Wavelet-based Cooking Phase Detection for Time Series of Pot Temperature

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***Abstract*—Reviewing cooking activities in a restaurant kitchen is useful for improving staff skills. This paper proposes a method for detecting the cooking phase in a time series of pot temperatures. The proposed method is based on a feature vector extracted by a wavelet transformation. A support vector machine (SVM) uses a feature vector that classifies every second as being in a "cooking" or "not-cooking" phase. Additional post processing consisting of erosion and dilation is carried out to reduce noise. An experiment with an actual dataset to evaluate the accuracy of the proposed method was conducted. The rate for correct classifications was 85%.**

I. Introduction

Restaurants need to avoid variation in the taste of each dish, regardless of the experience of the kitchen staff making the dish. To standardize the taste of dishes and to improve their skills, kitchen staff cook by following the restaurant's recipes and instructions. Recording and reviewing the activity of kitchen staff in a restaurant kitchen can be effective in improving their skills. However, installing a camera system in a kitchen is expensive, and it is often difficult to capture clear images of the cooking activities because of changes in object and staff positions. Installing a large number of cameras to overcome this problem is also undesirable.

Using thermometers preinstalled in pots or fryers is preferable to a camera system because the thermometer system is cost effective and saves time. Reviewing temperature data during cooking is effective in improving staff skills because appropriate temperatures directly contribute to improving the taste of a dish.

However, temperature data collected in kitchens includes temperatures from before, during, and after the actual cooking. Therefore, a method of picking out only the temperature data during cooking is required. This paper proposes a method of detecting the cooking phase by using pot temperatures. The proposed method detects the cooking phase by focusing on temperature characteristics, such as sharp fluctuations that occur when something is dropped into the cooking pot.

II. Cooking Environment and Recipes

Figure 1 illustrates a system implementing the proposed method. Data on the food cooked in a pot is collected. A thermometer is installed in the pot to collect temperature data in a time series. The system detects the cooking period by analyzing the collected data.

The cooking procedure is as follows:

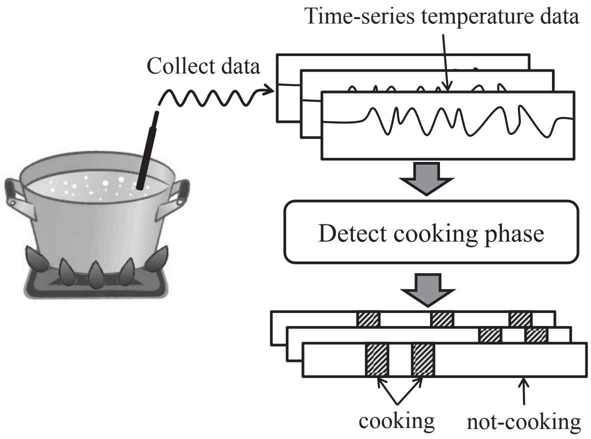

Figure 1. Overview of the system using the proposed method

Step 1. Boil water.
Step 2. Put in ingredient A and continue cooking.
Step 3. Put in ingredient B and continue cooking.
Step 4. Add other ingredients such as flavorings, soup stock, etc.
Step 5. Stir for a few seconds.
Step 6. Reduce the cooking heat when the pot temperature exceeds the threshold number of degrees.
Step 7. Increase the cooking heat when the pot temperature is under the threshold number of degrees.

The cooking phase includes the steps from 1 to step 5. The pot is kept warm even after cooking and meals are served directly from the pot. Steps 1 to 5 are repeated when a pot becomes empty, about 10 to 30 times a day. In order to detect the cooking phase, a method of classifying the phase into cooking (steps 1 to 5) and non-cooking (including steps 6 and 7, which keep the food warm) is required.

