Recognition of Dynamic Texture Patterns Using CHLAC Features and Linear Regression

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Abstract

In this paper, we propose a statistical scheme for recognizing three-dimensional textures shown in motion images, e.g., ultrasound imaging, which we call "dynamic textures". The texture characteristics emerge as the distinct movement in the motion images, and the dynamic cues would be useful especially for recognizing ambiguous texture patterns in noisy images. We apply cubic higher-order auto-correlation (CHLAC) to extract features both of the textures and their movements, and then linear regression to evaluate (recognize) the texture. For the linear regression, we extend ordinary multiple regression analysis so as to reduce within-class fluctuations. In the experiment for estimating quality of beef meat by using ultrasound motion images, the proposed method exhibits the favorable performances which are close to ground truth given by the experts.

Keywords: *CHLAC, multiple regression analysis, dynamic texture recognition, ultrasound image, beef mabling score*

1. Introduction

Texture classification is an important research topic in image processing and it provides important cues for many applications, such as object recognition and image retrieval. Many researchers have proposed successful methods [1,4,10] to classify the textures in a still image, which we call "static texture". On the other hand, the dynamic textures that appear in motion images have rarely been dealt with. The dynamic (motion) characteristics in such textures are useful for recognition especially when the texture patterns, such as in ultrasound images, can not be obviously recognized by their static characteristics due to noise. In fact, humans can perceive the distinct patterns by the movement, as stated by psychologists [2]. The traditional approaches to extracting texture features, e.g., derivative filter responses [1], gray-level co-occurrence matrix [4], wavelets [5] and local binary patterns [10], are not so much applicable to the noisy images.

Ultrasound imaging is useful for ultrasound diagnosis in medical examinations, although it provides noisy images. In addition, recent years, ultrasound images are useful to estimate fleshy substance in the live animal, since Greiner [3] found somewhat high correlations between ultrasound images and the actual quality of the fleshy substance. The actual estimation of quality of the flesh, however, is manually performed by experts, and it is desirable to automate the estimation from the ultrasound images without slaughtering.

In this paper, we propose a statistical scheme for estimating the quantitative scores associated with the dynamic textures in motion images. For extracting features of the texture patterns, we employ the method of cubic higher-order auto-correlation (CHLAC) [8] which has been mainly applied to motion recognition. CHLAC can naturally deal with the (three-dimensional) dynamic texture patterns whereas HLAC [9] that extracts features from static images is applied to the classification of static textures. The method of CHLAC extracts the features of the dynamic textures by spatio-temporal local auto-correlations of pixel values. After extracting the texture features, we can estimate the quantitative scores associated with the dynamic texture by applying linear regression. For the linear regression, we extend multiple regression analysis (MRA) to reduce within-class fluctuations of feature vectors since the quantitative scores are weakly categorized in this study. By reducing the fluctuations which are irrelevant to the estimation of the target scores, the method would increase generalization performance.

We apply the proposed method to automatically estimate the quality of beef flesh, i.e., beef marbling score (BMS), by using ultrasound motion images. In the experiment, the proposed method produces the favorable performances compared to the ground truth given by the experts, although the ultrasound images contain a large amount of noise complicating the recognition in static images. It should be noted that the proposed method is general and applicable to any kind of dynamic texture recognitions, such as for CT scan images in medical field.

The rest of this paper is organized as follows: in the next section, preprocessing for noisy motion images is mentioned. We describe the proposed method for recognizing dynamic texture in Section 3. In Section 4, the experimental results for estimating BMS from ultrasound motion images are shown. Finally, Section 5 contains our concluding remarks.

2. Preprocessing

The input motion images that we deal with are assumed to be noisy unlike the traditional researches for static texture classification. Such noise in the motion images has much effect on the extracted features and eventually on estimation results. Thus, preprocessing is usually applied to the noisy images so as to possibly suppress the noise. In this study, we apply piece-wise linear pixel value (in gray scale) restoration which consists of clipping and stretching the pixel values. The transformation function for the restoration is defined as follows:

$$f(I) = \begin{cases} 255 & I \geq \tau_H \\ (I-\tau_L)/(\tau_H-\tau_L) & \tau_L < I < \tau_H \\ 0 & I \leq \tau_L \end{cases},$$

where τ_L and τ_H are thresholds for clipping in lower and higher values, respectively. This function is often used for gray-scale enhancement. By this transformation, extreme pixel values which are too high or low are saturated (clipped), and the difference within the intermediate pixel values is enhanced by stretching them (see Figure 1). The restored image is also shown in Figure 2.

