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Sound Analysis to Recognize Cattle Vocalization in a Semi-open Barn

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ABSTRACT

In precision livestock, there has been a growing demand for innovative tools that collect and analyze information about individual animals. For this purpose, various variables of precision livestock such as monitoring the general condition of animals, activity and health status, food intake, or estrous activity are measured by using information technology. In recent years, the requirement for sound analysis to be used in these systems has increased. Because collecting sound signals do not require animal intervention. Dairy cattle make different sounds in cases of illness, pregnancy, feeding, etc., and by using sound signals, the diagnosis and status determination of the animal can be made. The aim of this study is to record the vocalization data of a dairy cattle in a semi-open barn and to investigate its differences from other barn sounds. It has been revealed that the frequency ranges of cattle, environment, bird, and machine sounds, which are analyzed by time domain, frequency domain, and spectrogram, are different and these differences can be used in a cattle identification system.

Yarı-açık bir Ahırda Sığır Vokalizasyonunu Tanımak için Ses Analizi

ÖZ

Hassas hayvancılıkta, hayvanlar hakkında bilgi toplayan ve analiz eden yenilikçi araçlara yönelik artan bir talep vardır. Bu amaçla, hayvanların genel durumlarının izlenmesi, aktivite ve sağlık durumu, gıda alımı veya kızgınlık aktivitesi gibi hassas hayvancılığın çeşitli değişkenleri bilgi teknolojileri kullanılarak ölçülür. Son yıllarda bu sistemlerde kullanılacak ses analizlerine olan ihtiyaç artmıştır. Çünkü ses sinyallerini toplamak hayvan müdahalesi gerektirmez. Süt sığırları hastalık, hamilelik, beslenme vb. durumlarda farklı sesler çıkarır ve ses sinyalleri kullanılarak hayvanın teşhis ve durum tespiti yapılabilmektedir. Bu çalışmanın amacı, ahırda bulunan bir süt sığırının vokalizasyon verilerini kayıt altına almak ve diğer ahır seslerinden farkını araştırmaktır. Zaman domeni, frekans domeni ve spektrogram ile analiz edilen sığır, ortam, kuş ve makine seslerinin frekans aralıklarının farklı olduğu ve bu farklılıkların bir sığır tanımlama sisteminde kullanılabileceği ortaya konulmuştur.

Anahtar Kelimeler: Sığır sesi, HFD Ses analizi, Spektrogram, Welch

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1. Introduction

One of the fields where the information technologies that have developed in recent years have benefited is livestock. The use of these technologies greatly improves livestock welfare enhancement, animal health monitoring, timely detection, and control of diseases [1]. Automated tools are being developed that use video and audio information to control and monitor the behavior and biological responses of animals and to develop an early warning system [2]. Recently, technology-based research is carried out for different situations such as identification of dairy cattle, estrous monitoring, yield status monitoring, diagnosis, follow-up, and treatment of diseases. Some of these studies include those who use physiological data [3], location and acceleration data [4], barcode obtained with video data [5], or sound data [6] or with an integrated video-sound system [7].

