Detection of seismic signals under low SNR condition using an artificial neural network: toward the development of a dense low cost citizen seismic network in Japan

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Summary

We have developed a low cost seismic network in Yokohama, Japan, called Citizen Seismic Network (CSN). Differently from national seismic networks that generally have high quality and high cost sensors nearly uniformly distributed all over the country, our seismic sensors devices are simpler and low cost. Therefore they can be placed in great number in homes, private buildings, schools etc. The network has the advantage to be dense and able to monitor local scale seismic motions in areas linked to community's life.

Each sensor unit is composed of a 12 bits MEMS accelerometer and a Raspberry Pi. Since the units are installed under high-noise environments made by human activity that are often misinterpreted as seismic signals, the application of conventional detection methods using amplitude ratio (e.g. STA/LTA) is problematic. To overcome this issue, we developed an original artificial neural network (ANN) that uses pattern recognition to recognize the seismic waves from other signals.

We trained the ANN using three-component accelerograms data sets obtained from conventional seismometers, but adding our sensor background noise for compatibility with signals output from our devices. In the first training stage, we optimized the number of input units and the size of training data. Then, using the trained ANN, we tried to identify seismic signals that were not used in the training process. As a result, 95% of the P-wave onsets were successfully detected. In addition, our results indicate that our method reduces the false detection significantly compared with STA/LTA methods.

Sensor Unit

＊Each unit includes a MEMS acceleration sensor and a Raspberry Pi.

[MEMS Acceleration Sensor]

Acceleration meter	Capacitance Type
Component	Three axis
Dynamic Range	±2G
Sampling Frequency	50Hz
Acceleration Resolution	1mG
A/D Resolution	12bit
Cost	US$49

[Raspberry Pi]

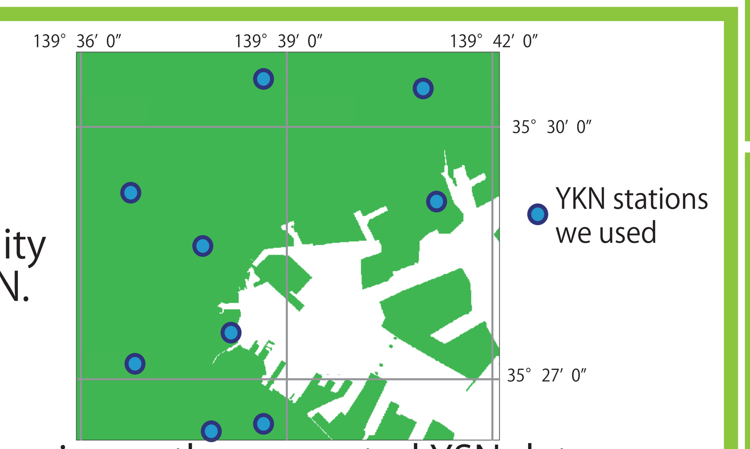
Low cost and credit card size computer.

Camera module can offer surround view.

Preparation of synthetic data

＊We used seismic data from Yokohama City Strongmotion Network (YSN), and converted it into reproduce CSN records format.

＊Using the waveforms as the training data we confirmed the feasibility of discrimination between the seismic signal and the others by ANN.