By applying this preprocessing, some noise in the image are suppressed while the image contrast is increased, which is favorable for the following recognition process. The features of dynamic textures are extracted from the restored motion images, as described in the next section.

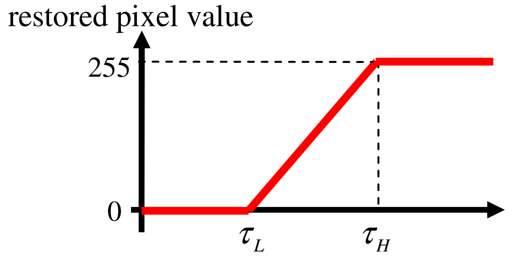

Figure1. The transformation function for restoring pixel values. The extreme pixel values at both ends are saturated by clipping and the intermediate values are stretched and enhanced.

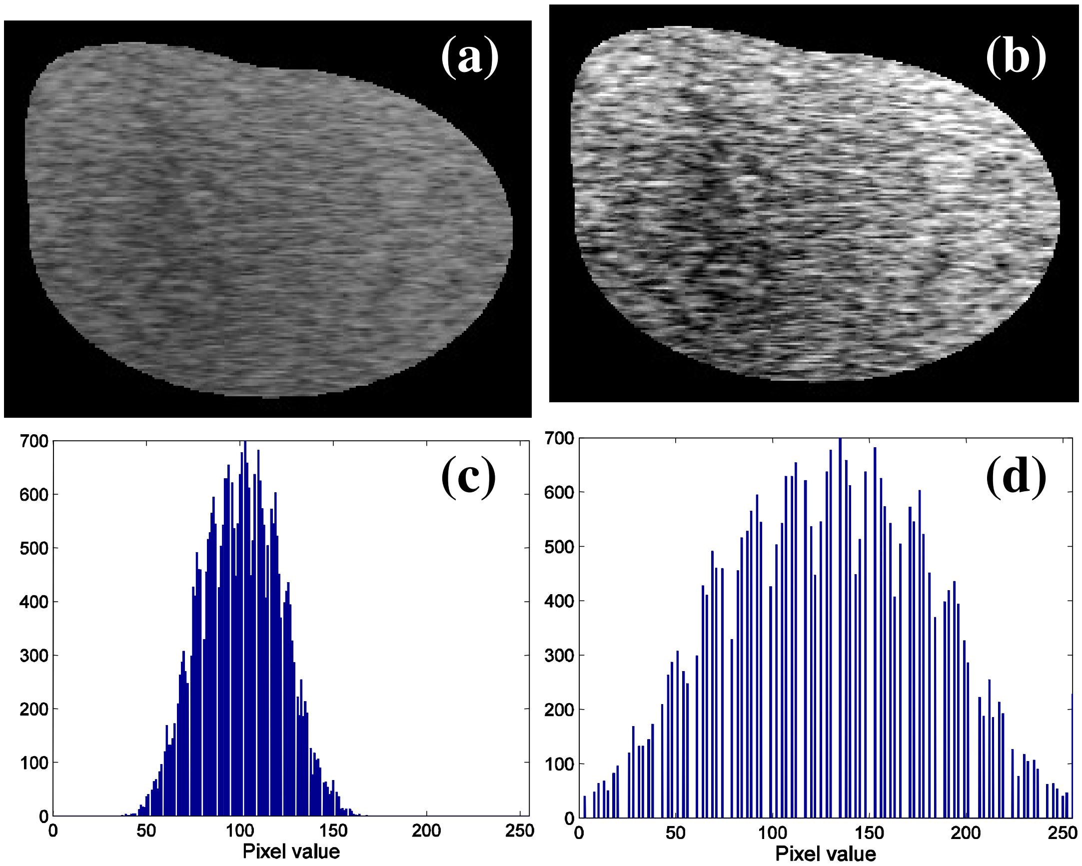

Figure 2. Input noisy image (a) and restored image (b) after preprocessing, and histograms of pixel values for the input image (c) and for the restored image (d). Image contrast is increased.

3. Proposed Method for Recognizing Dynamic Textures

We propose statistical approach to recognize dynamic textures. The proposed method is composed of two stages: 1) CHLAC [8] to extract features from three-way (spatio-temporal) dynamic texture patterns in motion images and 2) extended MRA to estimate the quantitative scores from the extracted features.

