Acoustic Features for Pig Wasting Disease Detection

Jonguk Lee, Long Jin, Daihee Park, Yongwha Chung, Hong-Hee Chang

Abstract

Failure to detect pig wasting disease in a timely and accurate manner can become a limiting factor in achieving efficient reproductive performance. In this paper, we discuss the methodology and results of a study we conducted to analyze for acoustic features for pig wasting disease and to use pattern recognition to examine the differences of the sounds pigs make when affected with pig wasting disease compared to normal sounds. The proposed acoustic feature subset selection algorithm indicated that \( \{F7, \text{RMS}, \text{Max Pitch}, \text{PSD1}, \text{Peak frequency}\} \) is the optimal feature subset that can be used to detect pig wasting disease. Finally, the results of the performance evaluation conducted using real sound data from an audio surveillance system showed that the average detection accuracy approached 98.4%, with FPR and FNR reaching on average 0.2% and 1.6%, respectively, when a support vector machine algorithm was used for detection. Moreover, we empirically confirmed that the performance of the optimal acoustic feature subset does not depend on the specific detector used.

Keywords: Pig Wasting Diseases Detection, Acoustic Feature Subset Selection Algorithm, Machine Learning Based Pattern Recognition

1. Introduction

Early detection of pig wasting disease is an important issue for herd management of pigs as respiratory diseases are one of the main causes of mortality and loss of productivity in intensive pig farming [1]. When wasting diseases are undetected or are detected late, profitability of the farms can be significantly affected.

Coughing is a central element to diagnose common respiratory disease. It is one of the body’s defense mechanisms against respiratory infections, and it can be a sign of a disorder of or infection in the respiratory system. This sound is so characteristic that it is possible to distinguish a cough from other vocal manifestations [1]. Clinically, coughing is the most frequently presented symptom of many diseases that affect the airways and lungs, and it is often an early symptom of respiratory disease [2].

Sound analysis is of considerable importance, because sound production by animals is a candidate bio-signal that can be easily measured at a distance without causing any additional stress to the animals [3-4]. Furthermore, in recent years, sound analysis has become an increasingly important tool to interpret behavior, health conditions, and well-being of animals [5-6]. In this study, we focus on detecting pig wasting disease using sound data.

According to a review of the literature, a rich variety of methods have already been introduced to detect anomaly events using sound data from animals [1, 6-15]. The bio-acoustic study by Gutierrez et al. [1] was aimed at classifying the different pig wasting diseases through sound analysis with emphasis given to differences in the acoustic footprints of coughs, and they stated that their study could be useful in supporting an early detection method based on the on-line cough counter algorithm for the initial diagnosis of sick animals in breeding farms. Hirtum and Berckmans [14] performed some experiments under laboratory conditions and introduced algorithms to detect cough sounds and to classify the animals as ill or healthy. Exadaktylos et al. [15] extended existing cough identification methods and proposed a real-time method for identifying sick pig cough sounds. However, few research attempts have been undertaken to identify the optimal acoustic feature subset selection for pig wasting disease.

In our study, we analyzed acoustic features to detect pig wasting disease and examined the differences between pig wasting disease sounds and normal sounds using machine learning-based pattern recognition. The acoustic feature subset selection algorithm that we developed found that \( \{F7, \text{RMS}, \text{Max Pitch}, \text{PSD1}, \text{Peak frequency}\} \) is the optimal feature subset.
PSD1, Peak frequency} is the optimal feature subset selection to detect pig wasting disease. Finally, with the obtained acoustic feature subset, a performance evaluation was conducted using real sound data from an audio surveillance system. The average detection accuracy approached 98.4%, with 0.2% and 1.6%, FPR and FNR, respectively, when a support vector machine was used as a detector. Moreover, we empirically confirmed that the performance of the optimal acoustic feature subset does not depend on the specific detector.

