Holstein Cow Identification using Black and White Pattern

Yoshio Ikeda[*1] Yoshinari Morio[*2] Shigekazu Matsui[*1]

[*1]Graduate School of Agricultural Science, Kyoto University, Sakyo-ku, Kyoto 606-8502

[*2]Faculty of Bioresources, Mie University,1515 Kamihama, Tsu, 514-8507

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1. INTRODUCTION

In September 2001 , BSE was found for the first time in Japan. From then, consumers have been more and more interested in the safety of food products. Therefore, breeders and participants have to make a tracing system of productive information of cows and guarantee the quality of products through that system in an emergency.

Then the government has decided to put ear tags with peculiar numbers on all the cows and control the information of individual production and transference. But the ear tag can be damaged and missing. There is also a research of identification by implanting a microchip into the cow's body. But there are problems that the research can give a distress on cows and the detectable distance is too short.

In this study, we considered the way of identification by representing the black and white patterns on the computer. Black and white patterns are always mentioned in the pedigree certificate and important items to identify individuals not only in Japan but also in Western countries.

2. MATERIALS AND METHODS

The way to determine the black and white pattern region

We defined the black and white pattern region to use for identification as the region without movable head and legs. Then, in order to determine the region of black-white pattern, we calculated head ratio (w_h / W) and stomach ratio (h_s / H) in the rectangular region circumscribing cow's outline as shown Fig.1(a).

Fig.1(b) shows how to define the head position of cows. We defined the left of the divided rectangular area as A_L and the right as A_R. The average of A_R / A_L was 1.3 ,so we could define the head position in the smaller area.

Fig.2 shows the results of the calculated head and stomach ratio of 20 cows. Head ratio distributed around 0.2 and stomach ratio distributed around 0.6.

(a)Head and Stomach ratio (b)define the head position

Fig. 1 Characteristic amount to define the black-white pattern region and head position.

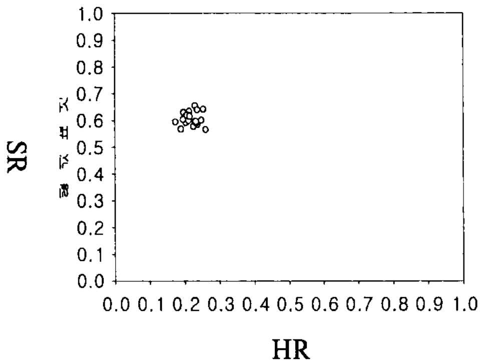
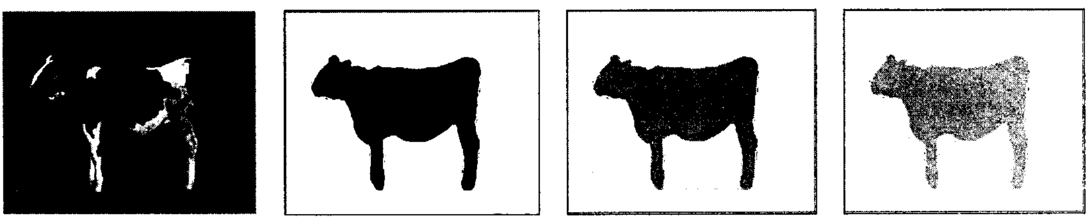


Fig. 2 Distribution of Head ratio(HR) and Stomach ratio(SR).

Fig.3 shows the transaction procedure to determine the region of black andwhite pattern. In detail, Fig.3(a) shows an original image whose background was set to blue(R=0,G=0,B=255). Fig.3(b) shows cow region by thresholding(threshold value=254). Fig.3(c) shows a rectangular area circumscribing cow's outline. Fig.3(d) shows the black and white pattern region for identification.



(a)original image (b)cow region (c)circumscribing rectangular (d)definition

Fig. 3 The procedure of defining the black and white pattern region.

The way to represent the black and white pattern by using KL expansion

Only black and white pattern region was divided into P blocks in the direction of y axis and was divided into Q blocks in the direction of x axis so that we could make PxQ blocks as shown in Fig.3(a). Then we calculated the average of brightness in each block and made a mosaic image as shown in Fig.4(b). We represented the black and white pattern by PxQ dimensional vector.

We defined PxQ dimensional black and white pattern vector of each cow as $\mathbf{X}_i$ and the number of cows as N . Then, the average vector of X_i , μ is represented by equation(1) and the variance-covariance matrix, $\mathbf{R}$ is represented by equation(2). And the projection of black and white pattern vector, $\mathbf{X}$,onto the eigenspace spanned by top L eigenvector $\mathbf{U}_k$ from KL expansion is represented by equation(3).

$$\mu = \frac{1}{N}\sum_{i=1}^{N}(X_i) \quad ...(1) \qquad R = \frac{1}{N}\sum_{i=1}^{N}(X_i - \mu)(X_i - \mu)^T \quad ...(2) \qquad y_k = (X - \mu)^T U_k \text{ ,} k = 1,K \text{ ,} L \quad ...(3)$$

(a)set blocks in black and white pattern region (b)8x16blocks mosaic image

Fig. 4 The set blocks and mosaic image.

