A force–voltage responsivity stabilization method for piezoelectric-based insole gait analysis for high detection accuracy in health monitoring

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Abstract
Gait analysis has become a hot spot in recent years, because it is proven that the status of a vast number of chronic diseases can be reflected by changes in gait. Furthermore, gait analysis can also help in improving the performance of athletes. Among the diverse gait analysis techniques, the piezoelectric-based insole technique has received broad attention due to its merits such as passive detection, high sensitivity, and low power consumption. However, the key coefficient of detecting plantar normal stress, the piezoelectric $d_{33}$ coefficient, relies on the force frequency, which occupies a relatively wide bandwidth (1 Hz–1 kHz) during walking events. In order to get the frequency information of the signal, in this work, empirical mode decomposition is used to separate the gait signal into several intrinsic mode functions, and then the frequency information of each function is interpreted using the normalized Hilbert transform. In this way, the piezoelectric $d_{33}$ coefficient is calibrated at every moment, obtaining higher accuracy (2.65% maximum improvement) in gait signal detection, promoting the development of gait analysis–based disease diagnosis and treatment.

Keywords
Insole gait analysis, piezoelectric sensing, piezoelectric coefficient dependency on frequency and responsivity calibration

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Introduction
Gait analysis has been widely used in recent years for sports training,¹,² chronic disease diagnosis,³,⁴ and emergency situation detection,⁵ attracting worldwide attention and yielding both commercial and research products.⁶ Conventional techniques for gait analysis include plate-based and insole-based architecture. Of these, the former provides higher detection accuracy and was the first generation of gait analysis.⁷ However, users are constrained in a limited space due to the small area of the plate, which prohibits its use for long-term disease analysis in daily life. Hence, insole-based techniques were rapidly developed.

Most reported insole gait analysis techniques are capacitive-, resistive-, piezoresistive-, or piezoelectric-
based methods. Capacitive-based techniques use flexible materials as insulating layers, which present significant deformations when suffering stress. Resistive techniques install strain gauges at desired locations to detect stress in the corresponding orientations. Piezoresistive architecture measures plantar stress information via piezoresistive effects, while piezoelectric architecture interprets plantar stress through analyzing the dipole movements. Among these methods, the first three require higher energy consumption than the last, owing to the nature of the active sensing mechanisms, which shorten the battery lifetime and limit their use for long-term monitoring. As a result, piezoelectric insole techniques have rapidly developed.

A variety of piezoelectric-based research outcomes have been reported in the literature. However, a key challenge for piezoelectric sensing—unstable force-voltage responsivity—has yet not been effectively addressed. This issue mainly originates from the dependency of the piezoelectric coefficient on frequency, indicating that when the same stress amplitude is applied to the piezoelectric device at different frequencies, the piezoelectric response varies due to the molecular structure. For applications that do not require high force sensitivity, for example, touch panels, the shift of piezoelectric coefficient is easily tolerated. However, for medical diagnosis based on gait monitoring, the unstable responsivity may bring inaccurate information.

In this article, to address this very issue, a Hilbert–Huang transform (HHT)–based technique is proposed and implemented. Experimental results demonstrate an improved detection accuracy of 2.65% (maximum)/2.5% (average), advancing the area of piezoelectric-based in-shoe gait analysis.

This article is structured as follows. The “Literature review on piezoelectric-based insole techniques” section reviews piezoelectric-based insole techniques. The “Methodology” section explains the proposed algorithm. The “Testbed description” section describes the testbed. Experimental results and corresponding discussion are provided in the “Results and discussion” section. Finally, conclusions are offered in the “Conclusion” section.

### Literature review on piezoelectric-based insole techniques

Plenty of piezoelectric-based insole architectures have been developed for gait analysis. Nevertheless, it is rare that commercialized products truly satisfy customers’ practical needs. This section briefly overviews existing work and then discusses their limitations.

Normal stress detection is supported in most, if not all, piezoelectric gait analysis prototypes. In Han et al., two artificial intelligence (AI)-coated discrete polyvinylidene fluoride (PVDF) sensors were attached at the front and rear area of the plantar for recognizing different human motions, such as walking and running.

