KSCE Journal of Civil Engineering (2017) 21(1):307-314

DOI 10.1007/s12205-016-0431-7

Structural Engineering

pISSN 1226-7988, eISSN 1976-3808
www.springer.com/12205

The Principle and Optimal Design of a Cochlea-inspired Artificial Filter Bank (CAFB) for Structural Health Monitoring

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Received June 2, 2015/Revised January 25, 2016/Accepted February 24, 2016/Published Online June 6, 2016

Abstract

Wireless sensor networks based-structural health monitoring is being widely researched. To make a better structural health monitoring, real-time acquisition of structural responses is indispensable. However, the data, which is large in number especially when they are of moving structures, are difficult to be measured, and the adaptation of wireless sensor networks further limits structural health monitoring within the capacity of radio frequency. In this study, cochlea-inspired artificial filter bank was developed as a technological way to efficiently acquire dynamic responses at a wireless sensor networks based-structural health monitoring. The cochlea-inspired artificial filter bank developed in this article was enabled to acquire valid dynamic responses of compressed size around the frequency range of interest by simulating raw data to the full regarding to time and frequency of dynamic responses. In addition, the digitalized cochlea-inspired artificial filter bank was also found to fix the disadvantages of analogue filters by its easy and efficient development of logics, optimization, design of software, and real-time autonomous execution. Finally, the cochlea-inspired artificial filter bank makes it possible to compress and reduce the vast amount of real-time dynamic responses usually obtained by means of a uniform rate of sample, into a manageable size. It is thus expected to open up a new paradigm in the Wireless sensor networks based-structural health monitoring of civil structures by facilitating an efficient measurement and management of data base.

Keywords: *Cochlear-inspired Artificial Filter Bank (CAFB), Band-pass filter Optimizing Algorithm (BOA), Peak-picking Algorithm (PPA), Reconstruction Error (RE), Compressive Ratio (CR), Structural Health Monitoring (SHM), Data Compressing*

1. Introduction

After constructing civil structures, their structural safety and maintenance need to be secured against unusual weather, increased load, gradual aging, etc. so that it is necessary to develop diverse and effective technological ways to do that. SHM (Structural Health Monitoring) is one of the ways to continuously assess the current state of civil structures and identify any damage on them (Yun *et al*., 2003; Wong, 2004; Ko and Ni, 2005; Altunişik *et al*., 2015; Bayraktar *et al*., 2014). A variety of SHM systems have been actively applied to civil structures in order to evaluate their structural condition and to locate damaged areas, but they have the following limitations in terms of system construction, operation, and management. Above all, their adoption of cables for data transmission does not only heighten cost when increasing measuring channels but also require managing technologies to deal with as much increased, enormous amount of data. Especially considering the fact that SHM requires a long-term measurement, the limitations caused by the use of cables should be overcome. To do that, Spencer *et al.* (2004) and Lynch and Loh (2006), and others developed a Smart SHM (S-SHM), in which the Technology of WSNs (Wireless Sensor Networks) was introduced to the SHM system. The S-SHM system has some advantages such as reduction of system-building cost, simple preprocessing of signals through sensors embedded with CPU and memory, and easy carry and installation through RF networking at some areas to which a wired system usually has no easy access. Nagayama *et al.* (2008) and Rice and Spencer (2008) also developed the Imote2, a wireless sensor node, using the concept of S-SHM system, and performed a health monitoring, applying the Imote2 on the 2nd Jindo Bridge in Korea, a full scale bridge, as a test-bed. It successfully evaluated the dynamic characteristics of the bridge by acquiring its acceleration responses in a long-term and real-time basis (Jang *et al.*, 2010). Kurata *et al.* (2013) developed the Narada, another wireless sensor node, by adopting a self-recharging and a sub-network method among sensor nodes for a stable acquisition of data, improving on the existing S-SHM system, and applied it to the New Carquinze Bridge in America (Swartz and Lynch, 2009; Heo and Jeon, 2009).

In the meantime, for a more accurate SHM, diverse structural responses are needed to be measured in real-time. Dynamic

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structural responses are not easy to be acquired due to their relatively large size in number, compared to static ones, and furthermore if WSNs are used, response measurement is to be limited within the capacity of RF. Particularly, as the number of input channels is increased, the existing S-SHM system is incapable to perform what it is supposed to perform because the amount of data storage is too much now. After all, in order to speed up data processing and increase storage capacity innovatively, it would be the best to configure a wireless sensor node to the level of high-performing PC. In addition, it should be noted that a transmission of a big size of dynamic responses through WSNs (Wireless Sensor Networks) can cause data loss, and its bottleneck effect cannot guarantee real-time operation. The best RF of SHM for large structures is supposed to be capable of long-distance, high speed, multi-channels. However, there is no way to satisfy all of them so that a careful modulation of communication methods has been chosen when adopting WSNs. However, to look from another perspective, the limitations of the existing wireless communication methods could be overcome if the initial data volume itself is reduced at the moment of acquiring the raw data of civil structures. After all, to realize a WSNs-based SHM properly, a data compression technology is required to acquire and transmit valid dynamic responses as well as an improvement of sensor node to the level of high-performance PC to acquire and save dynamic responses stably in real-time.

