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Film Thickness of Lithium Battery Fast De-Noising Based on Atomic Sequence Template Library

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Abstract

The natural frequency and scanning vibration frequency of C-dynamic scanning system of laser sensors are acquired for film thickness of lithium battery de-noising based on multi-resolution wavelet algorithm. For this reason, fast de-noising based on atomic sequence template library is present. First, under various mode of scanning, best atomic sequence template is built by sparse decomposition. Secondly, at the given mode, film thickness data is match to the best atomic sequence to de-nosing. Experimental results show that template-matching pursuit (MP) algorithm is effective and algorithm speed is higher than MP 57 times.

Keywords: *film thickness of lithium battery; template- matching pursuit; sparse decomposition*

1. Introduction

Real-time measurement automatically of lithium battery thickness can be realized by C-dynamic scanning system(Figure1)based on laser sensor, but scanning process of the system is accompanied with static and dynamic error including mechanical vibration noise、system error of C-dynamic scanning system、dynamic error of different scanning velocity. Performance could be achieved highly accurately based on multi-resolution wavelet algorithm. But natural frequency and vibration frequency are acquired to decide coefficient of wavelet decomposition and reconstruction coefficient [1-2].

Sparse decomposition proposed by Mallat and Zhang is hot recently, which has been widely used in image, video, medical signal processing [3-12]. Sparse decomposition algorithm is adapt to choose the appropriate basis functions to complete signal decomposition on the condition of lack of noise statistical characteristics, and get natural features of the original signal from redundancy dictionary [13]. During industrial surroundings, sparse decomposition algorithm regards actual thickness as a part of the sparse component and the vibration noise as the residual of film thickness.

Because of a large amount of computation, the data measured from static and dynamic industrial environment is trained to get over-complete dictionary of atoms based on matching pursuit of sparse decomposition. Then under various mode of scanning, best atomic sequence template is built by sparse decomposition. At last at the given mode, film thickness data is match with the best atomic sequence to de-nosing. The algorithm doesn't need to measure the natural frequency and scanning vibration frequency of C-dynamic scanning system and can adapt to different industrial environment to improve the efficiency of sparse decomposition.

2. Template-matching Pursuit Sparse De-noising

MP algorithm is an adaptive decomposition iterative algorithm which selects the best matching atom from highly redundant over complete dictionary to approach signal's time-frequency structure. The signal is sparse component from noisy signal, signal with firm structure is the same as atomic properties, but noise with random structure is uncorrelated. If meaningful atom can be extracted from the noisy signal, then the atom is the signal. If meaningful signal isn't continue to be extracted from the signal in residual, then the signal in residual is noise.

In the process of iterative, sparse decomposition is to choose the largest atom which is the inner product of signal or signal residual, sparse decomposition continues tracking and

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extracting the atom which is match to the original signal and residual signal. In the calculation of the inner product selection of gabor atom, it is very large, and if the length of the input signal is too large, the amount of calculation is even more astonishing [13].

For a large amount of calculation, template-matching pursuit sparse de-noising is proposed. First, best atomic sequence template is built by sparse decomposition under various mode of scanning. Secondly, at the given mode, film thickness data is match to the best atomic sequence to de-nosing. Although best atom is not extracted to calculate by means of iteration, the atom is to be the next best one. Compared with MP algorithm, this algorithm eliminates times of iteration. Template-matching pursuit algorithm raises the possibility of various signal's length and greatly improves the performance. Figure2 is a flow chart of the fast sparse de-noising based on template-matching pursuit.

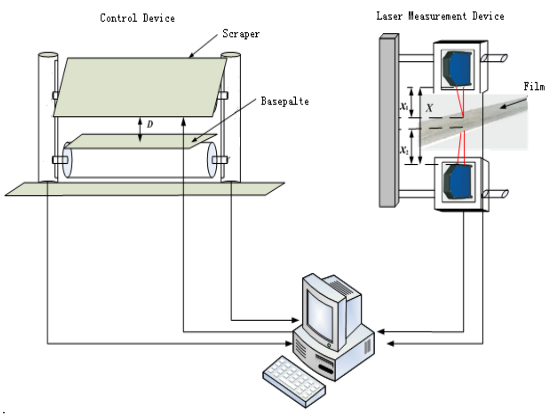


Figure 1. Film of Lithium Battery Detection

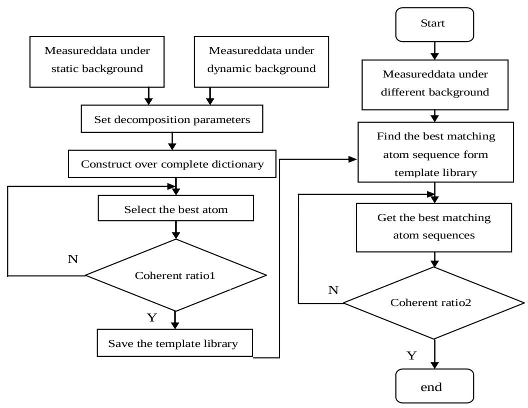


Figure 2. Flow Chart of the Fast Sparse De-noising

The steps are as follows:

Step 1: Train best atomic sequences and construct template under different mode.

