Acoustic Monitoring of Rice Milling Process

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1. Introduction

Sound has been rated negatively in many industrial areas as the noise to be removed. In the agricultural process such as rice milling based on grinding the surface of the rice, however, it may be anticipated that the sound can contain the some information on the process. In this research, on the assumption that variation of the shape of the rice kernel during milling may bring the change in frequency characteristic of sound signal, we tried to investigate the relationship between the milling degree in the grinding test mill and the resonance and anti-resonance frequencies (the frequencies at which the sound power has the extreme values).

2. Experimental Conditions

The test mill with exchangeable abrasive grind wheels of #30, #36, #40 and #46 (Satake, TM05) was used to mill the brown rice (*Koshi-hikari* produced in Niigata, MC 15.2% db). Rice of 200 g was milled for 5 min. The milling sound was recorded on the magnetic disk as the digital signal sampled at the rate of 48 kHz and 16 bits through the condenser microphone (Ono Sokki, MI-1233) of frequency range from 20Hz to 20 kHz. The microphone was placed over the hopper, and the distance between the opening of the hopper and the microphone was about 45 mm.

The milling ratio was evaluated for five milling time from 1 min to 5 min at the interval of 1 min.

3. Fundamentals of Sound Signal Analysis

3.1 Auto-regressive Moving Average (ARMA) Model

The sound signal x_t at time t is produced in the auto-regressive moving average (ARMA) process, and this process $\{x_t\}$ is expressed as

$$x_t + a_1 x_{t-1} + a_2 x_{t-2} + \Lambda + a_p x_{t-p} = e_t + b_1 e_{t-1} + b_2 e_{t-2} + \Lambda + b_q e_{t-q} \tag{1}$$

where e_t is the white nose sequence whose mean and variance are zero and σ_e^2, respectively. p and q are the order of the AR and MA processes, and a_i and b_i are the AR and MA parameters, respectively. In other words, the present sound signal x_t is a linear combination of the p past sound signals and the present and past q white noise signals. In Eq. (1), let q be zero, we obtain the AR model, and for $p = 0$, the MA model can be constructed. The parameters a_i and b_i in Eq. (1) can be estimated by the following algorithm(T. Nakamizo, 1988).

Step 1 Estimation of Parameters of Approximated AR Model for ARMA Model

The ARMA(p, q) model can be approximated by the following AR(M) model with enough accuracy for the large value of $M > p + q$.

$$x_t + \sum_{i=1}^{M} c_i x_{t-i} = e_t \tag{2}$$

Step 2 Estimation of AR Parameter c_i

The AR parameter c_i contained in Eq. (2) can be estimated by solving the following Yule-Walker equation.

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$$\begin{bmatrix} R_0 & R_1 & \cdots & R_{M-1} \\ R_1 & R_0 & \cdots & R_{M-2} \\ \vdots & \vdots & \ddots & \vdots \\ R_{M-1} & R_{M-2} & \cdots & R_0 \end{bmatrix} \cdot \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_M \end{bmatrix} = - \begin{bmatrix} R_1 \\ R_2 \\ \vdots \\ R_M \end{bmatrix} \tag{3}$$

where R_τ for $\tau = 0,1,\cdots,M$ is the auto-correlation function of the process $\{x_t\}$.

Step 3. Estimation of MA parameter

The MA parameter b_i can be estimated by solving the following linear equation.

$$\begin{bmatrix} c_p & c_{p-1} & \cdots & c_{p+1-q} \\ c_{p+1} & c_p & \cdots & c_{p+2-q} \\ \vdots & \vdots & \ddots & \vdots \\ c_{p+q-1} & c_{p+q-2} & \cdots & c_p \end{bmatrix} \cdot \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_q \end{bmatrix} = - \begin{bmatrix} c_{p+1} \\ c_{p+2} \\ \vdots \\ c_{p+q} \end{bmatrix} \tag{4}$$

Step 4. Estimation of AR parameter

The AR parameter a_i can be estimated by.

$$\begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_p \end{bmatrix} = \begin{bmatrix} c_1 & 0 & \cdots & 0 \\ c_2 & c_1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ c_p & c_{p-1} & \cdots & c_{p-q} \end{bmatrix} \cdot \begin{bmatrix} 1 \\ b_1 \\ \vdots \\ b_q \end{bmatrix} \tag{5}$$

The linear algebraic equations (3) and (4) can be solved with the public library LAPACK on the internet.