Sound data contains information about different states and intentions of animals [8]. Also, most animal species have vocal characteristics such as growling, barking, howling, whining, screaming. In the literature, there are studies using vocalization data of animals such as cat [9], dog [10], [11] bird [12] there are also vocalization studies of animals such as sheep [13], dairy cattle [7], [14] which living in farm/barn. Dairy cattle make sounds that involve different situations and intentions. These sounds are not completely meaningless, although they do not contain definite meanings involving a subject or concept. Cattle make sounds that probably make sense to other cattle. Dairy cattle have vocal sound characteristics. In general, vocalization behavior in cattle is examined more as an indicator of welfare [15]. As a means of socialization, cattle use their calls to communicate, to meet and react, to show fear and threat, as well as to show affection [16]. During the estrous period, the vocalization of cattle increases but this is not exact for vocalization number [17]. In particular, cattle showing abnormal estrous, call at low frequency and violently [15]. Schön et al. [18] showed that the estrous climax caused an increase in the vocalization rate using sound data they recorded with the neck microphone from the German Holstein heifers. Chung et al. [6] extracted the Mel frequency cepstrum coefficients from the voice data of Korean domestic cows and performed early anomaly detection with support vector machines. They detected estrous with over 94% accuracy. Lee et al. [19] created a formant-based feature subset selection algorithm using a spectrogram of Korean native cow vocalization for the detection of cow estrous vocalizations. They achieved an average detection accuracy of 97.5% with the AdaBoost.M1 using real vocalizations from a barn. Ding et al. [20] aimed at detection of rumination sound in dairy cows, they achieved this goal with an accuracy of 97% using zero cross ratio (ZCR), Mel-Frequency Cepstral Coefficients (MFCC) and Dynamic time warping (DWT) algorithms. Jung et al. [21] obtained Mel-frequency cepstral coefficients (MFCCs) from cattle sounds filtered by short-time Fourier transform using 12 sound sensors and they designed a Real-Time Livestock Monitoring System that provides 94.18% classification accuracy using a convolutional neural network (CNN) model. Bishop et al. [22] in order to classify and characterize animal sounds in livestock, first demonstrated the differences between sounds such as noise, wind, machinery, bird sounds in the environment, and the sounds they wanted to examine using the spectrogram method. And in the automatic segmentation of cattle, sheep, and dog sounds, they also took these sounds into account. The literature shows that there are studies aiming to detect cattle vocalization and to obtain information about the status of cattle from differences in cattle vocalization. The vocalization of cattle living in a semi-open barn can be recorded with a voice recorder to be worn around their neck. However, due to situations such as the cattle's neck rubbing against the irons in the barn, this is a difficult task that requires follow-up. In addition, the cattle sound in the barn can be recorded with microphones integrated into the cameras. However, in this case, there is a need to determine the distinctive features of the cattle's vocalizations due to other sounds in the barn.

The semi-open barn is a very noisy place that hosts various environmental sounds as well as cattle vocalizations. These noises can consist of external factors such as bird sounds, iron sounds during feeding of cows, milking machine sound, human voices. [7]. Therefore, individual sounds should be isolated from the ambient sound in cattle sound studies. However, due to the discontinuity of these sounds, it is not easy to filter out background sounds. For this reason, visual information about the sound is used in some studies to distinguish cow sounds from others [2]. The most common method for analysing audio data and extracting features is to convert the signal into a frequency domain with the Fourier transform [23]. In addition, audio signals can be visualized with Fourier-based methods such as Spectrogram, Mel-Frequency Cepstral Coefficients (MFCC). The spectrogram represents the energy in the frequency spectrum of a time-varying audio data in the frequency and amplitude spectrum, while the MFCC represents the power spectrum of the audio data on a log scale [24].

In the literature, there are studies that analyse animal sounds [25, 26] aiming at classification or automatic detection [27]. The main contribution of this study is to reveal the difference in cattle vocalization from other sounds encountered in the natural barn environment. It is also based on digital signal processing, and it is a preliminary study of automatic cattle vocalization detection. This study aims to analyse the sound data recorded with the microphone system integrated into the cameras placed at three different points in the barn and to investigate the differences of the ambient and cattle sound data with digital signal processing methods. Fast Fourier Transform (FFT), Welch and Spectrogram methods were used for the analysis of audio signals. In this study, barn sound data examined in the time domain were then analysed by time-frequency domain methods and a preliminary study of an automated vocalization recognition system to distinguish cattle sounds from barn sounds was carried out.

2. Material and Method

2.1. Data acquisition

In this study, video and sound recordings are obtained from three different cameras (front-rear and fish-eye camera) placed in the farm of Selcuk University Veterinary Faculty. Figure 1 shows the placement of the cameras, microphones and recording device on the farm. The Ethics Committee for Experimental Animal Studies of Selcuk University approved this study (2020/88).

