Dynamic speckle contrast and principal component analysis for infrasound frequency identification and clustering

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Abstract. Monitoring acoustic signals is straightforward when the audio signals can be directly accessed. In scenarios where direct audio capture isn't feasible, converting sound into optical data offers a powerful alternative. Optical data can then be encoded into speckle images. These images can be processed using various statistical tools for correlating the temporally spaced images with audio signals. We present a simple method using two tools: Dynamical Speckle Contrast (DSC) and Principal Component Analysis (PCA). Using these tools, we have successfully matched the temporal variation of the infrasound signal with that of speckle contrast and have been able to cluster the frequencies present in the signal.

1 Introduction

The acoustic frequency identification and classification have several applications such as seismic monitoring [1], structural health assessment [2], marine mammal tracking [3], ocean soundscape analysis [4], and human voice recognition [5]. Traditional methods require direct access to acoustic signals. For example, the Fast Fourier Transform (FFT) technique is commonly used for frequency extraction from acoustic signals [6]. It is an efficient and fast method but can be affected by low quality or noisy signals [7].

The remote sensing techniques are effectively applied for underwater communication networks [8], environmental biodiversity tracking [9], industrial tool condition monitoring [10], and atmospheric research for weather prediction [11]. One such non-contact method is Phase-Based Optical Flow (PBOF) method. PBOF is a video-based non-contact technique that allows us to measure tiny vibrations of an object. For this, it analyses changes in light patterns (phases) of the video frames [12]. PBOF is good for measuring in-plane tiny vibrations with good illumination but it depends on the reflectivity of the surface which adds complexity and may alter the natural vibrational behaviour of the object [13].

Laser Speckle Contrast Imaging (LSCI) and Laser Doppler Vibrometry (LDV) are other widely used techniques in biomedical monitoring and vibration analysis [14,15]. LSCI and

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LDV work by measuring fluctuations in laser speckle patterns and Doppler shifts in the reflected light to detect vibrations of a surface with good precision respectively [16]. Some of the applications of the LSCI technique include cardiac diagnostics [17] and blood flow analysis [18]. While LSCI mainly focuses on flow analysis, the speckle vibrometer targets vibration analysis. The speckle vibrometer is used to observe respiratory and cardiac functions in ventilated patients [19,20]. The applications of LDV are vibration measurement [21], structural health monitoring [22], ultrasonics velocity assessment [23] and in medical imaging [24]. However, LDV often introduces undesired noise [25]. Another non-contact method is called Dynamic Speckle Contrast (DSC). DSC works by analysing temporal variations in laser speckle patterns across consecutive frames. It computes temporal speckle contrast, unlike LSCI, which measures spatial contrast within a single frame [26]. Hence, DSC is useful for the remote monitoring of vibration [27,28].

In this paper, we present a non-contact technique for identifying and clustering infrasound frequencies. For this, we use temporal modulations of laser speckle contrast values and Principal Component Analysis (PCA). In DSC, the vibrating surface is detected, whereas we have tried to recognize the infrasound frequencies using the temporal variation in speckle contrast. The use of PCA is often limited to dimensionality reduction, but here we successfully used PCA to cluster acoustic frequencies in Principal Component (PC) space. The presented method employs a simple, inexpensive setup which is more robust to environmental noise, making it suitable for optical encoding and frequency discrimination.

2 Experimental setup

The experimental setup used for the present work is as shown in Fig.1. A diode laser with a wavelength of 650 nm and an output power of 5 mW passing through the beam expander was made to fall onto the round shape speaker with a diameter of 48 mm. The expanded laser beam illuminates the speaker surface uniformly. The speaker is connected to a frequency generator (Metravi FG-1000) of frequency range 0.1 Hz to 1 MHz. In the experiment we used infrasound frequencies ranging from 1 Hz to 5 Hz only. The speaker was driven by a square wave signal with a 5 V (peak-to-peak) amplitude. The light reflected from the vibrating speaker surface was passed through a diffuser plate to produce dynamic speckle patterns. These speckle patterns were recorded using a digital camera (CMOS Sensor 5 MP (MT9P031), Sensor Size 1/2.5", 30 fps).

