Timeliness of earthquake magnitude estimation from the prompt elasto-gravity signal using Deep Learning

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Prompt elasto-gravity signal (PEGS)

PEGS precedes P-waves in seismograms and its amplitude depends on earthquake magnitude. First observation on Tohoku-Oki earthquake (Montagner et al. 2016).

Vallée et al. 2017
 Few observations due to the low SNR. Observational limit is for $M_w = 7.9$ (strike-slip).
Assess PEGS potential for early magnitude estimation in operational early warning system.
Deep Learning for data discovery

PEGS signal is buried in noise. Can we use DL to extract $\mathcal{M}_w$ and location from the waveforms recorded by the full seismic network?
Experimental setup

Few real observations of PEGS are available: training must rely on synthetic data.

- Focus Japan subduction zone.
- 74 broadband stations with good quality data.
- 500k synthetic earthquake sources.
- Location, dip angle and strike from Slab2.0 (Hayes et al. 2018).
- $M_w \sim \mathcal{U}[5.5, 10.0]$
- rake $\sim \mathcal{N}(90, 10)$
Timeliness of $M_w$ with PEGS and Deep Learning

Deep Learning model and training

Source Time Function empirical model

- STF empirical model from Meier et al. 2017 based on statistical observations
- $f(t) = te^{-0.5(\lambda t)^2} \times (1 + N(t))$
- $\lambda = 10^{[7.24 - 0.41 \times \log_{10}(M_0) + N(0, 0.15)]}$
- Multiplicative noise term
- Stochastic variability of STF duration.
Timeliness of $M_w$ with PEGS and Deep Learning

Building the database

- Synthetic waveforms are augmented with empirical noise.
- 315 s from earthquake origin time.
- Bandpass filter: $0.002 \text{–} 0.03 \text{Hz}$.
- Traces are sorted by station longitude.
- Amplitudes are set to zero starting at the P-wave arrival.
- Scaling by a constant factor.
- 5% of the stations are randomly muted.
Timeliness of $M_w$ with PEGS and Deep Learning

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Deep Learning model and training

**Network architecture**

The **inputs** of the network are three-component seismograms recorded by the full seismic network. **Outputs** are $M_w$ (time dependent) and source location (latitude and longitude).
Tracking $M_w(t)$: learning strategy

- Start = -300 s
- Length = 315 s
- Start = -200 s
- Length = 315 s

Time dependent $M_w$ target
Results on test set
Accuracy map

(a) Accuracy
(b) Average residuals

- Timeliness of $M_w$ estimation
- Timeliness of $M_w$ with PEGS and Deep Learning
Accuracy map: low noise conditions \((0.5 \text{ \(nm/s^2\)})\)
Timeliness of $M_w$ with PEGS and Deep Learning

Timeliness of $M_w$ estimation

Predictions for the 2011 $M_w = 9.1$ Tohoku-Oki earthquake
Predictions for the 2003 $M_w = 8.16$ Hokkaido earthquake
Conclusions

- Applicability to $M_w > 8.0$ earthquakes.

- Instantaneous tracking of moment release.

- Tohoku-Oki timeliness around 60/70 seconds.

- Time scale for tsunami early warning.

- Easy to scale to different focal mechanisms and tectonic settings.

- Can be combined with additional observables (seismic waves, GPS ...) to increase performance.