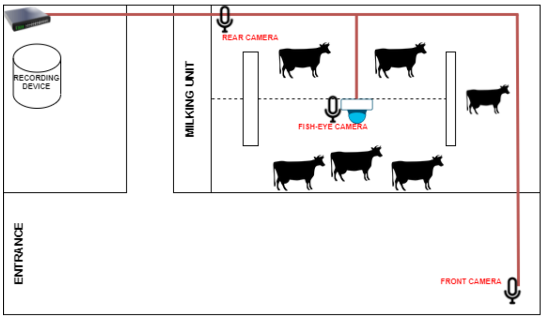

Figure 1. Layout and connection arrangement of cameras and microphones

Figure 2 shows the view on the barn after the rear camera and fisheye camera are placed. All cameras are equipped with an external microphone to get better quality sound. The setup is completed by connecting the cameras to the recording device. After the installation, it became possible to access the camera recordings directly and remotely over the internet on the DVR software. All records obtained on the farm can be accessed via web-based software over the internet and are in .DAV file format. Smart Player [28] was employed to read the .DAV files and to convert them to .AVI video file format. All .AVI files contain video data and 32-bit/16Khz mono channel audio data. .wav Audio files were extracted from the .AVI files by using MATLAB (2020) at 16 khz sampling frequency.

Figure 2. Rear Camera and Fisheye Camera View

2.2. Sound analysis

Signal analysis is used to evaluate variations in signal structure and can provide important clues to study the sound production mechanism [29]. The frequency-domain of discontinuous signals such as sound signals provides more detailed information than the time domain content, and the frequency content of a waveform can be determined by spectral analysis methods. Spectral analysis is mainly performed by classical methods based on Fourier Transform and modern methods based on estimation of model parameters. Spectral analysis applications of noisy signals, of which only a part can be analysed (discrete-time signals), are approximate estimates of the true spectrum [30]. The power spectrum (PSD) is calculated as the square of the magnitude of the Fast Fourier Transform (FFT) of the x(t) waveform and shown in Eq. (1) where $|X(f)|$ represents the energy density function over frequency.

$$PS(f) = |X(f)| \tag{1}$$

Instead of applying the FFT to the entire waveform to calculate the power spectrum, the averaging technique is often used, which improves the statistical properties [31]. The power spectrum obtained by applying FFT directly and then averaging is called averaged periodogram. The Welch approach is a widely used technique for estimating the average periodogram and is based on dividing the data into several overlapping segments, calculating an FFT on each segment, calculating the square of the magnitude, or power spectrum, then averages these spectra [30].

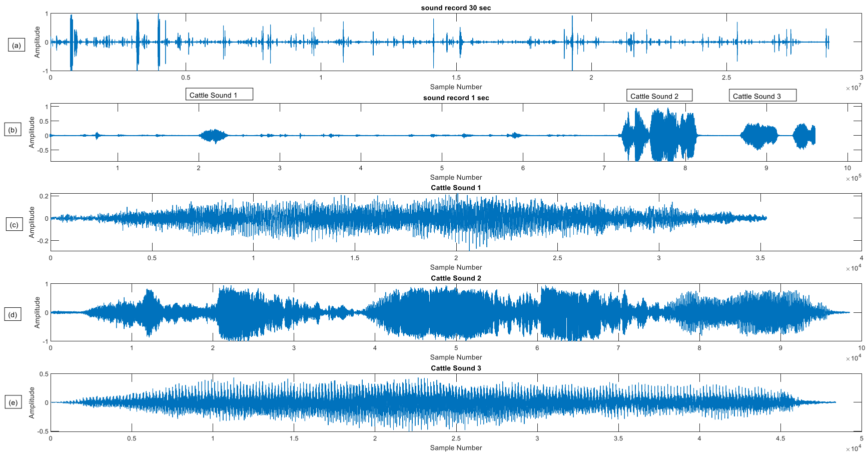

Figure 4. (a) 30 min recording containing cattle vocalizations (b) 1 min soundtrack (c)First cattle vocalization (d) Second cattle vocalization (e) Third cattle vocalization