In this vein, CAFB (Cochlea-inspired Artificial Filter Bank) is developed in this study to acquire dynamic responses required for a SHM of civil structure. CAFB includes a new concept of data compression technology using digital method not the existing analog method. It is composed of a band-pass filter optimizing algorithm (BOA) to select valid dynamic responses, and a peak-picking algorithm (PPA) to compress the selected dynamic responses. It is optimized with the El-centro earthquake wave, a representative random waveform. Finally, the validity of the developed CAFB is verified by evaluating its reconstruction effect and compression effect of the signals filtered using the Reconstruction Error (RE) and the data Compression Ratio (CR) compared to the raw data. The CAFB developed in this article will be able to acquire valid dynamic responses in a compressed size around the frequency range of interest simulating the time and frequency information of target dynamic responses sufficiently enough out of raw data. In addition, the artificial filter bank developed with digital method could develop and optimize logics and design, and execute the S/W quickly and easily by improving the weaknesses of the existing analog filter bank effectively. And the CAFB developed is finally proposed to be utilized as a new technical alternative to measure, transmit and manage the dynamic responses in real-time, which is required for a SHM of civil structure.

2. Principle of Cochlea-inspired Artificial Filter Bank (CAFB)

A filter bank is defined in the field of signal processing as an

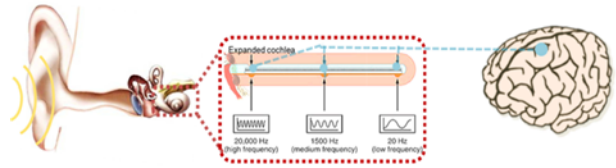

Fig. 1. Principle of the Auditory Organ in Human Body (collection-separation-reconstruction-delivery system)

array of band-pass filters designed to filter and output only specific components (information) of interest out of input signals. It performs a series of processes that separate input signals by band, reconstruct and output them. Its processing of signals (separation and reconstruction) is very similar to the way in which cochlea, an auditory organ, works in the human body, as shown in Fig. 1.

Cochlea, an auditory organ in the human body, is to sense a particular range of sound information out of the whole range of frequency, and to deliver it to a decision making organ (brain) through a neuro-transmission system. If the principle of how the auditory organ works, that is, how it limits its range of perception, is applied to a filter, it will be able to select a particular response information of civil structure and utilize it according to the user's need. The CAFB, based on human cochlea, will optimize its function considering the user's purpose and the frequency range of interest. In order to do that, the number of band-pass filter (quantity), its bandwidth, and its intervals will be considered as main design elements.

In the meantime, while the output signals separated and reconstructed through the band-pass filter within the filter bank include the specific contents (information) of interest only, they are valid by virtue of acquiring the target data. However, the sampling of filtered information has the same size and interval as those of input signals. There is still a large amount of information needed to pass through the filter especially for a WSN based system, whose bottleneck hinders operation speed. In order to efficiently acquire the dynamic responses of the civil structures with WSNs, it is necessary to develop data compression technologies.

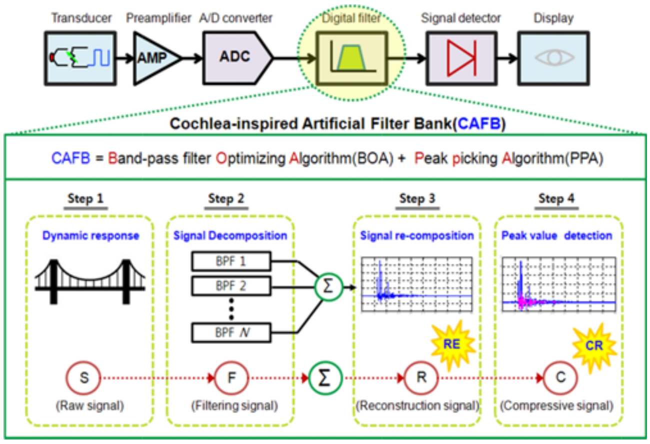

Fig. 2. Principle of Cochlea-inspired Artificial Filter Bank (CAFB)

In this article, we explain how to develop the CAFB based on the various design elements and the considerations mentioned previously: the band-pass filter optimizing algorithm (BOA) and the peak-Picking Algorithm (PPA). Fig. 2 shows the principle of the CAFB developed in this article in order to acquire the dynamic response of a civil structure efficiently.