III. Detecting The Cooking Phase from Time Series Data of Pot Temperatures

A. *Process flow for the proposed method*

Figure 2 shows the flow of processes in the proposed method. Temperature data in a time series is collected by a

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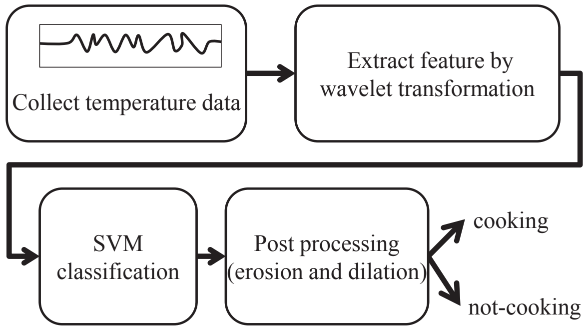

Figure 2. Flow of processes in the proposed method

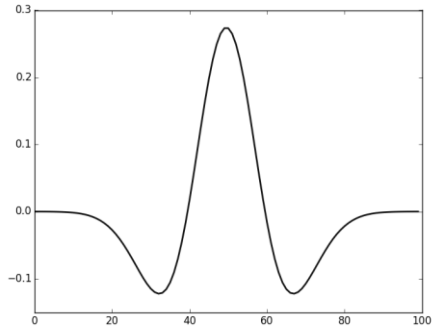

Figure 3. Mexican-hat wavelet

thermometer installed in the pot. Then, wavelet transformations are used to extract feature vectors from the data. A support vector machine (SVM), based on feature vectors, classifies the data into "cooking" or "not-cooking". Post processing, consisting of erosion and dilation, is carried out to reduce noise.

B. Extract features by wavelet transformation

Wavelet transformation is a common tool for decomposing a time series into local-variation components[1]. The transformation formula is defined as follows:

$$\tilde{x}(w,b) = \int_{-\infty}^{\infty} x(t)\psi^*_{w,b}(t)dt\,, \tag{1}$$

where * denotes complex conjugation. This formula shows that a function $x(t)$ is decomposed into a set of basis functions $\psi_{w,b}(t)$, called wavelets. The variables w and b indicate scale and translation after the wavelet transformation. The wavelets $\psi_{w,b}(t)$ are generated from a single basic function $\psi(t)$, which does not include w and b. The function is the so-called mother wavelet. The relation between a wavelets and the mother wavelet is as follows:

$$\psi_{w,b}(t) = \frac{1}{\sqrt{w}}\psi\left(\frac{t-b}{w}\right) \tag{2}$$

The factor $\sqrt{w}$ in the formula normalizes energies across the different scales.

A famous mother wavelet function, the Mexican-hat wavelet [2], is applied in order to detect sharp fluctuations when something is dropped into the cooking pot. The formula is as follows:

$$\psi(t) = (1-t^2)exp(-\frac{t^2}{2}) \tag{3}$$

This function is derived from the second derivative of a Gaussian function. Figure 3 illustrates the Mexican-hat wavelet for $w = 10$.

Figure 4 plots a time-series and its wavelet transformation components. Figure 4 (a) plots the original series, where the vertical axis is temperature (°C) and the horizontal axis is time (sec). Graphs Figure 4 (b), (c), (d), (e) and (f) plot the transformation components with $w = 15, 25, 125, 250,$ and 625 respectively. The vertical axis is the wavelet transformation $\tilde{x}(w,b)$ and the horizontal axis