Fourier analysis provides important information about the frequency of the wave, but it does not show in which time interval the frequencies are. So, it is a suitable method for stationary signals because the frequency of stationary signals does not change with time, but since the frequency of non-stationary signals changes with time, the information of time also needs to be considered. The methods developed to obtain both time and frequency components from the wave are divided into two as time-frequency methods and time scale methods. Short-time Fourier Transform (STFT, Spectrogram) one of the time-frequency methods, is based on the classical Fourier Transform and examines the signal in two dimensions as a function of time and frequency by using the windowing function. In this way, the non-stationary signal is divided into small segments and these segments are considered stationary. [30]. Eq. (2) shows the STFT equation of a two-dimensional function X(t,f) where w(t) is the sliding window function. τ represents the variable that slides the window through the waveform x(t) [31].

$$X(t,f) = \int_{-\infty}^{+\infty} x(\tau)w(\tau - t)e^{-i2\pi f\tau t}d\tau \tag{2}$$

The spectrogram (Eq.(3)) represents a real-valued, nonnegative distribution and the spectrogram of the x(t) is equal to the squared magnitude of the STFT presented in Eq. (2).

$$P(t,f) = |X(t,f)| \tag{3}$$

A spectrogram provides a graph that makes time, frequency, and PSD appears on the same graph and is generally used for visualizing sound signals. In this study, the power spectrum was calculated using the Fast Fourier Transform for a sampling frequency of 16 kHz. For obtaining the spectrogram, Hanning window with 1024 window size and 50% overlap was used.

3. Results and Discussion

This study aims to analyse cattle vocalization and other sounds in a semi-open barn. After visualizing the audio data with the Audacity audio editing program [32] the audio tracks used for this study were listened to and selected by using audio-visuals. In this study, the same date and time sounds were investigated for three cameras. According to our observations, the clearest cattle vocalization is recorded with the rear camera while the cattle is close to the camera. Besides, the front camera and fisheye camera provided low amplitude sound data because of the locations. Figure 3 shows the Audacity waveform and spectrogram of a .wav audio data recorded from the rear camera between April 2, 2021, 04.00:04.30.

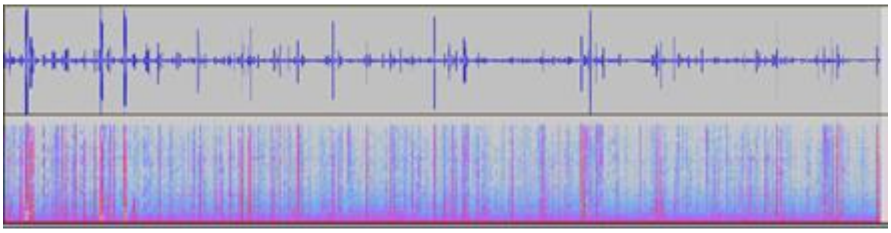

Figure 3. Audacity representation of time-domain (above) and Spectrogram (below) of 30-minute audio track