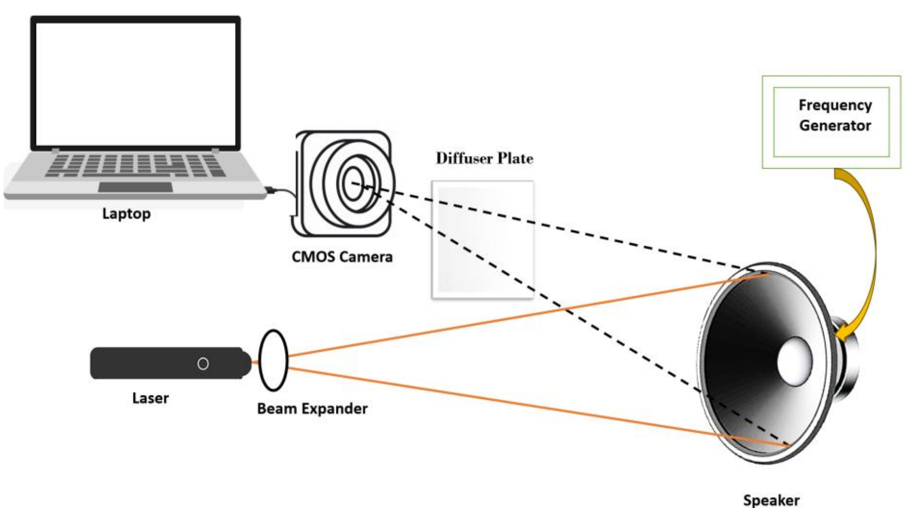


Fig. 1. Schematics of the experimental setup.

3 Results and Discussion

As mentioned in the last section, changes in the speckle pattern were recorded for three cases as mentioned below.

3.1 Monitoring of single frequency using speckle images

Fig. 2(a-e) shows the speckle patterns recorded from the vibrating surface of the speaker while playing frequencies of 1-5 Hz, respectively. These speckle patterns are dynamic and continuously change over time. To capture dynamic changes, a video was recorded over multiple cycles of frequency, and serial speckle patterns were then extracted from it. The speckle contrast was calculated for each speckle pattern [30,31]. Speckle contrast values were plotted against time for multiple cycles of different frequencies mentioned above. Fig. 3(a-e) shows the temporal variation of speckle contrast at frequencies ranging from 1-5 Hz.