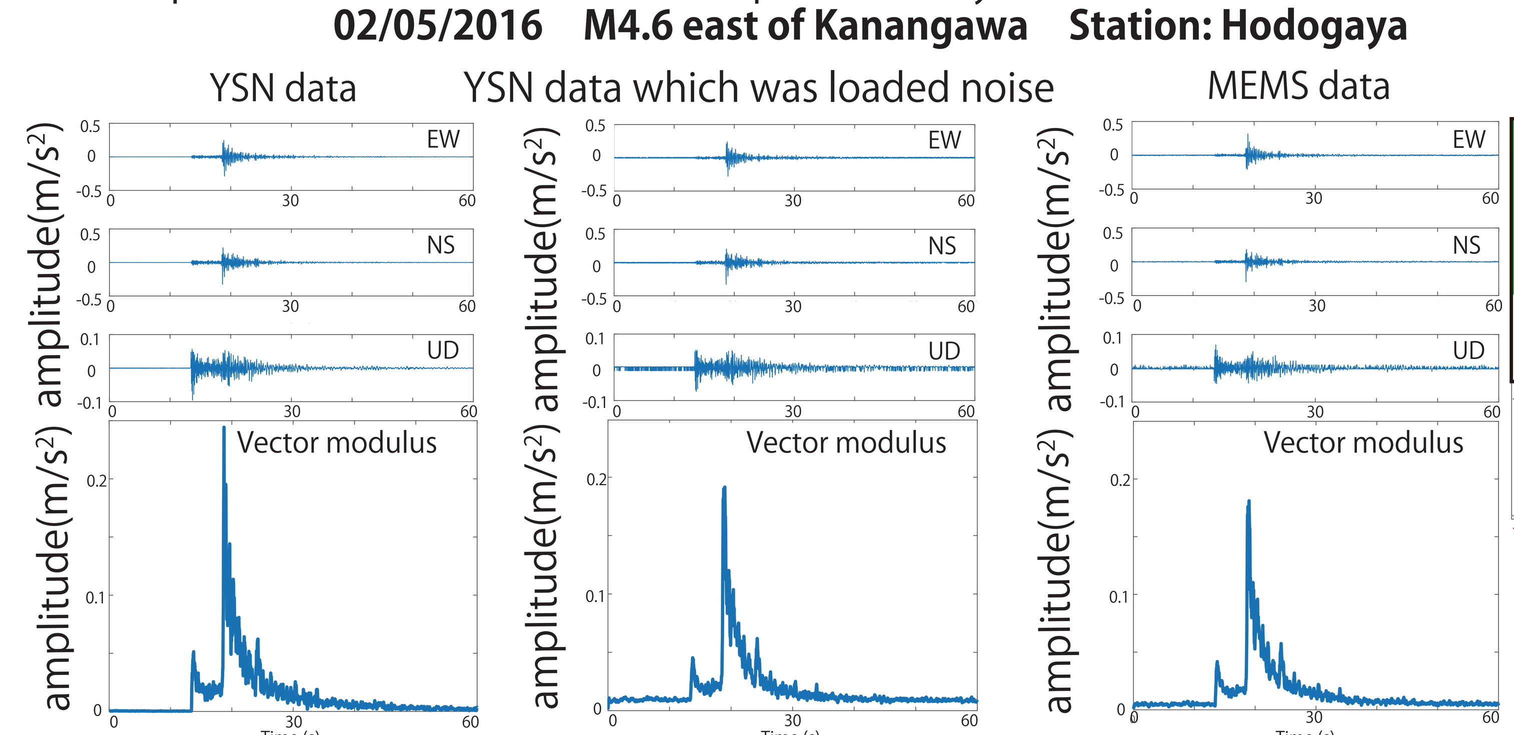


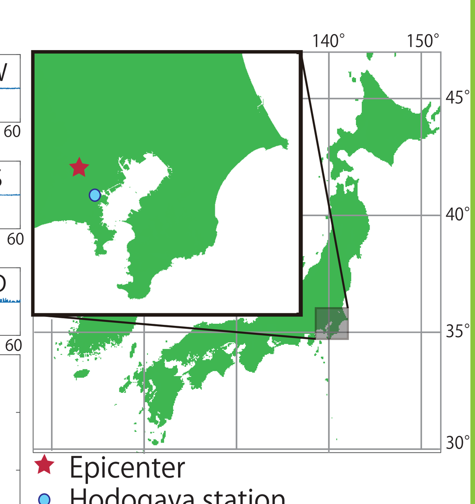
◆Preparation of synthetic data and validation

＊Convert the sampling frequency of YSN data from 100 Hz to 50Hz.

＊Intercept noise data from CSN static output randomly and load the noise on the converted YSN data.

02/05/2016 M4.6 east of Kanangawa Station: Hodogaya





(This map is created based on the white map published by Geospatial Information Authority of Japan.)

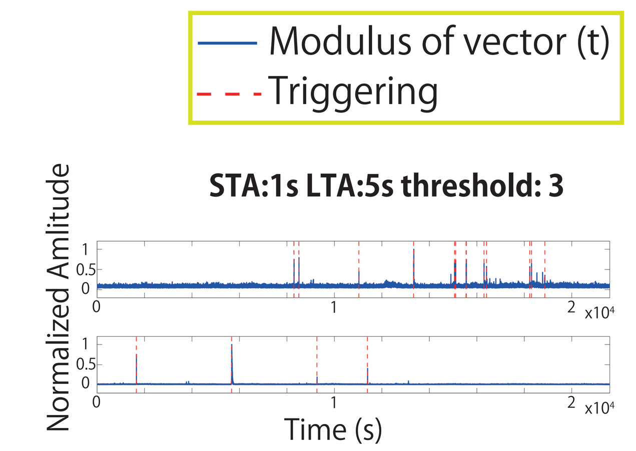
Seismic Signal Detection Method

◆STA/LTA Trigger Algorithm

＊Calculating the STA/LTA of the instantaneous vector modulus M(t) composed from three components of seismic signal. (STA: ShortTimeAverage, LTA:LongTimeAverage)

＊Event triggering level is controled by the STA/LTA threshold.

