Low-Frequency Noise Characteristic Extraction Method of Electronic Components Based on Data Mining

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Abstract. Aiming at the low accuracy of traditional extraction methods, a method based on data mining is proposed to extract low-frequency noise features of electronic components. Firstly, data mining is carried out. Based on this, the noise modulation model of electronic components is established. Combined with filtering, the low-frequency noise feature extraction method of electronic components is optimized, and the experimental analysis is carried out. The experimental results show that this method can effectively improve the accuracy of low frequency noise characteristics of electronic components, and has a certain practicality.

Keywords: Electronic components · Low-frequency noise · Characteristics · Extraction · Data mining

1 Introduction

Low frequency electrical noise of electronic devices is the manifestation of micro motion of electronic carrier. Its accurate measurement can provide the basis for noise characteristics, generation mechanism and analysis application. Noise measurement can effectively verify the basic theories related to carrier transport in electronic components, and also promote the exploration of the physical sources of noise phenomenon. The application of electric noise is one of the goals of noise mechanism research and noise testing technology research. Based on the research of low-frequency electrical noise, the correlation research of electronic component defects, stress damage, process level, quality and reliability is put forward, and applied to the optimization design of components, process control, quality evaluation and reliability screening.

Accurately measure the performance of carrier micro motion in low frequency noise of electronic devices, which lays a foundation for the study of noise characteristics, generation mechanism, analysis and application. Noise is a common phenomenon in nature. People's understanding of noise begins with the most intuitive sense of hearing and sight. The response of the auditory system and the visual system to the noise of the electronic system are “noise” and “noise” respectively [1]. The noise of electronic components restricts the noise level, detection sensitivity, false trigger rate, fidelity and resolution of the whole system. With the deepening of research, people gradually realize the dialectical relationship between noise and signal, that is,

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noise contains blood signal. Therefore, the connotation of noise research has been gradually expanded, and the extraction and detection of noise have also begun to receive attention. The internal noise of electronic components, especially the low frequency noise, is very sensitive to the difference of bystanders or the defects caused by different materials, structures and processes of hardware components. Therefore, the low-frequency noise of electronic components can also be applied to the study of device quality and reliability characterization [2, 3]. The research on noise extraction and measurement of electronic components needs the efforts and wisdom of scholars in various fields. On the one hand, the deep understanding and explanation of the essential laws of physical phenomena in the theoretical study of noise is the basis of noise testing, analysis and application research. On the other hand, the study of noise testing and analysis is the verification and supplement of theoretical research, and also the power of noise extraction and testing technology progress and application transformation. For this reason, this paper proposes a method of low frequency noise feature extraction of electronic components based on data mining. The innovation lies in the use of autoregressive model to extract the deterministic components and obtain the autoregressive model of low frequency noise. By linear transformation of the autocorrelation function of low frequency noise, the weight coefficient of linear prediction can be obtained. Experimental results show that this method can effectively improve the accuracy of low frequency noise characteristics, and has certain practicability.

2 Data Mining

Assuming that $\{X_n\}, n = 1, \ldots, N$ is the noise point of an electronic component, which is located in a phase space, and $C(\varepsilon)$ is the correlation function. Then the proportion of points whose distance is less than a certain value can be expressed as:

$$C(\varepsilon) = \frac{2}{N(N-1)} \sum_{i=1}^{N} \sum_{j=i+1}^{N} \theta(\varepsilon - \|X_i - X_j\|) \tag{1}$$

Among them, $\|X_i - X_j\|$ is the distance represented by the norm, and θ represents the Heaviside step function. When x takes different values, θ will take two different numbers. For the point pair (X_i, X_j) with a distance less than a certain value, it is recorded as the correlation dimension. When the distances of N meet certain requirements, $C(\varepsilon)$ obeys the exponential law and needs to meet:

$$D = \lim_{\varepsilon \to 0} \lim_{N \to 0} d(N, \varepsilon) \tag{2}$$

The above formula D is the correlation dimension. Envelope demodulation is a commonly used feature extraction method, which mainly includes two parts: the solution of analytical electronic component signals and the Fourier transform. Analyzing the solution of electronic component signals is a key technology [5], and the solution method is shown in formula (4):

$$x_H \sqrt{x(n,f,\Delta f)^2 + (Hilbert(x(n,f,\Delta f)))^2} \tag{3}$$

In the formula, x_H is the envelope signal of the frequency band signal, and $Hilbert(\cdot)$ is the Hilbert solution function.