The power spectrum of the ARMA(p , q) process expressed by Eq. (1) is given by

$$S(f) = \left| \frac{1 + \sum_{k=1}^{q} b_k e^{-j2\pi kf}}{1 + \sum_{k=1}^{p} a_k e^{-j2\pi kf}} \right|^2 \sigma_e^2 \tag{6}$$

In this estimation algorithm, the following unknown computational conditions should be examined for estimate of the model parameters, and some of these were determined through the numerical experiment by considering stability of the estimated values and similarity of spectrum computed by Eq. (6) to the FFT spectrum.

1) Number of Observations NMAX of Sound Signal for Estimation
2) Order of ARMA(p , q) Process p and q
3) Order M of Approximated AR(M) Process for ARMA

Moreover, it may be surmised that these parameters influence mutually the estimates of the model parameters, and then it is difficult to evaluate the effects of the individual condition to the estimation results independently.

3.2 Auto-regressive (AR) Model

In the analysis of speech signal, the AR model is used mainly (J.R. Deler, Jr. et al, 1993). The parameters of the AR model were estimated by the maximum entropy method (MEM) in this research (M. Hino, 1977).

4. Results and Discussions based on ARMA Model

4.1 Variation of Sound Power during Milling Process

For monitoring acoustically the rice milling process with milling sound, it is necessary to detect the change in acoustic characteristics. The sound power may vary during milling the rice, because the resistance of rotation of the grind wheel decreases due to size reduction of rice kernel. The variance of the short time (2 seconds in this research) reflects the sound power, and the temporal change of the short time variance may indicate the progress of milling. **Fig. 1** shows the temporal change of the short time variance during milling process. It is noticed that the milling sound become louder as the mesh of the grind wheel become greater. This may be due to difference of milling action of the grind wheel. Sound reached the maximum value about 100 to 200 seconds after beginning of milling. After reaching the maximum power, the sound decrease monotonically. Then the sound power for the short time may be used to detect the milling process of rice in the abrasive grind mill. In the following discussion, we will use the sound data obtained in the milling process under the #30 grind wheel.

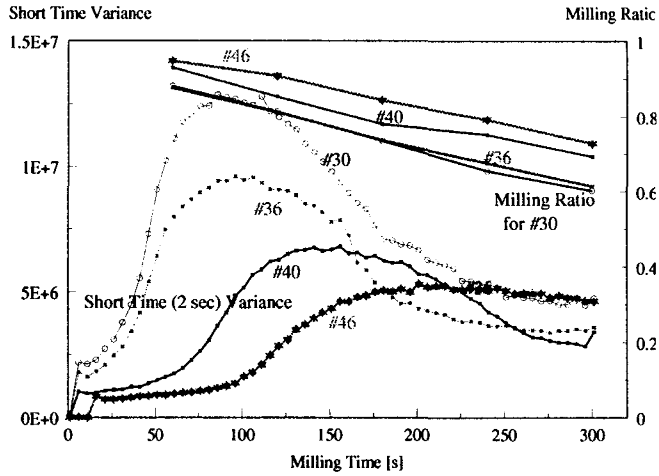

Fig. 1 Temporal Change of Short Time Variance

4.2 Examination of Order of ARMA Model

It was supposed the relationship between the AR model order p and the MA model order q is $p = q + 1$. To determine the appropriate order of the ARMA model, we compare the spectra of the ARMA(30,29), (35,34), (40,39) and (45,44) models and the spectrum estimated by FFT as shown in **Fig. 2**. The ARMA model of the order lower than (35,34) can not trace the FFT spectrum and has the sharp notch at the second resonance frequency f_{r2}. The ARMA model higher than (40,39) can trace the FFT spectrum smoothly. In the followings, we will use the ARMA model of this kind for discussing the characteristics of the milling sound. And the order M of the approximated AR model was fixed to $p + q + 10$, since too much order of the AR(M) make the coefficient matrix in Eq.(3) singular and the linear equation can not be solved.