The 30 minutes of audio data shown in Figure 3 are from a time when the vocalizations of cattle were clearly detected. This audio data includes low amplitude environment sound as well as higher amplitude audio data including cattle vocalization. However, it is not always possible to obtain such clear cattle vocalization data. During the day, there are many external sounds such as metal sounds, bird vocalization (d) Second cattle vocalization (e) Third cattle vocalization sounds, milking machine sounds in the barn, and the cattle generally call very rarely. In Figure 4, the 30-minute soundtrack given in Figure 3, the first one-minute part containing 96000 samples and the amplitude values of the three full cattle vocalization data of this piece presented according to the number of samples. Here, the 1st and 3rd cattle sound data consist of a single vocalization, but there are 3 significant vocalizations in the 2nd cattle sound data. By examining the audio track in Figure 4 in the frequency domain, the power spectrums seen in Figure 5(b) were obtained. To evaluate the audio signals with the power spectral density (PSD) on the time-frequency scale, spectrograms of the signals were obtained in Figure 5 (c). Each sound used in this study has different times to complete its own characteristic. For example, a typical cattle vocalization took 2.5 seconds, while a single bird sound takes 500 ms. Machine sound and the environment sound was analysed for longer time.

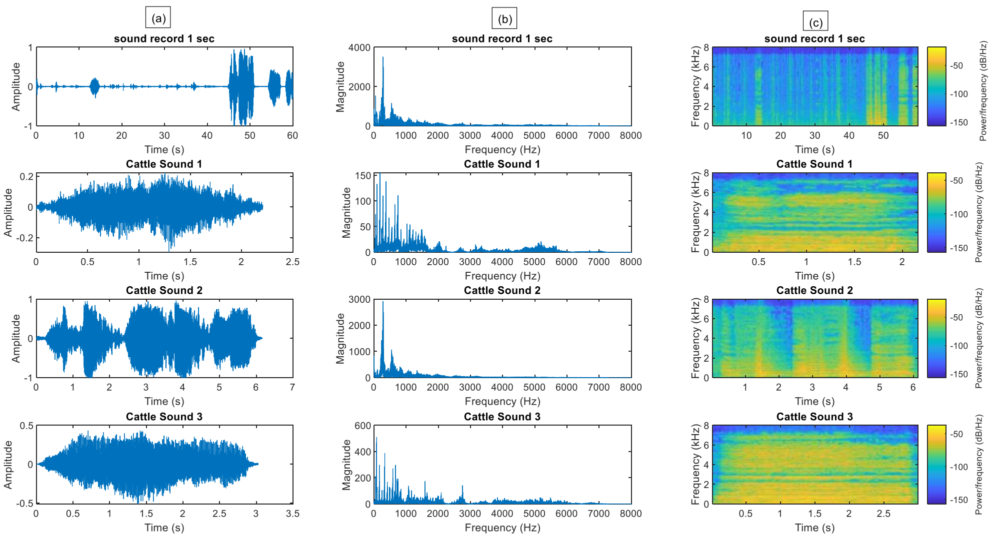

Figure 5. Cattle vocalization analysis represented in (a) time-domain (b) frequency-domain (c) spectrogram

In a spectrogram representation, the x-axis indicates the time the y-axis is frequency, and the colors indicate the PSD. In 3 different vocalizations of the same cattle, shown in Figure 5' (c), bright colors represent strong frequencies. According to the spectrograms, frequencies below 1kHz are strong, although there is little variation at high frequencies. This situation is also seen in the frequency spectrum given in (b). The amplitude, frequency, and spectrogram graphs of three different environment sounds that reflect the general condition of the barn, which are obtained from the same 1-minute soundtrack contains with occasional low-amplitude metal sound but do not contain any extra noise are shown in Figure 6. In addition, amplitude, frequency and spectrogram graphs of bird sounds (Figure 7) and machine sounds (Figure 8) obtained from a 30-minute soundtrack recorded from the rear camera between 23.29:23.59 of April 5, 2021 are presented. From the typical barn sounds presented in Figure 5-6-7-8, cattle, birds, environment, and machine sounds show different characteristics from each other. However, an automatic solution is needed to detect these sounds in hard barn conditions and to detect their differences and use them in an automated cattle voice recognition system.

