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題目：Development of Data Repairing for Composite Waves with Missing Data via An Iterative Filter

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若投稿論文為國科會研究計畫之成果，請註明國科會計畫編號：

NSC-93-2212-E006-037

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應用疊代式高低通濾波器於複合波數據修補之研究

Development of Data Repairing for Composite Waves with Missing Data via An Iterative Filter

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ABSTRACT

The iterative filter using the Gaussian smoothing method is employed to decompose and repair a tide data string composed of many tidal wave components. Since the iterative filter can ignore the effect of missing data to certain extent, the tidal wave components can be successively decomposed. However, because the employed wave decomposition method cannot decompose a composite wave found by two wave components whose frequencies close to each other, three beats are found. For those wave components whose wavelengths are larger than $\sqrt{2}$ times the drop-out period, the missing data can be satisfactorily achieved by merely applying the filter. For a longer period of missing data, an iterative technique is developed to repair the data. The tide data of the Houbihu harbor in Pingtung at south part of Taiwan during the period of Jan. 1 through Dec. 31/2001 was employed to demonstrate the procedure of wave decomposition and data repairing.

Keywords: FFT with small error, Time Frequency Analysis.

1. INTRODUCTION

Because of the rapid development of computer technique, people can collect many data string simultaneously now. In near future, the nano technology will further increase the number of data string exponentially. Today, before analyze a data string, people often classify, validate, and edit the data which exclude unavailable part, arrange the available part. For example, in Ref.[1], six types of random data anomalies are listed and are recommended to exclude them manually. However, as the number of data string increases to a certain level, it is impossible to do such a data qualification manually again. Therefore, the automatically data qualification procedure via a software becomes more and more important and urgent.

After the data anomalies are identified, one may employ available methods to repair the data anomalies. From the result of a previous study [2], it seems possible to repair short and moderate period of anomalies which may be missing data or abnormal data.

One of the important issue of data analysis is how to

decompose a composite wave. In Ref.[2], the technique of wave decomposition basing on the iterative filter of Ref.[3-5] is employed as a fundamental tool to repair data drop outs. After data repairing, is necessary to inspect whether or not the main features are captured or not. A classical method is to check the Fourier spectrum and examines if the dominate frequency is shifted. However, the Fourier spectrum is an overall property which can not reflect local properties.

A powerful to extract local features of a data string is the continuous wavelet transforms [6-9]. In Ref.[7,8] Farge pointed that the Fourier spectrum reflects the lumped information over the expansion range and can not provide the local information. Unfortunately, there are not much detailed information can be directly obtained from the resulting wavelet coefficient plot. From mathematical point of view, the wavelet transforms employs the convolution integral is in some sense equal to a projection method. However, a finite data string cannot be perfectly expanded by the Morlet and related transforms because the embedded kernel function

eliminates the orthogonal property between eigen functions. Consequently, the resulting wavelet coefficient evaluated at a specific scale function is contaminated by the effect of ignoring all the non-orthogonal functions corresponding to other scale functions. Recently, the continuous wavelet (Morlet) transform was enhanced by using a band-passed data to evaluate the wavelet coefficient rather using the original data [10,11]. It seems that the band-passed data does reduce the contamination to certain extent.

Tides around Taiwan result from shoaling effects of tidal constituents in the Pacific Ocean propagated westward to the continental shelf. According to the harmonic analyses of tide data at Houbihu harbor in southern coast of Taiwan, the Luni-solar Diurnal (K1) and the Principle Solar Diurnal (O1) are the largest diurnal tidal components, and the Principle Lunar (M2), the Principle Solar (S2), the Larger Lunar Elliptic (N2) and the Luni-solar Semidiurnal (K2) are the largest semidiurnal tidal components. Besides, the monthly, fortnightly, annual, semiannual and the long-term (18.61 years) variations of water level are also included. In other words, the tide wave data involves complex structure and is a good test case to examine the performance of a data analysis tool.

In this study, the wok of Ref.[2] will be completed by using the enhanced Morlet transform to check the main features of the tide wave which involves short and moderately long data missing periods.