3.1. Bag-of-Features Representation for Image Sequence

The dynamic texture appears in a motion image sequence, not in a still image. Since the sequence is usually rather long, we draw a lot of sub-sequences from the whole sequence and then describe the characteristics of the dynamic texture in the sequence by assembles ("bag") of feature vectors extracted from the sub-sequences, rather than a single feature vector of whole sequence. Thereby, the dynamic textures that change with times are effectively characterized by each feature vector at each time. This approach is called "bag-of-features" and is recently employed in static image classification [12].

An overview of the proposed method to recognize the dynamic textures is as follows. First, we draw substantial sub-sequences with time width T from the whole sequence. Note that, in this case, the sub-sequences with various T are drawn so as to allow a degree of time-scale variation. Then, CHLAC features are extracted from each of the sub-sequences (Section 3.2). For each sub-sequence, the quantitative score is estimated by linear regression from the feature vector (Section 3.3). The final estimation is obtained by averaging those estimated scores within the whole sequence.

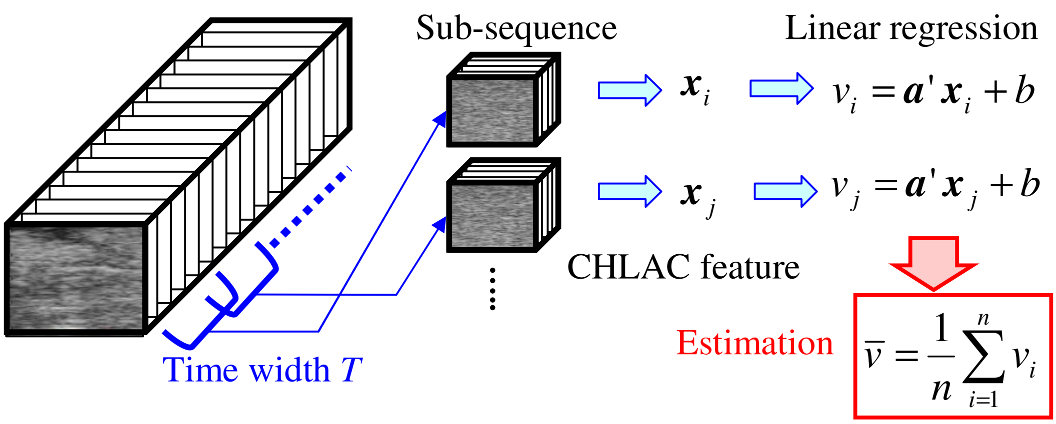

Figure 3. Overview of the proposed method for recognizing dynamic texture

3.2. Feature Extraction Method

We apply the method of cubic higher-order local auto-correlation (CHLAC) [8] to extract features of the dynamic texture in the motion image sequences. CHLAC simultaneously extracts spatio-temporal features from the motion image as follows. Let $f(\boldsymbol{r})$ be three-way data (dynamic texture) ($D: W \times H \times T$) defined on a sub-sequence with $\boldsymbol{r} = (x, y, t)^T$, where W and H are the width and height of the image frame and T is the time length of the sub-sequence. Then, the N-th order auto-correlation function on that three-way data can be defined as

$$x_N(t;\boldsymbol{a}_1,\ldots,\boldsymbol{a}_N) = \int_T \int_{W,H} f(\boldsymbol{r}) f(\boldsymbol{r}+\boldsymbol{a}_1) \cdots f(\boldsymbol{r}+\boldsymbol{a}_N) d\boldsymbol{r},$$

where the $\boldsymbol{a}_i$ ($i = 1, \cdots, N$) are displacement vectors from a reference point $\boldsymbol{r}$. The N-th order auto-correlation feature is based on the correlations of pixel values among N+1 points. The above formulation can take many different forms by varying N and $\boldsymbol{a}_i$, we limit $N \leq 2$ and $\boldsymbol{a}_i$ to a local region. The configurations of $\boldsymbol{r}$ and $\boldsymbol{a}_i$ are represented as local mask patterns shown in Figure 4. The features of dynamic textures are extracted by scanning the entire data region D with the local cubic mask patterns: the pixel values indicated in the mask patterns are multiplied and summed up over the whole region D. The dimension of CHLAC of $N \leq 2$ for the local 3×3×3 region is 279. The method of CHLAC has only a single parameter denoted by Δr which is the spatial interval of the auto-correlation along the x- and y- axes in the image frame (Figure 4). In this case, we consider $\Delta t = 1$.