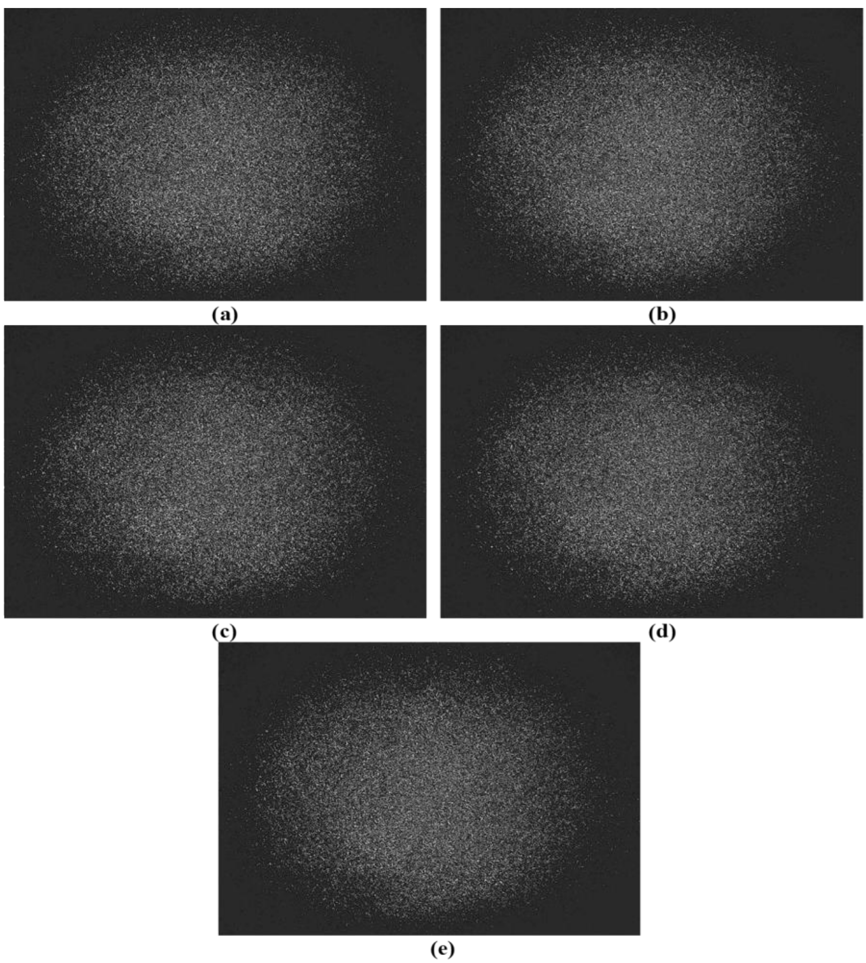
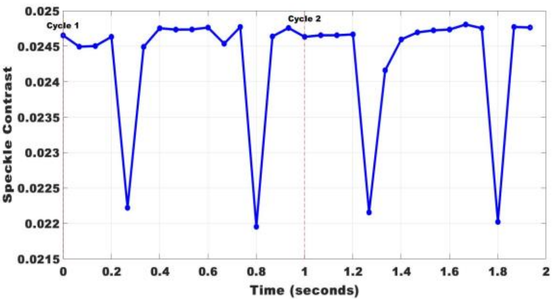
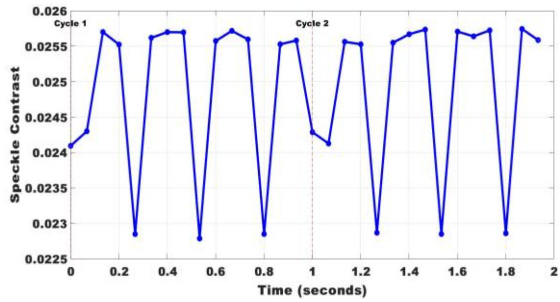


Fig. 2. (a)-(e) Examples of speckle images at 1-5 Hz frequencies, respectively.

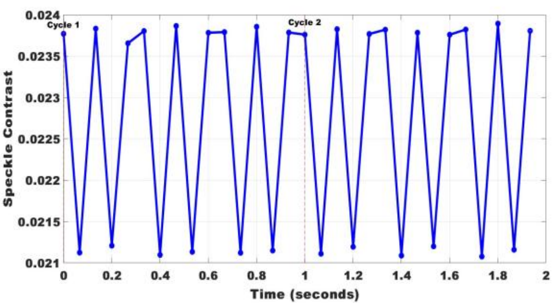
As seen in Fig. 3, the temporal variation of speckle contrast matches the speaker vibration frequencies. The maximum variation of speckle contrast amplitude for the presented data set is found to be 0.0257. Although it is tiny but it is consistent.



