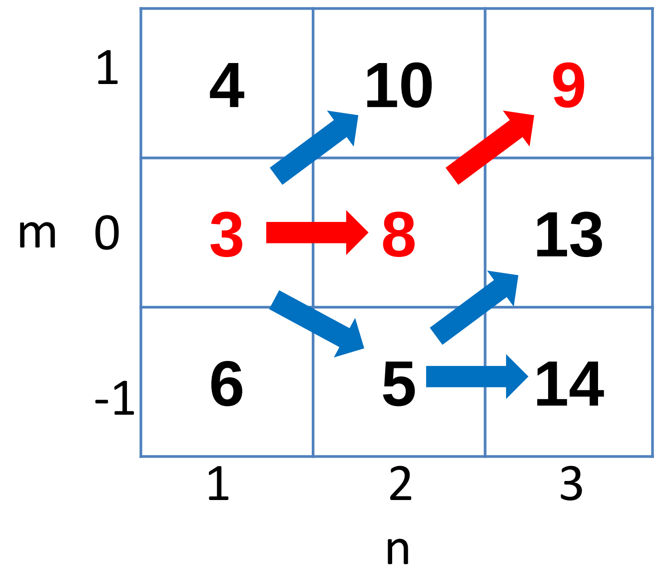
-1	6	2	9

27 possible paths

Cumulative alignment error array



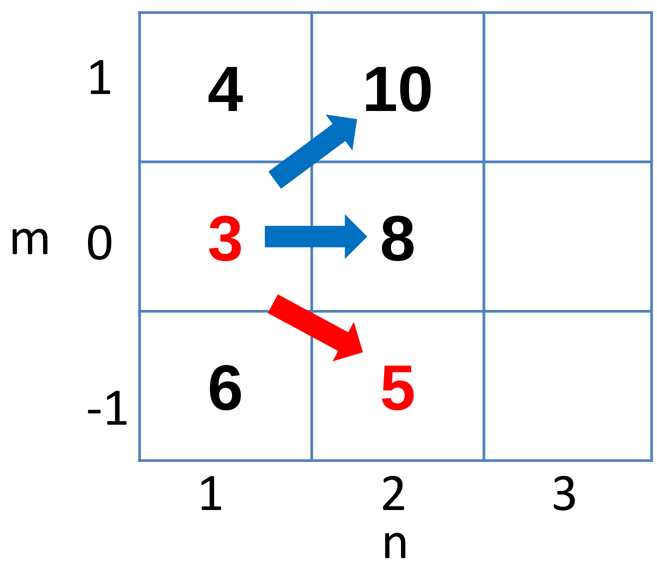
3 possible paths

Constraint: $|m(n) - m(n-1)| \leq 1$

Estimated drift lag: $m(n) = [0\ 0\ 1]$

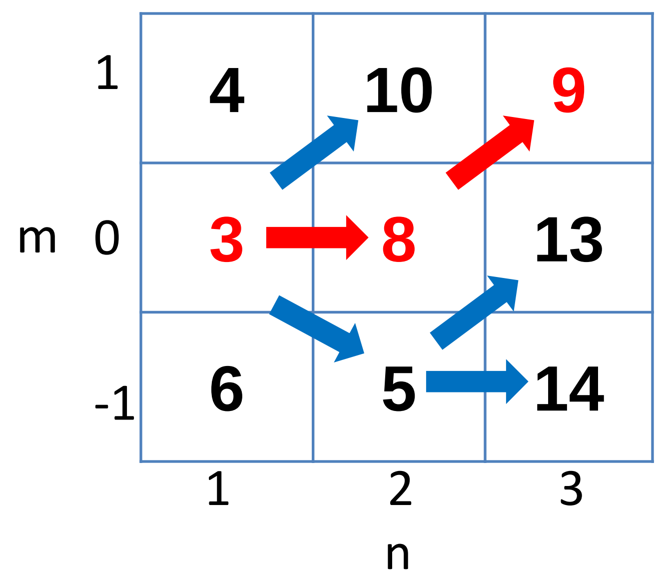
Dynamic Programming

Cumulative alignment error array



$$\boldsymbol{m(n) = [0, -1\,]}$$

Cumulative alignment error array

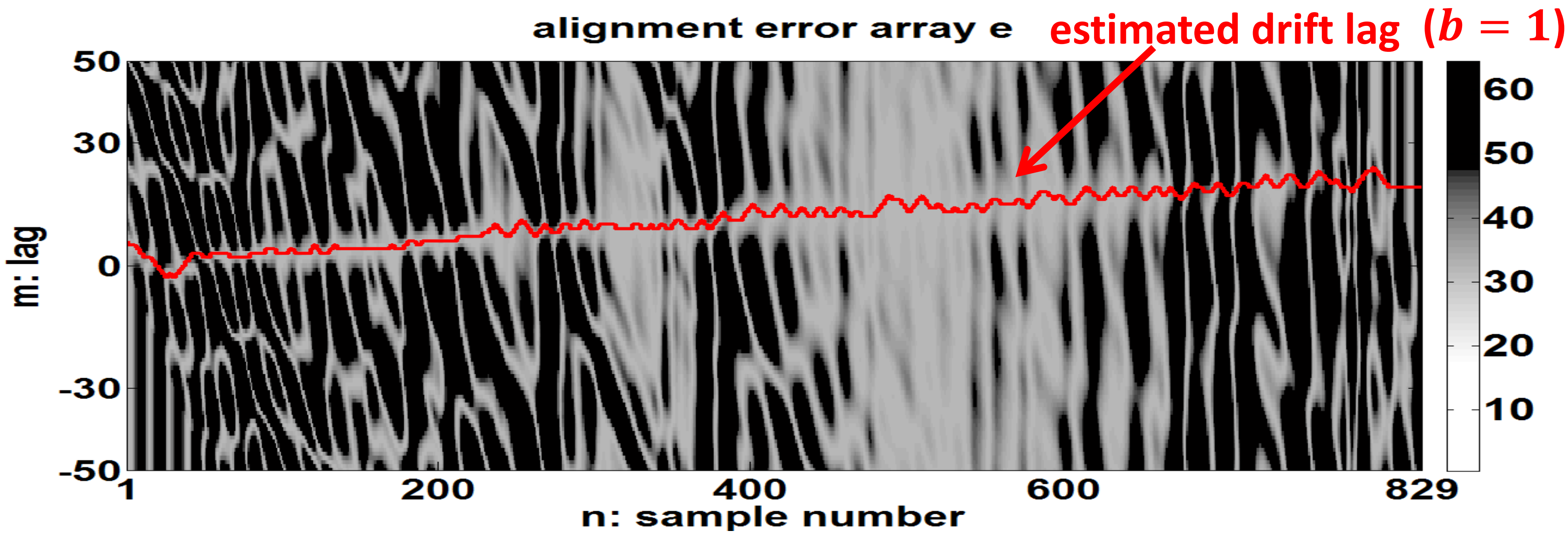


$$\boldsymbol{m(n) = [0, 0, 1]}$$