On this basis, select a reference point and make a neighborhood, find the trajectory distance from the neighborhood point to the reference point [6], and take the logarithm of the average distance to obtain the relevant data of the electronic components. The calculation formula is:

$$S(\nabla n) = \frac{1}{N}\sum_{n0=1}^{N} \ln\left(\frac{1}{|u(\beta_{n0})|}\sum_{\beta_n \in u(\beta_{n0})} |s_{n0} + \nabla n - s_n + \nabla n|\right) \tag{4}$$

In the formula, β_{n0} and $u(\beta_{n0})$ are the embedded vector and neighborhood respectively, $|u(\beta_{n0})|$ is the relevant data volume of electronic components, β_n is the salient feature point of electronic components, s_{n0} is the last salient element of β_{n0}, and $s_{n0} + \nabla n$ represents the time range beyond.

3 Extraction Method of Low-Frequency Noise Characteristics of Electronic Components Based on Data Mining

3.1 Noise Modulation Model of Electronic Components

The noise generated in the operation of electronic components contains obvious modulation signals, which are mainly caused by the periodic excitation force of electronic components. In this regard [7], the establishment of a single-component modulation model of electronic component noise is shown in the following formula.

$$x_{MA}(t) = A_m \cos(2\pi f_{ci} t) \tag{5}$$

In the formula, x_{MA} represents the noise modulation signal of electronic components, A_m is the amplitude of the noise modulation signal, f_m is the characteristic frequency of the modulation signal, f_{ci} is the frequency of the carrier signal, and N is the total number of carrier signals.

As a result, a noise modulation signal appears in the emitted noise of electronic components, and the established amplitude modulation-frequency modulation modulation signal of the low-frequency noise signal of electronic components is shown in formula (7). The characteristic frequency of the modulation signal can be solved by the derivative of the corresponding information [8], and its instantaneous modulation frequency is shown in formula (8).

$$x_{MAf}(t) = A_{mf}\cos(\theta_{mf}(t))\sum_{i}^{n}\cos(2\pi f_i \mathrm{t}) \tag{6}$$

In the formula, $x_{MAf}(\mathrm{t})$ represents the low-frequency noise signal, A_{mf} is the amplitude of the low-frequency noise signal, and $\theta_{mf}(\mathrm{t})$ is the change of the angle of the low-frequency noise modulation signal over time.

$$f_{mf}(\mathrm{t}) = \frac{d\theta_{mf}(\mathrm{t})}{dt} \tag{7}$$

In the formula, $f_{mf}(\mathrm{t})$ represents the instantaneous frequency of the low-frequency noise signal.

The autoregressive model is used to extract the deterministic components. The autoregressive model of low-frequency noise can be expressed by the following formula:

$$x_{AR} = -\sum_{i=1}^{p} q_i x(n-i) \tag{8}$$

In the formula, x_{AR} represents the deterministic signal component obtained by linear prediction of low-frequency noise, $q(i)$ represents the weight coefficient, and p represents the order of the AR model. The weight coefficient $a(k)$ of linear prediction can be obtained by linear transformation of the low-frequency noise autocorrelation function $r_{AA}(i)$. The weight coefficient $q(k)$ can be solved using Yule-Walker equations, and the noise modulation model of electronic components is obtained as shown below.