→Under high noise environment, it is difficult to discriminate between the earthquake signal and the noise signal.



◆ANN Detection Algorithm

Detect and identify seismic signals using an artificial neural network (ANN) based pattern recognition approach.

＊The network has three layers, input layer, hidden layer, and output layer.

＊Each layer has neurons and neurons are coupled respectively by weight.

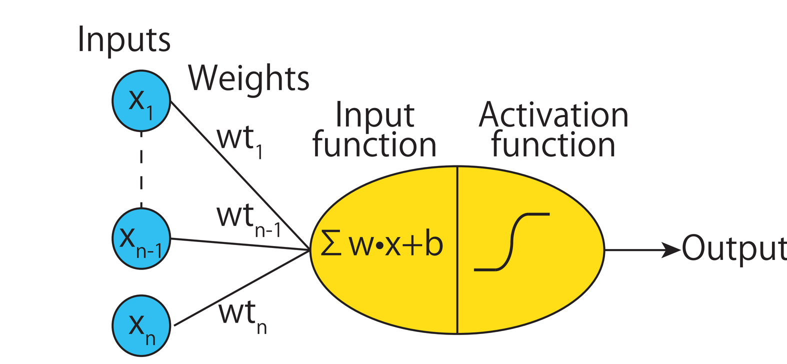
＊ANN is optimized by training datasets and recognize unknown seismic signal.

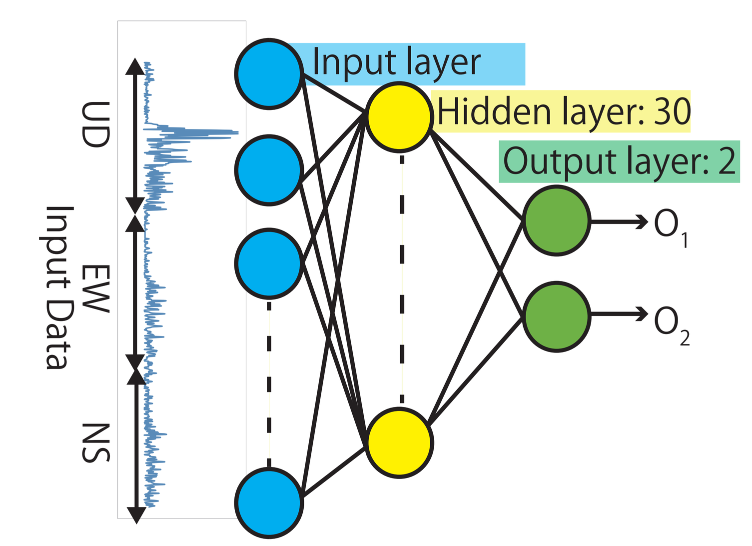
[Data]
Modulus of vecotor composed three component M(t).

[ID (O_1, O_2)]
seismic signal detected（1,0）, the others (0,1)

[Assessment method]
$F(t)=1/2\{O_1(t)^2+(1-O_2(t)^2)\}$ $F(t)>0.5$

(Dai and McBeth, 1995)





◆Results

[Test 1]

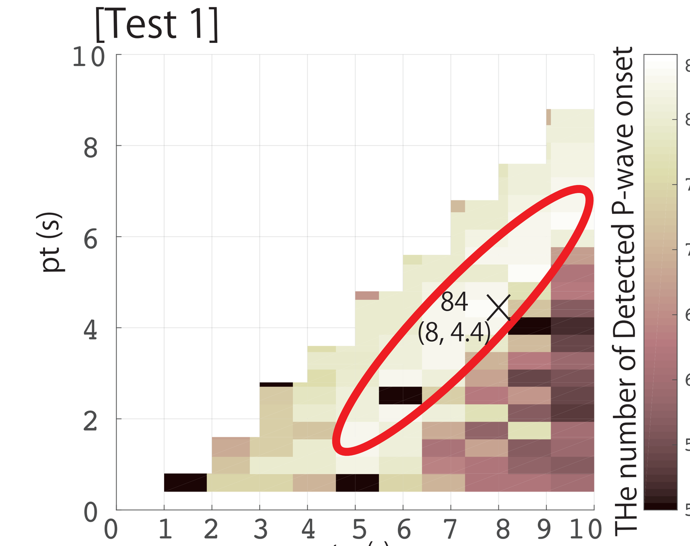


fig 1: Change of detection ability with respect to pt and tw

[Test 2]