2. ANALYSIS

The Iterative Filter Basing on Gaussian Smoothing

Assume that a discrete data string can be approximated by

$$y(t) = \sum_{n=0}^N b_n \cos\left(\frac{2\pi t}{\lambda_n}\right) + c_n \sin\left(\frac{2\pi t}{\lambda_n}\right) \quad (1)$$

In Ref.[5,6], it was proven that after applying the Gaussian smoothing once, the resulting smoothed data becomes

$$\bar{y}_1(t) \approx \sum_{n=0}^N a(\sigma/\lambda_n) \left\{ b_n \cos\left(\frac{2\pi t}{\lambda_n}\right) + c_n \sin\left(\frac{2\pi t}{\lambda_n}\right) \right\} \quad (2)$$

where $a(\sigma/\lambda_n)$ is the attenuation factor introduced by the smoothing and can be proven numerically that

$$0 \leq a(\sigma/\lambda_n) \approx \exp[-2\pi^2 \sigma^2 / \lambda_n^2] \leq 1 \quad (3)$$

If the removed high frequency part is denoted as y_1' and apply the same smoothing to it to obtain the second smoothed result as \bar{y}_2 and repeat the same procedure to obtain the m -th smoothed and high frequency part as \bar{y}_m and y_m' , respectively. The following relation can be built

$$\begin{aligned} y_m' &= \sum_{n=0}^N [1 - a(\sigma/\lambda_n)]^m \left[b_n \cos\left(\frac{2\pi t}{\lambda_n}\right) + c_n \sin\left(\frac{2\pi t}{\lambda_n}\right) \right] \\ \bar{y}(m) &= \bar{y}_1 + \bar{y}_2 + \dots + \bar{y}_m = y - y_m' \\ &= \sum_{n=0}^N A_{n,m,\sigma} \left[b_n \cos\left(\frac{2\pi t}{\lambda_n}\right) + c_n \sin\left(\frac{2\pi t}{\lambda_n}\right) \right] \end{aligned} \quad (4)$$

$\bar{y}(m)$ can be considered as the smoothed part and y_m' as the high frequency part. After substituting Eq.(3), the attenuation factor of employing the Gaussian smoothing method satisfies

$$\begin{aligned} A_{n,m,\sigma} &= 1 - [1 - \exp\{-2\pi^2 \sigma^2 / \lambda_n^2\}]^m \\ 0 &\leq A_{n,m,\sigma} \leq 1 \end{aligned} \quad (5)$$

Obviously, the accumulated smooth part is embedded by a diffusive attenuation factor without phase error. It was also proven in Ref.[5,6] that the transition region from $A_{n,m,\sigma} = 0$ to 1 is much narrower than that of the original $a(\sigma/\lambda_n)$ for a sufficiently large iteration step m .

Suppose that all the waveforms within the range of $\lambda_{c1} < \lambda < \lambda_{c2}$ are insignificantly small. The above mentioned iterative smoothing procedure can be an effective filter to give both the low and high frequency parts. The desired parameters σ and number of iteration steps m are solved by the following simultaneous equations.

$$\begin{aligned} 1 - [1 - \exp(-2\pi^2 \sigma^2 / \lambda_{c1}^2)]^m &= B_1 \\ 1 - [1 - \exp(-2\pi^2 \sigma^2 / \lambda_{c2}^2)]^m &= B_2 \end{aligned} \quad (6)$$

where $B_1, B_2 = 0.001, 0.999$ are employed in this study.

Before the iterative filter is employed, one can use a classical FFT algorithm to obtain a spectrum. After inspecting both the original data and spectrum, he can decide a suitable transition range defined by λ_{c1} and λ_{c2} to remove the non-sinusoidal and low frequency part or to separate the composite wave into high and low frequency parts. Moreover, the filter can also be repeatedly employed to give a band-passed data string to evaluate the time dependent spectrum within a specific frequency band. For such a requirement, the spectrums within two transition zones $\lambda_{c1}^H < \lambda < \lambda_{c2}^H$ and $\lambda_{c1}^L < \lambda < \lambda_{c2}^L$ in the high and low frequency sides of the band, respectively, should not be seriously counted. In fact, as comparing with the band-passed data obtained by just dropping the spectrum associated to $\lambda < \lambda_{c1}^H$ and $\lambda_{c2}^L < \lambda$, these transition zones are employed to keep the generality of the band-passed data string. The direct method of dropping undesired modes from the Fourier spectrum has the possibility of missing the information reflecting the frequency variation of waveforms.