However, merely detecting normal stress cannot satisfy the need for disease diagnosis, for example, diabetic feet. Hence, in previous studies, shear stress sensing is added, and two main methods are used to assemble an in-shoe device. The first method constructs a multilayered structure, in which piezoelectric films are stacked with different polarization orientations. In Chen et al., three sandwiched piezoelectric devices were positioned at the same point to detect three-axis stress. In Kärki et al., four PVDF sensor elements were combined as a single device to detect normal and shear plantar stress. A differential amplifier-based circuit was designed for improving detection accuracy, and averaged sensitivities at 12.6 mV/N for normal stress, and 223.9 and 55.2 mV/N for anterior–posterior and medical–lateral stress, respectively, were obtained. In contrast, in the second method, piezoelectric sensors for detecting different directions are arranged in the same layer, hence decreasing the thickness of the device. However, because the piezoelectric elements are positioned in parallel, they cannot accurately represent stress information for the same location.

The above literature showcases different piezoelectric techniques used in insole devices for gait analysis. Nevertheless, a common issue is the stability of their piezoelectric coefficients, which are unfortunately not always solid in practical scenarios. To address this, the next section proposes a calibration method.

### Methodology

The gait signal data were from the authors. The piezoelectric signal obtained contains a variety of frequency components, and each component has its own piezoelectric $d_{33}$ coefficient corresponding to its instantaneous frequency. Thus, to accurately calibrate the piezoelectric $d_{33}$ coefficient at a specific time, it is necessary to learn the corresponding instantaneous frequency, which is widely interpreted by the Hilbert transform–based algorithm in communication theories.

The Hilbert transform is a method to generate a signal $s_h(t)$ that is orthogonal to the original signal $s(t)$, expressed as

$$s_h(t) = \frac{1}{\pi} \int_{-\infty}^{+\infty} \frac{s(t)}{t-\tau} d\tau$$

(1)

Phase information is given in equation (2), and the calculation of frequency is provided in equation (3)
\[ \theta(t) = \arctan \left( \frac{s_0(t)}{s(t)} \right) \]  

(2)

\[ \omega_i = \frac{d\theta}{dt} = \omega_c + k_f m(t) \]  

(3)

where \( \omega_c \) represents the frequency of the carrier waveform, \( m(t) \) is the frequency of the modulation signal, and \( k_f \) is the proportionality factor.

Note that the signal needs to satisfy the Bedrosian theorem and Nuttall theorem before applying the Hilbert transform. In the Bedrosian theorem, the processed data should have a single frequency and a narrow band signal. However, in a practical case, amplitude modulation (AM) and frequency modulation (FM) coexist, and local changes in AM will affect the AM component. The Nuttall theorem is expressed in which AM and FM coexist due to the nonideal factors, for example, noise.\(^{33–36}\) Ignoring AM would result in a severe error in frequency interpretation. To address this, we adopted a normalized HHT, in which an empirical mode decomposition (EMD) algorithm\(^{31,37}\) divides the captured gait signal into several intrinsic mode functions (IMFs), the result being

\[ E = \int_{-\infty}^{+\infty} [x_{HT}(t) - x_{OR}(t)]^2 dt = 2 \int_{-\infty}^{+\infty} F_q(\omega) d\omega \]  

(4)

in which

\[ F_q(\omega) = F(\omega) + i \int_{-\infty}^{+\infty} a(t) \sin[\phi(t)] e^{-i\omega t} dt \]  

(5)

where \( F(\omega) \) is the spectrum of the signal, \( F_q(\omega) \) stands for the orthogonal spectrum, and \( a(t) \) is the amplitude component of the signal. It is obvious that the error level is closely associated with \( a(t) \); since if there is no fluctuation in \( a(t) \), \( E \) tends to zero.

As stated above, in a conventional situation, AM and FM coexist due to the nonideal factors, for example, noise.\(^{33–36}\) Ignoring AM would result in a severe error in frequency interpretation. To address this, we adopted a normalized HHT, in which an empirical mode decomposition (EMD) algorithm\(^{31,37}\) divides the captured gait signal into several intrinsic mode functions (IMFs), the result being

\[ S(t) = \sum_{i=1}^{K} IMF_i(t) + r_K(t) \]  

(6)

where \( S(t) \) is the signal, \( IMF_i \) is the intrinsic mode function component, and \( r_K(t) \) is the error term which comes from the negligible low-frequency component. Then \( r_K(t) \) is treated as a direct flow.