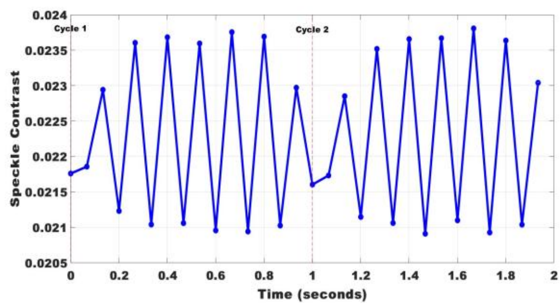
(a)



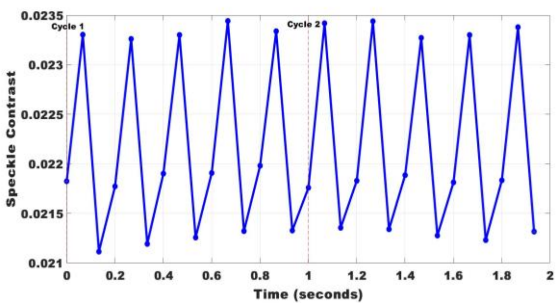
(b)



(c)



(d)



(e)

Fig. 3. Temporal variation of speckle contrast for (a) 1 Hz, (b) 2 Hz, (c) 3 Hz and (d) 4 Hz, and (e) 5 Hz frequencies respectively.

3.2 Detection of frequency transition using speckle contrast modulation

Next, speckle patterns were recorded to monitor the transition of the frequency of vibrations. To demonstrate this, two transitions were considered as follows: first is (a) 1.25 Hz followed by 2 Hz, and the second is (b) 4.25 Hz followed by 5 Hz. These recordings were saved, and images were extracted from them. Fig.4 (a) and (b) show the temporal variation of speckle contrast for these cases, respectively.

In the first case (Fig. 4 (a)), a total of 418 images/frames were extracted from the video. The first 221 images correspond to the applied frequency of 1.25 Hz, while images ranging from 222 to 418 belong to 2 Hz. For better visualization of the variation of the speckle contrast due to the transition of the frequency, the plot of Fig. 4 (a) focuses on the frames ranging from 150 to 300. Initial and final frequency of speckle variation from Fig. 4 (a) were found to be 1.25 Hz and 2 Hz, respectively, which match the vibrating frequencies of the speaker.

In the second case (Fig. 4 (b)), the video has 453 total images. The first 222 images belong to the initial frequency of 4.25 Hz, and the remaining 223 to 453 images correspond to 5 Hz. Similarly, the plot in Fig. 4 (b) highlights frames from 150 to 300 to clearly perceive the modulation in speckle contrast during the frequency transition. Initial and final frequency of speckle variation from Fig. 4 (b) is found to be 4.25 Hz and 5 Hz, respectively which are matching with vibrating frequencies of the speaker.

In both cases, the change in frequency results in a modulation of speckle contrast, serving as a distinguishable marker of the frequency transition. This enables effective identification of transitions between different vibration frequencies of the speaker.