2.1 Principle of Band-pass Filter Optimizing Algorithm (BOA)

The CAFB developed in this article used the various band-pass filters in order to acquire the target dynamic response from a civil structure. The band-pass filter filters only the specific frequency contents out of the initial raw data (having diverse frequency contents) based on the number of filters, bandwidth, spacing, etc., determined initially. Therefore, these 3 filter design elements must be optimized. To do that, the band-pass filter optimizing algorithm was developed. The processing process of the BOA developed is as follows. First, select the interested frequency band. Second, assume the number of the band-pass filters based on the selected frequency range of interest. Third, determine the interval between the bandwidth of the filter and the central frequency based on the assumed number of the band-pass filter. Fourth, calculate the Reconstruction Error (RE) and the Compression Ratio (CR) based on the bandwidth and the central frequency of the band-pass filter previously determined. Fifth, determine the number of filters based on the reconstruction error and the compression ratio calculated.

$$RE = \frac{\int_0^T |(u(t) - y(t))| / |u(t)|}{T} \tag{1}$$

In order to optimize the filter bank, the Reconstruction Error (RE) and the Compression Ratio (CR) in performing the processing process of BOA were defined. The compression ratio (CR) is mentioned in Section 2.2 and in this section, the Reconstruction Error (RE) is defined. The reconstruction error is the relative difference between the initial raw data and the reconstruction signal; the combination of the filtered signals and can be expressed Eq. (1) from the principle shown in Fig. 3. In Eq. (1), $u(t)$ is the initial raw data by response time (acceleration), $y(t)$ is the reconstruction signal by response time (acceleration), T is the total length of the response time (sec), and the closer to 0 the reconstruction error is, the better the reconstruction effect is.

2.2 Principle of Peak-Picking Algorithm (PPA)

In order to acquire the dynamic response of a civil structure with the WSNs basis efficiently, compression technology is required in addition to the selective sorting of the data. To do that, the peak-Picking Algorithm (PPA) was developed for the purpose of data compression. The PPA processing process is as follows. First, enter the reconstruction signal determined in the preceding process of the artificial filter bank. Second, classify the reconstruction signals entered in order into 3 data bundles. Third, calculate the derivative based on the 3 data sets of each bundle. Fourth, obtain the peak value by evaluating the inclination (sign) of the derivative by bundle. Fifth, reconstruct the signal of peak value obtained with the time information of the relevant peak value.

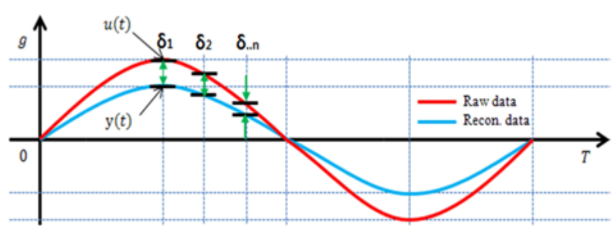

Fig. 3. Principle of Reconstruction Error (RE)

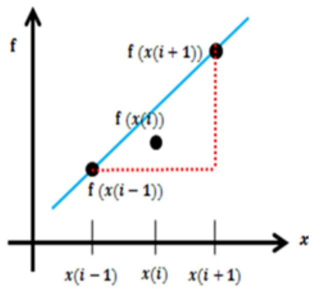

Fig. 4 Concept of Central Difference

In order for the method to obtain the peak value in the PPA processing process, the central difference method was used. Generally, if the interval between the neighboring data is constant, the central difference method can calculate the derivative with the least error. Fig. 4 shows the principle of the central difference method and the derivative that can be calculated with Eq. (2).

$$f'(x(i)) = \frac{f(x(i+1) - f(x(i-1)))}{x(i+1) - x(i-1)} \tag{2}$$

$$CR = \frac{NS_c}{NS_o} \tag{3}$$

In the meantime, the PPA compression effect can be defined through the comparison of the relative size in the compressed data re-sampled based on the reconstruction signal determined through Eq. (1) and the peak value obtained through Eq. (2). To evaluate the compression effect, the data Compression Ratio (CR) was defined as Eq. (3). In Eq. (3), NS_c is the number of data in the compressed signal, NS_o is the number of data in the reconstruction signal. The closer to 0 the compression ratio is, the better the compression effect is.

3. Optimal Design of Cochlea-inspired Artificial Filter Bank (CAFB)

As detailed in Chapter 2, to acquire the dynamic response of civil structures efficiently, the CAFB was developed. In Chapter 3, based on the El-centro earthquake waveform (the representative random waveform used in the construction field) the process to optimally design the CAFB developed previously will be shown