Dynamic: optimal solution varies at different stage

Warping path: drift lag

DTW: drift time estimation



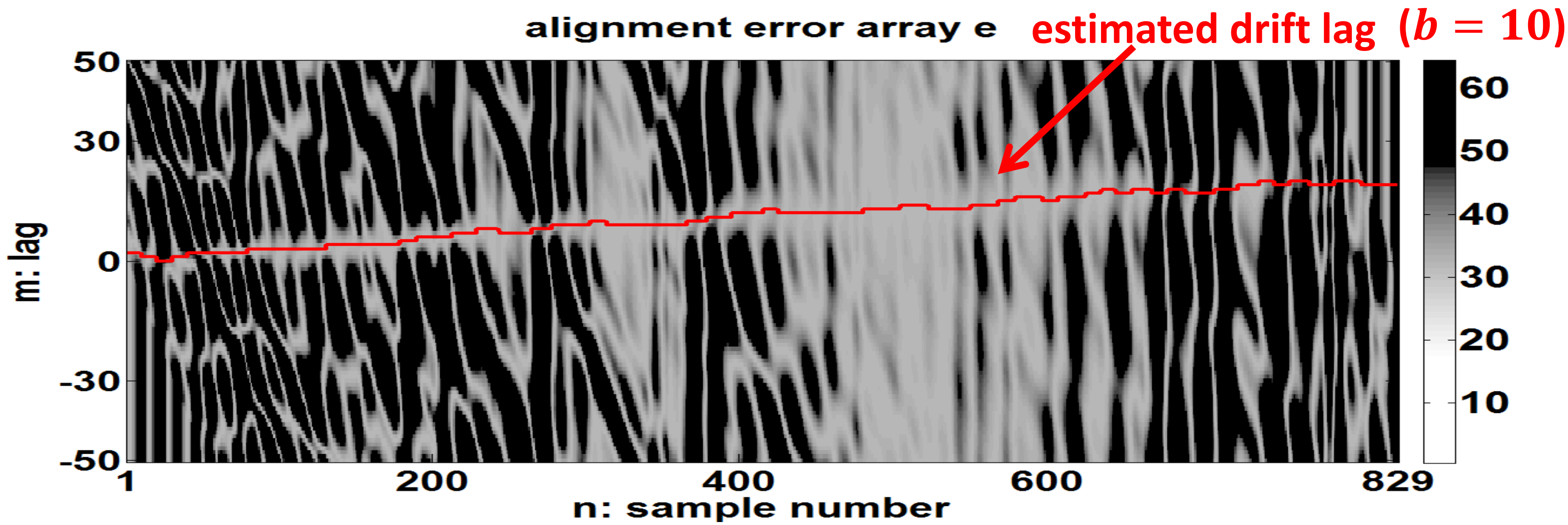
$101^{829} \Rightarrow$ infinite

Constraint: $|m(n) - m(n-1)| \leq 1$

Further Constraint:
$\sum_{k=1}^{b} |m(n-k+1) - m(n-k)| \leq 1$

The drift lag sequence is constrained to change in blocks of b samples

DTW: drift time estimation



101^{829} ⇒ infinite

Constraint: $|m(n) - m(n-1)| \leq 1$

Further Constraint:

$\sum_{k=1}^{b} |m(n-k+1) - m(n-k)| \leq 1$

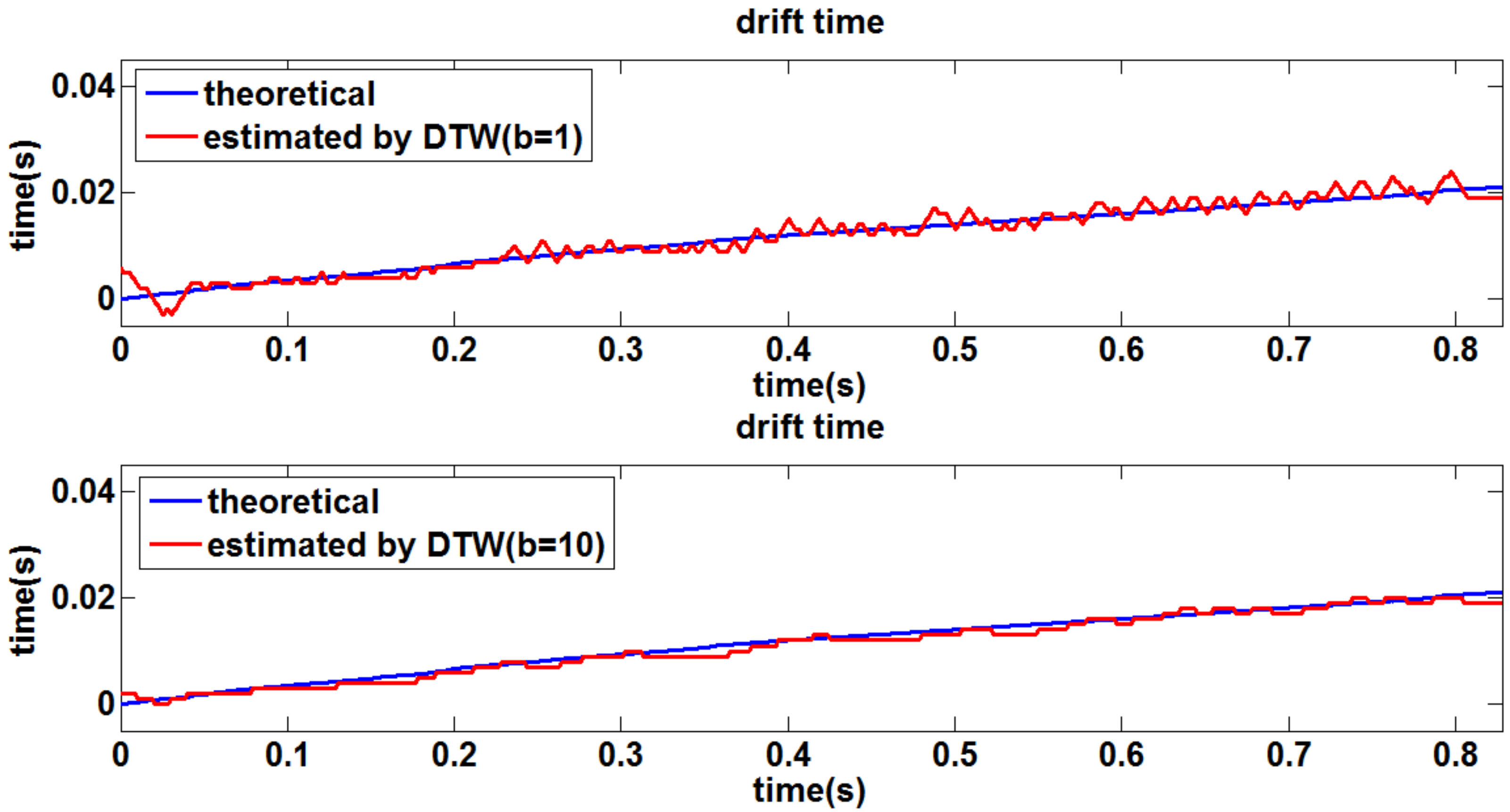
The drift lag sequence is constrained to change in blocks of b samples