The rest of this paper is organized as follows: Section 2 describes the proposed acoustic feature subset selection method for pig wasting disease detection with some background concepts. In Section 3, machine learning-based detectors are explained. Section 4 describes the sample sound collection. The simulation results are presented in Section 5, followed by the discussions in Section 6. Finally, some concluding remarks are given in Section 7.

2. Acoustic feature subset selection method

In this paper, we introduce a new Acoustic Feature Subset Selection Algorithm (AFSSA) to detect pig wasting disease. AFSSA uses the features’ predictive performance and inter-correlations to guide the search for a good feature subset. AFSSA can drastically reduce the dimensionality of data sets while maintaining or improving the performance of learning algorithms. At the heart of the AFSSA algorithm is a heuristic that evaluates the worth or merit of a subset of features. This heuristic takes into account the usefulness of individual features to predict class labels by means of a statistical $t$-test and through information gain, along with the level of inter-correlation among them. AFSSA then searches the feature subset space using a Sequential Forward Search (SFS) algorithm [16].

The following is a summary of AFSSA with some mathematical background [17-20]. Note that the universal sound features set was initially set from the popular acoustic features found in acoustic literatures such as {RMS, Power, Energy, Absolute extremum, Intensity, Pitch, Duration, Shimmer, Jitter, HNR} in the time domain and {Formant F1~F9, Power Spectral Density PSD1~PSD39, Peak frequency} in the frequency domain.

1) $t$-test

$$t = \frac{\bar{x} - \bar{y}}{\sqrt{\frac{S_x^2}{n} + \frac{S_y^2}{m}}}$$

where $n$ and $m$ are the number of data points; the corresponding data means are $\bar{x}$ and $\bar{y}$; and the variances for each class are $S_x^2$ and $S_y^2$.

2) Information gain: Let $D$ be the set consisting of $d$ data samples with $m$ distinct classes. The expected information $I$ is given by

$$I(D) = - \sum_{i=1}^{m} p_i \log_2(p_i)$$

where $p_i$ is the probability that an arbitrary sample belongs to class $C_i$.

Let attribute $A$ have $v$ distinct values. Let $d_{ij}$ be the number of samples of class $C$ in a subset $D_j$. $D_j$ contains those samples in $D$ that have a value $a_j$ of $A$. The entropy, or expected information based on the partitioning into subsets by $A$, is given by

$$E(A) = - \sum_{i=1}^{m} I(D) \frac{d_{3i} + d_{2i} + \cdots + d_{mi}}{d}$$

The encoding information that would be gained by branching on $A$ is
Information Gain\( (A) = I(D) - E(A) \) \hspace{1cm} (4)

3) Correlation analysis: For a pair of variables \((X, Y)\), the linear correlation coefficient \(\rho_{xy}\) is given by the formula:

\[
\rho_{xy} = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2 \sum_i (y_i - \bar{y})^2}} \hspace{1cm} (5)
\]

where \(\bar{x}\) is the mean of \(X\), and \(\bar{y}\) is the mean of \(Y\).

4) Between Class Distance (BCD):

\[
d_{ij} = \frac{1}{N_i N_j} \sum_{k=1}^{N_i} \sum_{m=1}^{N_j} dist(x_i^k, y_j^m) \hspace{1cm} (6)
\]

In this equation, let \(X_i\) and \(Y_j\) be the sets of samples in classes \(C_i\) and \(C_j\) and \(x_i^k\) be the \(k\) - th sample in \(X_i\). \(N_i\) and \(N_j\) are the numbers of samples in each class, and \(dist(x_i^k, y_j^m)\) is the Euclidean distance between points \(x_i^k\) and \(y_j^m\).

### Acoustic Feature Subset Selection Algorithm (AFSSA)

**Definition:** Pig’ sound data set \(A = \alpha \cup \beta\): porcine wasting disease sound, \(\beta\): non-porcine wasting disease sound samples.

Universal sound features set = \(\{F_1, F_2, ..., F_k\}\), where \(k\) is the number of features that can be extracted from \(A\).

**Input:** Universal feature set \(F\).

1. Compute \(t\)-test and obtain the first candidate set \(F'\):
   - if \(p\)-value of \(F_i \geq 0.05\) then remove \(F_i\) in \(F\).