After that, empirical AM-FM decomposition is performed to separate each IMF into AM and FM components. The FM components are used to figure out the instantaneous frequency of each IMF, as well as its instantaneous amplitude. The flowchart for implementing the complete HHT-based algorithm for calibrating the piezoelectric \( d_{33} \) coefficient is illustrated in Figure 1, and a practical gait signal from a single piezoelectric sensor is given in Figure 2(a). In Figure 2(b), we list four IMFs of the gait signal. In fact, this signal can be divided into eight IMFs. The instantaneous frequency of \( IMF_1 \) to \( IMF_4 \) is given in Figure 2(c).

Based on the proposed algorithm above, the calibrated signal \( S_{real}(t) \) can be expressed as a function of the directed obtained piezoelectric signal \( S(t) \)

\[ S_{real}(t) = \sum_{i=1}^{K} IMF_i(t), \frac{d_{33}(f_i)}{d_{330}} + r_K(t) \cdot \frac{d_{33K}(f_K)}{d_{330}} \]  

(7)

where \( d_{33} \) is the piezoelectric \( d_{33} \) coefficient at 100 Hz (30 pC/N), which is used as a default value for sensing normal stress. With the amplitude and instantaneous frequency given from empirical AM-FM decomposition, we use equation (7) to calibrate the piezoelectric \( d_{33} \) coefficient.

**Testbed description**

A testbed was assembled to validate the proposed algorithm. PVDF films were selected as the functional material for their good mechanical and piezoelectric responses.\(^{38–42}\) In the constructed piezoelectric insole device, one PVDF film was settled as the intermedia layer with top (sensing) and bottom (ground) electrode layers on and underneath it. A PET/Cu/PVDF/Cu/PET\(^{41–48}\) structured device was integrated with the electrode substrate layers. At the sensing electrode layer, 36 round (radius = 5 mm) individual sensing locations (as shown in Figure 3) were patterned to reflect major gait information during walking.

During a walk event, plantar stress induced charges are converted to voltage signals by charge amplifier-based readout circuitry, whose block diagram is shown in Figure 3. Gait information could be obtained for further analysis through processing the voltage...
Figure 2. (a) The actual gait signal, (b) the separated IMFs (IMF₁–IMF₄) of the signal with empirical mode decomposition (EMD), (c) the separated IMFs (IMF₅–IMF₈) of the signal, and (d) the instantaneous frequency of IMF₁ to IMF₄ by the normalized Hilbert transform.

Figure 3. Block diagram of the readout circuit and the fabricated piezoelectric insole prototype (left foot).
distribution. The developed piezoelectric insole system can provide high detection sensitivity at 56 mN with responsivity at 680 mV/N.

Results and discussion

As stated in the previous sections, the responsivity is associated with the frequency of the force signal. Hence, the force-to-voltage responsivity of the device was tested from 1 Hz to 1 kHz, and the obtained results for one sensing location are offered in Figure 4. Due to the limited test frequencies carried out, a curve fitting method was used to model the characterization of $d_{33}$ versus frequency, which is expressed as

$$d_{33} = -160.7 \cdot f^{0.004} + 193.68$$

To validate our proposed algorithm for calibration of the instability issue introduced by the piezoelectric $d_{33}$ coefficient’s dependency on frequency, 10 walking events were performed to obtain sufficient plantar normal stress data. Part of the data from one channel during a walking event are shown in Figure 5(a), which is also used to demonstrate the detection accuracy improvement after calibration.

We used a force plate to record the accurate maximum force of each walking event. In Figure 5(a), there are spikes in the stepping states, and some vibrations during the dangling state mean that the signal contains high-frequency components. The figure also shows that the calibrated signal is closer to the reference signal from the force plate than its counterpart. For the data plotted in Figure 5(b), the mismatches between the directly measured/calibrated signal and the force reference signal were 89.53 and 87.27 N, respectively, demonstrating a 2.65% improvement in detection accuracy. In all 10 test sets, the average detection accuracy was boosted by 2.50%, validating the adaptability of our developed algorithm in calibrating the dependency on frequency of the piezoelectric coefficient.