Materials

In this study, we used the images of 20 holstein cows. Fig.4 shows 10 of them. There are various kinds of cows. C2 and C13 have only black pattern, but C14 has only white pattern.

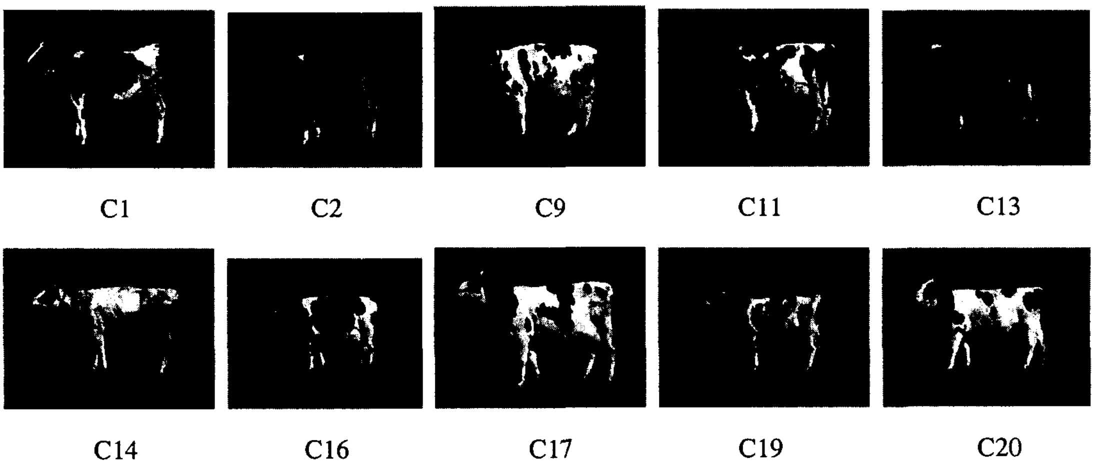


Fig. 5 Sample Cows.

3. RESULTS AND DISCUSSION

Eigenspace

Eigenspace of the black and white pattern was spanned by some eigenvectors from KL expansion. The ratio of the second eigen value in the first eigen value was 0.21 and that of the third eigen value was 0.11 as shown in Fig.6.

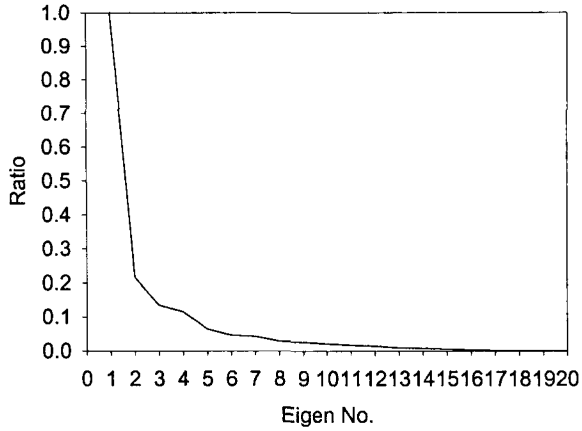


Fig. 6 The ratio of the n-th eigen value in the first eigen value.

Projection

Fig.7 shows the projection of the black and white pattern onto the 2 dimensional eigen space. From this result, the similar pattern ,like C2 and C13 distributed very closely on the eigen space. And they distributed clearly different from C9 and C14. But C1 and C16 distributed closely even though their patterns are obviously different.

As we increased the number of divided blocks, identification of the black-white pattern got easier on the 2 dimensional eigen space.

We could represent approximately the difference of the black and white pattern on the 2 dimensional eigen space.

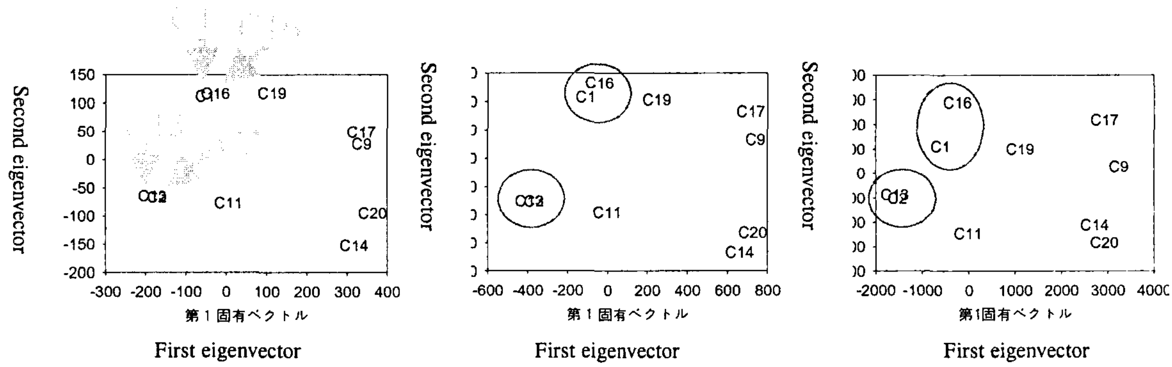


Fig. 7 The Projection of black andwhite pattern.