2. Compute the information gain of each formant in \(F'\).

3. Apply correlation analysis to \(F'\) using information gain and obtain the second candidate set \(F'':\)
   - if |correlation value| \(\geq threshold\) then select the highest ranked sound feature.

4. Apply SFS to \(F''\) with BCD as an evaluation function:
   - search the best formant feature subset

**Output:** an optimal sound feature subset \(F'''\).

### 3. Machine learning-based detectors

In this section, we briefly review some of the basic work on several machine learning-based detectors that were used in the experiments.

1) **C4.5:** C.5 is based on the well-known ID3 tree learning algorithm that is able to learn pre-defined discrete classes from labeled examples. Classification is done using axis-parallel hyperplanes and, hence, learning is very fast. This makes C4.5 a good subject for boosting [21].
2) **Bayesian Network**: A Bayesian network is a directed acyclic graph (DAG) where the nodes correspond to random variables (features). Each node is associated with a set of conditional probabilities, \( P(x_i|A_i) \), where \( x_i \) is the variable associated with the specific node and \( A_i \) is the set of its parents in the graph [22].

3) **Naïve Bayesian**: The Naïve Bayesian classification is based on Bayes’ theorem of posterior probability. It assumes class-conditional independence, which means that the effect of an attribute value on a given class is independent of the values of the other attributes [18].

4) **RBF Network**: The training of feed forward ANN is based on a nonlinear optimization technique, and the parameter estimate may get trapped at a local minimum of the chosen optimization criterion during the learning procedure when the gradient descent algorithm is used. Therefore, a viable alternative to highly nonlinear-in-the-parameter neural networks is the radial basis function (RBF) networks [23].

5) **SVM**: The support vector machine (SVM) is a method for classification of both linear and nonlinear data. It uses nonlinear mapping to transform the original training data into a higher dimension. Within this new dimension, it searches for the optimal linear separating hyperplane (i.e., a “decision boundary” separating the tuples of one class from another). With an appropriate nonlinear mapping to a sufficiently higher dimension, data from two classes can always be separated by a hyperplane. The SVM finds this hyperplane using support vectors (“essential” training tuples) and margins (defined by the support vectors) [18, 24-25].

![Figure 1. Picture of a pig house with an installed stationary CCTV with an audio sensor.](image)

4. **Sample sound collection**

The experiment was conducted in a commercial swine production farm located in Chungnam Province, South Korea. A total of 36 pigs (Yorkshire×Landrace×Duroc) were used in this experiment with an average weight ranging between 25 - 30 kg. Twenty-two pigs were housed in a 1.8 m × 4.8 m sized pen at a room temperature of about 23 °C. Blood samples of the suspected infected pigs were collected and subjected to serological analysis to determine the presence of Postweaning Multisystemic Wasting Syndrome (PMWS), Porcine Reproductive and Respiratory Syndrome (PRRS), and Mycoplasma Hyopneumoniae (MH) infections. The coughing sounds emitted by the infected pigs were recorded individually for 30 minutes depending on the cough
attacks using a digital camcorder (JVC GR-DVL520A, Japan) placed within a distance of one meter from the sick pigs. Observations were recorded under field conditions. Although pigs were allowed to move around the pen, most of our recordings were taken when they were lying on the floor. The cough sounds emitted by each infected pig were recorded individually, and the recorded signals were digitalized in a PC with a Realtek AC97 soundcard at 16 bits, mono, and 44.1 Hz sampling rates using Cool Edit (Adobe, San Jose, CA) program. They were then used as reference data to detect pig wasting disease (for more details refer to Gutierrez et al., [1]).