According to further data analysis, the calibration effect on the frequency component of IMFs is constant. EMD was used to separate the signals into $IMF_i$, and we normalized their amplitudes through the envelope line (AM part) depicted from the peak values. The algorithm works well in the high-frequency range (>200 Hz), because there are enough peaks to correctly reconstruct the frequency-modulated part of each IMF ($IMF_1$–$IMF_4$, shown in Figure 2(b)), which can be used to calibrate the piezoelectric $d_{33}$ coefficient. However, at low frequency (<5 Hz), as shown in Figure 2(c) ($IMF_5$–$IMF_8$ of signal), there are fewer peak values with the increment of $i$, resulting in more fitting errors in the envelope line. However, the algorithm can still improve the accuracy by 2%.

Although the proposed algorithm demonstrates its power at improving detection accuracy, it is difficult to use the algorithm in real time due to its high complexity, which comes from the convolution process.
However, real-time analysis is not a must when assisting chronic disease diagnosis. Sufficient gait signals can be calibrated before once being used. Our tests took around 12 s with EMD processing, and around 8 s using the normalized HHT to get the calibrated signals of all 36 channels with the maximum SRAM usage at 532 kB.\(^{49}\) Nai-Fu Chang et al. have reported an online EMD microprocessor, which can decompose the signal with 256 sps sampling rate into five IMFs.\(^{50}\) This work may greatly improve the efficiency of EMD in the future.

In addition, if the calibration speed is more important than the accuracy, some quicker, more compressed but less accurate algorithms can be used in our application such as TEO (Teager Energy Operator,\(^{51}\) a method but less accurate algorithms can be used in our application such as TEO (Teager Energy Operator,\(^{51}\) a method)

\[\text{EMD} = \sum_{i=1}^{N} \text{IMF}_i\]  

average frequency in the selected time domain,\(^{53}\) which needs a modest computational effort (O(N)) but low time resolution), or the wavelet-based HHT (using integration, but without needing to generate the orthogonal signal and construct the analysis signal, though the wavelet selection\(^ {54}\) limits its accuracy). These algorithms may be suitable for real-time applications, but some additional work should be done before they can be used.

Conclusion

This article addresses the instability responsivity of the piezoelectric-based gait signal. By separating the detected signal into several IMFs with EMD, both frequency and amplitude information are used to obtain an accurate instantaneous frequency at each stepping moment. The proposed algorithm offers an average improvement in detection accuracy of 2.50%. The study in this article potentially enables high detection accuracy for chronic disease analysis, advancing the area of insole gait analysis.

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References

1. Tao W, Liu T, Zheng R, et al. Gait analysis using wearable sensors. Sensors 2012; 12(2): 2255–2283.
2. Wahab Y and Bakar NA. Gait analysis measurement for sport application based on ultrasonic system. In: 2011 IEEE 15th international symposium on consumer electronics (ISCE), Singapore, 14–17 June 2011, pp.20–24. New York: IEEE.
3. Bamberg SJM, Benbasat AT, Scarborough DM, et al. Gait analysis using a shoe-integrated wireless sensor system. IEEE T Inf Technol B 2008; 12(4): 413–423.
4. Ghi G, Ghi G, Schmitz G, et al. Effect of rhythmic auditory cueing on parkinsonian gait: a systematic review and meta-analysis. Sci Rep 2018; 8(1): 506.
5. Steele KM, Rozumalski A and Schwartz MH. Muscle synergies and complexity of neuromuscular control during gait in cerebral palsy. Dev Med Child Neurol 2015; 57(12): 1176–1182.
6. Rocco R, Agosti V, Jacini F, et al. Spatio-temporal and kinematic gait analysis in patients with Frontotemporal dementia and Alzheimer’s disease through 3D motion capture. Gait Posture 2017; 52: 312–317.
7. Oatis CA and Craik R. Gait analysis: theory and application. St. Louis, MO: Mosby, 1994.
8. Budsp M, Verstraete MC and Soutas-Little RW. Force plate analysis of the walking gait in healthy dogs. Am J Vet Res 1987; 48(6): 915–918.
9. Lei KF, Lee KF and Lee MY. Development of a flexible PDMS capacitive pressure sensor for plantar pressure measurement. Microelectron Eng 2012; 99: 1–5.
10. Muro-De-La-Herran A, Garcia-Zapirain B and Mendez-Zorrilla A. Gait analysis methods: an overview of wearable and non-wearable systems, highlighting clinical applications. Sensors 2014; 14(2): 3362–3394.
11. Renaud M, Sterken T, Fiorini P, et al. Scavenging energy from human body: design of a piezoelectric transducer. In: The 13th international conference on solid-state sensors, actuators and microsystems, 2005, Digest of technical papers. TRANSDUCERS ’05, 5–9 June 2005, vol. 1, pp.784–787. New York: IEEE.
12. Tsutsunino T, Suzuki Y, Kasagi N, et al. Seismic power generator using high-performance polymer electret. In: 19th IEEE international conference on micro electro mechanical systems, Istanbul, 22–26 January 2006, pp.98–101. New York: IEEE.
13. Jiang Y, Shiono S, Hamada H, et al. Low-frequency energy harvesting using a laminated PVDF cantilever with a magnetic mass. Power MEMS 2010; 2010: 375378.
14. Fu JY, Liu PY, Cheng J, et al. Optical measurement of the converse piezoelectric d 33 coefficients of bulk and microtubular zinc oxide crystals. Appl Phys Lett 2007; 90(21): 212907.
15. Malmonge LF, Malmonge JA and Sakamoto WK. Study of pyroelectric activity of PZT/PVDF-HFP composite. Mater Res 2003; 6(4): 469–473.
16. Mohabbi A, Mighri F, Ajii A, et al. Cellular polymer ferroelectret: a review on their development and their piezoelectric properties. Adv Polym Technol 2018; 37(2): 486–483.
17. Cha Y, Song K, Shin J, et al. Gait analysis system based on slippers with flexible piezoelectric sensors. In: 2018...
IEEE international conference on robotics and biomimetics (ROBIO). Kuala Lumpur, Malaysia, 12–15 December 2018, pp.2479–2484. New York: IEEE.