$$r_{xx}(i) = \frac{1}{N}\sum_{n-0}^{N-1} x(n)x(n-i), 0 \le i \le p-1 \tag{9}$$

3.2 Normalized Processing of Low-Frequency Noise Performance of Electronic Components

When the low-frequency noise intensity $D = 0$, there is a critical value $A_\tau = \sqrt{4a^3/27b}$. When A_0 is greater than, the low-frequency noise balance of the entire electronic components will no longer be maintained. For this reason, for simplicity, let $b = 1$, and the bistable potential function is $U(x) = -ax/2 + x^4/4$. For small parameter signals (amplitude, frequency and noise intensity <<1), as the time of occurrence of resonance of electronic components increases [9], the signal-to-noise ratio of the response of electronic components reaches the maximum. At this time, the output power spectrum $S(f)$ consists of two parts of the power spectrum, namely:

$$S(f) = S_1(f) + S_2(f) \tag{10}$$

In the formula, $S_1(f)$ represents the power spectrum caused by the input low-frequency noise periodic signal, which is equal to the frequency spectrum of the input signal; $S_2(f)$ represents the power spectrum caused by the low-frequency noise, showing the form of Lorentz distribution [10]. Among them, the Lorentz distribution characteristic curve is shown in Fig. 1, and the respective expressions are as follows:

$$S_1(f) = \frac{2a^4 A^2 \exp(-a/2D)/(\pi^2 D^2)}{(2a^2 \exp(-a/2D)/\pi^2) + \left(2\pi f_0^2\right)} \times \delta(f_0 - f) \tag{11}$$

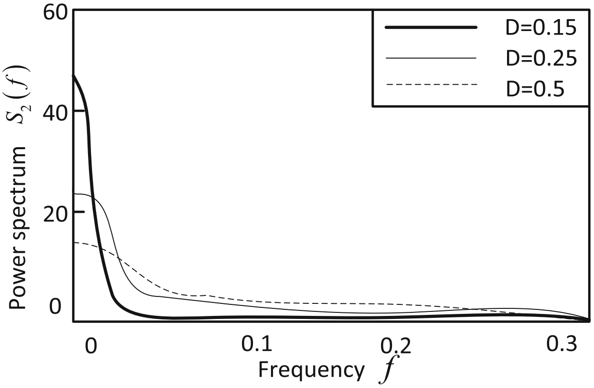

Fig. 1. Characteristic curve of Lorentz distribution

When the value of low-frequency noise intensity D is different, the corresponding noise output power spectrum $S_2(f)$ varies with frequency. It can be seen that within a certain range, the greater the noise intensity, the smoother the Lorentz distribution characteristic curve; the smaller the noise intensity, the curve The steeper [11]. The output power of noise has the characteristic of Lorentz distribution.

The method of extracting the low-frequency characteristics of electronic components by entropy is usually to estimate the entropy by $C_2(m, \varepsilon)$. The main principle is as follows: Let $\hat{C}_q(\varepsilon)$ represent the generalized $C_2(m, \varepsilon)$ estimate, and the expression between $\hat{C}_q(\varepsilon)$ and entropy is as follows:

$$C_q(m, \varepsilon) \propto \varepsilon^{(1-q)Dq} e^{(q-1)Hq(m)} \tag{12}$$

D_q is the q-order generalized dimension, and $H_q(m)$ is the generalized sum of entropy. If you want to divide the low-frequency noise performance of electronic components into countless parts, the parameter ε needs to meet the $\varepsilon \to 0$ condition, but at the same time it will bring about some problems, that is, the number of points in the field is too small, resulting in obvious fluctuations, and it is difficult to apply it in practice [12]. In order to have practical application value, the following conditions must be met: Entropy is independent of parameter ε. The usual practice is to determine the appropriate scale range, draw the $C_2(m,\varepsilon)$ local slope $d(m,\varepsilon) \sim \varepsilon$ curve, and observe the visible platform of each curve. If there is a visible platform, the size of D_p does not change, when ε selects a different value, the value of ε^{Dq} is always the same, then h_q can be obtained by the following formula:

$$\mathrm{h}_q(m,\varepsilon) = H_q(m+1,\varepsilon) = 1\mathrm{n}\frac{C_q(m,\varepsilon)}{C_q(m+1,\varepsilon)} \tag{13}$$

According to the characteristics of noise modulation of electronic components, the frequency of carrier noise is much greater than that of modulation noise, so the first wavelet packet decomposition frequency band is not included in noise demodulation [13]. The energy coefficient of the noise decomposition frequency band can be expressed by the proportion of the energy of each frequency band in the total energy, as shown in the following formula:

$$\eta_i^n = \frac{1}{\sum_{i=2}^{2^n} E_i^n} \cdot 100\% \tag{14}$$

In the formula, η_i^n represents the energy coefficient of the i-th frequency band of the n-th order.