(a) The waveforms of the pig’s sound

(b) The spectrograms of the pig’s sound

Figure 2. Waveforms and spectrograms of the pig wasting disease cough sound and normal sound samples.
Apart from the cough sounds due to pig wasting diseases, we collected pig sounds for a month between August and September 2013 in a real pig farm located in Jochiwon, Korea. The pen had a stationary CCTV with an audio sensor (PILLAR CM-5010Pro, Korea) installed at the center of the 2.5 m height ceiling (see Figure 1). Then, normal pig sounds (such as non-infectious coughs, screams, footprint, and grunts) were recorded, noisy data was excluded, and features were labeled accordingly by auditory processing. Please note that in the normal sound group, we assumed that a normal cough (non-infectious cough) was caused by some environmental irritants, such as dust and ammonia, that are usually found in an intensive farm or that it may due to other infectious pathogens other than PMWS, PRRS, or MH.

5. Results

In our experiment, 305 (MH: 31, PRRS: 128, PMWS: 146) wasting disease sound data and 449 (grunt: 117, health cough: 83, footprint: 112, scream: 137) normal sound data were used. Figure 2 shows the sound waveforms and spectrograms of the different cough sounds acquired from normal, PMWS, PRRS, and MH samples, respectively. SPSS 20 (IBM, New York, USA) was used for the statistical analysis, and Weka 3.6.9 [26] was used to implement the various data mining classifiers.

We used three important formulas [18] to evaluate the performance of the proposed method. These are the disease detection rate (DDR), false positive rate (FPR), and false negative rate (FNR). They are given as follows:

\[
\text{Disease Detection Rate (DDR)} = \frac{\sum_{i=1}^{n} T_i}{\sum_{i=1}^{n} I_i} \times 100 \tag{7}
\]

\[
\text{False Positive Rate (FPR)} = \frac{\sum_{i=1}^{n} P_i}{\sum_{i=1}^{n} N_i} \times 100 \tag{8}
\]

\[
\text{False Negative Rate (FNR)} = \frac{\sum_{i=1}^{n} F_i}{\sum_{i=1}^{n} T_i} \times 100 \tag{9}
\]

In the above equations, \(I\) represents the individual wasting disease sound data and \(N\) the normal sound data. \(T\) represents the wasting disease sound data classified as such by the system. \(P\) indicates the normal sound data that are misclassified as wasting disease sound data, and \(F\) indicates the wasting disease sound data that are misclassified as normal sound data.

<table>
<thead>
<tr>
<th>F1</th>
<th>F2</th>
<th>F3</th>
<th>F4</th>
<th>F5</th>
<th>F6</th>
<th>...</th>
<th>PSD 39</th>
<th>Peak frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>1092.6±162.1</td>
<td>2129.3±156.8</td>
<td>3018.1±144.8</td>
<td>3953.5±205.0</td>
<td>5170.8±219.9</td>
<td>6232.4±238.0</td>
<td>...</td>
<td>0.0044±0.0019</td>
</tr>
<tr>
<td>Wasting disease</td>
<td>1025.5±218.0</td>
<td>2003.2±219.8</td>
<td>2997.2±251.8</td>
<td>4091.4±234.4</td>
<td>4938.3±239.3</td>
<td>5915.4±295.0</td>
<td>...</td>
<td>0.0009±0.0001</td>
</tr>
<tr>
<td>Species effect</td>
<td>0.000**</td>
<td>0.000**</td>
<td>0.000**</td>
<td>0.017*</td>
<td>0.103</td>
<td>0.000**</td>
<td>...</td>
<td>0.000**</td>
</tr>
</tbody>
</table>

Note. The \(p\) levels are for one-way analysis of variance for main effect of species on the acoustic measure. \(\alpha = 0.05\). 
\(p^* < 0.01, p^{**} < 0.001\). 
Significance levels for tests are listed numerically.