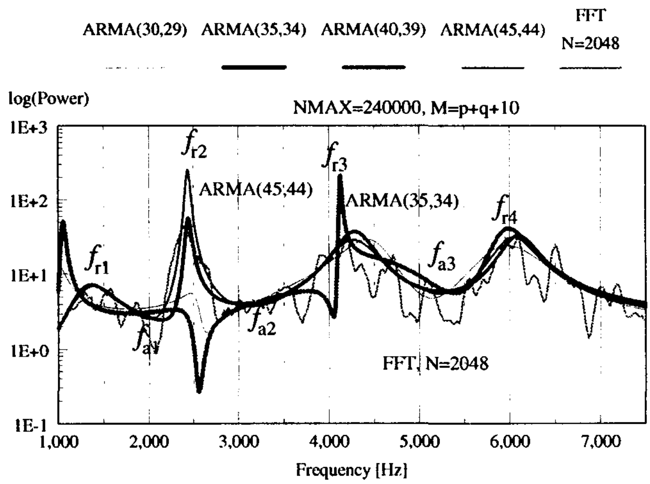

Fig. 2 Spectra estimated by ARMA Model and FFT

4.3 On the Number of Observation

The number of data points used for estimation may have an influence on the value of the ARMA parameters a_i and b_i. As shown in **Fig. 3**, the estimated parameters are affected considerably by the number of data points less than 150,000. For the data points larger than 200,000, the stable estimates could be obtained.

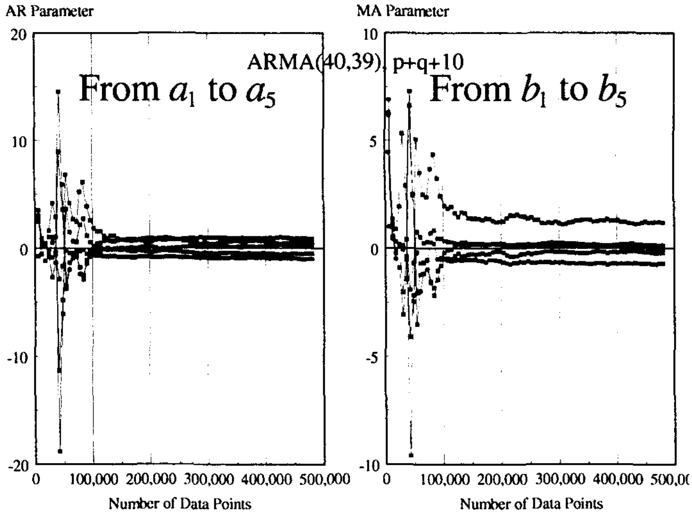

Fig. 3 Effect of Number of Data Points to Estimates of ARMA Parameters

4.4 Resonance and Anti-resonance frequencies

In Fig. 2, f_{ri} represents resonance frequency at which the power has the i-th peak value, and f_{ai} is the anti-resonance frequency corresponding to the i-th trough of the power spectrum. **Fig. 4** shows the temporal change in these frequencies during milling of rice. Power spectrum was estimated for the ARMA(42,41) model of 240,000(5 sec) data points. The extreme values of the power were determined by the numerical differentiation of the spectrum in the frequency range from 1,000 Hz to 7,500 Hz. Before scanning the frequency for differentiation, the spectrum was smoothed by the arithmetic moving average of five terms, because differentiation is very sensitive to the ripple on the spectrum. In the frequency range higher than 5 kHz, the resonance frequency f_{r4} could not be detected automatically and smoothly due to the extreme change in the spectral structure of the signal. The 1st and 3rd resonance and the 2nd anti-resonance frequencies changed as the milling process proceeded. **Fig. 5** shows that the width of variation of these frequencies ranged from 300 Hz for f_{r1} and f_{a2} to 700 Hz for f_{r3}. The straight line regression of f_{r1} and f_{r3} with the milling time, however, were not so good for the overall milling time. In case where the end of milling process should be detected with the sound, the latter period of the milling is important. So in the final 100 seconds, the frequency change was regressed with the straight line, and the regression coefficients higher than 0.75 were obtained.