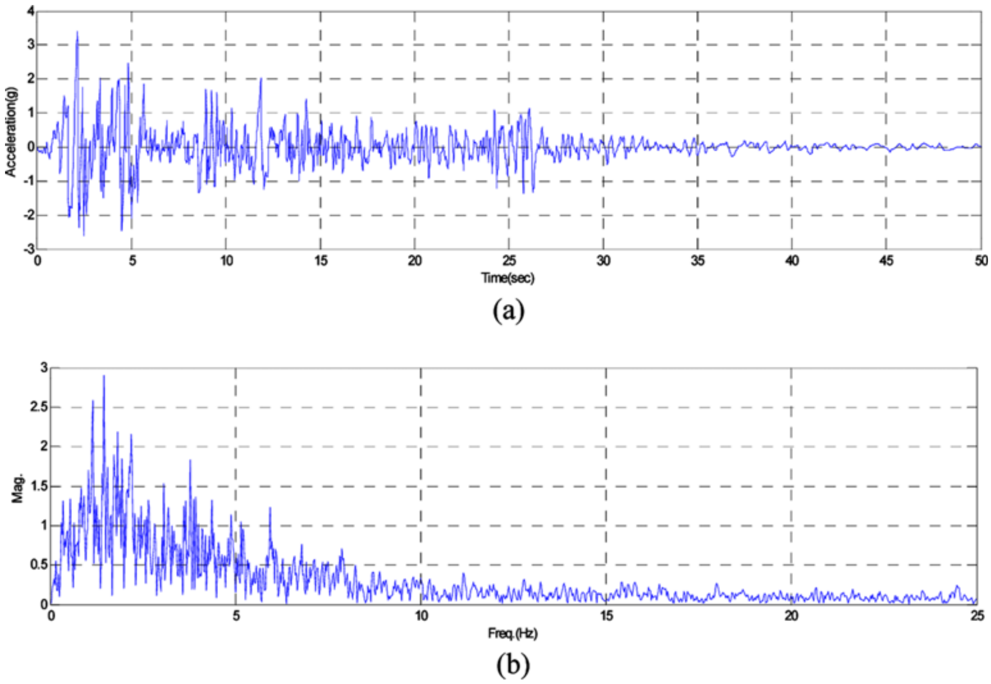

Fig. 5. El-centro Earthquake Wave for Optimizing of CAFB: (a) Time Domain of El-centro Wave, (b) Frequency Domain of El-centro Wave

Table 1. Reconstruction Error (RE) for a Filter Bank with 10 Filters

		Bandwidth of filters (Hz)										
		0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Filter spacing (Hz)	1.0	-	0.19930	0.16497	0.13378	0.10931	0.09347	0.08713	0.09036	0.10278	0.12373	0.15250
	0.9	-	0.19515	0.15896	0.12816	0.10692	0.09705	0.09893	0.11214	0.13588	0.16920	0.21118
	0.8	-	0.19374	0.15711	0.12810	0.11125	0.10870	0.12073	0.14650	0.18474	0.23406	0.29320
	0.7	-	0.18970	0.15631	0.13387	0.12719	0.13762	0.16462	0.20688	0.26290	0.33124	0.41053
	0.6	-	0.18396	0.14814	0.13360	0.14171	0.17114	0.21986	0.28583	0.36719	0.46229	0.56957
	0.5	-	0.18357	0.14861	0.14443	0.17345	0.23217	0.31612	0.42141	0.54484	0.68378	x
	0.4	-	0.19240	0.17890	0.21053	0.28428	0.39277	0.52962	0.68971	x	x	x
	0.3	-	0.19745	0.21661	0.29817	0.42797	0.59387	0.78741	x	x	x	x
	0.2	-	0.23026	0.29689	0.42203	x	x	x	x	x	x	x
	0.1	-	0.25073	x	x	x	x	x	x	x	x	x
	0.0	-	-	-	-	-	-	-	-	-	-	-

and the numerical study results for the CAFB in optimum condition will be drawn. Fig. 5 shows the El-centro earthquake wave used as a raw data with the time and frequency response.

Generally, since a large civil structure in the construction field has relatively flexible behavior characteristics, the distribution range of the target mode required for health monitoring can be limited within the specific frequency band under 10Hz. Therefore, the range of the frequency was selected under 10Hz for the band-pass filter optimizing algorithm of the artificial filter bank and the number of the band-pass filter was assumed initially as 10. As the number of the band-pass filter is optimized in the BOA processing process, it was assumed randomly.

Table 1 and Fig. 6 show the results of Reconstruction Error (RE) calculated through Eq. (1) when considering the 10 band-pass filters assumed initially in the interested frequency range under 10 Hz selected previously. The reconstruction error was calculated finally for a total of 100 cases by increasing the bandwidth and the interval of the band-pass filter in the range of 0 - 1 Hz by 0.1 Hz.

In the Table 1 and Fig. 6, the condition, in which the reconstruction error becomes minimum when the number of the initial band-pass filter was 10, was evaluated when the bandwidth was 0.6Hz and the interval was 1.0Hz. In our findings, the bandwidth and the interval for that case were determined as the optimum condition for the BOA. Fig. 7 shows the results compared to the reconstruction signal passed through the filter bank with the initial raw data under the condition that the reconstruction error becomes minimum from Table 1 and Fig. 6.