CHLAC features have several favorable properties for recognition. First, the features are robust to additive noise since these are based on auto-correlation. The robustness of auto-correlation to noise is shown as follows:

$$\boldsymbol{E}(s_i + n_i)(s_j + n_j) = \boldsymbol{E}(s_i s_j + \sigma^2 \delta_{ij}) \approx \boldsymbol{E} s_i s_j,$$

where s_i are signal values, n_i is random additive noise with zero mean and variance of $\sigma^2 (<< s)$, $\boldsymbol{E}$ is the expectation, and δ_{ij} is the Kronecker delta. This property is quite effective for recognizing noisy images that we deal with in this study. The second property is shift-invariance, which renders the proposed method segmentation-free. In addition, computational cost to calculate the CHLAC features is quite low (about 6 msec/frame for QVGA on Xeon 3.2GHz PC).

In the traditional methods for the static texture classification, derivative filter responses, such as Gaussian derivatives and Gabor filters, are often employed as texture features. Since the responses of the derivative filters are noise-sensitive, for the noisy dynamic textures shown in motion images, especially in ultrasound images, those derivative features would be unstable. It should be also noted that optical flows are still less feasible for such noisy motion images.

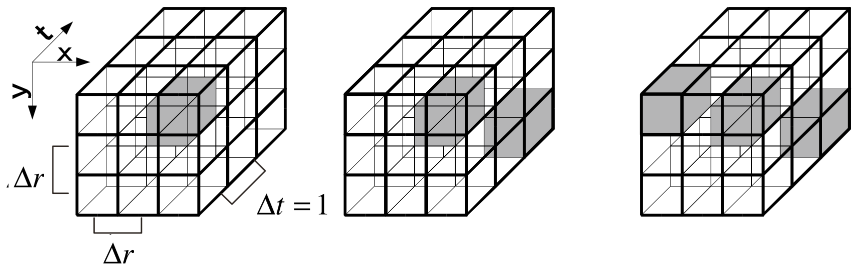

Figure 4. CHLAC mask patterns. Δr indicates the spatial correlation interval.

3.3. Linear Regression Method

3.3.1. Multiple regression analysis: Next, we estimate the quantitative score associated with the dynamic texture. Given scores for respective sequences, we can apply multiple regression analysis (MRA) [6,13] which determines the optimal linear coefficients for estimating the scores from feature vectors. Let $\boldsymbol{x}_j^{(i)}$ be the j-th feature vector (within bag-of-features) extracted from the i-th sequence and y_i be the score for the i-th sequence. The MRA minimizes sum of squared error for linear regression in the following optimization problem:

$$\begin{aligned} &\min \sum_i \sum_j \| y_i \text{-} \boldsymbol{a}^T \boldsymbol{x}_j^{(i)} \text{-} b \|^2 \\ &\Rightarrow a = (\overline{\boldsymbol{X}}\overline{\boldsymbol{X}}^T)^{-1} \overline{\boldsymbol{X}}\overline{y}, \quad b = \overline{y} - \overline{\boldsymbol{x}}^T (\overline{\boldsymbol{X}}\overline{\boldsymbol{X}}^T)^{-1} \overline{\boldsymbol{X}}\overline{y} \end{aligned},$$

where

$$\begin{aligned} &\overline{\boldsymbol{X}} = [\boldsymbol{x}_1^{(1)} - \overline{\boldsymbol{x}}, \cdots, \boldsymbol{x}_{n_N}^{(N)} - \overline{\boldsymbol{x}}] \\ &\overline{y} = [\underbrace{y_1 - \overline{y}, \ldots, y_1 - \overline{y}}_{n_1}, \cdots, \underbrace{y_N - \overline{y}, \ldots, y_N - \overline{y}}_{n_N}]^T, \\ &\overline{\boldsymbol{x}} = \boldsymbol{E}_{ij}(\boldsymbol{x}_j^{(i)}), \quad \overline{y} = \boldsymbol{E}_i(y_i) \end{aligned}$$

and $n_i (i = 1, \cdots, N)$ is the number of features (sub-sequences) extracted from the i-th sequence, and N is the number of sequences. The score for the j-th sub-sequence drawn from a (new) input sequence is estimated by

$$\hat{y}_j = \boldsymbol{a}^T \boldsymbol{x}_j + b,$$

and then the final score for the whole sequence is predicted by averaging above estimated scores of sub-sequences:

$$\hat{y} = \boldsymbol{E}_j(\hat{y}_j) = \frac{1}{n} \sum_{j=1}^{n} \hat{y}_j.$$

