Post-disaster Rescue Heartbeat Detection Signal Processing Algorithm Based on Laser Speckle Vibration Measurement Principle

Yutong Liu[1], Haiyang Tu[2,*], Chen Lou[3]
[1]*School of Mathematical Sciences, University of Electronic Science and Technology of China, Chengdu, Sichuan, China*
[2]*Yibin Research Institute, University of Electronic Science and Technology of China, Yibin, Sichuan, China*
[3]*School of Computer and Computing Science, Hangzhou City University, Hangzhou, Zhejiang, China*
**Corresponding Author.*

Abstract: This paper proposes a heartbeat detection signal-processing algorithm based on the laser speckle vibration measurement principle, specifically designed for life-sign detection in post-disaster rescue operations. Laser speckle vibration measurement is a non-contact measurement technique that extracts vibration information of a target by illuminating its surface with a laser beam and detecting changes in the speckle pattern caused by minute surface vibrations. In this study, we use the laser speckle vibration measurement principle to acquire heartbeat signals from trapped individuals. To enhance detection accuracy and noise resistance, we have designed a series of signal processing steps, including signal preprocessing, noise filtering, multi-scale analysis, and precise extraction and identification of heartbeat frequency. Experimental results show that this algorithm effectively extracts weak heartbeat signals in complex post-disaster environments, demonstrating excelent robustness and high-precision detection performance. This technology provides a reliable and practical solution for life detection in post-disaster search and rescue operations.

Keywords: Laser Speckle Vibration Measurement; Heartbeat Detection; Signal Processing Algorithm; Post-disaster Rescue

1. Introduction

In post-disaster rescue, quickly and accurately identifying survivors' vital signs is crucial for improving rescue efficiency. Traditional vital sign detection methods, such as acoustic detection and thermal imaging, while effective in some cases, are often affected by noise, obstacles, and other factors in complex post-disaster environments, reducing their accuracy and effectiveness. Recently, non-contact measurement methods based on laser technology have gained significant attention, with laser speckle vibration measurement technology showing great potential in vital sign detection due to its high sensitivity to small vibrations.

The use of lasers for vibration measurement has been a long-standing area of interest. Optical vibrometers can achieve sub-wavelength mechanical vibration measurements without contacting the object[1]. Laser speckle vibration measurement is a technique that detects small vibrations by analyzing changes in the speckle pattern produced when a laser beam illuminates an object's surface. Since the small movements of the chest caused by the heartbeat are reflected in subtle changes in the speckle pattern, laser speckle vibration technology can be used to acquire heartbeat signals. However, the complex background noise and interference in post-disaster environments pose significant challenges to accurate signal extraction.

To address this challenge, this paper proposes a heartbeat detection signal processing algorithm based on the laser speckle vibration measurement principle. The algorithm is designed with multiple steps, including signal preprocessing, noise filtering, and multi-scale analysis, to enhance the accuracy and robustness of heartbeat detection in complex environments. Experimental validation shows that the algorithm effectively extracts weak heartbeat signals, demonstrating excellent detection performance.

This research provides a new technical approach for life detection in post-disaster rescue operations, with significant practical application value. Future research will focus on further optimizing the algorithm to handle more extreme environmental conditions and applying this technology to actual post-disaster rescue missions.

2. Principle Introduction

2.1 Origin of Speckle

Speckle is a complex pattern that results from the scattering of electromagnetic waves or particle beams by a rough surface. When a laser is directed at a rough surface, each small surface element acts as a diffraction unit, with the surface resembling a "phase grating" composed of many diffraction components[2]. The random arrangement of these surface elements leads to interference of the scattered light, creating an irregular speckle pattern. In optical systems, the width of the point spread function affects image quality, causing the light rays from the surface elements to overlap during imaging, thereby producing the speckle phenomenon[3], as shown in Figure 1.