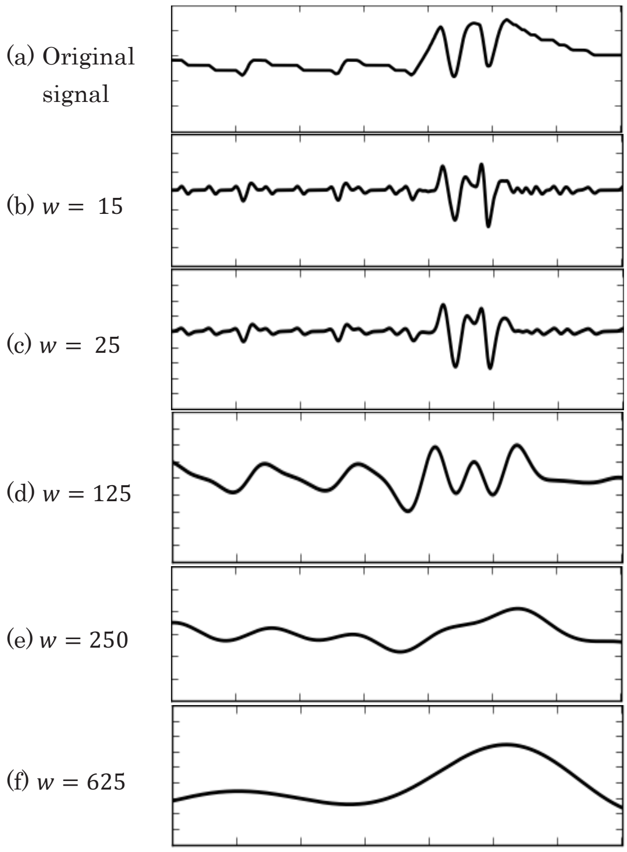

Figure 4. Examples of wavelet transformation results

indicates the translation variable b. The scale variable w is clearly correlated to the frequency of the original series. As shown in Figure 4, the components of small w such as (b) and (c) are strong when the original series changes sharply, while the components of a large w, such as (e) and (f), are strong when the original series changes gradually.

A vector consisting of these 5 components is used as a feature vector to classify the state into "cooking" or "not-cooking" for the proposed method.

C. SVM Classification

SVM [3] is one of the popular supervised learning methods used to perform classification. SVM can be applied to a non-linear classification with a kernel trick,

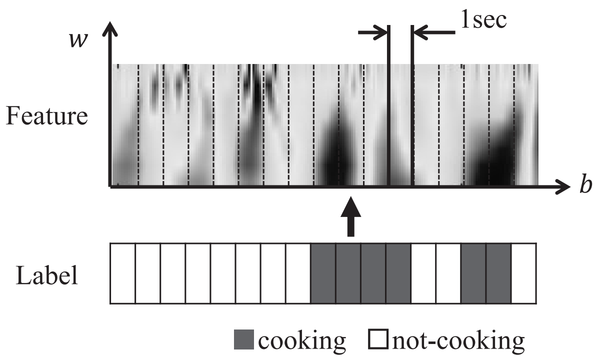

Figure 5. Classification by SVM

which is a technique to map implicitly input feature vectors into high-dimensional feature spaces.

Figure 5 illustrates a training dataset used in the proposed method. The feature vectors discussed above are calculated for every second, and are drawn in the Feature graph.In Figure 5, the color tone indicates the strength of the components for every scale *w*. The labels "cooking" or "not-cooking" are generated manually in advance. The labels, shown in the Label graph, are related to the feature vectors for generating a training dataset. SVM is trained with the training dataset consisting of pairs of the feature vectors and its labels.

D. Post processing to specify the cooking period

In the classification results, the series includes frequent alternation between cooking and not-cooking phases, over a period of several minutes. When a pot is used, however, the cooking phase is usually longer than 10 minutes. Accordingly, frequent alternations within a period of several minutes should be removed, because they are likely to be caused by classification errors. Erosion and dilation processing, shown in Figure 6, contributes to reduction of such alternations. The erosion processing extends the duration of cooking and the dilation processing shortens it. After the erosion and dilation, any small gaps between cooking states are filled as a cooking state.