Step 1.1: Define over-complete dictionary $D=\{g_{r_m}\}(m=0,1,\cdots,M-1)$ in Hilbert space, $\|g_{r_m}\|=1$, m defines as iteration times, M defines as iteration termination value.

Step 1.2: Define measured data as $x(n)$, $n=1,2,\cdots N$ from static and dynamic industrial environment. N defines as length as signal. Define $x(n)=R^0x$, $n=1,2,\cdots N$, R^0x is original residual signal.

Step 1.3: Select the best atom $g_{r_o}\in D$ by MP algorithm to make $|\langle R^0x, g_{r_0}\rangle|$ maximum, get the residual $R^1x=R^0x-\langle R^0x, g_{r_0}\rangle g_{r_0}$. Select the best atom by MP algorithm, and get the residuals $R^2x=R^1x-\langle R^1x, g_{r_1}\rangle g_{r_1}$, $\cdots\cdots$, $R^mx=R^{m-1}x-\langle R^{m-1}x, g_{r_{m-1}}\rangle g_{r_{m-1}}$ again.

Step 1.4: Define coherent ratio $\lambda(R^mx)=\sup_{g_{r_m}\in D}|\langle R^mx, g_{r_m}\rangle|/\|R^mx\|$ which decreases with the increasing of iteration. If set to one convergence value, iteration will end up to M th and get $M+1$th residual signal $R^{M+1}x=R^Mx-\langle R^Mx, g_{r_M}\rangle g_{r_M}$ .In order to ensure the coherent ratio reaches the set, the iteration value adds up to $M+10$ times.

Step 1.5 : Save and construct template library, the best atom defines as $G_l=\{g^l_{r_0}, g^l_{r_1},\cdots g^l_{r_M},\cdots g^l_{r_{M+10}}\}$, $l=1,2,\cdots L$, L is the number of template under various mode.

Step 2:De-noise under given surrounding.

Step 2.1:Input measured data $xx(n)$, $n=1,2,\cdots N$ under some kind of mode. Set $xx(n)=R^0xx$ 。

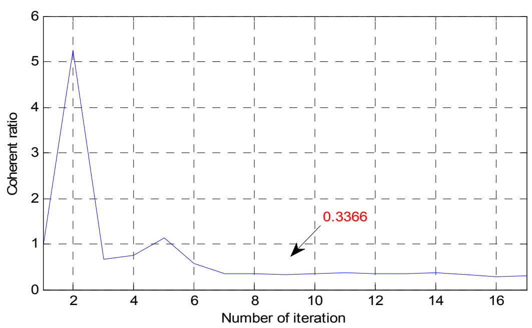
Step 2.2: Select the proper parameter l from the template library and get G_l. The best atomic sequences are involved in the iteration $R^m xx = R^{m-1}xx - \left\langle R^{m-1}xx, g^l_{r_{m-1}} \right\rangle g^l_{r_{m-1}}$, $m = 1, 2, \cdots MM$. MM is defined as iterative times, $MM < M + 10$.

Step 2.3: Finally $y(n) = \sum_{m=0}^{MM} \left\langle R^m xx, g^l_{r_m} \right\rangle g^l_{r_m} + R^{MM+1}xx$, $n = 1, 2, \cdots N$ is got, Define $y(n)$ as reconstructed de-noising signal.