3.3.1. Extended multiple regression analysis: The method of MRA described above, however, aims only to minimize the sum of squared estimation error without regarding the within-class fluctuations. In this study, we assume that the target is quantitative score value including weak class (qualitative) information, e.g., BMS$\in \{4,6,8,10\}$. For such target values, not only the estimation error but also the fluctuations of feature vectors within each class should be minimized like Fisher discriminant analysis (FDA) [7,13] which is solely based on class information. FDA is considered to be composed of two processes: first, sample vectors are whitened so as to have unit within-class covariance and then principal component analysis is applied to mean vectors in classes. First process is for minimizing the within-class fluctuations and second one is for enhancing discrimination between classes. In manner similar to FDA, we extend MRA to take into account the minimization of the within-class fluctuations (within-class covariance) as follows. First, we apply within-class whitening to feature vectors:

$$\boldsymbol{C}_w \boldsymbol{W} = \boldsymbol{W} \boldsymbol{\Lambda}$$

where $\boldsymbol{W}$ and $\boldsymbol{\Lambda}$ are eigenvectors and eigenvalues, respectively, and $\boldsymbol{C}_w$ is the within-class covariance:

$$\boldsymbol{C}_w = \underset{ij}{\boldsymbol{E}}\left(\boldsymbol{x}_j^{(i)} - \bar{\boldsymbol{x}}_{y_i}\right)\left(\boldsymbol{x}_j^{(i)} - \bar{\boldsymbol{x}}_{y_i}\right)^T$$
$$\bar{\boldsymbol{x}}_y = \underset{j,i=y}{\boldsymbol{E}}\ \boldsymbol{x}_j^{(i)}$$

For within-class whitening, the feature vectors are projected by using $\boldsymbol{W}$:

$$\tilde{\boldsymbol{x}} = \boldsymbol{\Lambda}^{-1/2}\boldsymbol{W}^T\boldsymbol{x}.$$

And then the MRA described above is applied to the transformed feature vectors $\tilde{\boldsymbol{x}}$. Thus, the resultant linear regression formulation is described by

$$\hat{y}_j = \boldsymbol{a}^T\tilde{\boldsymbol{x}}_j + b = \boldsymbol{a}^T\boldsymbol{\Lambda}^{-1/2}\boldsymbol{W}^T\boldsymbol{x}_j + b = \tilde{\boldsymbol{a}}^T\boldsymbol{x}_j + b.$$

In the extended MRA, linear regression is realized by the regression coefficient vector $\tilde{\boldsymbol{a}}$ whose dimensionality is same as $\boldsymbol{a}$ in MRA, and thus the computational cost is also same as that of MRA. The extended MRA would increase generalization performance since the within-class fluctuations which are irrelevant to the estimation are reduced like FDA. The comparison to FDA is shown in Figure 5.

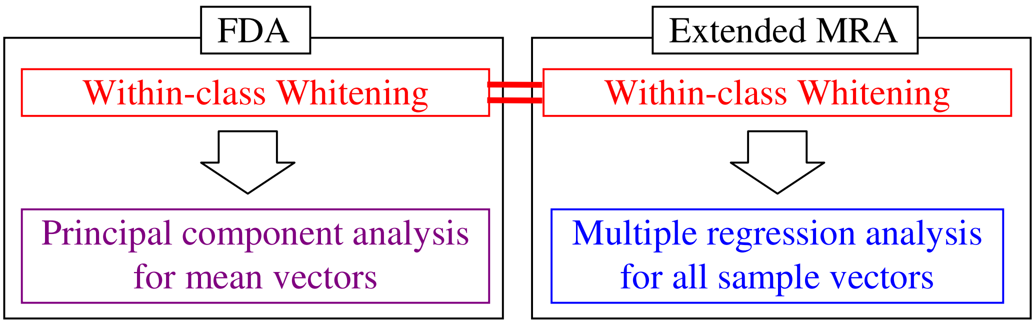

Figure 5. Comparison between Fisher discriminant analysis (FDA) and extended multiple regression analysis (Extended MRA)

4. Experimental Result

We apply the proposed method to estimate quality of beef meat, i.e., beef marbling score (BMS), from ultrasound motion images as shown in Figure 6. Through the ultrasound images, we can investigate growth of the flesh and estimate the quality (BMS) without slaughtering cattle. This provides the breeders quite useful information by which strategy of breeding cattle can be adaptively determined. However, it is difficult to identify the textures and to estimate BMS from ultrasound images, because the texture characteristics are ambiguous due to a large amount of image noses. Only the experts who have been trained for a long time are able to recognize such texture characteristics and to estimate BMS from the ultrasound images with their eyes.