Euclid Distance

We defined the projection of the i -th cow's black and white pattern onto the top e eigenvectors as $\mathbf{T}_{\mathrm{i}}^{\mathrm{e}}$, and defined the Euclid distance between the i -th cow and the j -th cow as $D_{ij}^{e} = \left|\mathbf{T}_{\mathrm{i}}^{\mathrm{e}} - \mathbf{T}_{\mathrm{j}}^{\mathrm{e}}\right| \quad (i \neq j)$.

Fig.8 shows the average , standard deviation and the minimum value of D_{ij}^{e}, caluculated in all combinations of (i, j) in e dimension. As we increased the number of used eigenvector, the average and the minimum value of D_{ij}^{e} increased. But at the same time, the standard deviation decreased. Using more eigenvectors could identification easier.

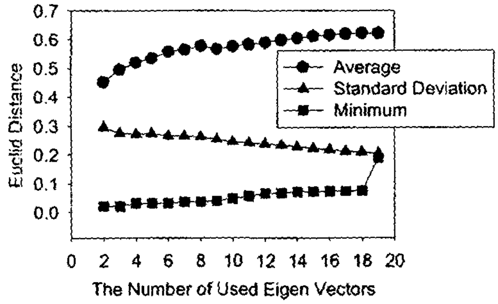


Fig. 8 The used eigenvectors and Euclid distance.

Then we focused on C2 and C13 because they had almost the same pattern. Fig.9 shows the Euclid distance between C2 and other cows. The Euclid distance of C2 and C13 increased as we increased the number of used eigenvector.

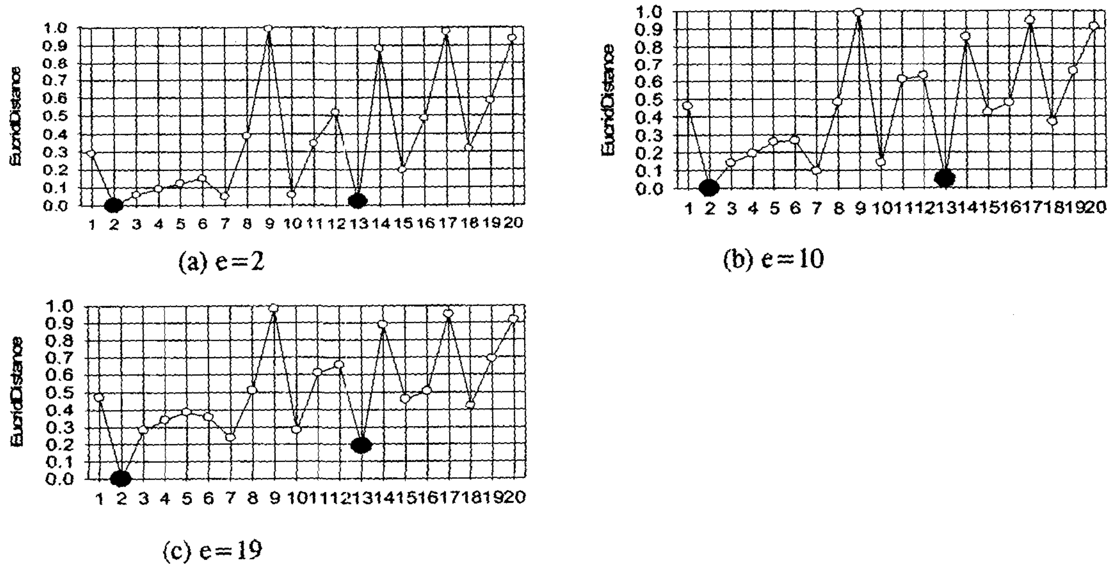


Fig. 9 Euclid distance between C2 and C13.

4 . CONCLUSION

We could represent approximately the difference of the black-white pattern on the eigenspace spanned by top 2 eigenvector. Main results were summarized as follows:

1. Increasing the number of used eigenvectors made identification easier.

2. Increasing the number of divided blocks made the identification easier.

In this study, we used the still images but we will use animation. And we should consider the affect of illumination and cow's growth from now as well.

5. REFERENCES

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