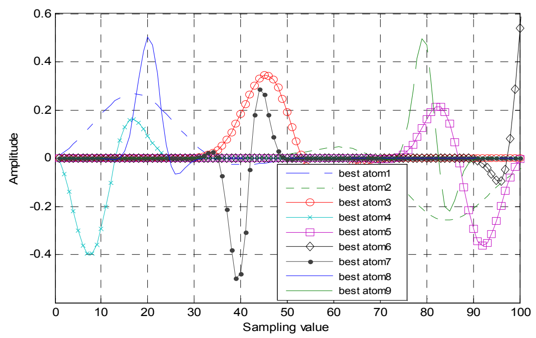
3. Experimental Results

3.1. Simulation of Fast MP Signal De-noising

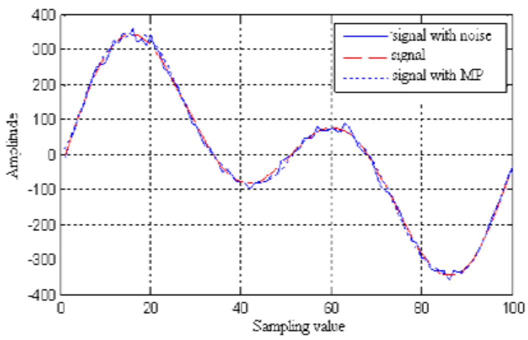
Construct signal with noise $x(n) = 190\sin(2\pi f_{s1}n) + 200\sin(2\pi f_{s2}n) + z(n)$ in training stage, $f_{s1} = 10$, $f_{s2} = 20$, $n = \{0, 0.001, 0.002\cdots, 0.099\}$, $z(n)$ defines as gaussian noise which complies with *N(0,10)*. Set the coherent ratio 0.34. Figure 3(a) is coherent ratio convergence value when number of iteration is changing. Figure 3(b) is the 9 best atomic sequences diagram. Figure 3(c) is signal with noise, clean signal and signal after sparse decomposition.



(a)



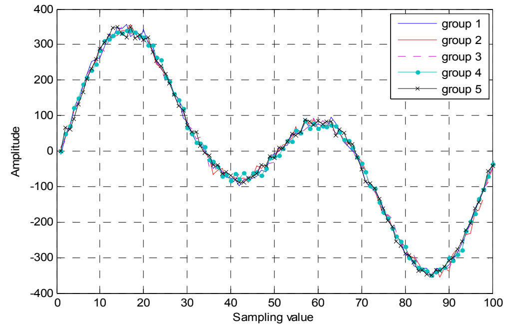
(b)



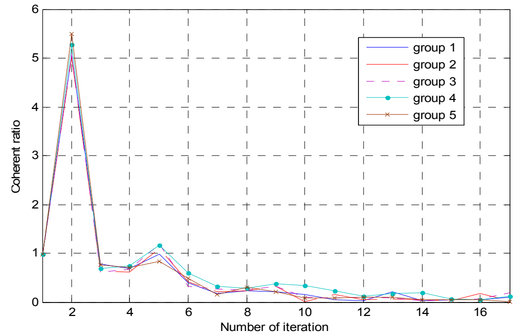
(c)

Figure 3. Template Constructed by MP Sparse Decomposition during Training

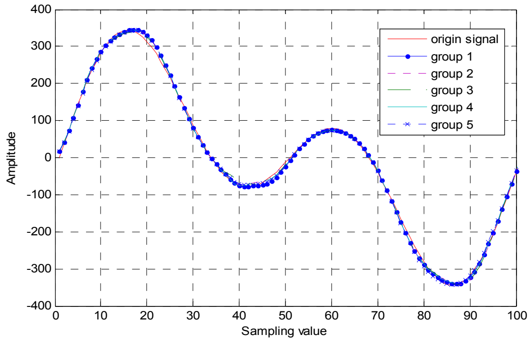
Best atom sequences are got by template-MP while five groups of gaussian noise complying with *N(0,10)* are adding to bouble-sinusoidal signal.



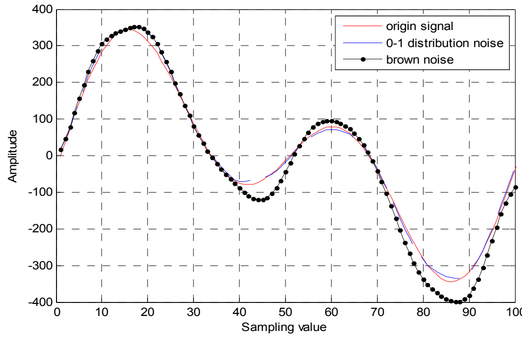
(a) Five groups of signal with noise



(b) Five groups of coherent ratio



(c) Clean signal and signal after MP



(d) De-noising when the best atom under gaussian noise used to others

Figure 4. Fast Sparse De-noise by Template-MP

Table 1. Contrasting of Different Mean Square Error (MSE)

MSE	gaussian noise				
	group 1	group 2	group 3	group 4	group 5
MP	7.5366	6.5356	7.4436	6.2355	7.6123
Template-MP	7.1876	7.1099	7.4642	6.7696	7.1404

Table 2. Contrasting of both Algorithms

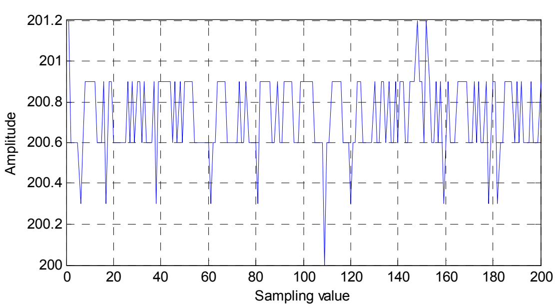
	MP	Template-MP
time(s)	10.88	0.19
enthance	1	57

From Figure 3, 4 and Table1, MSE by template-MP is close to MP algorithm. Performance under gaussian noise template is decreasing in brown and 0-1 distribution noise. Atom sequence shows the distribution of gauss under gaussian and non-gaussian noise. Therefore waveform of signal after de-noising deviates from the actual distribution, it is concluded that atomic sequence is selectivity under different noise environments.