Monotonic Cubic Interpolation Method

For the sake of simplicity and to employ the data structure of a computer, it seems convenient to use the simple FFT algorithm whose data points are exactly equal to 2^m . Because a real data string may not have exactly the number of integer powers of 2 in uniform spacing form, a interpolation scheme proposed in Ref.[12,13] should be employed to redistribute the points.

Fast Fourier Transform Algorithm

The following FFT algorithm of Ref.[13] will be employed in this study to find spectrum.

Data Repairing

According to Ref.[1], before performing the data analysis, the data qualification should be made. One of the qualifications is to check if there is data missing. If there do have data missing, one can mark the missing location with certain constants that are easily be recognized by program.

In Ref.[2], it had been proven that to decompose the original data string with data missing into several waveforms is a useful procedure for data repairing. The decomposition procedure is achieved by the iterative filter. It had also been found that, if the data drop-outs are at isolated points or only but a few continuous points, the iteration can be done automatically.

For those missing data running over a long period, the following strategy of Ref.[2] is restated below for the sake of completeness. The waveform decomposed by the iterative filter has abnormal regions around a long data drop-out region. The region runs across a length $\approx \sqrt{2}\sigma$ (or one wavelength) next to the missing points. Beyond the region, the resulting wave component data is nearly not influenced. Consider the data drop-outs of a beat wave shown in Fig.1. Basing on the above mentioned fact, most data remote from the missing point can be employed to be a reference data string. Around the data drop-out region, the upper and lower envelopes are constructed by connecting the local maximum and minimum points via the above mentioned monotonic cubic spline interpolation [3,4], respectively.

Next, these envelopes are employed to scale up the wave data outside the drop-out region and the scaled data is shown as thin line whose amplitude is almost constant. Third, as shown in Fig.2, a segment of scaled wave data within the range marked by two arrows is shift to the drop-out region and is shown as dotted line. Fourth, the shift data is scaled back as shown in Fig.3. Fifth, in the drop-out region, this shifted data is chosen as the repaired data component. Note that the original wave component is different from the repaired one outside the drop-out region because the original one is seriously affected by the missing data.

The same procedure is applied to all wave components except the highest frequency part which is referred as noise. For those wave components with long

enough wave length, the short period data drop-out region is automatically repaired and need not to treat it. Finally, the repaired data of all wave components are summed up to replace the data drop-out points. However, as the above mentioned discussion about Fig.3, the repaired data may or may not consist with the existing data. Therefore, the above procedure should be repeatedly applied until the slopes at all end points of every drop-out region are smooth.

Enhanced Morlet transforms

The following Morlet transform transfer a data string $y(t)$ into the wavelet coefficient.

$$W(a, \tau) = 1/\sqrt{a} \int_{-\infty}^{\infty} y(x) \psi^*[(x-\tau)/a] dx \quad (7)$$

where $\psi(x) = e^{i6x} e^{-|x|^2/2}$ and a is called as the scale function. If this transform is applied over a range $a_0 \leq a \leq a_1$, a two-dimensional wavelet coefficient plot is obtained on the (a, τ) plane. By applying Eq.(7) to Eq.(1) it can concluded that the scale function a can be closely related to the wavelength λ_n such that the mode with $\lambda_m = a\pi/3$ gives a maximum response. The work of Ref.[10,11] performs a band-passed filter to the original data and eventually gives the following wavelet coefficient.

$$\bar{W}(a, \tau, y) \approx \sqrt{\frac{\pi a}{2}} \times \left\{ \sum_{n=0}^{\infty} b_n \exp\left[-\left[\frac{a^2}{2} + \frac{T^2}{8\pi^2 a^2}\right] \cdot \left[\frac{2\pi}{\lambda_n} - \frac{6}{a}\right]^2\right] \exp\left[\frac{i2\pi\tau}{\lambda_n}\right] + \sum_{n=0}^{\infty} c_n \exp\left[-\left[\frac{a^2}{2} + \frac{T^2}{8\pi^2 \sigma^2}\right] \cdot \left[\frac{2\pi}{\lambda_n} - \frac{6}{a}\right]^2\right] \exp\left[-\frac{i2\pi\tau}{\lambda_n}\right] \right\} \quad (8)$$