18. Han Y, Cao Y, Zhao J, et al. A self-powered insole for human motion recognition. Sensors 2016; 16(9): 1502.

19. Chen X, Shao J, Tian H, et al. Flexible three-axial tactile sensors with microstructure-enhanced piezoelectric effect and specially-arranged piezoelectric arrays. Smart Mater Struct 2018; 27(2): 025018.

20. Kärki S, Lekkala J, Kuokkanen H, et al. Development of a piezoelectric polymer film sensor for plantar normal and shear stress measurements. Sens Actuat A: Phys 2009; 154(1): 57–64.

21. Guo Y. An insole device based on piezoelectric sensor to assess plantar pressure during daily human activity. Sens Trans 2012; 147(12): 53.

22. Bui LA, Pelusi MD, Vo TD, et al. Instantaneous frequency measurement system using optical mixing in highly nonlinear fiber. Optics Express 2009; 17(25): 22983–22991.

23. Xianglong L. An instantaneous frequency estimation approach in a high noise environment. Procedia Eng 2012; 29: 1862–1866.

24. Luo X and Gao J. Instantaneous frequency estimation using WVD and local SVD. In: 2009 2nd international congress on image and signal processing, Tianjin, China, 17–19 October 2009, pp.1–4. New York: IEEE.

25. Huang NE. Hilbert-Huang transform and its applications, vol. 16. Singapore: World Scientific, 2014.

26. Lin CF, Yeh SW, Chien YY, et al. A HHT-based time frequency analysis scheme for clinical alcoholic EEG signals. In: WSEAS international conference. Proceedings. Mathematics and computers in science and engineering (No. 9), May 2009. World Scientific and Engineering Academy and Society, https://dl.acm.org/doi/10.5555/1576659.1576667.

27. Goswami JC and Hoefel AE. Algorithms for estimating instantaneous frequency. Signal Process 2004; 84(8): 1423–1427.

28. Griffiths L. Rapid measurement of digital instantaneous frequency. IEEE T Acoust Speech 1975; 23(2): 207–222.

29. Huang NE, Shen Z and Long SR. A new view of nonlinear water waves: the Hilbert spectrum. Ann Rev Fluid Mech 1999; 31(1): 417–457.

30. Tang J, Zou Q, Tang Y, et al. Hilbert-Huang transform for ECG de-noising. In: 2007 1st international conference on bioinformatics and biomedical engineering, Wuhan, China, 6–8 July 2007, pp.664–667. New York: IEEE.