DTW: drift time estimation

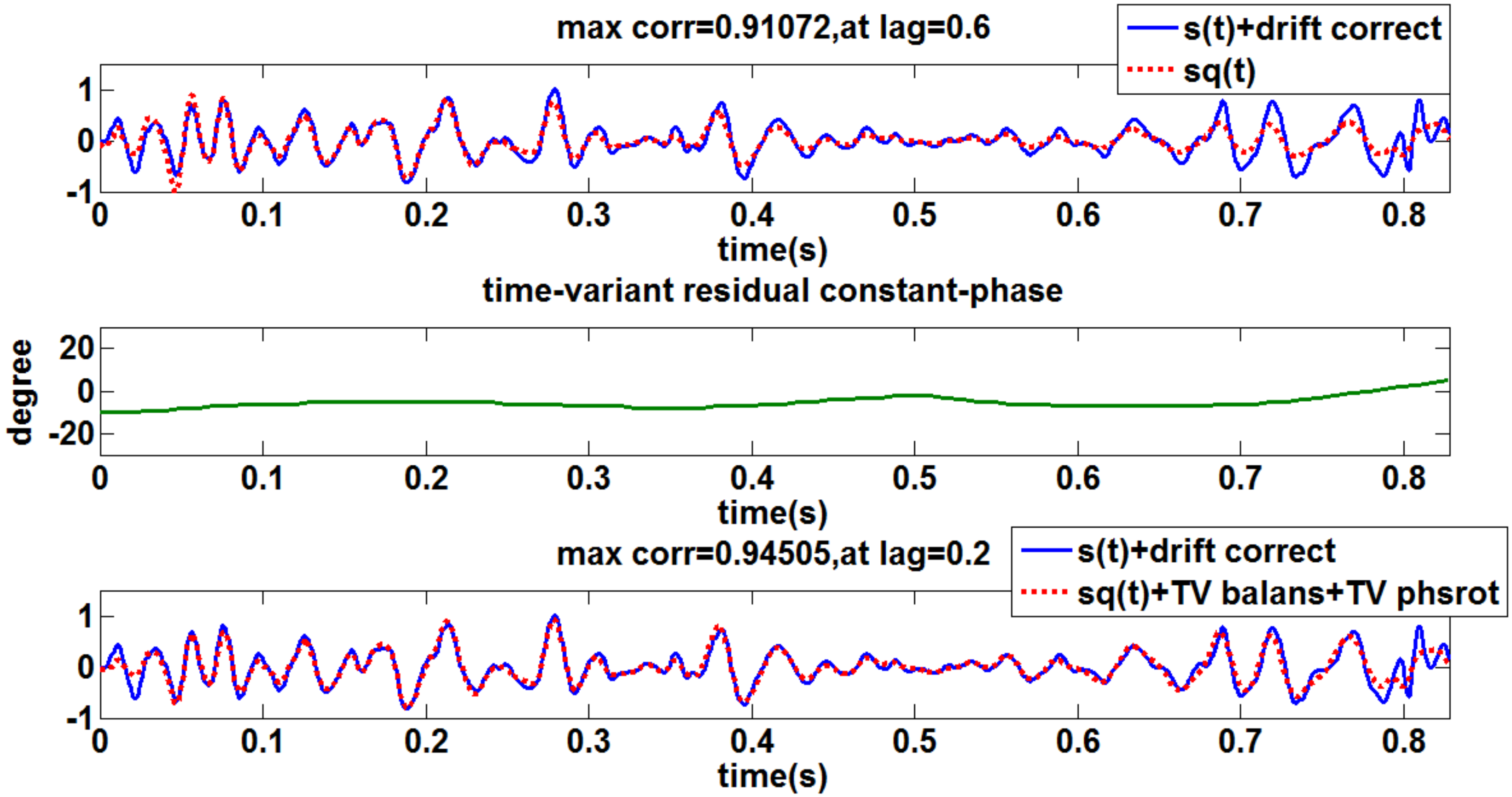
$$drift(t) = m(t) * dt$$

$m(t)$: estimated drift lag

$drift(t)$: estimated drift time



DTW: matching seismograms