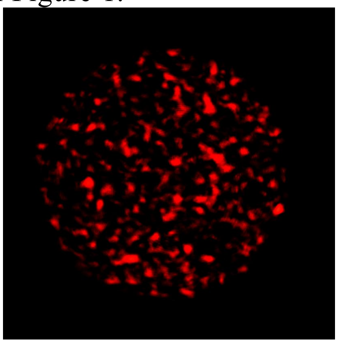


Figure 1. Laser Speckle Pattern

Speckle metrology includes various methods, primarily speckle interferometry, speckle photography, partial coherence speckle interferometry, and white light speckle methods. Among these, speckle interferometry and speckle photography are the most widely used[4]. In 1970, Leendertz introduced the speckle interferometry method[5], This method involves splitting the laser scattered back from the object's surface and analyzing the resulting interference fringes. There are four types of speckle interferometry: reference beam type, double beam type, double aperture type, and shear type. Speckle photography, on the other hand, involves directly imaging the scattered light with photographic equipment and analyzing the original speckle images frame by frame to obtain information about surface shape changes. This approach was first explored by Burch in 1968[6]. With advancements in technology, traditional film and plate recording methods have shown limitations, particularly in terms of time consumption and inability to meet real-time requirements[7]. The development of electronic and computer technologies has led to the application of optoelectronic imaging devices in speckle metrology, driving the emergence of Electronic Speckle Pattern Interferometry (ESPI) and digital speckle correlation techniques[8]. This paper will briefly describe the principles and characteristics of these two technologies and analyze typical optical systems.

2.2 Speckle Vibration Calculation

In 2009, Israeli researcher Zalevsky[9] and colleagues utilized high-speed area cameras to record laser speckle and extract subtle vibrations through inter-frame speckle matching, marking one of the earliest reports on using high-speed imaging for weak vibration detection, as illustrated in Figure 2. In laser speckle measurement, the rough surface of the object causes laser scattering, creating a speckle image. If the object's tilt angle is α, the displacement δ of the speckle image can be expressed as $\delta = Z2\tan\alpha$, where Z2 is the distance from the object to the observation plane. According to geometric optics, the speckle displacement Δx on the imaging sensor can be calculated by $\Delta x = (f/Z3) * \delta$, where Z3 is the distance between the observation plane and the imaging system's principal plane, and f is the lens focal length. Combining these formulas, the final relation is $\Delta x = (Z2/Z3)*f\tan\alpha$, showing the relationship between speckle displacement and the object's tilt angle[10].

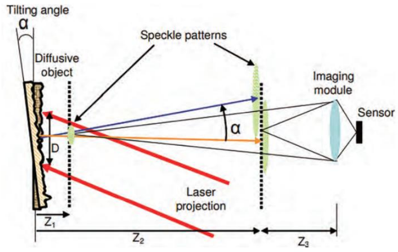


Figure 2. Schematic Diagram of Laser

3. System Implementation

The system structure proposed in this paper is illustrated in Figure 3. A spatially coherent laser beam is directed at the rough surface of a vibrating object[11], creating objective speckle patterns upon reflection. These patterns generally follow a Gaussian distribution. During detection, vibrations on the object's surface cause movement in the speckle pattern, leading to variations in light intensity and enabling the measurement of vibrations[12]. When a body is buried, its heartbeat vibrations are transmitted through the covering material to the surface. Laser speckle vibrometry can then detect these vital signs.

Lens 1 collects speckle energy, the aperture controls the speckle size, Lens 2 is used for collimation, and the mask plate controls the light aperture, ensuring the speckle size reaching the APD (Avalanche Photodiode) is smaller than its detection area, and helps find the optimal detection position. An ADC (Analog-to-Digital Converter) is used for analog-to-digital conversion to measure the speckle vibrations. The power P(t) detected by the photodiode in the system can be represented by a truncated Taylor expansion:

$$P(a(t)) \simeq p_0 + p_1 a(t) + \frac{1}{2} p_2 a(t)^2 + \cdots + \xi(t) \quad (1)$$

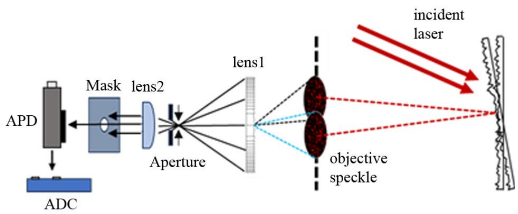


Figure 3. Schematic Diagram of a Heartbeat Detection System

4. Algorithm Processing

4.1 Algorithm Processing Scheme

Detecting vital signs is challenging due to the weak heartbeat signals, which are further attenuated after transmission through covering materials. Extracting coherent heartbeat information from noise is therefore a key difficulty in this system. The data processing approach first employs low-pass filtering to remove high-frequency noise, followed by normalizeation enhancement. Moving average filtering is then used for coherent heartbeat detection. The flowchart for this process is shown in Figure 4.