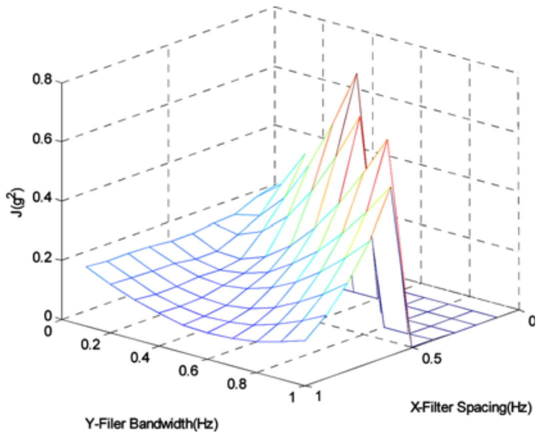

Fig. 6. Reconstruction Error Results for a Filter Bank with 10 Filters

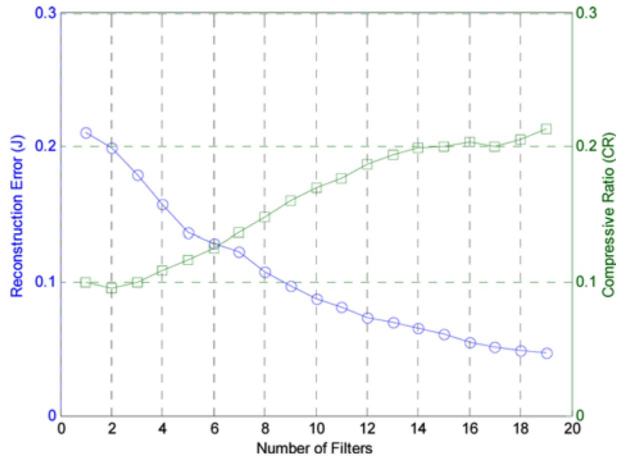

Fig. 9. Optimization of Number of Filters (Reconstruction error (RE) vs. Compressive Ratio (CR))

In Fig. 6, it was observed that the reconstruction signal reproduced (simulated) the raw data. As shown above, it was observed that the initial frequency range of interest and the number of the band-pass filters assumed initially for the artificial filter bank were enough to reproduce (simulate) the raw data, and the bandwidth and the interval determined in that case were optimum.

In the meantime, the data size of the reconstruction signal calculated here is the same as the raw data. That is, although the ability to separate and reconstruct the signal by selecting the frequency band of interest was only based on the target mode, it cannot obtain any gain in order to acquire it in the WSNs basis. Therefore, in order to reduce the size of acquired data, peak-picking algorithm was developed. Fig. 7 shows the result of compressed signal calculated using Eq. (2) based on the reconstruction signal.

In Fig. 8, it is observed that the compressed signal picks the peak value of the reconstruction signal. The number of the compressed signals was a total of 424 and the compression effect was represented approximately 84% compared to the number of data in the reconstruction signals (total 2,500 signals). From this result, the performance of PPA developed described in this article is good and as the data compression effect can be expected when acquiring the dynamic response if the developed

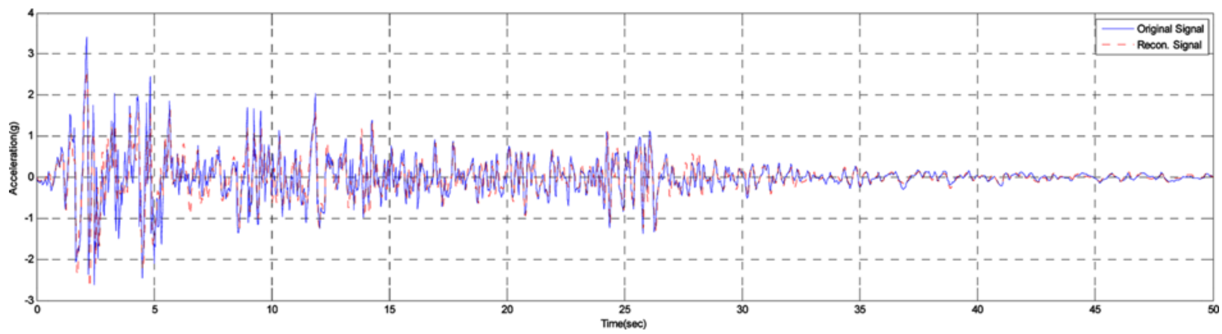

Fig. 7. Original Signal vs. Reconstruction Signal (10 filters, 0.6 bandwidth, 1.0 spacing)