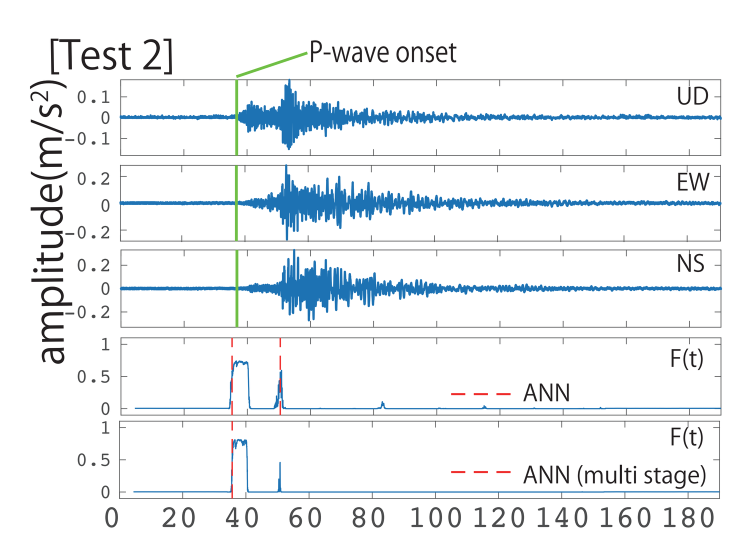


fig 2: Comparision with ANN trained with multi stage methods (An example of result with synthetic data)

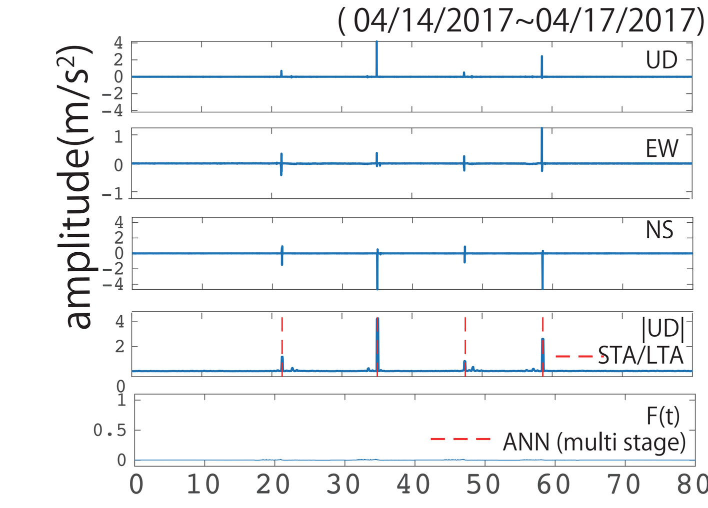


fig 3: Comparision between STA/LTA and ANN trained with multi stage methods (An example ofresut with CSN noise data)

Signal detection test

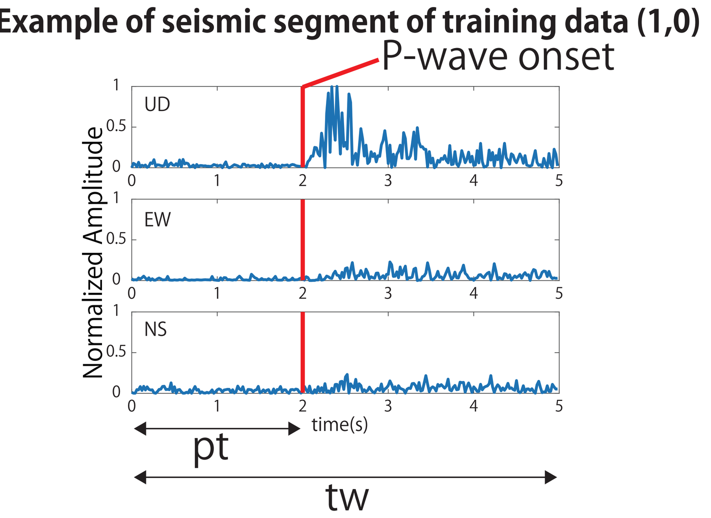
We used the synthetic data as training data and verified the reliability of our ANN algorithm that discriminated between the seismic signal and the others.