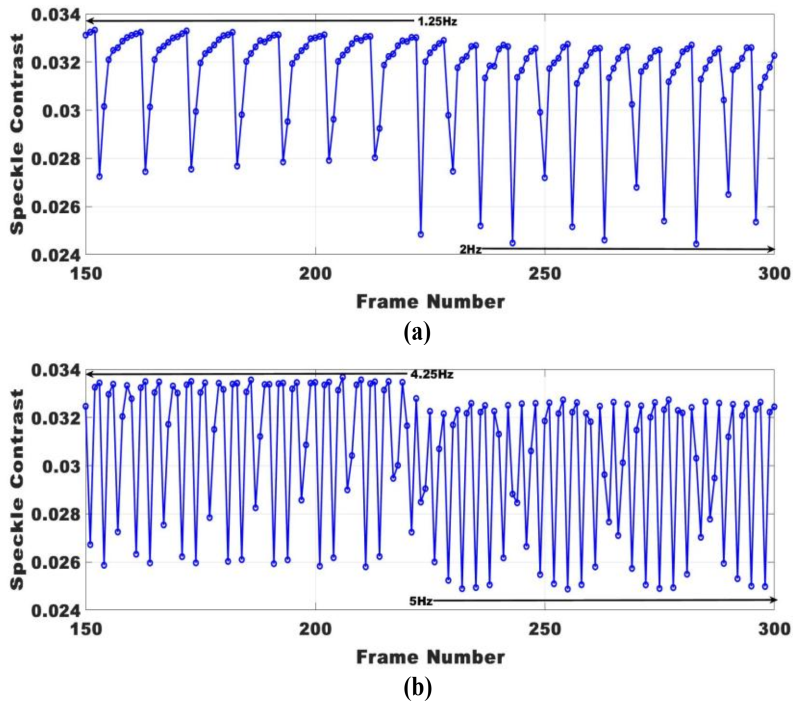


Fig. 4. Variation of speckle contrast versus frame number for the frequency transitions: (a) 1.25 Hz to 2 Hz and (b) 4.25 Hz to 5 Hz.

3.3 Principal component analysis (PCA) for transition-frequency analysis

The PCA is a well-known technique for dimensionality reduction and extracting important features from complex datasets [32]. The PCA technique has been successfully applied for biometric recognition [33], face image analysis [34], biospeckle data processing [35-38], and acoustic signal separation [39,40]. The application list of PCA is extensive; hence we are mentioning only a few representative examples here due to space limitations. Moreover, it is not the focus of this paper to provide an exhaustive overview of PCA applications.

Section 3.2 shows that the temporal modulation of speckle contrast reliably exposes frequency transitions. However, the high dimensionality and intrinsic (uncorrelated) noise of speckle data sometimes make it challenging to monitor and distinguish transition-frequency components. To address this, we apply PCA to project the extracted frames onto a low-dimensional subspace. This helps improve the signal-to-noise ratio (SNR) and cluster distinct frequency components in the speckle data. The dataset used for this analysis is the same as discussed in Section 3.2. The PCA technique was implemented on this dataset. Fig. 5 (a), (b), (c), and (d) shows the score plots along PC1, PC2, PC3, and variance explained by principal components (PCs). Fig. 5 (a), (b) and (c) shows a clustering of similar frequencies present in the speckle patterns indicating the existence of both frequency components (1.25 Hz and 2 Hz). Especially, in Fig. 5(c) where PC2 and PC3 are plotted, visually discernible clustering is seen for the frequencies mention above. This is consistent with the structure already evident in the PC1–PC3 plot of Fig.5b. Fig. 5 (d) shows the percentage of variance for the top four PCs, calculated as, 21.66%, 18.51%, 9.21% and 2.88% respectively.