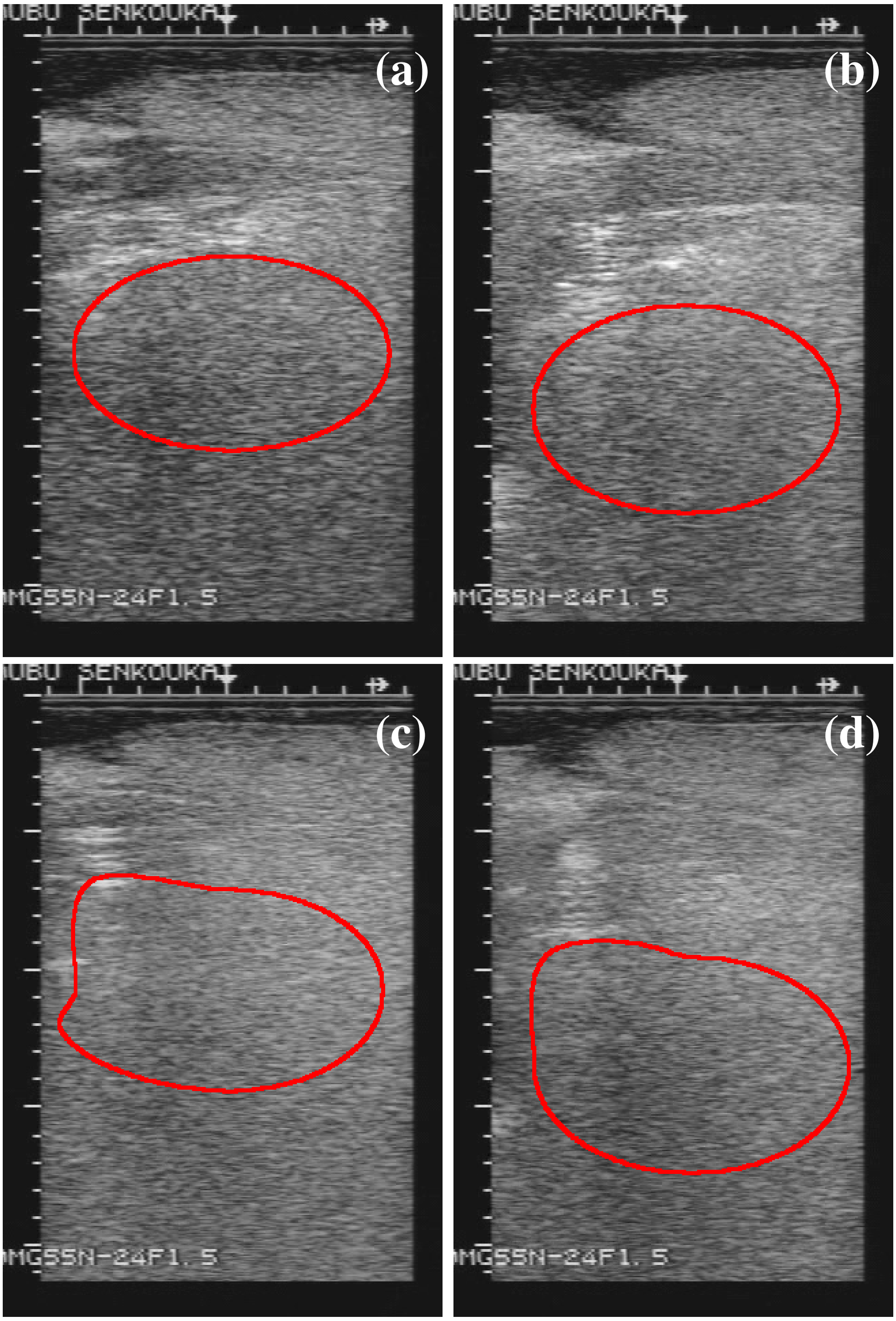

Figure 6. Examples of ultrasound images. The target region is indicated by red curves. (a) BMS = 4, (b) BMS = 6, (c) BMS = 8, and (d) BMS = 10.

4.1. Experimental Setup

We have 18 sequences for various BMS: three sequences for BMS-4, six sequences for BMS-6, seven sequences for BMS-8, two sequences for BMS-10 as shown in Table 1. The examples of ultrasound images are also shown in Figure 6. In this study, the target region (the averaged region size is about 250×180) is set as the location of rib eye as indicated by red curves in Figure 6.