where the factor $T^2/(8\pi^2\sigma^2)$ added to $a^2/2$ is result of band-passed filter with σ as the window size on spectrum domain. If one perform the summation over all the values of a 's, the inverse transform can be easily obtained from the real part because the factor embedded to the spectrum b_n and c_n in Eq.(8) are the same. If the band-passed data is not added, the parameter $a^2/2$ of the exponential function shows that, in the high frequency part (with a smaller a), the contaminated bandwidth running over a wider range of different modes (denoted by n) than that in low frequency part (with a larger a). This property reflects the fact of violating the completeness of the Weistrass approximation theorem such that a expansion should starts from the lowest order eigen function rather than just use a high order eigen function.

In order to effectively reflect the original data's character, let

$$k_{n-1} = T/\lambda_{n-1}, \quad k_n = T/\lambda_n, \quad k_{n+1} = T/\lambda_{n+1} \quad (9)$$

The window size scale σ takes the following value

$$\sigma = c \cdot \max[|k_n - k_{n-1}|, |k_{n+1} - k_n|] \quad (10)$$

where $c = 1$ or 2 is recommended.

3. RESULTS AND DISCUSSIONS

The tide data of the Houbihu harbor in Pin-Tung at south Taiwan in the period of Jan.1 through Dec. 31/2001 is employed to illustrate the proposed repairing procedure. The data is the water level in mini-meter recorded at every hour. It contains many isolated data drop-out points, a three-hour missing period, a one day drop-out, and a two day drop-out region. The Original data is decomposed by a 10 stages filtering procedure. At first $\sigma = 0.1$ $m = 30$ is employed to eliminate the noise. Then, $\sigma = 90, 30, 10, 5, 3, 1, 0.4, 0.25, 0.125$ and $m = 120$ are successively employed to generate waveforms for repairing. In order to demonstrate the efficiency of data repairing, the data after repairing is again drops for a period of 2 or 9 days. That shown in Fig.4 is data missing of 2 days. Because the data missing period is shorter than $\sigma = 5$ days, the repaired waveform of Fig.4b closes to the original data. In Figs.4c and 4d, because there are not suitable sinusoidal data to be employed, the departure of the repaired waveform from the original data is significant. For such a situation, the neuro-network method is a possible solution provided that there are many available data base. The repaired data of Fig.4e and 4f are reasonable, while that in Fig.4g has a large departure. On the whole the over repaired data closes to the original data reasonably.

For the case of artificially drop out of 9 days long, the resulting repair is shown in Fig.5. The departure is significantly large. From these two tests, the following conclusions can draw: (1) for those waveforms whose data missing period much less than the damping factor σ (to remove the high frequency part), the iterative filter can automatically recover the original data with insignificant error; (2) for those waveforms with a missing period less than 10 times of damping factor σ , the repairing is acceptable; (3) for those waveforms with a missing period in the range of 10σ to 20σ , the repaired data has significant error; and (4) for a missing period in the range longer than 20σ , the repairing is only but for reference but is better than nothing. In fact, for the missing period longer than 10σ , one should try another possible repairing method.

The result of repairing the original data with true data missing is shown in Fig.6. In Fig.6a, the short period data missing is repaired easily by the iterative filter. For the one and two days data missing, shown in Fig.6b and 6c, respectively, the two cycle repairing seems reasonable.

In order to check whether the repaired data capture the main features or not, the enhanced Morlet transform is employed to generate the two-dimensional wavelet coefficient plots. That shown in Fig is the resulting plot

of the whole-day tide. Those for other tide waveforms are not shown here because of length limitation. Fig.8 shows the spectrum of the repaired data but filtered by $\sigma = 4$ days and $m = 30$. The resulting spectrum and wavelet plots construct a good checking mechanism to examine the effect of data repairing. It seems that the data repairing do not introduce significant error to the wavelet coefficient plot so that the main features are clearly captured. Those shown in Table 1 through 4 are the comparison between the standard waves and estimated waves for the whole-day, half-day, 1/3 day, and 1/4 day tides, respectively. A careful inspection upon these tables reveals that the present data repair method works very well for this data string with a moderate data missing period.