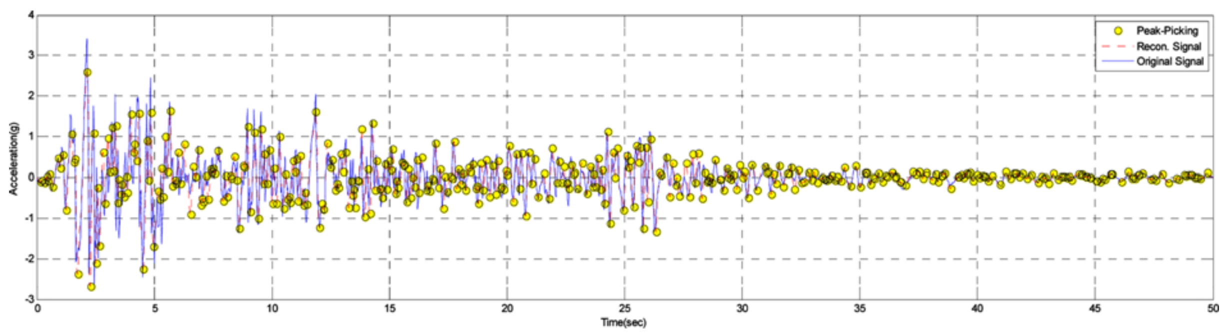

Fig. 8. Original signal vs. Reconstruction Signal vs. Compressive Signal

Table 2. Optimization of Number of Filters (Reconstruction error (RE) vs. Compressive Ratio (CR))

No. of Filters	1	2	3	4	5	6	7	8	9	10
	11	12	13	14	15	16	17	18	19	20
RE	0.2108	0.1997	0.1792	0.1571	0.1366	0.1289	0.1222	0.1072	0.0965	0.0871
	0.0808	0.0732	0.0694	0.0650	0.0605	0.0545	0.0516	0.0489	0.0473	-
CR	0.1000	0.0952	0.0992	0.1080	0.1160	0.1248	0.1368	0.1480	0.1600	0.1696
	0.1768	0.1872	0.1944	0.2000	0.2008	0.2040	0.2008	0.2056	0.2136	-
No. of P-p's	250	238	248	270	290	312	342	370	400	424
	442	468	486	500	502	510	502	514	534	-

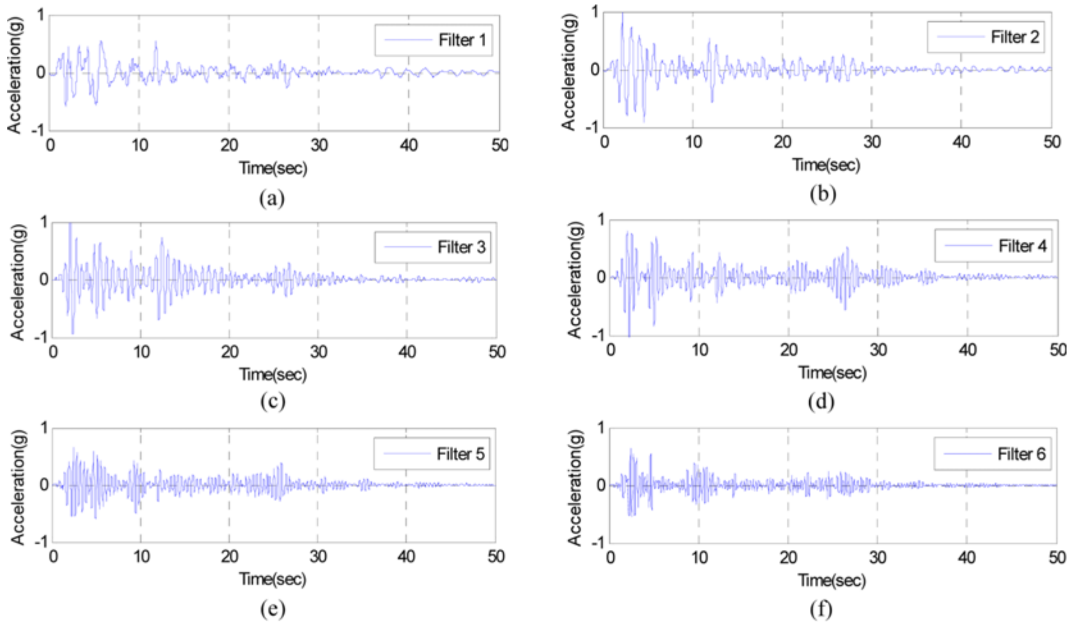

Fig. 10. Time Domain of Optimal Condition (6 filters, 0.6Hz bandwidth, 1.0Hz spacing): (a) Band-pass Filter 1, (b) Band-pass Filter 2, (c) Band-pass Filter3, (d) Band-pass Filter 4, (c) Band-pass Filter 5, (f) Band-pass Filter 6

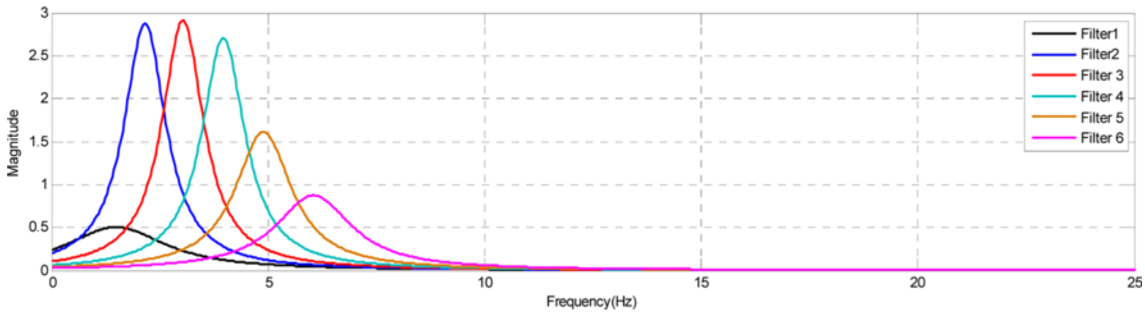

Fig. 11. Frequency Domain of Optimal Condition (6 filters, 0.6Hz bandwidth, 1.0Hz spacing)