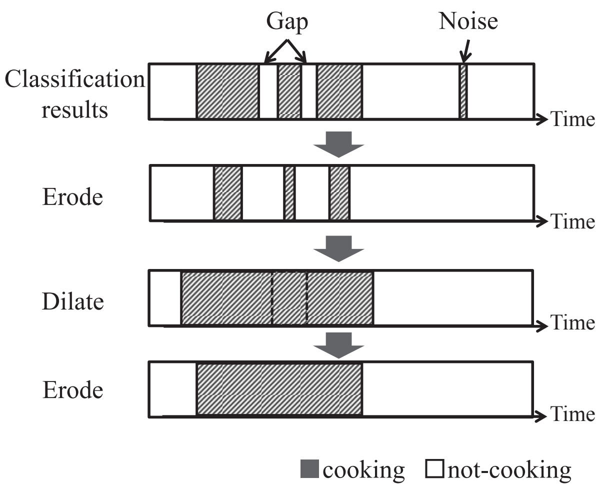

Figure 6. Post processing classification

IV. Experiment

A. Dataset

We conducted an experiment to evaluate the accuracy of the proposed method. Figure 7 shows the experiment setup. A digital thermometer DS18B20 was used to collect temperature data. This sensor can measure temperatures from -55°C to +125°C, with an error of less than ±0.5°C. An aluminum pot and a portable cooking stove were used for cooking. The cooking processes were carried out from steps 1 to 5, as defined in Chapter 2. The process finished in 10 minutes, on average. The not-cooking periods, between every two cooking periods, were based on steps 6 and 7. The temperature was measured by the thermometer during all of the steps. 28 cooking processes were carried out over 24 hours. The collected temperature data (called the *evaluation dataset* hereafter) was gathered into a dataset to evaluate the accuracy of the proposed method.

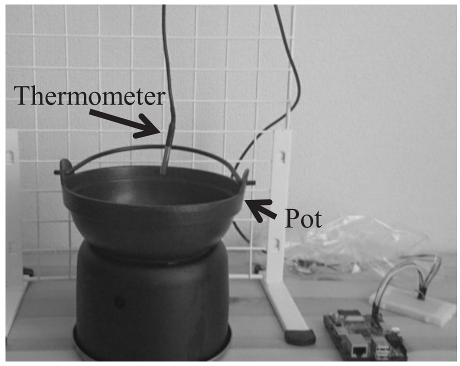

Figure 7. Experiment setup

B. Evaluation procedure

An accuracy evaluation was carried out along a cross-validation-like procedure. First, the evaluation dataset was divided into 7 blocks, which include 4 cooking periods. Next, one block was used for training, while the others were used for testing. This test was carried out for all settings. That is, the test was repeated 7 times, with changes to the training data and test data. The average period of the divided time series data was 210 minutes, with a minimum of 90 minutes and a maximum of 235 minutes. The accuracy was calculated by the number of correct and incorrect classifications. In this experiment, a correct classification was defined as one in which the error in the predicted start time and end time of each cooking period was less than 3 minutes. Additionally, the precision of the start time and end time of correctly classified results was also evaluated.

The proposed method uses feature vectors consisting of 5 wavelet transformation components. For comparison, three different versions using feature vectors consisting of 2 components were also tested. The first one consisted of w=15 and w=25 (called "type A"), the second was w=25 and w=625 (called "type B"), and the third was w=250 and w=625 (called "type C").

C. Results

Figure 8 plots the recall and precision rates of the experimental evaluation, where the recall rate and precision rate are defined as follows.

Recall rate:

$$= 100 \times \frac{\text{The number of correct cooking classification}}{\text{The number of all classified into cooking}} \quad (4)$$

Precision rate:

$$= 100 \times \frac{\text{The number of correct cooking classification}}{\text{The number of actual cooking phases}} \quad (5)$$

As shown in the figure, the proposed method using 5 dimensional feature vectors achieved the highest accuracy among all the methods. The F-measure of the proposed method was 85%, and the recall rate was 90%. Based on the results, we could confirm that the proposed method can detect cooking phases, with few missing.

Figure 9 plots a histogram of the differences between the actual and predicted start/end times. The horizontal axis is the time differences between actual and predicted times. The vertical axis is frequency. The time difference is 0 when the start time is completely correct. The time difference is negative when the predicted time is earlier than the actual time. The time difference is positive when the predicted time is later than the actual time. As shown in Figure 9, the predicted start times tend to be earlier by 60 to 120 seconds. A wavelet transformation causes such an error on the border between cooking and not-cooking phases because the wavelet transformation extracts feature vectors by using data from around the target period.