The proposed method has several parameters. In preprocessing, two thresholds τ_L, τ_H are set as $\tau_L = 50, \tau_H = 150$. When extracting sub-sequences from the whole sequence, we take various time-width $T \in \{10,20,30,40,50\}$. In feature extraction by CHLAC, we consider various size of auto-correlation by varying spatial correlation interval $\Delta r \in \{1,...,8\}$ and then concatenate all feature vectors with various Δr into single feature vector whose dimensionality is $279 \times 8 = 2232$. In this experiment, the BMS ranges from 4 to 10 (ref. Table 1) and therefore the range of the estimation is also restricted to the same range by

$$\hat{y} \leftarrow \max(\min(\hat{y}, 10), 4).$$

Table 1. Number of sequences with BMS

BMS	4	6	8	10
Number of sequence	3	6	7	2

4.2. Evaluation Protocol

The performance is evaluated based on leave-one-sequence-out scheme for the 18 sequences. That is, the linear regression coefficients are learnt by applying the extended MRA to feature vectors extracted from 17 sequences, and then BMS of the remained one sequence is estimated by using the learnt linear regression. This leave-one-out scheme is commonly employed to evaluate the generalization performances of the method when the number of training sample is small. The mean absolute error is the criterion to evaluate overall performance of the method.

4.3. Results and Discussion

We apply various methods to estimate BMS and discuss the effectiveness of each process in the proposed method based on the performance results in Table 2 and Figure 7. In Table 2, the performance results, i.e., mean absolute errors, of various methods are summarized. In Figure 7, the estimation results are summarized according to BMS. For each BMS, mean and standard deviation of the estimation is plotted along with the ground truth BMS. This figure shows the tendency of the performances for each BMS.

[Preprocessing]

In this study, we apply the pixel value restoration to ultrasound images with reducing noise (see Figure 2). By comparing the performance results of (b) and (c) in Table 2 and Figure 7, it is shown that the preprocessing works effectively for recognizing dynamic textures. In this preprocessing, however, two thresholds τ_L, τ_H for clipping pixel values affect the performance to some extent. In case that τ_H is set as low value or

τ_L is set as high value, the performance is degraded. In this study, these thresholds are manually determined on the basis of the distributions of pixel values (ref. Figure 2 (c,d)) as described in Section 4.1.