4. CONCLUSIONS

A complete procedure of data repairing employing the iterative filter, monotonic cubic interpolation and a simple FFT algorithm are successively constructed. The test cases show that the method are suitable for a moderate and small data missing period.

ACKNOWLEDGEMENT

This work is supported by the National Science Council of Taiwan under the grant number NSC-93-2212-E006-037.

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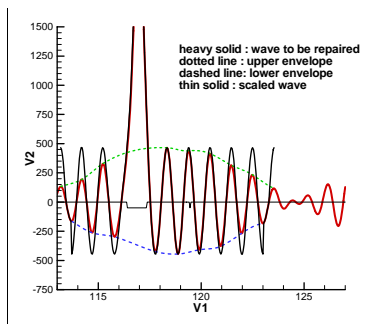


Fig.1 The schematic diagram of data repairing. For the central line: 0 denotes regular data, -50 is drop-out point; dotted lines are upper and lower envelopes; heavy line is the original decoupled wave; thin solid line is the scaled wave.

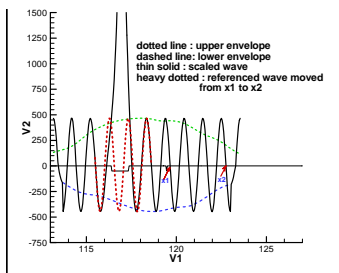


Fig.2 Wave data in the region marked by two arrows are moved to the data drop-out region and is shown as dotted line.

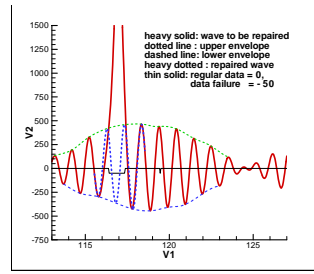


Fig.3 The shifted data string is scaled back as the dotted line.

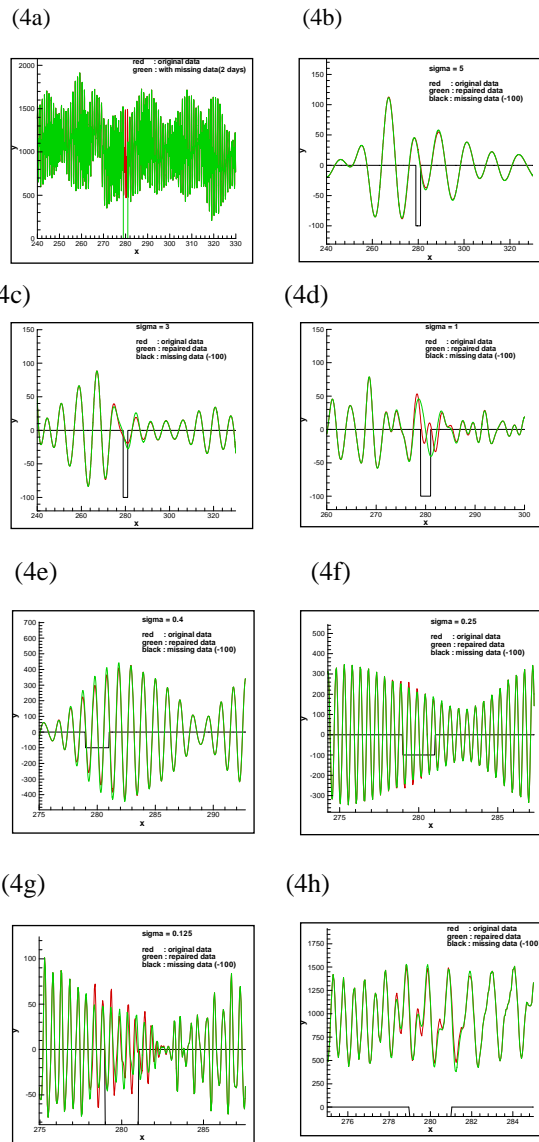


Fig.4 The original and repaired data plots for 2 days data drop-out, horizontal line is days and vertical is mm height of wave: (a) original data; (b) 3 cycle repaired data of the long waveform decoupled by $\sigma = 10$ and 5 days; (c) by $\sigma = 5$ and 3 days; (d) by $\sigma = 3$ and 1 days; (e) $\sigma = 1$ and 0.4; (f) $\sigma = 0.4$ and 0.25; (g) $\sigma = 0.25$ and 0.125; and (h) The comparison between original and repaired data strings.