◆Method

[Test 1]
To find the optimum length of input data (time window: tw) and P-wave arrival time in seismic segment of training data (pt), we changed tw and pt from 1 second to 10 seconds, and find the optimum parameter.

Input Data
The input data are absolute values of acceleration for each components. The training data was set to consider the P-wave onset as the earthquake trigger.

Example of seismic segment of training data (1,0)



[Test 2]
We tried to train the ANN with multi stage methods, which includes batch learning approach and segmentation learning approach (modified Yamanaka *(2004) et. al.*,). In this test, the pt and tw are set to be 8.0s and 4.4s.

Flow of multi stage training

Divide training data into A ~ C

Data set A | Data set B | Data set C

1st training

Apply trained ANN to A and B. Extract additional noise data.

Noise data detected as "seismic signal" is included in the next training process as " noise".

2nd training

Apply trained ANN to A, B and C. Extract additional noise data.

3rd training

Apply trained ANN to A, B and C. Extract additional noise data.

4th training
End of the training

◆Data

We use synthetic data with instrumental seismic intensity of over 3 (50 for training and 84 for test). Also we use data for one week observed by a CSN sensor installed at a house.

[Training]
＊50 synthetic data (07/09/1997~07/17/2004)

[Test]
＊84 synthetic data (08/06/2004~07/03/2012)
＊4 days of the data that CSN sensor recorded (04/14/2017~04/17/2017)

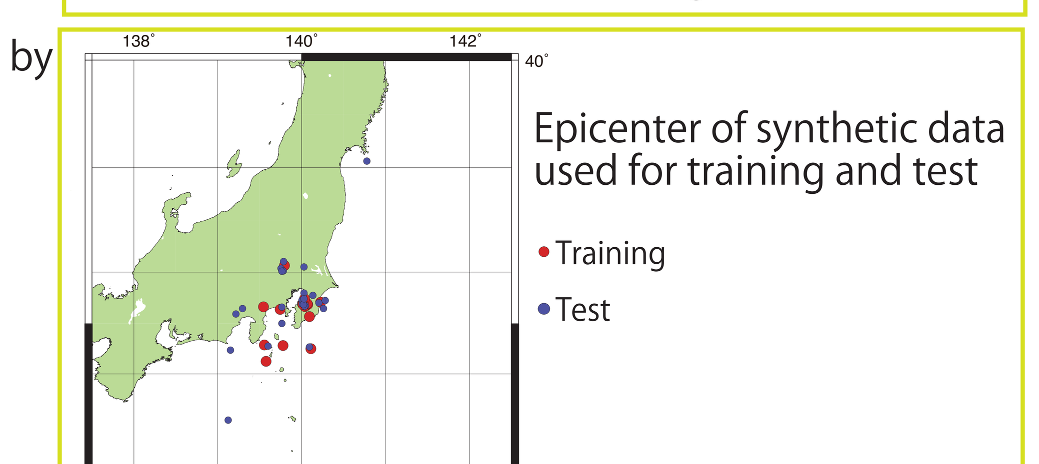


table 1: Result with synthetic data and CSN data

	synthetic data (84seismic data)			CSN data
	detected	undetected	miss-detected	miss-detected
STA/LTA	67	17	3	26
ANN	84	0	5	0
ANN (multistage)	84	0	2	0

Conclusion

1. The conventional method (STA/LTA) tends to unstable under noisy circumstance.
2. Our ANN algorithm significantly improved the seismic signal discrimination.
3. Detection is further improved with multiple stages training.
4. It is possible to realize low cost MEMS accelerometer can be used for P-wave detectors for instrumental seismic intensity above 3.

References

Hengchang Dai, Colin MacBeth (1994). Automatic picking of seismic arrivals in local earthquake data using an artificial neural network. Geophysical journal international, 120 (3):758-774.

Hiroaki Yamanaka, Aki Hidani, Nobuyuki Yamada (2004). Estimation og arrivak times of initial P and S waves in strong motion records using artificial neural networks -Estimation of travel time delay for sedimentary layers in Kanto district-. BUTSURI-TANSA, 57 (3): 255-266

Acknowledgment

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