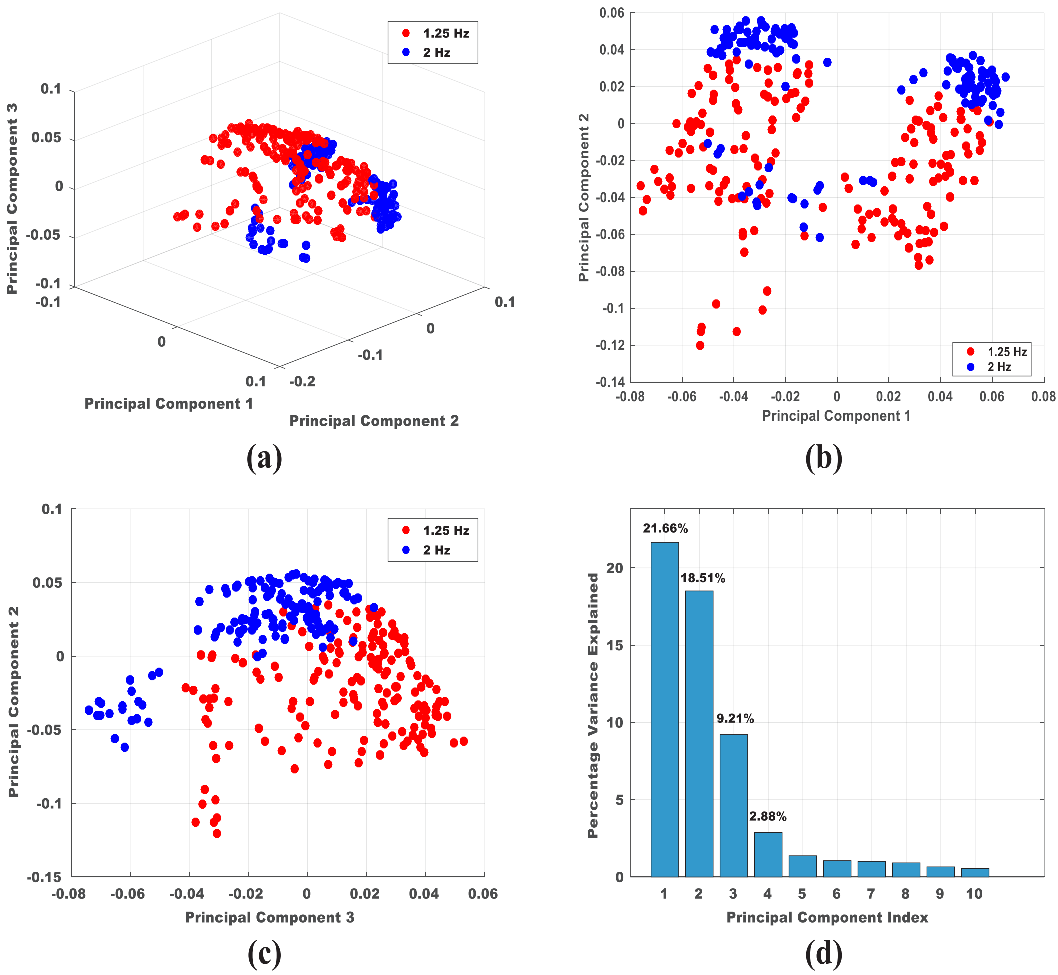


Fig. 5. Score Plot of (a) PC1 vs PC2 vs PC3, (b) PC1 vs PC2, (c) PC2 vs PC3, and (d) Variance explained by Principal Components for speckle patterns corresponding to transition of frequency from 1.25 Hz to 2 Hz.

Likewise, the PC1 vs PC2 vs PC3 score plot shown in Figure 6 (a) illustrates clear clustering of frequencies of 4.25 Hz and 5 Hz present in the speckle patterns. Figure 6(d) shows the percentage of variance for the top four PCs, calculated as, 26.27%, 17.48%, 5.65% and 2.72% respectively. The clear separation in PCA score plots shows that this technique is suitable for classifying multiple frequency components in transition frequency signals. This has potential engineering applications in vibration analysis and monitoring of acoustic signals.