According to the definition of the spectral correlation density function, the corresponding signal $x(t)$, its spectral correlation density function is [14]:

$$S_x(\omega,f) = \frac{1}{T}X(f+\omega/2)X^*(f-\omega/2) \tag{15}$$

From Eq. (15), it can be known that the spectral correlation density function of signal $x(t)$ represents the correlation of its spectrum on two different frequency components $f+\omega/2$ and $f-\omega/2$. The weaker the correlation, the more characteristic the low-frequency noise performance at the cycle frequency is ω. Significantly. In order to be able to quantitatively describe the strength of the low-frequency noise performance of electronic components [15, 16], the statistic $\rho_x(\omega,f)$ is defined as the spectral coherence function of the low-frequency noise $x(t)$), which normalizes $S_x(\omega,f)$:

$$\rho_x(\omega,f) = \frac{S_x(\omega,f)}{\sqrt{S_x(0,f+\omega/2)S_x(0,f-\omega/2)}} \tag{16}$$

3.3 Low-Frequency Noise Performance Extraction of Electronic Components

In order to simplify the extraction process, assuming that the low-frequency noise of electronic components is dominated by white noise [17], it can be obtained from Eqs. (19) and (20):

$$\frac{dx}{dt} - U'(x) + s(t) + n(t) \tag{17}$$

In the formula, $s(t)$ is the input signal, $n(t) = \sqrt{2D}\xi(t)$ is the white noise, $\xi(t)$ is the Gaussian white noise, $n(t)$ satisfies $\langle n(t) \rangle = 0, \langle n(t)n(t-\tau) \rangle = 2D\sigma(\tau)$, D is the noise intensity, $U(x)$ is the potential function of the electronic component, and $x(t)$ is the output signal of the electronic component [18]. Then the potential function of the electronic component, the expression is as follows:

$$U(x) = -\frac{ax^2}{2} + \frac{bx^2}{4} \tag{18}$$

In the formula, a and b are parameters whose potential function of electronic components is greater than 0. The potential function has a minimum value $U(x) = -a^2/4b$ at $x = \pm\sqrt{a/b}$ and a maximum value $Ux = 0$ at $x = 0$.

According to the linear prediction, the deterministic signal composition of the signal can be obtained, and then the residual signal formula composed of the low-frequency noise modulation signal component and the noise signal can be obtained as follows [19, 20]. Therefore, linear prediction based on AR model is an effective signal pre-whitening tool.

$$x_{AM}(t) + x_e(t) = x(t) + \sum_{k=1}^{p} a(k)x(t-k) \tag{19}$$

In the formula, $x_{AM}(t)$ represents the modulation noise signal, and $x_e(t)$ is the noise component in the monitoring signal.

The choice of modulation frequency band has an important influence on the demodulation effect of the final algorithm. When the carrier frequency band is modulated, the modulation frequency band is mostly the frequency band with higher energy. In this study [21], the modulation noise energy is used as the selected basic index. The calculation of frequency band energy is shown in the following formula.

$$E_i^n = \left\| wpc_i^n \right\|_2^2 \tag{20}$$

In the formula, $\|\cdot\|_2$ is the solution function of 2 norm, E_i^n represents the energy of the i-th frequency band of the nth order, and wpc_i^n represents the signal of the i-th frequency band of the nth order [22].