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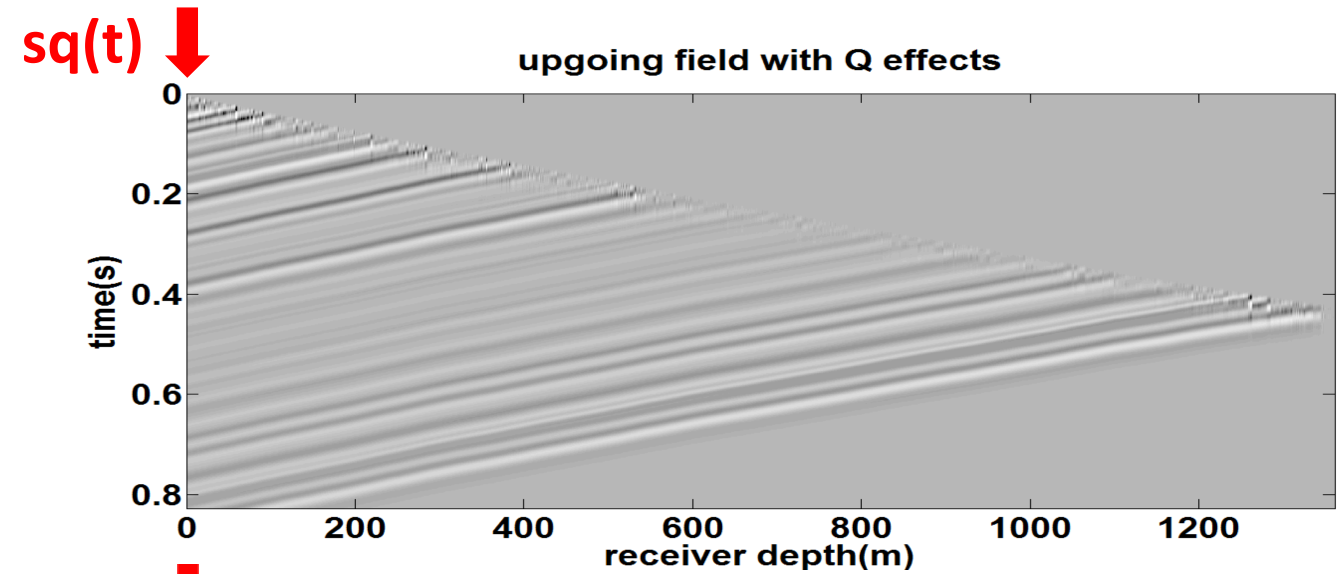
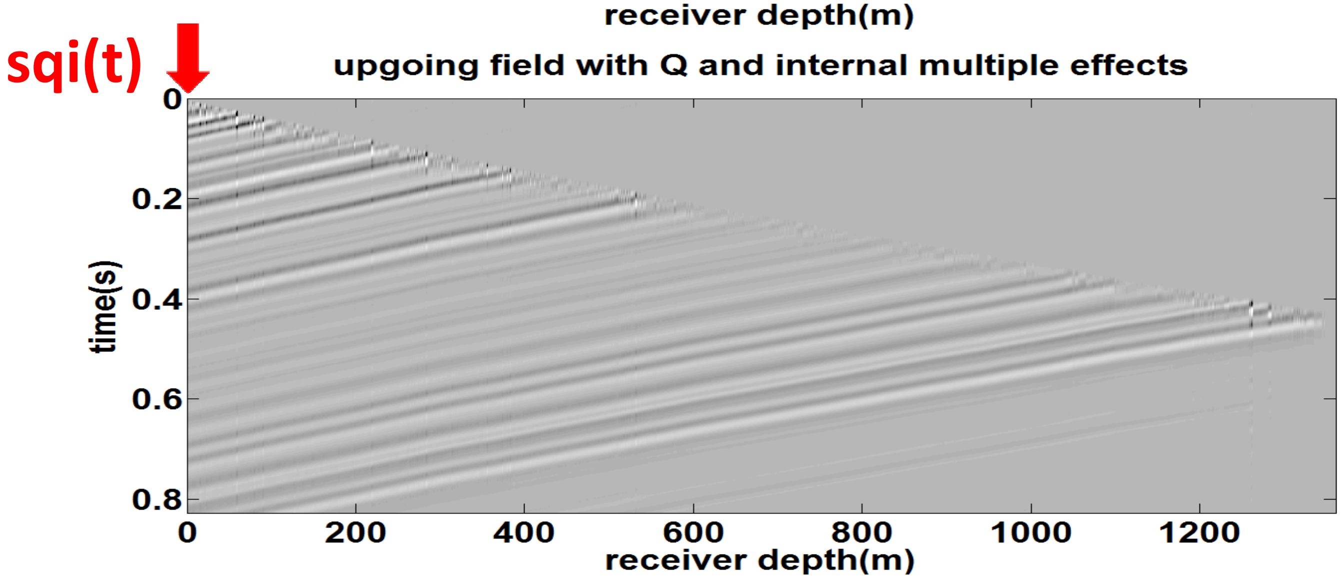
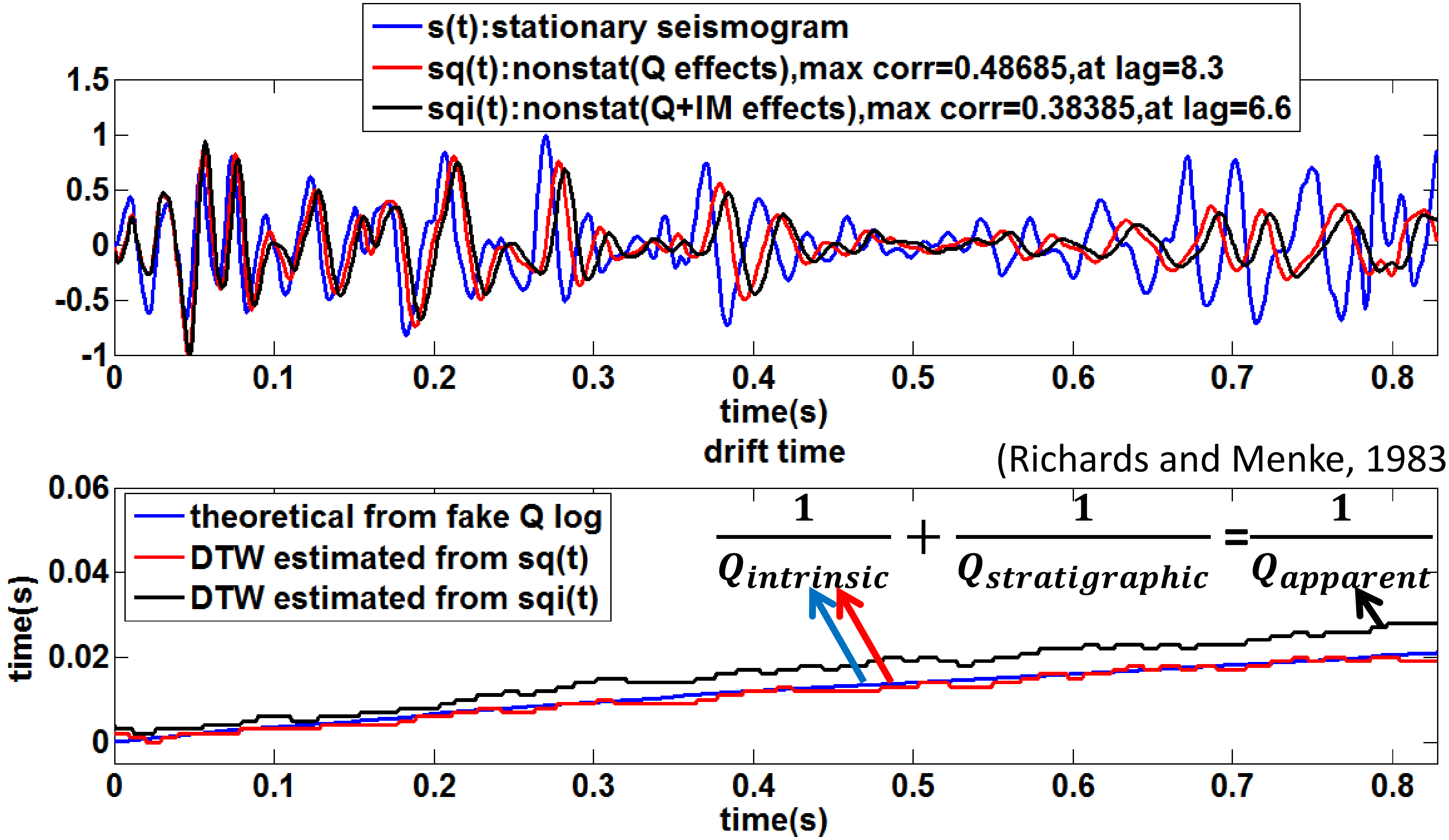
Inclusion of internal multiples