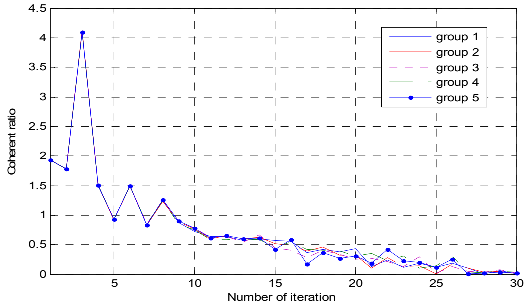
Table 2 presents a comparison of both algorithms, template-MP algorithm is superior to MP algorithm 57 times.

3.2. De-noising by Template-MP under Static and Dynamic Mode

When C scanning system is stopped, experiment result shows MSE of template-MP and MP algorithm is less than data unprocessed, and increasing of template-MP is slightly worse than MP, but speed of operation of template-MP is satisfied with measurement under industrial surroundings.



(a) Static original film thickness distribution



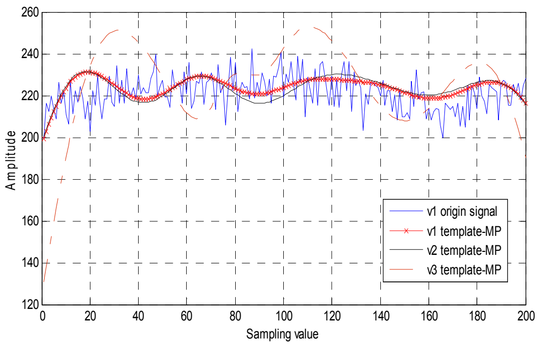
(b) Five groups of coherent ratio

Figure 5. Fast Sparse De-noising of Static Film Thickness by Template-MP

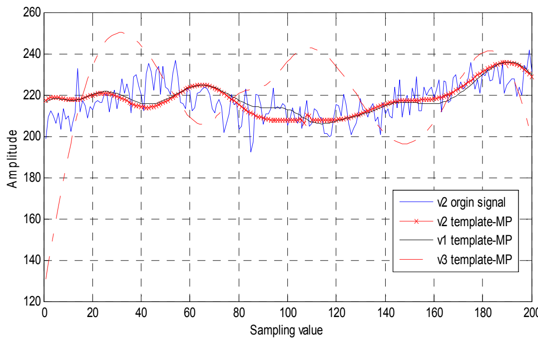
When scanning, different speed will cause various vibration noise added in the origin thickness of film thickness. Figure 6 shows the different among the v1 (slow), v2 (middle) and v3 (fast) scanning speed mode. From the figure, speed of v1 is close to v2,distribution difference isn't obvious, but v3 is faster than v1, v2, difference among them is notable. Atoms of template library are match to different scanning speed, but data unmatched deviates from the original thickness distribution of lithium film.

Table 3. Contrasting of Different Mean Square Error (MSE)

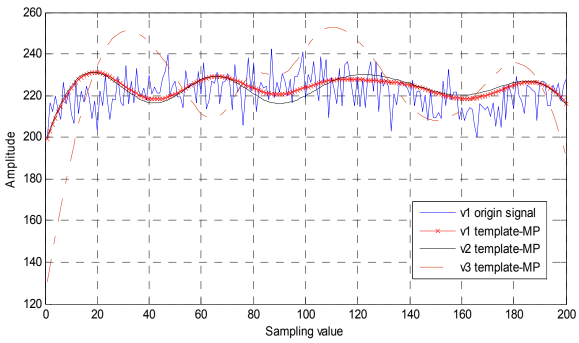
thickness (μm)	group1	group2	group3	group4	group5	group6	group7
original	0.1887	0.1873	0.1993	0.1932	0.1977	0.1936	
template-MP	0.1495	0.1789	0.1512	0.1548	0.1971	0.1663	14.1%
MP	0.1522	0.1709	0.1544	0.1556	0.1934	0.1653	14.6%



(a) v1



(b) v2



(c) v3

Figure 6. Fast Sparse De-noising of Static Film Thickness by Template-MP

4. Conclusion

It is required for real-time, untouched, on-line measurement of thickness of lithium battery film under industrial environment, but multi-resolution wavelet algorithm makes measurement complex because of natural frequency and scanning vibration frequency of C-dynamic scanning system. Fast de-noising which best atomic sequence template is built by sparse decomposition selects the best atomic sequence to de-nosing. Study of simulation data and analysis of industrial surroundings show that the algorithm is efficient to filter noise and algorithm is effective and algorithm speed is higher than template- matching pursuit 57 times.

Acknowledgements

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