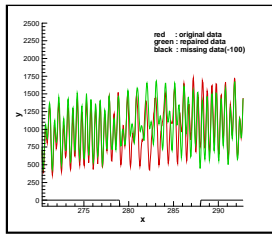
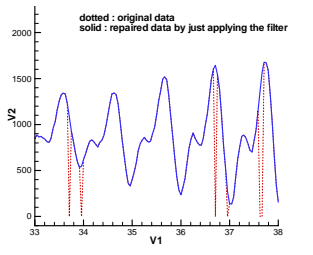
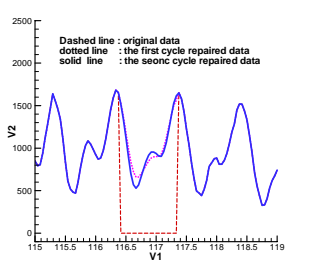


Fig.5 The original data with 9 days long artificial data missing and repaired data.

(6a)



(6b)



(6c)

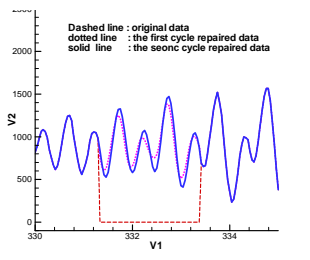
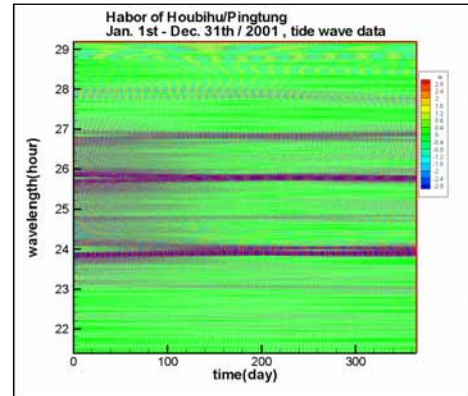


Fig.6 The repaired data compares with original data: (a) short period data missing repaired by $\sigma = 0.075$; (b) 1 day data dropout, dotted line is the first cycle repaired and solid line is the second cycle result; and (c) 2 days drop out with the same symbol as that in (b).

(7a)



(7b)

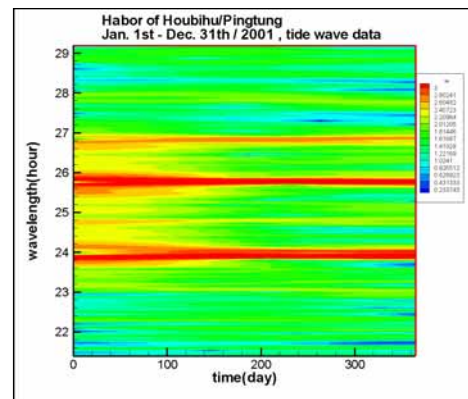


Fig.7 The two-dimensional wavelet plot for the whole-day tide waveform: (a) real part plot and (b) amplitude plot.

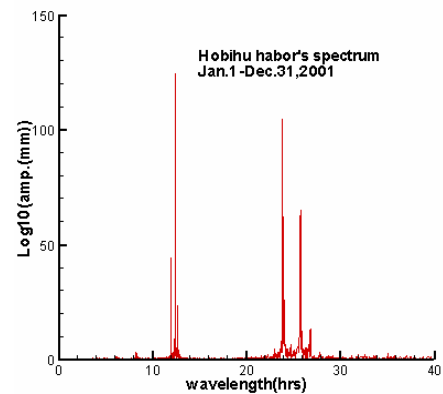


Fig.8 The resulting spectrum of repaired data filtered by $\sigma = 4$ days.