PPA is used, the limit of WSNs having limited communication speed can be overcome.

In the final phase of designing the optimum artificial filter bank, the number of the band-pass filters was determined based on the bandwidth (0.6Hz) and the interval (1.0Hz) of the band-pass filter determined previously. In order to do that, the reconstruction error and the data compression ratio were calculated varying the number of the band-pass filters. The reconstruction error and the data compression ratio calculated are shown in Fig. 9 and the resultant values are shown in Table 2 together with the compressed data size (the size of peak-picking values).

Figure 10 and Fig. 11 show the response time and frequency response of the filter bank according to the optimum condition of the band-pass filter (number is 6, bandwidth is 0.6Hz, and the interval is 1.0Hz) determined previously. In Fig. 10 and 11, it is observed that the filter bank is designed with the optimum condition determined previously.

Here, the reconstruction signal obtained with the optimum condition is shown in Fig. 11. In the value of the reconstruction error shown in Table 2, although it was increased by

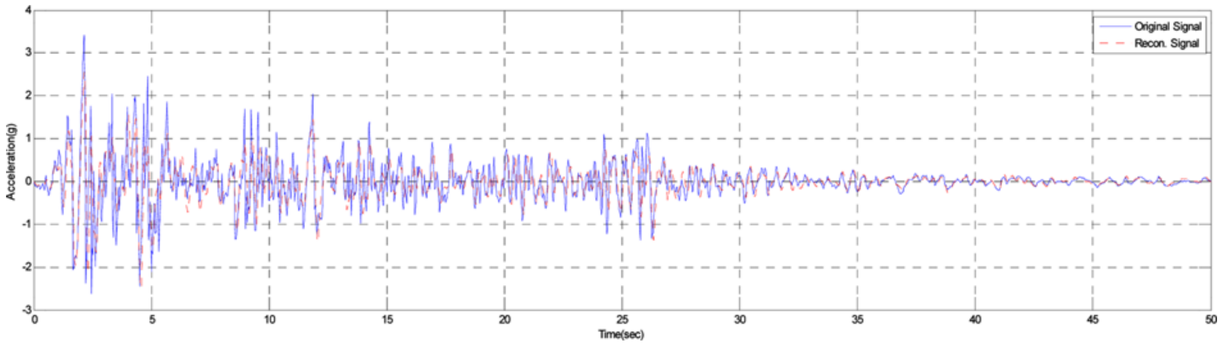

Fig. 12. Original Signal vs. Reconstruction Signal (6 filters, 0.6Hz bandwidth, 1.0Hz spacing)

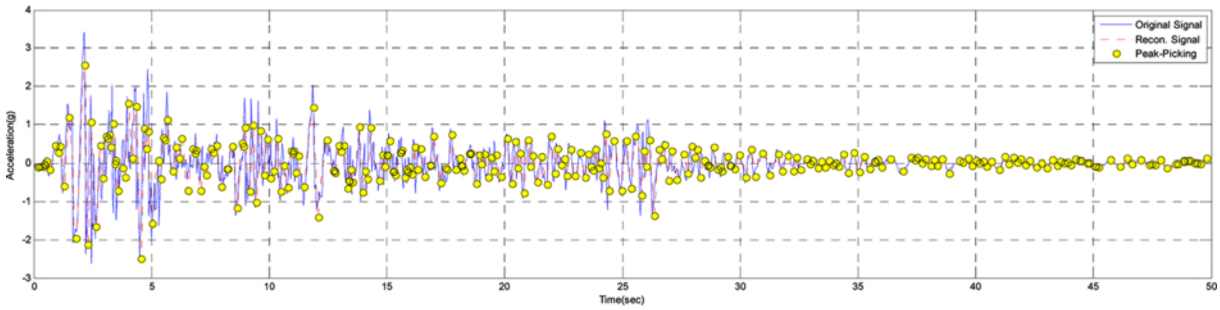

Fig. 13. Original Signal vs. Reconstruction Signal vs. Compressive Signal (6 filters, 0.6 bandwidth, 1.0 spacing)