By synergizing the low-frequency noise and intensity of electronic components, a simple model that can produce stochastic resonance is obtained:

$$\frac{dx}{dt} = ax - bx + A_0 \cos(2\pi f_0 t) + n(t) \tag{21}$$

In the case of no change, the potential function of the electronic component is constrained by the periodic signal $s(t) = A_0 \cos(2\pi f_0 t)$, and the modulated bistable potential function is obtained as:

$$U(x) = -\frac{1}{2}ax^2 + \frac{1}{4}bx^4 - A_0 x(2\pi f_0 t) \tag{22}$$

The ratio of the low-frequency noise of electronic components to the average power of the unit noise spectrum at $f = f_0$ is called the signal-to-noise ratio of electronic components, namely:

$$SNR_{out} = \frac{\int_0^\infty S_1(f)df}{S_2(f = f_0)} \tag{23}$$

Based on the calculation result of the signal-to-noise ratio, several low-frequency noise components are removed to ensure that the remaining low-frequency noise performance is significant [23], which is equivalent to filtering by a high-pass filter. The filter bank is completely adaptive, and the high-pass filter can be expressed as:

$$x_h(t) = \sum_{j=1}^{k} c_j(t) \tag{14}$$

In the formula, j = 1, 2,…, which means to retain the first k IMF components of the signal, so that a high-pass filter can be constructed. Retain the significant performance of low-frequency noise, and transfer high-frequency energy to low-frequency.

Assuming the center frequency $f(m)$ of each filter, the frequency response of the filter is $H_m(k)$:

$$H_m(k) = \begin{cases} 0, k \le f(m-1) \\ \frac{k - f(m-1)}{f(m) - f(m-1)}, f(m-1) \le k \le f(m) \\ \frac{f(m+1) - k}{f(m+1) - f(m)}, f(m) \le k \le f(m+1) \\ 0, k > f(m+1) \qquad\qquad 0 \le m \le M-1 \end{cases} \tag{25}$$

In the formula, the center frequency $f(m)$ of each filter is:

$$f(m) = \left(\frac{N}{f_n}\right)B^{-1}\left(B(f_1) + m\left(\frac{B(f_n) - B(f_t)}{M+1}\right)\right) \tag{26}$$

In the formula, f_h and f_t are the highest and lowest frequencies of the filter bank, f_s is the sampling frequency, N is the number of sampling points per frame, and M is the number of filters. B^{-1} is the inverse function of B.

The energy spectrum $P(f)$ is passed through the Mel filter bank. The passable frequency range of this wave device group is $0 \sim f_N/2$ (f_N^- is the sampling frequency).

$$E(m) = \sum_{k=0}^{N-1} p(f) \cdot H_m(f) \tag{27}$$

Among them, N is the total number of points of each frame signal, and M is the number of filters.

From the design idea of the Mel filter, it can be known that when the center frequency of a certain Mel filter is $f(m)$, the frequency response function of the filter is $H_m(k)$.

$$H_m(k) = \begin{cases} 0 & k \le f(m-1) \\ \frac{k - f(m-1)}{f(m) - f(m-1)} & f(m-1) \le k \le f(m) \\ \frac{f(m+1) - k}{f(m+1) - f(m)} & f(m) \le k \le f(m+1) \\ 0 & k > f(m+1) \end{cases} \tag{28}$$

In the formula, $0 \le m \le M - 1$, the number of filters is M, and the calculation formula for the center frequency $f(m)$ of the Mel filter is:

$$f(m) = \left(\frac{N}{f_s}\right)Mel^{-1}\left(Mel(f_1) + m\frac{Mel(f_h) - Mel(f_l)}{M+1}\right) \tag{29}$$

In the formula, f_s is the sampling rate, f_l and f_h are the lowest and highest frequencies of the filter bank respectively, N is the number of sampling points of each frame of data, and Mel^{-1} is the inverse function of Mel.