Table -1 The Whole-Day Tide Data Comparison

wave	Exact λ	Cal. λ	$\Delta\lambda$	A_{max}	A_{min}	\bar{A}
OO1	22.306	22.36	.009~-.007	2.078	0.371	1.842
J1	23.1	23.06	.021~-.013	2.437	1.736	2.348
K1	23.935	23.92	.012~-.038	3.774	3.423	3.747
P1	24.066	24.03	.155~-.012	3.323	2.761	3.196
M1	24.86	24.81	.06~-.024	2.826	2.123	2.609
O1	25.819	25.81	.003~-.061	3.714	3.101	3.645
Q1	26.868	26.85	.048~-.086	3.063	2.62	2.996
SIG1	27.848	27.83	.137~-.03	2.337	1.945	2.293
---	---	28.83	.04~-.044	2.022	1.676	1.989
ALP1	29.095	29.04	.015~-.002	2.048	1.178	1.915

Table -2 The Half-Day Tide Data Comparison

wave	Exact λ	Cal. λ	$\Delta\lambda$	A_{max}	A_{min}	\bar{A}
ETA2	11.754	11.745	.003~-.011	2.101	1.703	2.019
K2	11.967	11.967	.002~-.006	3.176	2.756	3.042
S2	12	11.993	.009~-.0006	3.437	3.019	3.398
T2	12.01	12.02	.005~-.002	3.052	2.466	2.747
L2	12.19	12.19	.009 ~-.003	2.247	1.5	2.074
LDA2	12.22	12.225	.01~-.002	2.257	1.869	2.16
M2	12.42	12.415	.002~-.001	3.841	3.526	3.836
NU2	12.626	12.619	.012~-.009	2.618	2.266	2.519
N2	12.658	12.656	.011~-.004	3.12	2.739	3.082
MU2	12.87	12.868	.001~-.011	2.49	2.07	2.407
2N2	12.905	12.898	.016~-.001	2.163	1.693	2.087

Table -3 The 1/3 Day Tide Data Comparison

wave	exact λ	Cal. λ	$\Delta\lambda$	A_{max}	A_{min}	\bar{A}
---	---	7.835	.001~-.003	1.264	0.684	1.18
SK3	7.992	7.984	.01~-.004	2.107	1.521	1.923
---	---	8.166	.006~-.004	2.168	1.75	2.12
MK3	8.177	8.177	.005~-.002	2.303	1.771	2.202
SO3	8.192	8.191	.008~-.001	2.071	1.532	1.957
M3	8.28	8.273	.006~-.001	2.125	1.545	2.018
---	---	8.302	.001~-.001	1.541	1.12	1.455
---	---	8.335	.003~-.002	1.574	1.269	1.556
---	---	8.364	.005~-.003	1.784	1.078	1.387
MO3	8.386	8.387	.004~-.005	2.132	1.808	2.113

Table -4 The 1/4 Day Tide Data Comparison

wave	exact λ	Cal. λ	$\Delta\lambda$	A_{max}	A_{min}	\bar{A}
SK4	5.992	5.995	.002~-.001	1.795	0.904	1.584
S4	5.999	6.004	.004~-.002	1.561	1.214	1.513
---	---	6.014	.001~-.002	1.582	0.631	1.368
---	---	6.029	.002~-.005	1.726	1.029	1.465
MK4	6.095	6.095	.005~-.002	1.781	1.315	1.674
MS4	6.103	6.102	.001~-.010	1.867	1.479	1.841
---	---	6.146	.001~-.004	1.568	0.949	1.482
SN4	6.16	6.156	.002~-.003	1.674	1.069	1.513
---	---	6.209	.001~-.004	2.023	1.514	1.9

應用疊代式高低通濾波器於複合波數

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摘要

本文應用移動式高斯平滑法做為疊代式濾波器，對潮汐之波形所組成的複合波數據進行拆解和修補。對於單一和少數連續數據之空缺點，疊代式濾波器可以自動修補之。然而對於兩頻率相近的波所組合而成的複合波，本文所應用的波拆解法尚不能成功的將此複合波拆解出兩個獨立的波，因此本文發展出針對各波形修補的簡易方法。

對於較長時間的空缺數據點，若波長大於空缺時間波形的 $\sqrt{2}$ 倍，空缺數據可以疊代式濾波器自動修補之。若波長小於空缺時間波形的 $\sqrt{2}$ 倍，將使用簡易的修補方法，對各個短波長的波形進行修補。本文並以屏東後壁湖漁港的水位數據為例，說明複合波的拆解和數據修補的過程。

關鍵詞：數據修補，疊代型濾波器，快速傅立葉轉換式，小波法。