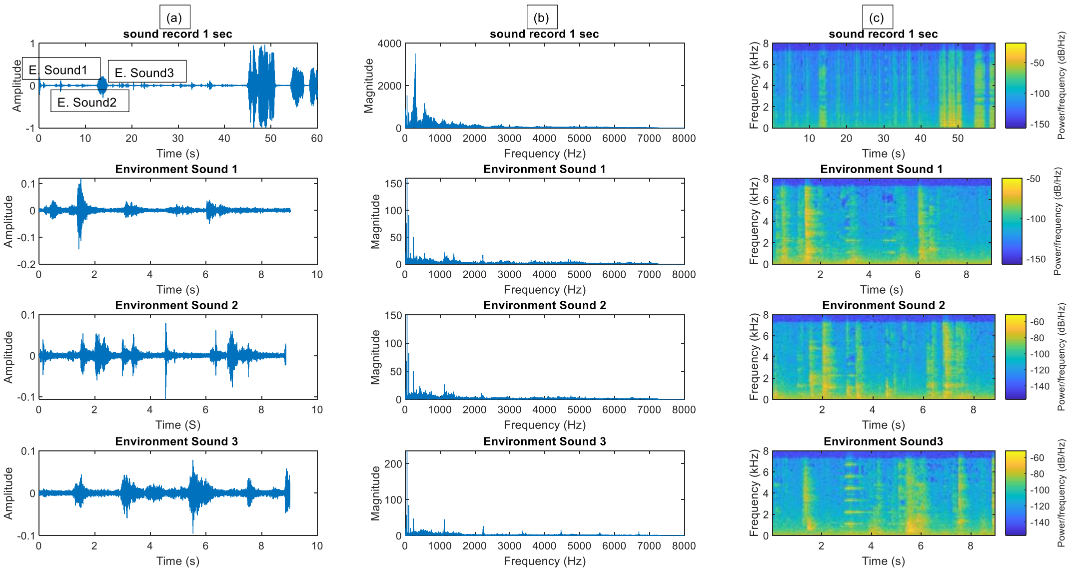

Figure 6. Environment sounds analysis represented in (a) time domain (b) frequency domain (c) spectrogram

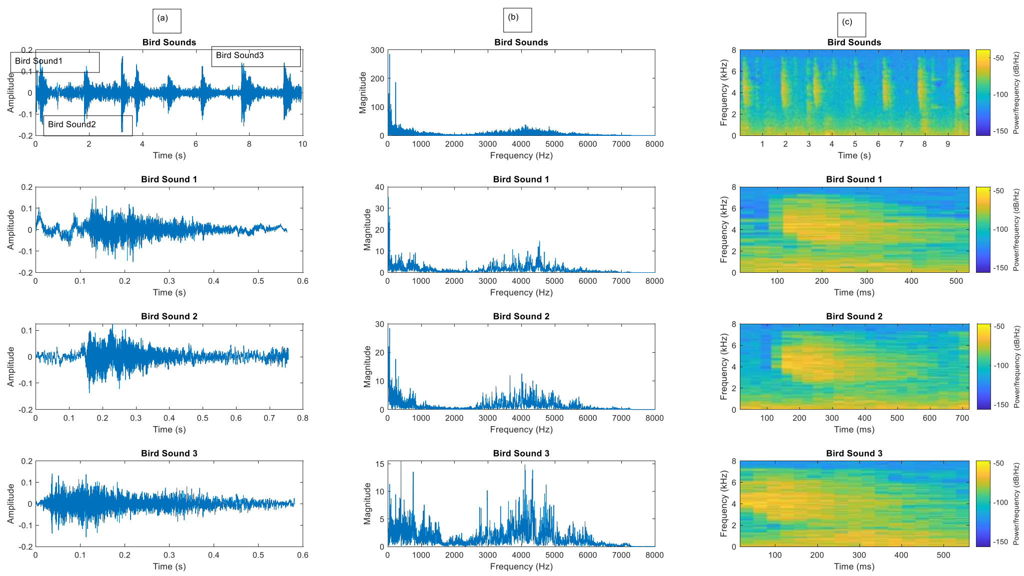

Figure 7. Bird sounds analysis represented in (a) time domain (b) frequency domain (c) spectrogram