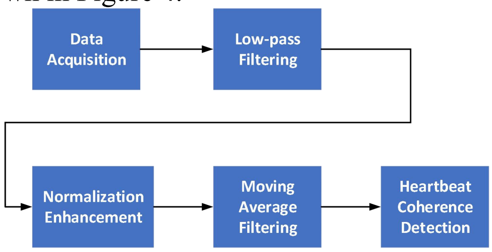


Figure 4. Algorithm Processing Flow

In this study, we employed advanced methods based on laser speckle vibrometry to detect and analyze vital signs beneath buried materials in post-disaster scenarios. The following is a detailed description of the data processing workflow we used:

Signal Acquisition: Signal acquisition was performed using laser speckle technology combined with a high-sensitivity Avalanche Photodiode (APD) detector[13]. This method effectively captures weak vital signs signals, such as periodic vibrations caused by heartbeat, by monitoring changes in the laser speckle pattern induced by the minute vibrations of the living body.

Low-pass Filtering: A low-pass filter was applied to the raw signal to remove frequency components above 400Hz. The cutoff frequency of the low-pass filter was set at 400Hz to eliminate high-frequency noise and irrelevant interference, while retaining the primary frequency components of the heartbeat signal. This step is crucial for extracting low-frequency physiological signals, as heartbeat signals typically fall within this frequency range[14].

Normalization Enhancement: The signal, after low-pass filtering, was normalized to standardize its amplitude range. This process maps the signal amplitude to a uniform standard range (e.g., [0, 1]), eliminating differences in signal amplitude, enhancing the signal features, and providing stable input data for subsequent processing steps[15].

Moving Average Filtering: A moving average filter was used to smooth the normalized signal. By applying a sliding window average, moving average filtering effectively reduces the impact of random noise, improving the smoothness and stability of the signal. The window size was chosen based on the signal characteristics and noise level to optimize the smoothing effect[16].

Heartbeat Coherence Detection: Finally, heartbeat coherence detection was performed to analyze the processed signal. Specifically, we used a combination of Autocorrelation Function (ACF) and Power Spectral Density (PSD) analysis. The autocorrelation function identifies periodic features in the signal by calculating the correlation of the signal with itself at different time delays, revealing periodic patterns. Power spectral density analysis quantifies the energy distribution of the signal across different frequencies, further confirming the presence and frequency characteristics of the heartbeat signal[17]. By integrating these techniques, we effectively extracted the periodic components of the heartbeat and distinguished the vital signs from background noise[18].

4.2 Algorithm Processing Results

In analyzing the algorithm processing results, we followed a series of steps to ensure accurate extraction of heartbeat signals from complex environments. Initially, during the signal acquisition phase, a high-sensitivity Avalanche Photodiode (APD) detector combined with laser speckle technology successfully captured weak heartbeat signals. The raw signal was then processed using a low-pass filter to remove frequency components above 1000Hz. This step was crucial for eliminating high-frequency noise and irrelevant interference, as heartbeat signals typically fall within a lower frequency range. The low-pass filter's cutoff frequency was set at 1000Hz, preserving the primary frequency components of the signal and effectively reducing background noise.

Next, the normalization enhancement step standardized the amplitude of the filtered signal. By mapping the signal amplitude to a uniform range (e.g., [0, 1]), amplitude differences were eliminated, enhancing signal features. This process improved signal stability and provided stable input data for subsequent steps. After normalization, the signal features became more pronounced, aiding further analysis.

Moving average filtering was then applied to the normalized signal for smoothing. This technique effectively reduced random noise by averaging over a sliding window, improving signal smoothness and stability. The window size was selected based on signal characteristics and noise levels to optimize the filtering effect. After this step, the periodic characteristics of the signal became clearer, and noise interference was effectively suppressed.

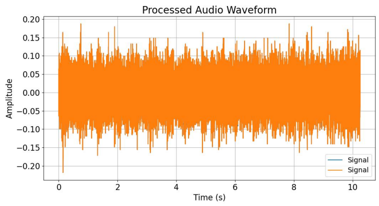
Finally, we used a combination of Autocorrelation Function (ACF) and Power Spectral Density (PSD) analysis for heartbeat coherence detection. ACF successfully identified periodic features in the signal by calculating correlations at different time delays, which is crucial for extracting heartbeat signals. PSD analysis quantified the energy distribution across different frequencies, further confirming the presence and frequency characteristics of the heartbeat signal. Combining these techniques allowed for clear extraction of heartbeat's periodic components and effective differentiation of vital signs from complex background noise.

Overall, the algorithm demonstrated excellent performance in complex post-disaster environments. Experimental results showed that the method effectively extracts weak heartbeat signals with good robustness and high precision. This technology provides a reliable and practical solution for vital signs detection in post-disaster rescue operations, significantly improving rescue efficiency and success rates.