31. Huang NE, Shen Z, Long SR, et al. The empirical mode decomposition and Hilbert spectrum for nonlinear and nonstationary time series analysis. Proc Royal Soc A 1998; 545(1971): 903–995.

32. Djurović I and Stanković L. An algorithm for the Wigner distribution based instantaneous frequency estimation in a high noise environment. Signal Process 2004; 84(3): 631–643.

33. Lerga J and Sucic V. Nonlinear IF estimation based on the pseudo WVD adapted using the improved sliding pairwise ICI rule. IEEE Sig Process Lett 2009; 16(11): 953–956.

34. Cohen L. Time-frequency distributions—a review. Proc IEEE 1989; 77(7): 941–981.

35. Hassanpour H. A time-frequency approach for noise reduction. Dig Sig Process 2008; 18(5): 728–738.

36. Hlawatsch F and Boudreaux-Bartels GF. Linear and quadratic time-frequency signal representations. IEEE Sig Process Mag 1992; 9(2): 21–67.

37. Dong H, Qi K, Chen X, et al. Sifting process of EMD and its application in rolling element bearing fault diagnosis. J Mech Sci Technol 2009; 23(8): 2000–2007.

38. Braña GO, Segovia PL, Magrader F, et al. Influence of corona charging in cellular polyethylene film. J Phys: Conf Series 2011; 301(1): 012054.

39. Yang J. The mechanics of piezoelectric structures, 2006.

40. Gerhard-Multhaupt R. Less can be more. Holes in polymers lead to a new paradigm of piezoelectric materials for electret transducers. IEEE T Dielectr Electr Insul 2002; 9(5): 850–859.

41. Gao S, Wu X, Ma H, et al. Ultrasound multifunctional graphene-PVDF layers for multidimensional touch interactivity for flexible displays. ACS Appl Mater Inter 2017; 9(22): 18410–18416.

42. Gao S and Nathan A. A flexible multi-functional touch panel for multi-dimensional sensing in interactive displays. In: 2017 IEEE sensors, Glasgow, 29 October–1 November 2017, pp.1–3. New York: IEEE.

43. Vijaya M. Piezoelectric materials and devices: applications in engineering and medical sciences. Boca Raton, FL: CRC Press, 2016.

44. Narita F and Fox M. A review on piezoelectric, magnetostrictive, and magnetoelectric materials and device technologies for energy harvesting applications. Adv Eng Mater 2018; 20(5): 1700743.

45. Gao S and Nathan A. A flexible multi-functional touch panel for multi-dimensional sensing in interactive displays. Cambridge: Cambridge University Press, 2019.

46. Mishra YK and Adelung R. ZnO tetrapod materials for piezoelectric nanogenerators based on BaTiO3 nanofibers in different alignment modes. ACS Appl Mater Inter 2016; 8(24): 15700–15709.

47. Yang J and Jeong YG. High performance flexible piezoelectric nanogenerators based on BaTiO3 nanofibers in different alignment modes. ACS Appl Mater Inter 2016; 8(24): 15700–15709.

48. Moh S-N, Kim S, Hwang D-K, et al. Self-powered flexible touch sensors based on PZT thin films using laser lift-off. Sens Actuat A: Phys 2017; 261: 288–294.

49. Kleta V and Laub A. The singular value decomposition: its computation and some applications. IEEE T Automat Contr 1980; 25(2): 164–176.

50. Chang NF, Chen TC, Chiang CY, et al. On-line empirical mode decomposition biomedical microprocessor for Hilbert Huang transform. In: 2011 IEEE biomedical circuits and systems conference (BioCAS), San Diego, CA, 10–12 November 2011, pp.420–423. New York: IEEE.

51. Potamianos A and Maragos P. A comparison of the energy operator and the Hilbert transform approach to signal and speech demodulation. Sig Process 1994; 37(1): 95–120.

52. Friedman V. A zero crossing algorithm for the estimation of the frequency of a single sinusoid in white noise. IEEE T Signal Process 1994; 42(6): 1565–1569.
53. He P and Greenleaf JF. Attenuation estimation on phantoms—a stability test. *Ultrason Imag* 1986; 8(1): 1–10.

54. Gao QW, Li HY, Zhuang ZQ, et al. De-noising of ECG signal based on stationary wavelet transform. *Acta Electronica Sinica* 2003; 31(2): 238–240.