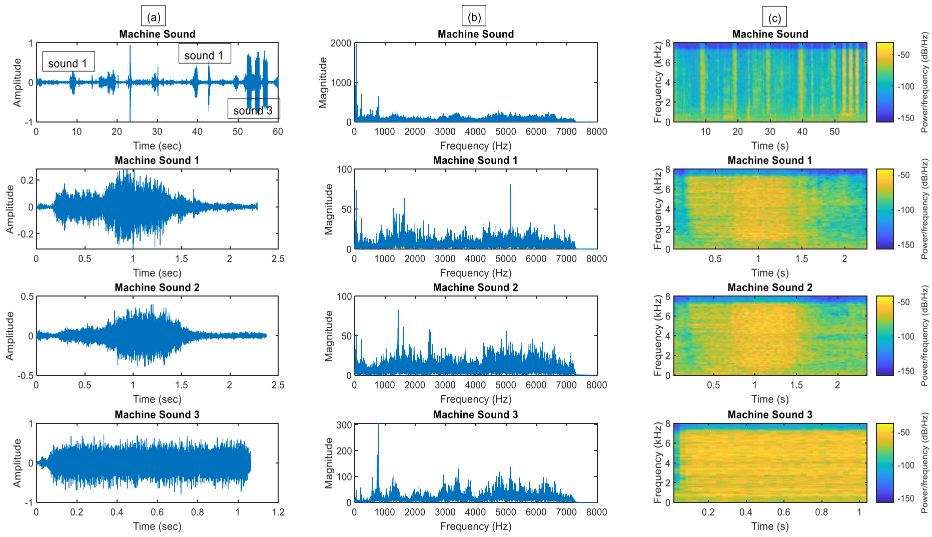

Figure 8. Machine sounds analysis represented in(a) time domain (b) frequency domain (c) spectrogram

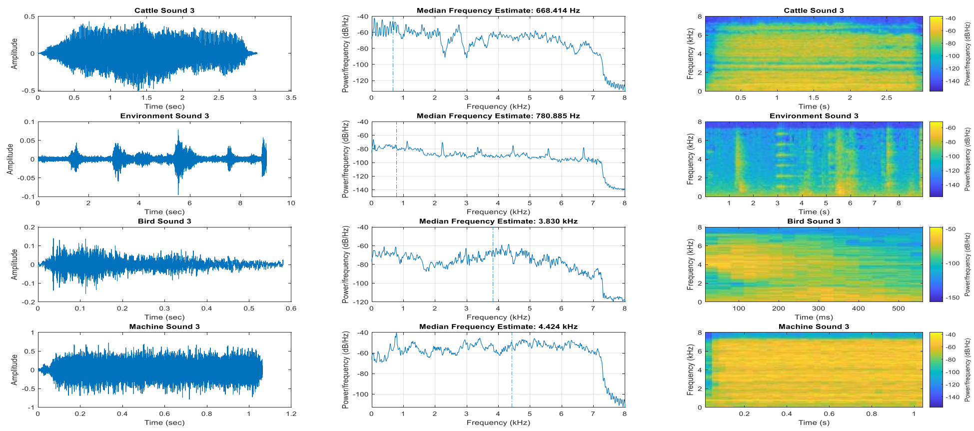

Figure 9. Cattle -Environment- Bird- Machine sounds time domain, PSD with median frequency and spectrogram graphs

The amplitude, PSD, and spectrogram graphs of different soundtracks in the barn are presented in Figure 9. The median frequency was calculated using one sound from each of the Cattle-Environment-Bird-Machine sounds. The PSDs of the sound data were calculated by the Welch method using the same parameters in the spectrogram. In addition, in Figure 9 (b), the median frequency values of each sound data are plotted on the PSD. In Figure 9, the median frequency value of a typical vocalization of cattle, calculated for each sound data and shown in the power spectrum, was found to be 668.414 Hz. Environment median frequency is very close to this value at 780.885 Hz, but this situation differs in the spectrogram. The median frequency of the bird sound is at 3.83 kHz and the machine sound is at 4.424 kHz, which has much higher than the cattle sound.