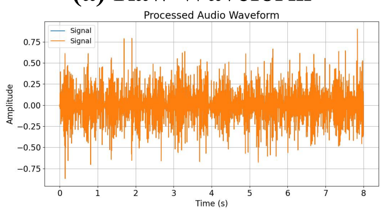
Figure 5 shows the experimental processing results: (a) displays the original audio waveform, (b) shows the processed audio waveform, and (c) presents the processed audio spectrogram. The spectrogram clearly reveals independent heartbeat envelopes, indicating high accuracy of the proposed algorithm. The clear display of heartbeat signal features in the spectrogram allows for precise identification of heartbeat presence after processing.

By generating voice files from the processed results and playing them in real-time for rescuers, the detection can be verified by the human ear. This approach simplifies the algorithm's complexity and reduces reliance on computational power. Traditional AI algorithms often require high computational power and hardware resources, while this method, using human hearing instead of complex AI algorithms, lowers processor power consumption and hardware resource demands. This optimization not only reduces algorithm complexity but also simplifies hardware system design, making the system overall more efficient.

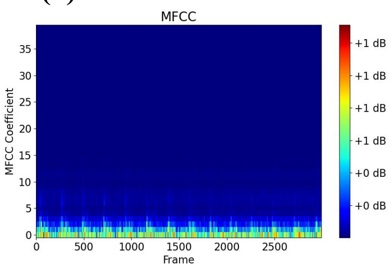
This method's advantage lies in its ability to perform real-time heartbeat detection without relying on high computational resources, making it particularly suitable for battery-powered rescue devices. This optimization enhances system reliability and maintains high performance in resource-constrained environmentts[19], providing a practical solution for vital signs detection in post-disaster rescue tasks.



(a) Raw Waveform



(b) Processed Waveform



(c) Spectrogram

Figure 5. Algorithm Processing Results

5. Conclusion

This paper presents a heartbeat detection signal processing algorithm based on laser speckle vibrometry, aimed at enhancing vital signs detection capabilities in post-disaster rescue operations. By applying laser speckle vibrometry technology, we have designed a signal processing scheme incorporating steps such as signal preprocessing, noise filtering, and multi-scale analysis to improve the extraction accuracy and robustness of heartbeat signals.

Experimental results demonstrate that the algorithm effectively extracts weak heartbeat signals from complex environments. Specifically, through low-pass filtering to remove high-frequency noise, normalization enhancement to standardize signal amplitude, moving average filtering for signal smoothing, and combining Autocorrelation Function (ACF) and Power Spectral Density (PSD) analysis for heartbeat coherence detection, the algorithm exhibits excellent detection performance. The processed audio waveforms and spectrograms clearly reveal the features of the heartbeat signal, validating the algorithm’s high accuracy and robustness.

Additionally, experiments show that generating audio files from the processed results and playing them in real-time for rescue personnel makes heartbeat recognition by the human ear feasible. This approach not only simplifies the complexity of the algorithm but also reduces reliance on computational power, making it particularly suitable for battery-powered rescue devices. Compared to traditional high computational power AI algorithms, this method lowers processor power consumption and hardware resource demands, optimizing the system.

However, the current experimental results are primarily obtained in controlled laboratory environments. In practical applications, various challenges such as environmental noise variations, diversity of interference sources, and real-world operational conditions may arise. Therefore, when applying this technology to real post-disaster rescue scenarios, it is crucial to address these practical issues to ensure its stability and reliability in various complex and extreme environments.

Future research should focus on the following aspects: First, further optimizing the algorithm for extreme environmental conditions encountered in real-world applications to enhance its robustness. This includes improving noise suppression techniques, enhancing signal processing capabilities, and increasing the algorithm’s adaptability to different backgrounds. Second, integrating real-time processing and data analysis technologies with existing methods to improve the efficiency and accuracy of heartbeat detection.

Additionally, with ongoing advancements in computational technology, exploring the integration of this method with advanced machine learning techniques could further enhance detection performance. Practical field testing and optimization in actual post-disaster rescue tasks should also be a key focus for future work to ensure the reliable application of this technology in real-world environments.

In summary, the laser speckle vibrometryased heartbeat detection signal processing algorithm demonstrates excellent performance in laboratory settings, providing a powerful tool for vital signs detection in post-disaster rescue operations. Future research should not only focus on further optimizing the technology but also addressing the challenges of practical applications to advance its real-world use and development.

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