Figure 10 shows examples of misclassified temperature data. The horizontal axis is time, and the vertical axis is temperature. The lower fields in the graph indicate the predicted results. The filled region indicates “cooking” and the non-filled region indicates “not-cooking”. Figure 10 (a) is an example of one cooking period being recognized as two cooking periods. In this case, step 4 in the cooking procedure was delayed and, as a result of the gap, steps 1 to 3 and steps 4 and 5 were recognized as being separate. (b) is an example of a not-cooking period being misclassified into a cooking period. In this case, a few dishes were reheated. This misclassification occurred because the obtained signal including sharp fluctuations was quite similar to a pattern frequently observed during cooking. To reduce such types of misclassifications, the entire sequence pattern of cooking (the overall procedure of steps 1 to 5) should be taken into account. For example, a future approach could be to apply HMM (Hidden Markov Model) to the problem.

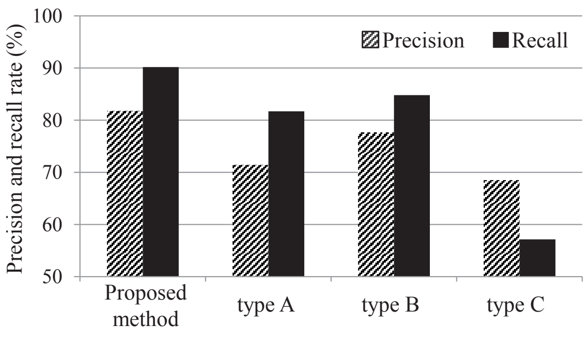

Figure 8. Precision and recall rate for state classification

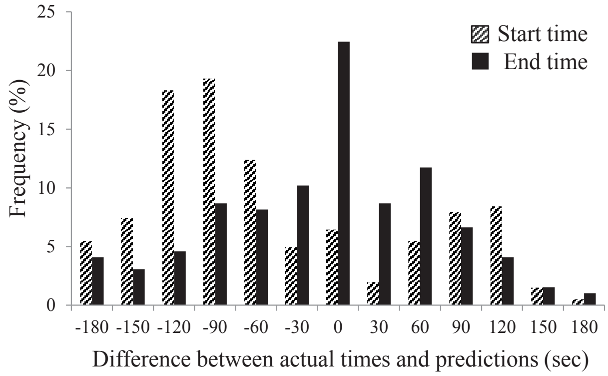

Figure 9. Differences between actual start/end times and predictions

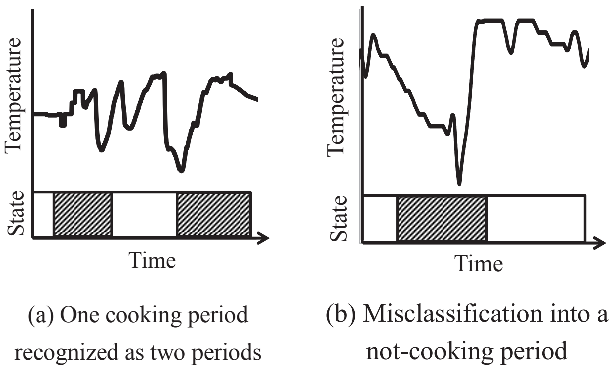

Figure 10. Examples of misclassified temperature data

V. CONCLUTION AND FUTURE WORK

This paper proposed a method to detect cooking periods from pot temperatures in a time series. The proposed method is based on wavelet transformation and SVM. The wavelet transformation generates feature vectors, and SVM then classifies every second into “cooking” or “not-cooking” states. As post processing, erosion and dilation processing was applied to reduce frequent alternations. By experiment, the precision of the proposed method was determined to be 85%.

The proposed method does not handle the time series as a sequence. This causes some types of errors. To avoid such problems, a future approach will be to handle sequences by applying HMM.

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