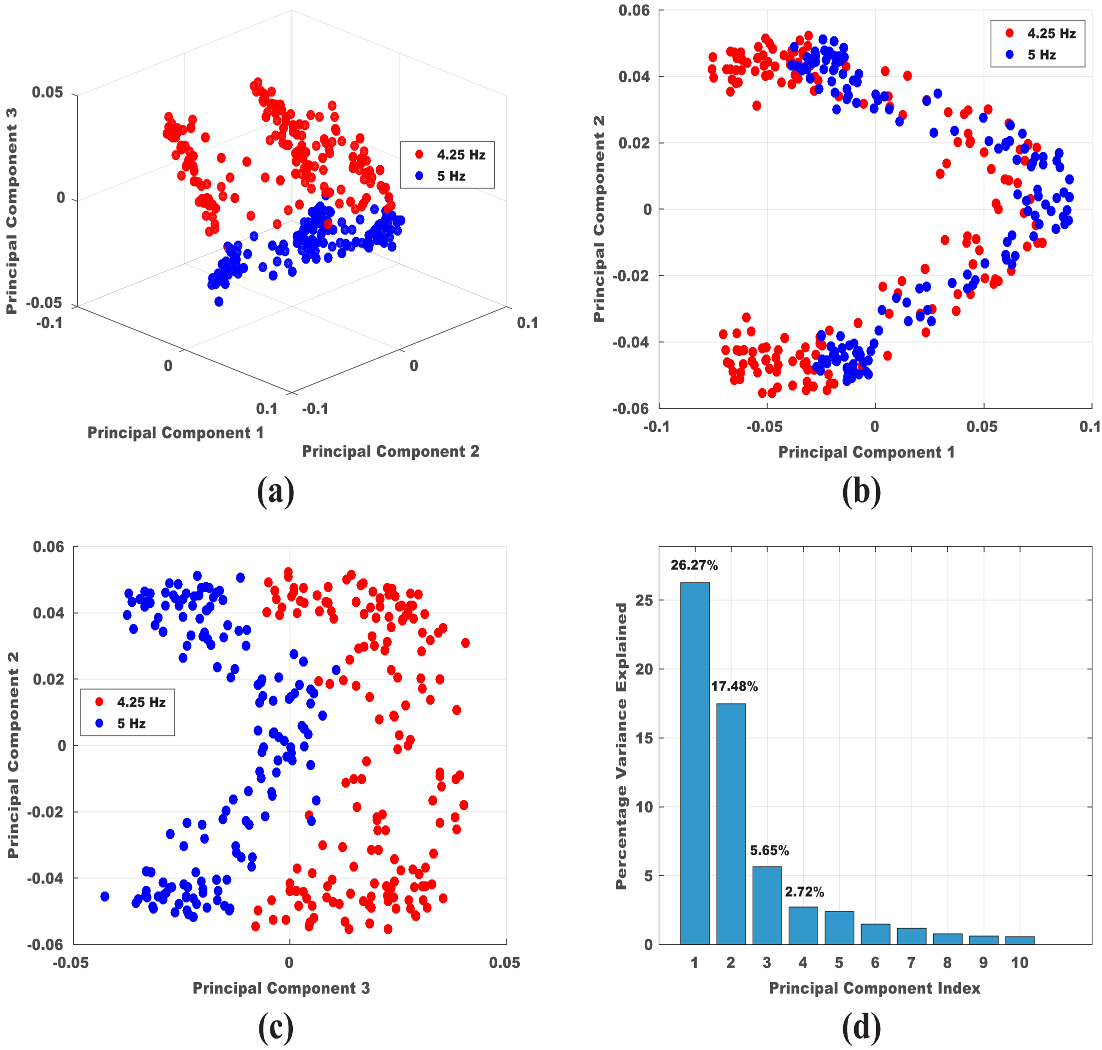


Fig. 6. Score Plot of (a) PC1 vs PC2 vs PC3, (b) PC1 vs PC2, (c) PC2 vs PC3, and (d) Variance explained by Principal Components for speckle patterns corresponding to transition of frequency from 4.25 Hz to 5 Hz.

4 Conclusion

This paper has shown that identifying and clustering of infrasound frequencies from 1-5 Hz is possible using DSC and PCA. It can also be used to detect changes in the signal's frequency. The setup used in this researh is simple and low-cost. Sensitivity and temporal resolution of the technique can be improved using better illumination schemes and improving camera specifications (like frame rate). Ideally, any vibrating surface can be monitored remotely using this technique. This method can be further extended to human voice clustering or mapping. Although PCA is a powerful tool that can be useful for voice clustering, the use of dynamic speckle contrast values is limited due to the frame rate of the camera and overlapping of different frequency components present in the acoustic signal. Nevertheless, just by analyzing speckle images using statistical tools, we have been able to identify and cluster infrasound frequencies.

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Nikhil Bhagat conducted the experiments, performed data analysis, and prepared the manuscript. Prafull Padghan contributed to conceptualization, methodology, and interpretation of results. Kamlesh Alti supervised the research work and reviewed the manuscript.

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