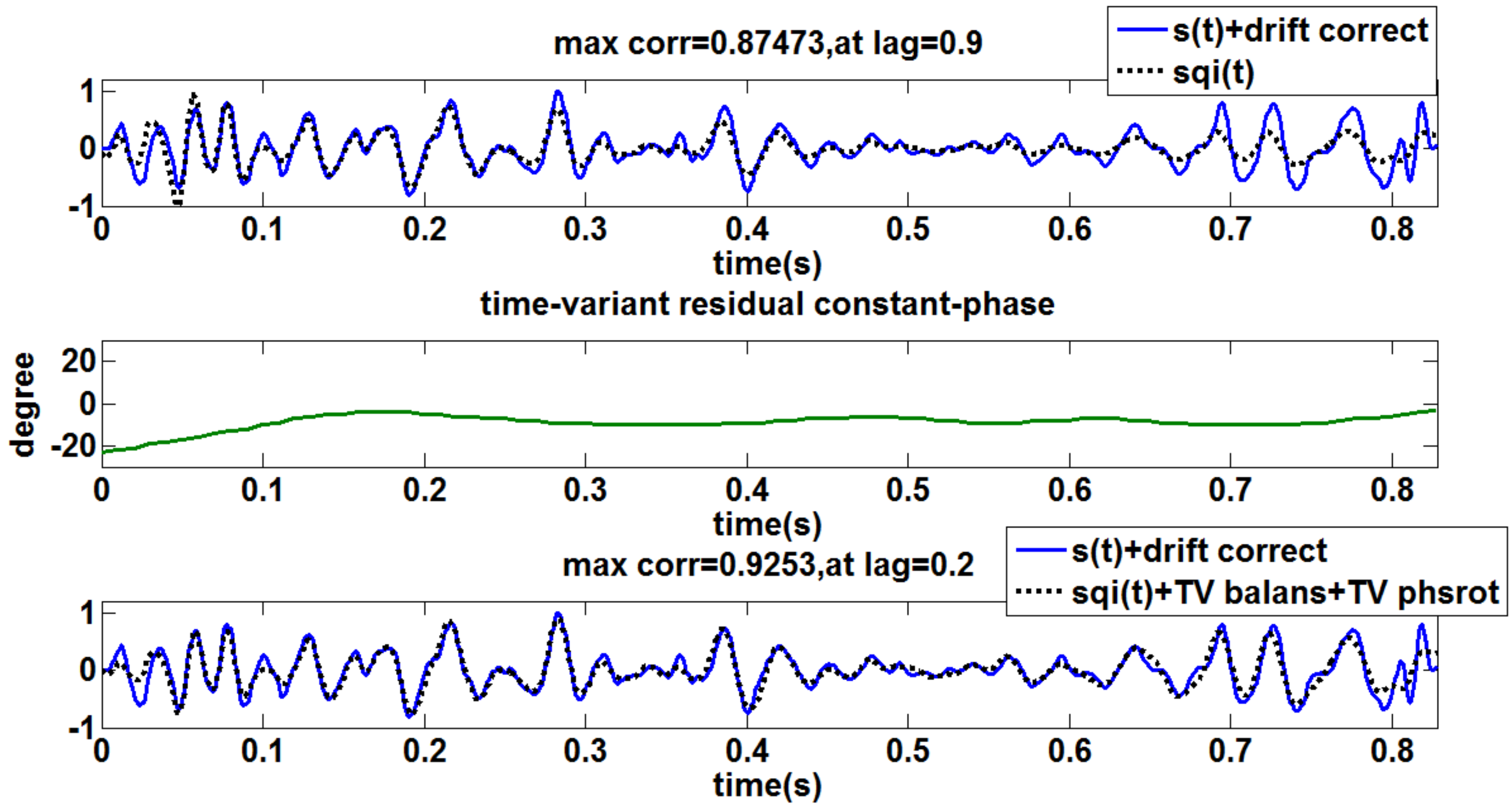
Inclusion of internal multiples: sqi(t)