Assuming that $x(t)$ is the most stable low-frequency noise performance of electronic components, it is assumed that the correlation function $R_x(t,\tau)$ of $x(t)$ is a periodic function with T as the period in the time delay domain. That is $R_x(t,\tau) = R_x(t+T)\tau$. Then F is expanded in the form of $R_x(t,\tau)$ ourier series, and the low-frequency noise performance extraction results of electronic components are:

$$R_x(t,\tau) = \sum_{\omega=-\infty}^{\omega=\infty} R_{x\omega}(\tau) \cdot e^{j2\pi\omega t} \tag{30}$$

4 Analysis of Results

To verify the application performance of the low-frequency noise extraction method of electronic components.

4.1 Basic Settings

The low-frequency noise performance of electronic components is selected for reconstruction, and the result is shown in Fig. 2 below.

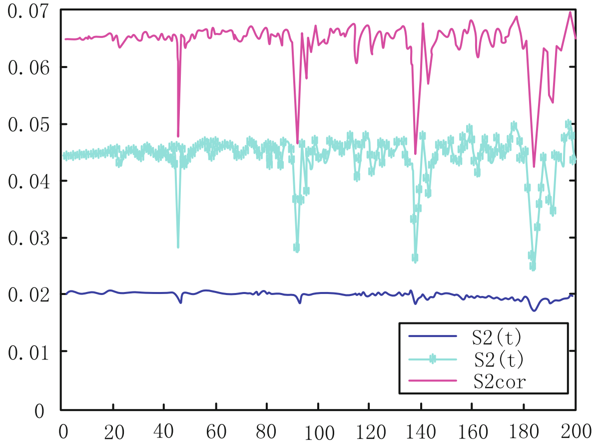

Fig. 2. Low-frequency noise performance reconstruction

In the above figure, the horizontal axis t represents the time variable, and the three different colored curves from top to bottom represent the values of the relevant index S_{2cor} of the statistic, the difference $\Delta\overline{S_2}(t)$ of the statistic, and the statistic $\overline{S_2}(t)$. The time delay parameter is determined by the first zero point of $\overline{S}_2(t)$, or the time corresponding to the first minimum value of $\Delta\overline{S}_2(t)$, and the time window τ_w is determined by the time corresponding to the minimum value of S_{2cor}. Phase space is the model basis for the extraction of chaotic characteristics and the basis for the extraction of low-frequency noise performance of electronic components.

4.2 Comparison of Extraction Accuracy

In order to make the proposed method effective, the following experimental tests further compare the accuracy of different extraction methods. The specific experimental comparison results are shown in Table 1:

Table 1. Accuracy comparison of different extraction methods

Number of test samples/ (a)	Accuracy/(%)		
	The proposed method	Literature [5] method	Literature [6] method
15	0.958	0.508	0.652
20	0.924	0.578	0.674
25	0.945	0.557	0.685
30	0.974	0.595	0.602
35	0.986	0.512	0.754
40	0.935	0.604	0.771
45	0.957	0.634	0.774
50	0.964	0.645	0.781

The analysis of the experimental data on Table 1 shows that the accuracy of the literature [5] method reaches 0.645, and the literature [6] method is 0.781, while the accuracy of this method is up to 0.964,. It is seen that this method effectively solves the problem of low-frequency noise performance extraction of electronic components, effectively avoids external interference, effectively improves the accuracy, and significantly outperforms the other two extraction methods. The superiority of the extraction results of the proposed method is fully demonstrated.

5 Conclusion

To solve the problem of low extraction accuracy in traditional extraction methods, a data mining-based low-frequency noise performance extraction method of electronic components is proposed. By introducing data mining methods, the analysis of low-frequency noise performance can be effectively improved, and the improved method is effectively improved by combining modulation and filtering. The effectiveness of extraction and the significant increase in extraction accuracy have certain advantages.