We executed the optimal acoustic feature subset experiments with the proposed algorithm. Let the universal set be \{F1−F9, RMS, Power, Energy, Absolute extremum, Intensity, Mean Pitch, Minimum Pitch, Maximum Pitch, Duration, Shimmer, Jitter, HNR, PSD1−PSD39 and Peak frequency\}. First, a \(t\)-test was performed to select the statistically significant features, and we
obtained a subset from the universal set that excluded \{F5, Jitter, PSD7, PSD8, PSD10~PSD22, PSD24, PSD27, PSD28 and PSD30\} (see Table 1). In a univariate \(t\)-test analysis, each feature was considered separately, ignoring feature dependencies that could lead to a degraded classification performance [27]. Second, we computed the information gain for each of the features obtained in the first step. The attribute with the highest information gain was considered to be the most discriminating attribute of the given set. Therefore, by computing the information gain for each attribute, we obtained a ranking of the attributes such as \{RMS, Power, Intensity, Absolute extremum, Duration, PSD1, F7, F9, PSD2, Peak frequency, PSD39, PSD38, F6, PSD3, PSD37, PSD36, PSD34, F8, PSD33, PSD35, Energy, PSD31, PSD32, PSD4, PSD25, PSD26, PSD29, PSD6, PSD23, PSD5, F2, PSD9, Shimmer, Maximum Pitch, Mean Pitch, F3, F4, Minimum Pitch, F1, and HNR\} in descending order.

We could then use this ranking for the relevance analysis described below. Some redundancies can be detected through correlation analysis, and based on the available data, such an analysis can measure how strongly one attribute implies the other for two given attributes [18]. The correlation analysis was performed to uncover interesting statistical correlations between associated attribute-value pairs (see Table 2). After the correlation analysis, we obtained the candidate acoustic feature set \{RMS, PSD1, F7, F9, Peak frequency, Energy, F2, Shimmer, Max Pitch, F3, F4, and F1\} to detect Korean porcine wasting diseases using sound data. Finally, we obtained the optimal feature subset \{F7, RMS, Max Pitch, PSD1, Peak frequency\} using an SFS algorithm in the feature subset space.

<table>
<thead>
<tr>
<th>F1</th>
<th>F2</th>
<th>F3</th>
<th>F4</th>
<th>F5</th>
<th>F6</th>
<th>F7</th>
<th>F8</th>
<th>F9</th>
<th>RMS</th>
<th>Power</th>
<th>PSD39</th>
<th>Peak F.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.624</td>
<td>0.406</td>
<td>0.301</td>
<td>0.163</td>
<td>0.115</td>
<td>0.189</td>
<td>-0.047</td>
<td>-0.099</td>
<td>-0.100</td>
<td>-0.061</td>
<td>0.375</td>
<td></td>
</tr>
<tr>
<td>0.624</td>
<td>1</td>
<td>0.599</td>
<td>0.308</td>
<td>0.143</td>
<td>0.058</td>
<td>0.127</td>
<td>-0.112</td>
<td>-0.209</td>
<td>-0.185</td>
<td>-0.074</td>
<td>0.339</td>
<td></td>
</tr>
<tr>
<td>0.406</td>
<td>0.599</td>
<td>1</td>
<td>0.567</td>
<td>0.462</td>
<td>0.381</td>
<td>0.405</td>
<td>-0.126</td>
<td>-0.016</td>
<td>-0.002</td>
<td>-0.015</td>
<td>0.129</td>
<td></td>
</tr>
<tr>
<td>0.301</td>
<td>0.308</td>
<td>0.567</td>
<td>1</td>
<td>0.706</td>
<td>0.705</td>
<td>0.698</td>
<td>-0.170</td>
<td>0.261</td>
<td>0.229</td>
<td>0.053</td>
<td>-0.047</td>
<td></td>
</tr>
<tr>
<td>0.163</td>
<td>0.143</td>
<td>0.462</td>
<td>0.706</td>
<td>1</td>
<td>0.881</td>
<td>0.798</td>
<td>-0.104</td>
<td>0.461</td>
<td>0.409</td>
<td>0.096</td>
<td>-0.034</td>
<td></td>
</tr>
<tr>
<td>0.115</td>
<td>0.058</td>
<td>0.381</td>
<td>0.705</td>
<td>0.881</td>
<td>1</td>
<td>0.855</td>
<td>-0.145</td>
<td>0.547</td>
<td>0.500</td>
<td>0.082</td>
<td>-0.114</td>
<td></td>
</tr>
<tr>
<td>0.189</td>
<td>0.127</td>
<td>0.405</td>
<td>0.498</td>
<td>0.798</td>
<td>0.855</td>
<td>1</td>
<td>-0.176</td>
<td>0.437</td>
<td>0.394</td>
<td>0.067</td>
<td>-0.101</td>
<td></td>
</tr>
<tr>
<td>-0.047</td>
<td>-0.112</td>
<td>-0.126</td>
<td>-0.170</td>
<td>-0.104</td>
<td>-0.145</td>
<td>-0.176</td>
<td>1</td>
<td>-0.169</td>
<td>-0.197</td>
<td>0.018</td>
<td>0.056</td>
<td></td>
</tr>
<tr>
<td>-0.099</td>
<td>-0.209</td>
<td>-0.016</td>
<td>0.261</td>
<td>0.461</td>
<td>0.547</td>
<td>0.437</td>
<td>-0.169</td>
<td>1</td>
<td>0.972</td>
<td>0.078</td>
<td>0.010</td>
<td></td>
</tr>
<tr>
<td>-0.100</td>
<td>-0.185</td>
<td>-0.002</td>
<td>0.229</td>
<td>0.409</td>
<td>0.500</td>
<td>0.394</td>
<td>-0.197</td>
<td>0.972</td>
<td>1</td>
<td>0.058</td>
<td>0.025</td>
<td></td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td></td>
</tr>
<tr>
<td>-0.061</td>
<td>-0.074</td>
<td>-0.015</td>
<td>0.053</td>
<td>0.096</td>
<td>0.082</td>
<td>0.066</td>
<td>0.018</td>
<td>0.078</td>
<td>0.058</td>
<td>1</td>
<td>-0.013</td>
<td></td>
</tr>
<tr>
<td>0.375</td>
<td>0.339</td>
<td>0.129</td>
<td>-0.047</td>
<td>-0.034</td>
<td>-0.114</td>
<td>-0.101</td>
<td>0.056</td>
<td>0.010</td>
<td>0.025</td>
<td>-0.013</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>