(Richards and Menke, 1983)

$$\frac{1}{Q_{intrinsic}} + \frac{1}{Q_{stratigraphic}} = \frac{1}{Q_{apparent}}$$

Inclusion of internal multiples



Conclusions

- **DTW succeeds in estimating drift time automatically without knowledge of Q or a check-shot survey.**
- **Application of drift time correction results in a much simpler residual phase.**
- **DTW estimates drift time associated with apparent Q including both intrinsic and stratigraphic effects.**

Future work

- **Conduct stationary and nonstationary deconvolution on the seismic trace and tie the deconvolved seismic trace to well log reflectivity by DTW**

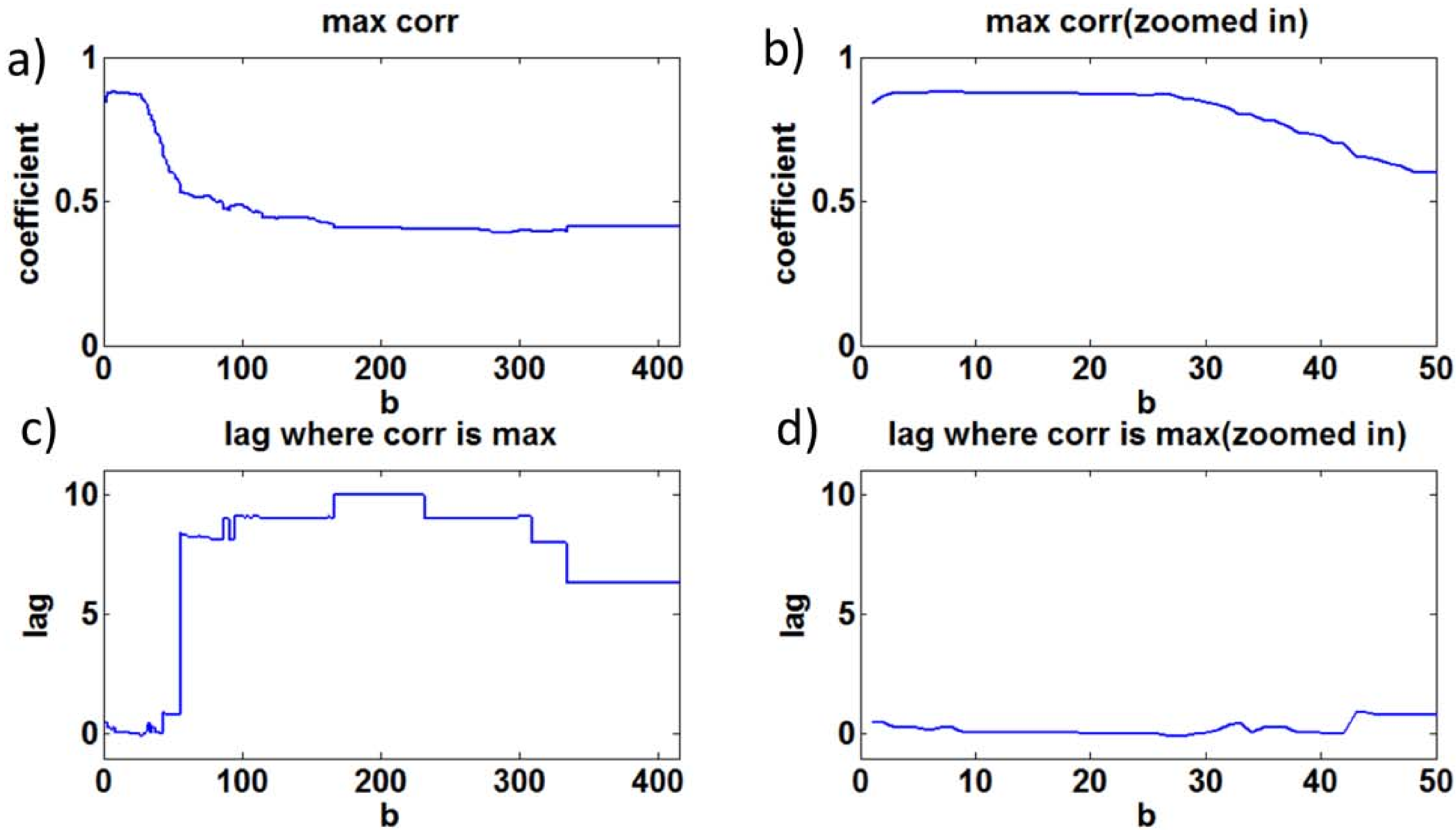
- **Estimate Q value from the drift time estimated by DTW**