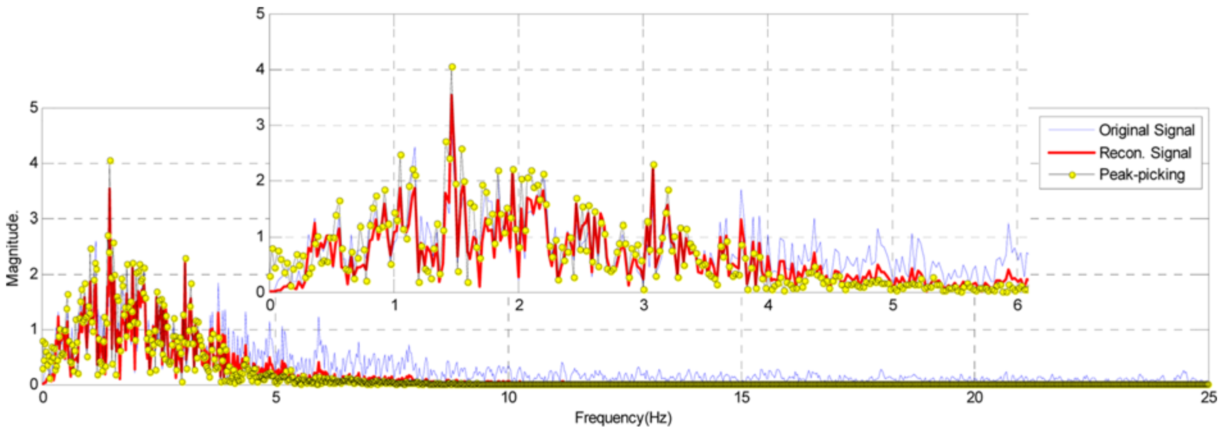

Fig. 14. Original Signal vs. Reconstruction Signal vs. Compressive Signal (6 filters, 0.6Hz bandwidth, 1.0Hz spacing)

approximately 48% compared to the condition that the number of the band-pass filter was 10, in Fig. 12, it is observed that under the optimum condition, the reconstruction signal still reproduces (simulates) the raw data enough. In addition, to compress the data in the optimum condition, the compressive signal detailed in this article was acquired using the PPA tested and evaluated previously as shown in Fig. 13 where it is observed that the compressed signal picks the peak value only from the complete reconstruction signal.

In the meantime, for the health monitoring of civil structures, the reproduction (simulation) ability of the frequency response must be evaluated at the same time together with the reproduction (simulation) ability of the time response of the reconstruction signal and the compressed signal. That is, the compressed signal calculated from the PPA must include not only the compression effect of the obtained data through the peak-picking of the reconstruction signal, but also the information of the initially targeted frequency information of interest. To test that, the frequency response based on the reconstruction signal calculated from the BOA and the compressed signal calculated from the PPA is shown in Fig. 14.

In Fig. 14, it is observed that above all, the reconstruction signal contains the initially targeted frequency information of interest compared to the raw data. Next, the frequency response of the compressive signal calculated based on the reconstruction signal was enough to reproduce (simulate) the raw data in the frequency range of interest. From these results, it is proven in the numerical study that the artificial filter bank developed with the band-pass filter optimizing algorithm and the peak-picking algorithm can acquire the dynamic response of a civil structure efficiently through optimized design and that, in particular, the compressive signal calculated contains both the time information and the frequency information of the raw data together with the reconstruction signal.

4. Conclusions

1. The band-pass filter optimizing algorithm of the CAFB developed was effective in acquiring the specific frequency signal contained in the significant mode (mode of interest) out of the wide frequency contents of the random signals. In particular, the CAFB optimized by using the representative random waveform (El-centro) used as we detailed in this article can be utilized as a technology to acquire the dynamic response of a large civil structure with flexible behavior characteristics.
2. The peak-picking algorithm of the CAFB developed is effective at compressing the data size by re-sampling only the peak values containing the valid modal information selectively out of the random dynamic responses. This data compression technology can overcome the limitation of the wireless (RF) communication, which has emerged in existing WSN-based health monitoring technology having limited communication performance (communication speed and data transmission volume), and can furthermore be used to operate and manage the measurement DB(Data-base) efficiently for long-term SHM.
3. In contrast to existing filter banks developed based on analog technology, the CAFB described in this article can be coated with software using high level language and can be embedded completely. Therefore, it has fundamental differences with the analog-based filter bank design method and since this technology can correct/modify the filter bank flexibly and reconstruct the software by increasing/decreasing the diverse logics and functions when necessary, it can provide greater convenience in the aspect of economy and efficiency.
4. Ultimately, The S/W based CAFB, developed in this study, effectively improves on the H/W based analogue filter bank by compressing the vast amount of real-time dynamic responses usually acquired by means of a uniform rate of sample, into the range of frequency concerned. Eventually, it is expected to become a new paradigm in the WSNs based SHM of civil structures by facilitating an efficient measurement and management of data base.

Acknowledgements

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (grant number: NRF-2013R1A2A1A01016192), and funded by the Ministry of Science, ICT & Future Planning (grant number: NRF-2013R1A1A1063540).

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