Table1. Average median and mean frequency of the barn sounds

Sounds	**Median Frequency (Hz) ± std**	**Mean Frequency (Hz)± std**
Cattle Sound	525.376±209.052	826±364
Environment Sound	851.939±239.571	1369±188.471
Bird Sound	3512±292.890	2697±297.214
Machine Sound	4047±518.063	3749±245.864

Table 1 presents the average median and average mean frequency values of the sounds used in this study. Also Figure 10 shows the graphical representations of the values. The average median and mean frequency were calculated using three sounds from each of the Cattle-Environment-Bird-Machine sounds. Among the sounds recorded for this study, cattle sounds have the lowest median and mean frequencies as seen from Table 1. According to the spectrograms, the cattle's vocalization is strong below 1 kHz, the environment sound is between 1 kHz and 2 kHz, the bird's sound is in the range of 3 kHz-4 kHz, and the machine sound is greater than 4 kHz.

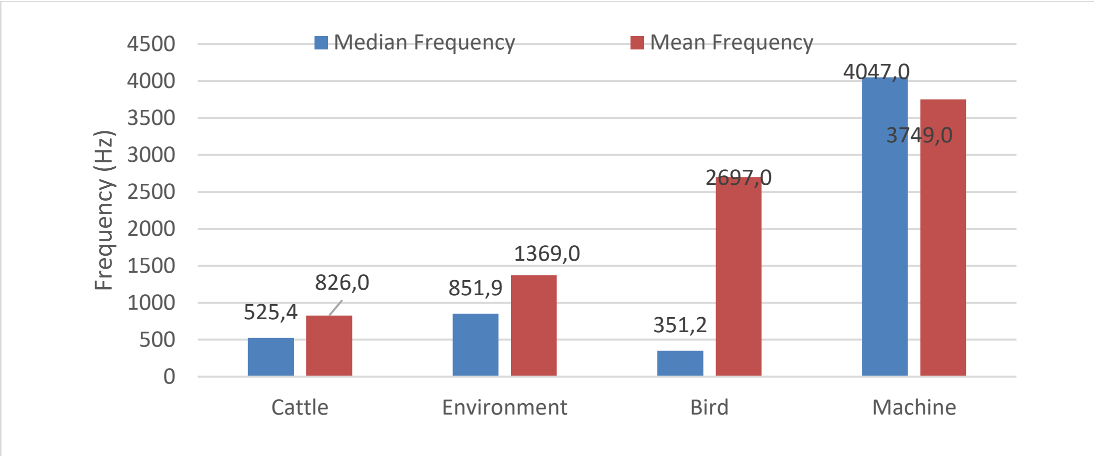

Figure 10. Graphical representations of the frequency values

4. Conclusion

The data used in this study were collected from a real barn environment with hard conditions, and the audio files recorded during the day were examined and the most specific ones were selected. It is known that the sound frequency of a dairy cattle is lower than 5 kHz [8]. The frequency range may vary for different conditions of the cattle. In this study, the typical sounds that occur in the barn during the day were examined and it was shown that the cattle's vocalization was in a frequency range that could be distinguished from other sounds. This study will lead an automated cattle vocalization recognition study with the audio data from the barn. Besides, with the increase in the number of data, creating labeled data, firstly separating the cattle's vocalization from the ambient sounds, and then obtaining information about the cattle's condition from the detected cattle vocalizations are among the future studies.

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Conflict of Interest Statement

The authors declare that there is no conflict of interest

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