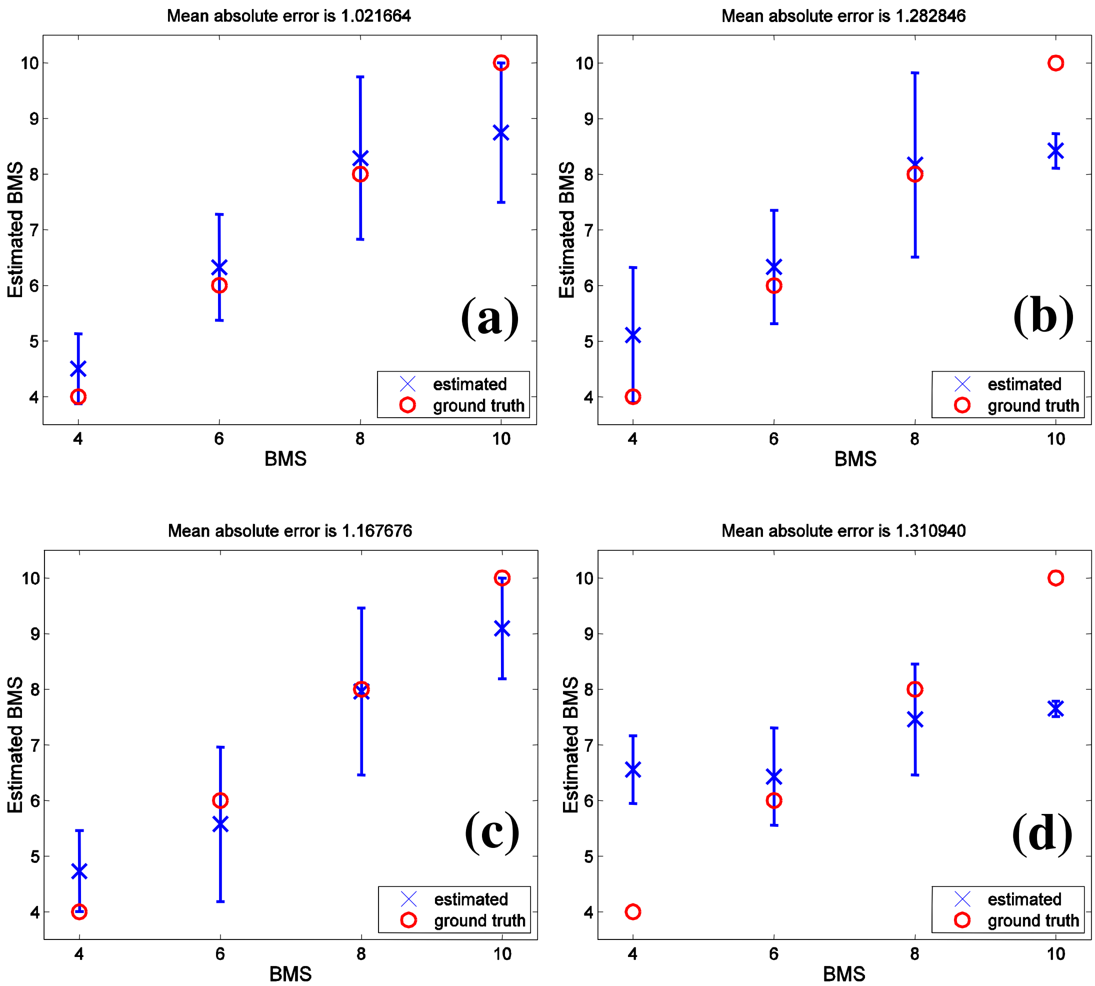

Figure 7. Performance results for each BMS. (a) Extended MRA with preprocessing, (b) MRA without preprocessing, (c) MRA with preprocessing, (d) SVR with preprocessing

[Linear regression]

For comparison, the method of support vector regression (SVR) [14] is applied. Although SVR also optimizes linear regression from feature vectors to BMS, the estimation error is measured as Hinge loss and the optimization problem results in quadratic programming [11] unlike MRA. Based on the comparison between (a) and (d), we can see that the performance of SVR is inferior to that of MRA. The definitions of estimation error in these two methods are different and this causes the performance difference. In this case, mean squared error employed in MRA is shown to be effective. By comparing (a) and (c), the extended MRA which we propose in this paper performs well. Within-class whitening improves the performance.

[Overall performance]

In total, the proposed method, which consists of pixel-value (gray-scale) restoration, CHLAC feature extraction and extended MRA, performs best among four methods as shown in Table 2. In addition, the estimated BMS is roughly linearly related to the ground truth BMS as shown in Figure 7 (a). The task to estimate BMS from ultrasound images is quite difficult since even humans who are not trained can hardly distinguish the BMS from the images (see Figure 6). Thus, the performance that the mean absolute error is 1.02 is considered to be favorable. This experimental result indicates that BMS can be automatically estimated without the experts, which significantly reduces human efforts. It should be noted that the proposed method employing linear regression, not nonlinear regression using kernel function [15], requires little computational cost and thus on-line system would be feasible.

Table 2. Performance results of various methods

Preprocessing	Restoration	None	Restoration	Restoration
Regression method	Extended MRA	MRA	MRA	SVR
Mean absolute error	1.02	1.28	1.17	1.31
In Figure 7	(a)	(b)	(c)	(d)

5. Concluding Remarks

We have proposed a statistical scheme for recognizing dynamic texture patterns shown in noisy motion image sequences. In the proposed scheme, the characteristics of the dynamic textures are efficiently extracted by CHLAC, and the target score is estimated from the extracted feature by using extended multiple regression analysis. CHLAC is based on the auto-correlation of pixel values in the dynamic texture patterns and is robust to additive noise contained in the motion images. The extended MRA estimates target scores by linear regression while minimizing the within-class fluctuations of feature vectors. Even in the preliminary experiment of estimation of beef meat quality (BMS) by using ultrasound motion images, the proposed method produced the favorable performances, in spite that the ultrasound images contain a large amount of noise. The result shows that CHLAC can extract sufficient texture features from the ultrasound motion images and the extended MRA effectively estimates BMS. It should be noted that the proposed method requires little computational cost for the estimation. Therefore the automated system, even on-line system, to estimate BMS would be feasible without needs for slaughtering cattle and help of the experts.

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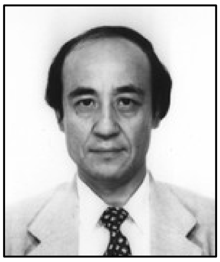

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