A summary of detection results with various machine learning-based detectors is shown in Table 3. Our experimental results (selected optimal feature subset) show that the average detection accuracy approached 98.4%, with 0.2% FPR and 1.6% FNR on average when SVM was used with the obtained optimal formant feature subset. We used 10-fold cross validation in all our experiments. Note that even when other detectors were used, the accuracy of the detection, the FPR, and the FNR were satisfactory. Accordingly, we empirically confirmed that the performance of the optimal formant feature subsets does not depend on the specific detector used.

Classification may need to be preceded by relevance analysis, which attempt to identify attributes that do not contribute to the classification process. These attributes can then be excluded [18]. So, it is needed to select relevant and important features among various features for stable classification result. Our feature selection method (AFSSA) is used to remove attributes that are uncorrelated with the class labels. This reduced the set of attribute to be used in classification, thus improving both efficiency and accuracy (see Table 3).
Table 3. Performance of the proposed method in pig wasting disease detection

<table>
<thead>
<tr>
<th>Dimension</th>
<th>C4.5 DDR (%)</th>
<th>Bayes Net DDR (%)</th>
<th>Naïve Bay DDR (%)</th>
<th>RBF Net DDR (%)</th>
<th>SVM DDR (%)</th>
<th>RBF Net FPR (%)</th>
<th>SVM FPR (%)</th>
<th>RBF Net FNR (%)</th>
<th>SVM FNR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>60 (All features)</td>
<td>96.7</td>
<td>95.4</td>
<td>82.6</td>
<td>92.1</td>
<td>97.7</td>
<td>0.4</td>
<td>10.9</td>
<td>6.5</td>
<td>4.0</td>
</tr>
<tr>
<td></td>
<td>3.3</td>
<td>4.6</td>
<td>17.4</td>
<td>7.9</td>
<td>2.3</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5 (Selected optimal feature subset)</td>
<td>97.4</td>
<td>98.4</td>
<td>97.4</td>
<td>98.0</td>
<td>98.4</td>
<td>0.9</td>
<td>3.1</td>
<td>2.0</td>
<td>2.4</td>
</tr>
<tr>
<td></td>
<td>2.6</td>
<td>1.6</td>
<td>2.6</td>
<td>2.0</td>
<td>1.6</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