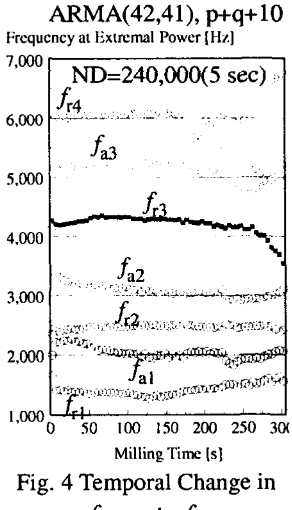

Fig. 4 Temporal Change in f_{ri} and f_{ai}

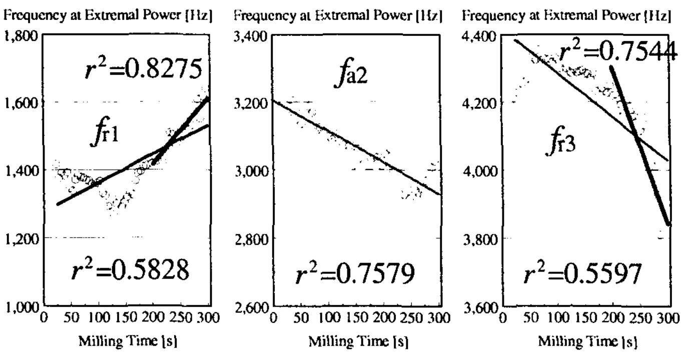

Fig. 5 Temporal Change in Resonance Frequencies f_{r1} and f_{r3}, and f_{a2}

5. Results and Discussions based on AR Model

5.1 Investigation of Order of AR Model

Generally speaking, for the reasonable order of the AR model the final prediction error (FPE) reaches the minimum value (K. Akaike et al, 1972). As shown in **Fig. 6**, for the sound signal of the milling process the FPE continue to decrease. This monotonic decrease of the FPE may be partly due to the data window of Hanning. Then, the order of the AR model should be determined by other criteria such as similarity of AR spectrum with FFT spectrum. As shown in **Fig. 7**, the spectrum by the AR model of order lower than 40 can trace the FFT spectrum. The spectrum of the AR(50) model departs from the FFT spectrum in frequency range higher than 3000 Hz. Therefore it may be said that the reasonable order of the AR model is lower than 45.