References

1. Wang, F., Ni, M., Zhou, M., et al.: The optimal solution of quantum adiabatic approximation for maximum cut problem. Comput. Eng. **509**(01), 31–36 (2020)
2. Wu, S., Luo, Y., Chen, J.: Steady state characteristics of power function single well system driven by multiplicative and additive noise of color correlation. Vibration Shock **39**(5), 244–249 (2020)
3. Chen, J., Liang, Z., Fu, C.: Research on speech noise power spectrum estimation algorithm based on time recursive average. J. Sichuan Ordnance Eng. **040**(001), 135–139 (2019)
4. Zhu, M., Duan, Z., Guo, B.: Noise reduction effect analysis of vibration screen bearing signal based on EEMD and wavelet packet. Mech. Design Manuf. **351**(05), 70–74 (2020)

5. Geng, Y., Zhang, R.: Channel equalization algorithm for MIMO filter banks based on SINR. Sci. Technol. Eng. **478**(09), 138–142 (2019)
6. Xia, W., Cai, Z.: Performance analysis of power spectrum entropy detection for unknown sinusoidal signal. Signal Process. **34**(12), 109–117 (2018)
7. Wang, M., Liu, Y.: Partial discharge ultrasonic signal monitoring and digital noise reduction. Mech. Manuf. Autom. **258**(05), 208–211 (2018)
8. Du, F., Tang, L.: Convergence analysis of frequency spectrum and Fourier series of unit impulse sampling sequence. Vibration Shock **38**(04), 20–24 (2019)
9. Liu, H.: Order analysis method of nonstationary exhaust noise signal based on wavelet transform. Vibration Shock **038**(022), 29–35, 51 (2019)
10. Chen, P., Xiang, S., Li, M., et al.: Frequency estimation of multi-stage signals based on linear predictive autocorrelation. Sensors Microsyst. **336**(02), 63–65 + 69 (2020)
11. Liu, S., Liu, D., Muhammad, K., Ding, W.: Effective template update mechanism in visual tracking with background clutter. Neurocomputing (2020). https://doi.org/10.1016/j.neucom.2019.12.143
12. Liu, S., Liu, X., Wang, S., Muhammad, K.: Fuzzy-aided solution for out-of-view challenge in visual tracking under IoT assisted complex environment. Neural Comput. Appl. **33**(4), 1055–1065 (2021)
13. Liu, S., Liu, D., Srivastava, G., Połap, D., Woźniak, M.: Overview and methods of correlation filter algorithms in object tracking. Complex Intell. Syst. **7**(4), 1895–1917 (2020). https://doi.org/10.1007/s40747-020-00161-4
14. Liu, H., Ran, H.: Simulation of medical data information extraction based on data mining technology. Comput. Simul. **37**(05), 375–378472 (2020)
15. Peng, Y., Tao, S., Peng, T., et al.: Extraction method of parallel arrangement entropy characteristics of time series data under cloud platform. Power Autom. Equipment **39**(04), 217–223 (2019)
16. Wang, D., Xu, T.: Low frequency generation and compound noise behavior in blue violet light emitting diodes. Acta Physica Sinica **68**(012), 273–278 (2019)
17. He, Y., Liu, Y., Zhang, X.: Analysis of hot carrier injection effect in 65nm process NMOS devices based on low frequency noise. Semiconductor Technol. **44**(07), 50–55 (2019)
18. Dong, S., Guo, H., Ma, W., et al.: Ionizing radiation damage mechanism and bias dependence of AlGaN/GaN high electron mobility transistor devices. Acta Physica Sinica **69** (07), 294–302 (2020)
19. Luo, Z., Yan, H.: Robust laser micro Doppler feature extraction method based on pca-clean. Laser Infrared **50**(11), 27–35 (2020)
20. Hu, Q.G., Zhou, L.: Analysis of secondary transmission path of low frequency noise in car compartment and noise reduction control. Noise Vibration Control **40**(01), 80–85 (2020)
21. Sun, Z., Ye, Q.: Physical unclonable function for extracting reliable information entropy of multiple bits by using frequency characteristics of oscillating ring. Acta Electronica Sinica **43**(01), 234–241 (2021)
22. Jia, X., He, L.: Low frequency noise test method for microwave integrated circuits. Semiconductor Technol. **44**(02), 67–71 (2019)
23. Chen, L.: Anechoic properties of acoustic metamaterials for low frequency noise. Appl. Acoust. **39**(03), 438–444 (2020)