Acknowledgements

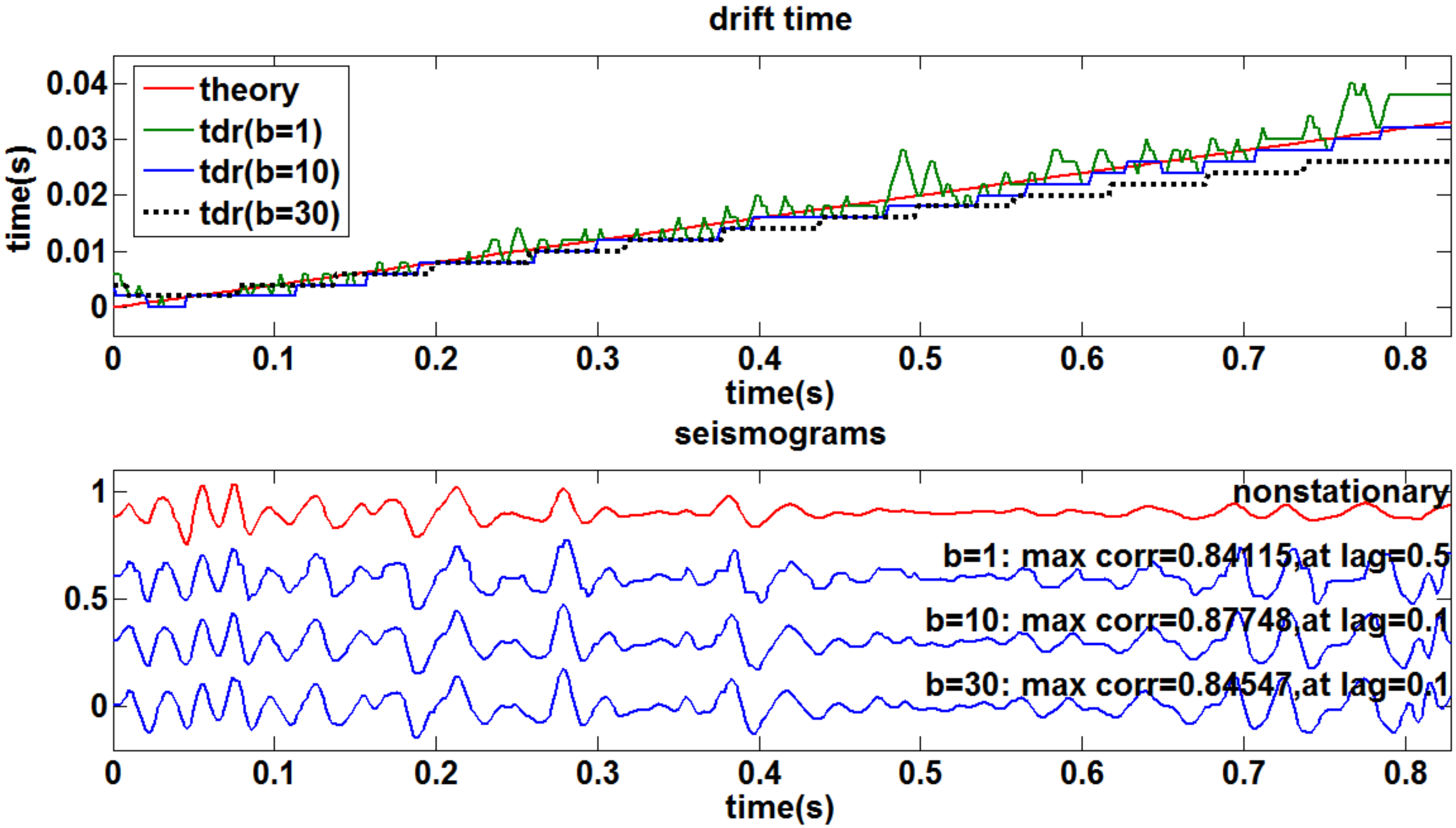
- CREWES sponsors
- NSERC: grant CRDPJ 379744-08
- CREWES staff and students

THANK YOU !

Choosing b values



Choosing b values



Applications of DTW

- **Tying synthetic to recorded seismograms**
- **Registration of P– and *S*–wave images**
- **Residual normal moveout correction**
- **Alignment of images computed for different source-receiver offsets or propagation angles.**