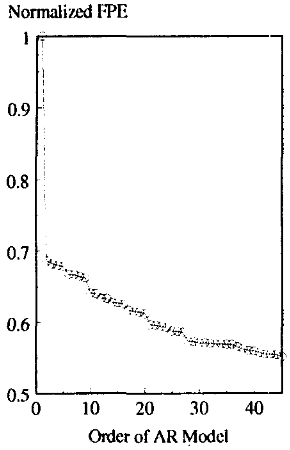

Fig. 6 Normalized Final Prediction Error

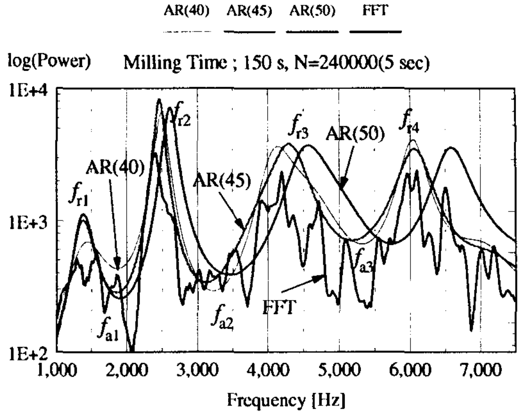

Fig 7 Spectra estimated by AR Model and FFT

5.2 Resonance and Anti- resonance frequencies

The temporal change of the resonance and ant-resonance frequencies detected on the AR spectra is as shown in **Fig. 8**. The model order are 40, 45 and 50, and in AR(45) spectrum the peak and trough frequencies change with progress of milling little bit obviously than others. In **Fig. 9**, the temporal change of the 1st, 2nd and 3rd resonance frequencies and 2nd anti-resonance frequency is shown for the AR(45) model. The width of change ranges from 100 Hz to 600 Hz. The correlation between the peak and trough frequencies and the milling time was high and it may be possible to monitor the rice milling process by the sound. For the 3rd resonance frequency, correlation was high in the latter 100 sec of the milling process. It may be said the AR model is more effective than ARMA model for the stable detection of frequencies

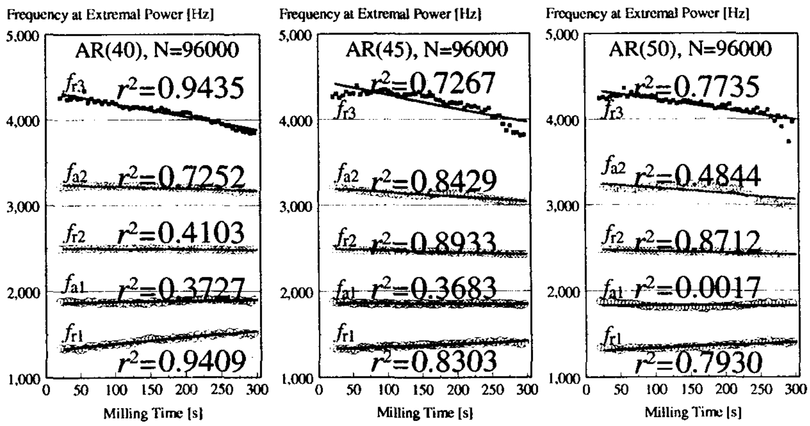

Fig. 8 Temporal Change in f_{ri} and f_{ai} determined in AR model

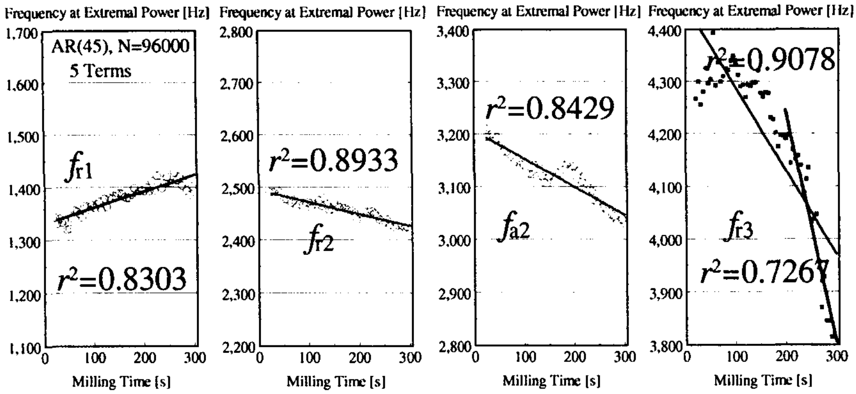

Fig. 9 Temporal Change of Resonance and Anti-resonance Frequencies detected in AR model of Milling Sound

6. Conclusions

The acoustic properties such as the power and frequency of the sound signal produced in the rice mill with an abrasive grind wheel were examined. The temporal change of variances for the short time of 2 seconds reflected the change of the sound power, and then progress of rice milling process. This change might be used to monitor the rice milling process.

The resonance and anti-resonance frequencies were detected on the spectra estimated from the ARMA(42,41) and AR(45) models, and it was found that some of these frequencies could be used to monitor progress of rice milling process.

In the future, the sound produced in the milling facility should be analyzed for a practical purpose. In this case, the microphone system isolated from the surrounding machine noise should be developed.

7. References

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