6. Discussion

According to a literature review, a rich variety of methods have already been introduced that use sound data to detect pig wasting disease. In particular, two interesting papers were recently published. First, Chung et al. [6] proposed an efficient data mining solution to detect pig wasting disease. In this method, the researchers extracted Mel Frequency Cepstrum Coefficients (MFCC) from sound data and used a Support Vector Data Description (SVDD) as an early anomaly detector. Chung et al. used the MFCC, which have been proven to be good features within human speech recognition, because they model the human perception of sound and are therefore widely used features of sound analysis. However, animal sound perception can be different from human sound perception [28], and other feature vector representation methods might be more suitable to detect pig wasting disease sounds. Second, Gutierrez et al. [1] found that formant analysis had an important role in discriminating between a normal sound and a sound of pig respiratory disease. That is, the formant variables of calls could be used to detect porcine respiratory disease. Gutierrez et al. empirically chose four formants {F1, F2, F3, F4} in a 0 ~ 5,000Hz, including a few variables (pitch, intensity).

For many machine learning tasks, the input data is composed of a very large number of features, but only few of those are relevant for prediction [29]. If we select features with little discrimination power, the designed classifier would have poor performance. On the other hand, if information-rich features are selected, the design of the classifier can be greatly simplified [22]. Nguyen et al. [30] described how failure to discard irrelevant features (e.g. noise, outliers, and redundant features) will affect system performance, including classification accuracy, computational efficiency, and learning convergence. Therefore, feature selection is a very important process for a detection system since even the best detector will perform poorly if features are not chosen well [31].

In this paper, we analyzed acoustic features to detect pig wasting disease, and we examined the differences between pig wasting disease sounds and normal sounds using machine learning-based pattern recognition. Primarily, we introduce the acoustic feature subset selection algorithm that, to the best of our knowledge, found {F7, RMS, Max Pitch, PSD1, Peak frequency} to be the optimal feature subset to detect pig wasting disease from a set of universal sound features, including popular acoustic features found in prior literature. Finally, the obtained acoustic feature subset was used to evaluate the performance, which was independent of the specific detector used.

7. Conclusions

In this paper, we have discussed the methodology and the results of the study we conducted to analyze acoustic features of pig vocalizations to detect pig wasting disease. We also examined the differences between pig wasting disease sounds and normal vocalizations using pattern recognition. Primarily, we introduce the acoustic feature subset selection algorithm and found that {F7, RMS, Max Pitch, PSD1, Peak frequency} is the optimal feature subset to detect pig wasting disease. Finally, a performance
evaluation of this new method was verified using real sound data from an audio surveillance system. The experiments showed that the average detection accuracy of the optimal acoustic feature subsets approached 98.4%, with 0.2% FPR and 1.6% FNR on average when SVM was used as a detector. The performance was adequate in all cases and did not depend on a specific detector. Our experimental results indicate that this new method can be used to detect pig wasting disease in both an economical (even a cheap microphone can be used) and accurate manner, either as a standalone solution or to complement known methods to obtain a more accurate solution.

A complete, real-time system capable of incorporating automatic detection and recognition of a pig’s vocalization in a commercial production setting is part of our ongoing research.

8. Acknowledgement

This research was supported by Basic Science Research Program (through the NRF funded by the Ministry of Education, Science and Technology, No. 2012R1A1A2043679) and BK (Brain Korea) 21 Plus Program.

9. References


J. Han, M. Kamber, and J. Pei, Data Mining: Concepts and Techniques. 3rd Ed. Morgan Kaufmann Publishers, Burlington, Massachusetts, USA, 2011.


